frontiers | Research Topics

Multilevel medical security systems and big data in healthcare: trends and developments, volume II

Edited by
Fei Fan and Siqin Wang

Published in
Frontiers in Public Health

ISSN 1664-8714
ISBN 978-2-8325-6716-6
DOI 10.3389/978-2-8325-6716-6

Generative AI statement
Any alternative text (Alt text) provided alongside figures in the articles in this ebook has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

About Frontiers

Frontiers is more than just an open access publisher of scholarly articles: it is a pioneering approach to the world of academia, radically improving the way scholarly research is managed. The grand vision of Frontiers is a world where all people have an equal opportunity to seek, share and generate knowledge. Frontiers provides immediate and permanent online open access to all its publications, but this alone is not enough to realize our grand goals.

Frontiers journal series

The Frontiers journal series is a multi-tier and interdisciplinary set of open-access, online journals, promising a paradigm shift from the current review, selection and dissemination processes in academic publishing. All Frontiers journals are driven by researchers for researchers; therefore, they constitute a service to the scholarly community. At the same time, the *Frontiers journal series* operates on a revolutionary invention, the tiered publishing system, initially addressing specific communities of scholars, and gradually climbing up to broader public understanding, thus serving the interests of the lay society, too.

Dedication to quality

Each Frontiers article is a landmark of the highest quality, thanks to genuinely collaborative interactions between authors and review editors, who include some of the world's best academicians. Research must be certified by peers before entering a stream of knowledge that may eventually reach the public - and shape society; therefore, Frontiers only applies the most rigorous and unbiased reviews. Frontiers revolutionizes research publishing by freely delivering the most outstanding research, evaluated with no bias from both the academic and social point of view. By applying the most advanced information technologies, Frontiers is catapulting scholarly publishing into a new generation.

What are Frontiers Research Topics?

Frontiers Research Topics are very popular trademarks of the *Frontiers journals series*: they are collections of at least ten articles, all centered on a particular subject. With their unique mix of varied contributions from Original Research to Review Articles, Frontiers Research Topics unify the most influential researchers, the latest key findings and historical advances in a hot research area.

Find out more on how to host your own Frontiers Research Topic or contribute to one as an author by contacting the Frontiers editorial office: frontiersin.org/about/contact

Multilevel medical security systems and big data in healthcare: trends and developments, volume II

Topic editors
Fei Fan — Wuhan University, China
Siqin Wang — The University of Queensland, Australia

Citation
Fan, F., Wang, S., eds. (2025). *Multilevel medical security systems and big data in healthcare: trends and developments, volume II*. Lausanne: Frontiers Media SA.
doi: 10.3389/978-2-8325-6716-6

Table of contents

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 03 September 2024
DOI 10.3389/fpubh.2024.1367447

Check for updates

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Vishnunarayan Girishan Prabhu,
University of North Carolina at Charlotte, United States
Eugenio Martelli,
Sapienza University of Rome, Italy

*CORRESPONDENCE
Martina Holá
✉ holamar4@fbmi.cvut.cz;
✉ martina22.hola@seznam.cz

RECEIVED 08 January 2024
ACCEPTED 19 August 2024
PUBLISHED 03 September 2024

CITATION
Kamenský V, Rogalewicz V, Gajdoš O, Donin G, Mašková B, Holá M and Tichopád A (2024) Cost-effectiveness of diagnostic imaging modalities in symptomatic patients with lower limb peripheral arterial disease: discrete event simulation model. *Front. Public Health* 12:1367447.
doi: 10.3389/fpubh.2024.1367447

Cost-effectiveness of diagnostic imaging modalities in symptomatic patients with lower limb peripheral arterial disease: discrete event simulation model

Vojtěch Kamenský, Vladimír Rogalewicz, Ondřej Gajdoš, Gleb Donin, Barbora Mašková, Martina Holá* and Aleš Tichopád

Department of Biomedical Technology, Faculty of Biomedical Engineering, Czech Technical University in Prague, Prague, Czechia

Objective: Lower limb peripheral arterial disease in the symptomatic stage has a significant effect on patients´ functional disability. Before an intervention, an imaging diagnostic examination is necessary to determine the extent of the disability. This study evaluates cost-effectiveness of duplex ultrasonography (DUS), digital subtraction angiography (DSA), computed tomography angiography (CTA) and magnetic resonance angiography (MRA) in the diagnostics of symptomatic patients with lower limb peripheral arterial disease indicated for endovascular or surgical intervention.

Methods: Discrete event simulation was used to capture lifetime costs and effects. Costs were calculated from the perspective of the health care payer, and the effects were calculated as quality-adjusted life year's (QALY's). The cost-effectiveness analysis was performed to pairwise compare CTA, MRA and DSA with DUS as the baseline diagnostic modality. A scenario analysis and probabilistic sensitivity analysis were carried out to evaluate the robustness of the results.

Results: In the basic case, the DUS diagnostic was the least expensive modality, at a cost of EUR 10,778, compared with EUR 10,804 for CTA, EUR 11,184 for MRA, and EUR 11,460 for DSA. The effects of DUS were estimated at 5.542 QALYs compared with 5.554 QALYs for both CTA and MRA, and 5.562 QALYs for DSA. The final incremental cost-effectiveness ratio (ICER) value of all evaluated modalities was below the cost-effectiveness threshold whereas CTA has the lowest ICER of EUR 2,167 per QALY. However, the results were associated with a large degree of uncertainty, because iterations were spread across all cost-effectiveness quadrants in the probabilistic sensitivity analysis.

Conclusion: For imaging diagnosis of symptomatic patients with lower limb peripheral arterial disease, CTA examination appears to be the most cost-effective strategy with the best ICER value. Baseline diagnostics of the DUS modality has the lowest costs, but also the lowest effects. DSA achieves the highest QALYs, but it is associated with the highest costs.

KEYWORDS

discrete event simulation, cost-effectiveness, diagnostic modalities, symptomatic lower limb peripheral disease, lifetime costs and effects

1 Introduction

The study evaluates atherosclerotic disease of lower limb arteries, which can cause partial or complete obstruction of the peripheral artery (1). In developed countries, it is estimated that the prevalence of the peripheral arterial disease (PAD) is between 3 and 10% in the population over 50 years of age, while it rises to 15–20% in the population over 70 years (2).

The disease can manifest with a variety of clinical symptoms ranging from asymptomatic patients to intermittent claudication (IC), or chronic limb-threatening ischemia (CLTI) with possible ulcerations and gangrene (3). Most patients with confirmed lower limb PAD do not have classic symptoms like claudication, but other limb symptoms, or are asymptomatic (4, 5). However, symptomatic patients have significant functional impairment. Claudication is defined as pain in the calf area (it can also appear in the thigh or buttocks) when walking, which does not stop during walking and does not appear when the patient sits or stands. The pain thus forces patients to slow down or stop walking (4, 6).

According to the Inter-Society Consensus for the Management of Peripheral Arterial Disease (TASC II) (2), the prevalence of IC is around 6% in the population of 60-year-old patients. Focusing on the occurrence of IC in patients with low ankle-brachial index (ABI) values, Fowkes et al. (3) mention the results of The Copenhagen City Heart Study, where they found a prevalence of 31% in the 65–74 age group. The authors further state that the prevalence of IC decreases in older age groups, which is probably caused by less mobility of these patients. The prevalence of IC is higher in men than in women.

Patients with IC are limited in physical activities (especially walking), and the goal of their therapy is therefore to provide relief from the pain symptoms associated with IC. The primary treatment approach is structured exercise therapy and pharmacotherapy to modify risk factors and reduce the risk of cardiovascular morbidity and mortality (2). If the patient does not respond to the exercise therapy, revascularization treatment is indicated for patients based on information from imaging methods (2, 4, 6).

Commonly used imaging methods include duplex ultrasonography (DUS), digital subtraction angiography (DSA), computed tomography angiography (CTA), and magnetic resonance angiography (MRA). The choice of the diagnostic modality should be based on patient's characteristics and the expected size and nature of the impairment. Methods such as CTA and MRA can provide a 3D image of the examined area, whereas DSA only provides a 2D image. Similarly, DUS has limited imaging options, but it is an accessible examination without the use of ionizing radiation and at low cost (7).

There are different diagnostic modalities with different advantages and disadvantages and with different costs associated with the examination. The objective of this study is to evaluate the cost-effectiveness of DUS, DSA, CTA and MRA in the diagnosis of symptomatic patients with lower limb peripheral arterial disease indicated for endovascular or surgical intervention.

2 Materials and methods

Previously published discrete event simulation model (8) [used to evaluate cost effectiveness of lower limb PAD screening with measurement of ankle-brachial index (ABI) in asymptomatic patients] was used to evaluate different diagnostic modalities in symptomatic patients. The simulation was carried out during the first half of the year 2022. The model was created using the R programming language in the RStudio software environment (9).

Input data are considered for the femoro-popliteal vessels, particularly for the superficial femoral artery, if data are available. The model does not evaluate the occurrence of disease in other vessels of the limb or the occurrence of disease in the contralateral limb. The clinical states considered in the model are presented in Figure 1.

The model simulates IC, CLTI, limb amputation, patient death and, in case of successful treatment, asymptomatic condition. The sensitivity of diagnostic methods is simulated for diagnostic tests, technical success, 30-day morbidity and mortality are simulated for treatment intervention, primary patency time is simulated for successful intervention, and secondary patency time is simulated for repeated intervention. For limb amputation, the type of amputation (above/below the knee) is simulated. Different time of death of patients is simulated for different stages of the disease. The following text summarizes the structure and logic of the model and describes, in more detail, the input parameters, assumptions and the different model setting related to the evaluated diagnostic modalities. More detailed settings of other parameters are presented in Supplementary Table 1.

Compared to our former study (8), the patients did not enter the model in an asymptomatic state, and therefore they were not indicated for a screening examination. Symptomatic patients are simulated at beginning of the simulation – patients enter the model with IC or CLTI and with both limbs, but a limb may be amputated during the simulation. Since patients with lower limb symptoms are simulated, it is assumed that all patients were indicated for a diagnostic examination. In the baseline scenario, all patients are assumed to have already received pharmacological treatment. Furthermore, the model is set up in such a way that patients with the disease in the stage IIa or IIb do not undergo exercise therapy and are immediately referred for diagnosis and subsequent interventional treatment (although the first line treatment for these patients is the exercise therapy).

A cohort of 66-year-old patients was simulated with a gender distribution according to the 2021 data of the Czech Statistical Office for the simulated age group (47.2% men) (10). The cohort size was determined based on IC and CLTI prevalence data for this age group. The prevalence of IC was determined according to the information provided in the TASC II recommendation (2), and the prevalence of CLTI according to the publication by Fowkes et al. (3). A cohort of 9,546 patients (7,955 with IC and 1,591 with CLTI) was simulated from the total population of 66-year-olds of a size of 132,576 persons assuming the IC prevalence of 6% and the CLTI prevalence of 1.2% (2, 3).

To compare the diagnostic modalities, the same cohort of patients was always simulated (using the same pseudorandom numbers), where the model settings differed only in which diagnostic examination the patients were referred for. The sensitivity values of the diagnostic modalities are shown in Table 1 and were taken from published papers (6, 7). Different values for IC and CLTI were not considered in the model. In the case of a negative result of the diagnostic examination, the patient of classification III or IV [according to the Fontain classification (11)] was sent to another diagnostic examination. In the case of stage IIa or IIb, the patient should undergo a repeated diagnostic examination after a year.

All patients with a positive diagnostic result are indicated for a therapeutic intervention. The technical success and the 30-day postoperative mortality and morbidity are simulated for each

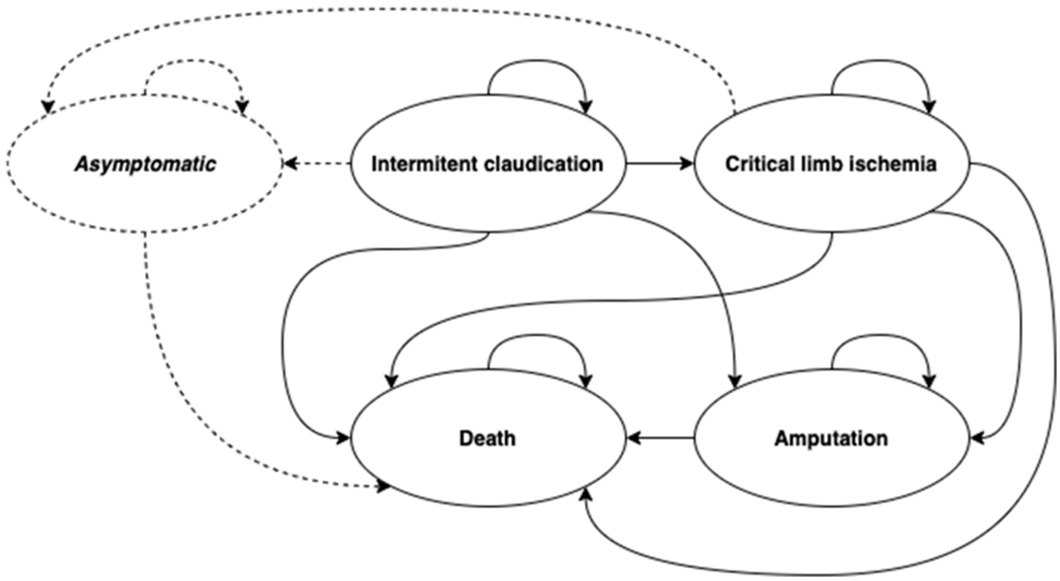

FIGURE 1
Model structure and transitions between health states.

TABLE 1 Sensitivity inputs for diagnostic modalities.

Diagnostic modality	Sensitivity	Sensitivity analysis	Source
DUS	86%	beta (2.03; 0.06)	(6)
DSA	100%	beta (12.13; 1.81)	(7)
CTA	96%	beta (3.04; 0.13)	(6)
MRA	96%	beta (3.04; 0.13)	(6)

DUS, duplex ultrasonography; DSA, digital subtraction angiography; CTA, computed tomography angiography; MRA, magnetic resonance angiography.

intervention. In the case of a technical success, the time of vessel patency is simulated (primary for the first successful intervention and secondary for the second successful intervention) during which the patient is in an asymptomatic state. In the case of a technical failure, the patient is indicated for a repeated intervention. A model patient can undergo a maximum of two successful interventions; in the case of two consecutive technical failures, it is assumed that the patient cannot undergo any further interventional therapy. In the case of repeated interventions, for any reason, a part of the patients are simulated unsuitable for reoperation.

The model considers the percutaneous transluminal angioplasty (PTA and PTA/S) treatment interventions and the bypass surgery. The model does not distinguish whether it is PTA with a drug-eluting balloon or with an uncoated balloon, and in the case of stent implantation, it is not distinguished what type of stent is used (plain metal stents, drug-coated stents, etc.). In the bypass surgery, a distinction is made between the treatment using an autologous vessel, and that using an artificial vascular prosthesis. In the case of an artificial vascular prosthesis, its type is not distinguished as well. Intervention outcome data were simulated separately for the populations of IC and CLTI patients, provided appropriate clinical evidence was available. If evidence was not available separately for IC and CLTI, the same values were considered for both subpopulations. The assignment to the type of intervention therapy is random in the model. The setting of parameters for simulation of transition times between states are the same as in Kamenský et al. (8) More detailed parameter settings are shown in Supplementary Table 1.

Limb amputation may occur during the simulation; the model distinguishes the below-knee and above-knee amputations (which affects the utility value and the cost of amputation). The states that the patient is going through affect the time to the occurrence of the patient's death. To maintain consistency, the procedure proposed by Corro Ramos et al. (12) is used in the study, so that there is no increase in time to occurring of the event. Remaining life expectancy must be adjusted for the time elapsed since the simulation started and any changes in the patient's condition. This adjustment is made by calculating the ratio of the expected life expectancy at baseline using updated values at time of event and expected life expectancy at baseline using baseline values. This ratio reflects any improvement or deterioration in the patient's health status over time.

The costs were simulated from the perspective of a health care payer (a health insurance company). All costs were converted from CZK to EUR at the average exchange rate for Q2 2022 (24.64 CZK per EUR 1). Only direct medical costs were considered. In the baseline scenario, costs were discounted at the rate of 3%. The effect of other discount rates (0 and 5%) was analysed in the sensitivity analysis (see below). Table 2 summarizes the costs associated with the studied diagnostic modalities (incl. Their sources). All other costs considered in the model are listed in Supplementary Table S2.

Since the model, in the basic scenario, only simulates disability of one limb and one segment based on the data on the duration of the examination taken from the studies by Di Minno et al. (13) and Pollak et al. (7) (5–15 min for CTA, 20–30 min for MRA, 30 min for DSA, 30–45 min for DUS), the costs are calculated for one medical procedure (even if it is possible to repeat the medical procedure in a single day). CTA, MRA and DSA examinations require an application of a contrast agent. Available contrast agents, their recommended dosage according to the Summary of Product Characteristics (SPC),

TABLE 2 Cost input data for modeling diagnostic modalities.

Diagnostic modality	Costs [EUR]	Sensitivity analysis	Cost of contrast agents [EUR]	Source
DUS	47	Uniform distribution with parameter variation ±20%	–	(32)
DSA	416		6	(32, 33)
CTA	64		36	(32, 33)
MRA	259		35	(32, 33)

DUS, duplex ultrasonography; DSA, digital subtraction angiography; CTA, computed tomography angiography; MRA, magnetic resonance angiography.

TABLE 3 Utility values for health states (used as the model inputs).

Health state	Utility	Sensitivity analysis	Source
Asymptomatic 66–74 years	0.89	beta (10.11; 1.25)	(34)
Asymptomatic 75+ years	0.84	beta (15.16; 2.89)	(34)
IC (Fontaine class IIa)	0.63	beta (36.37; 21.36)	(35)
IC (Fontaine class IIb)	0.52	beta (47.48; 43.83)	(35)
CLTI (Fontaine class III)	0.44	beta (55.56; 70.71)	(35)
CLTI (Fontaine class IV)	0.40	beta (59.60; 89.40)	(35)
Below-knee amputation	0.61	beta (38,0.9; 24.54)	(36)
Above-knee amputation	0.40	beta (79.80; 319.20)	(36)

IC, intermittent claudication; CLTI, chronic limb-threatening ischemia.

and their reimbursement were found in the database of the national regulator, the State Institute for Drug Control (SUKL) (14). The dosage depends on the area of use and on the patient's body weight. In the basic scenario, a patient of 70 kg was considered (for both men and women).

The evaluated effect is QALY. The underlying utility values were taken from studies using the EQ-5D questionnaire, and are the same as in Table 3 (8).

ICER ratio is used to evaluate the cost effectiveness. This parameter is calculated assuming average lifetime costs and effects for the simulated cohort of patients. Based on the recommendations of the State Institute for Drug Control, the value of EUR 48,700 per QALY (CZK 1.2 million per QALY) is considered to be the cost-effectiveness (sometimes called willingness-to-pay) threshold (14).

When evaluating the validity of the model, face validity, internal validity, and cross validity were evaluated based on the ISPOR-SMDM recommendations (15). Face validity was confirmed through consultation with a cardiology expert. The model's structure and assumptions were reviewed by clinicians and compared with other lower limb PAD models. Health technology assessment experts validated the study's aim, modeling techniques, and cost analysis. A co-author, experienced with R but not involved in coding, assessed internal validity by verifying the simulation scripts and results. Cross validity was ensured by comparing the model's structure with other lower limb PAD models. Furthermore, probabilistic sensitivity analysis, two-way deterministic sensitivity analysis and scenario analysis were performed to evaluate the robustness of the results based on ISPOR-SMDM recommendations (16). In the probabilistic sensitivity analysis, 1,000 iterations were simulated using the same pseudorandom numbers as in the baseline scenario, but the input parameters were changed based on pre-defined probability distributions [a detailed information on setting the parameters can be found in (8) and Supplementary materials], cost and effect differences are presented with 95% confidence interval (CI). In the analysis of the scenarios, the effect of the choice of the particular discount rate was evaluated; the effect of combining diagnostic DSAs with an interventional procedure; indications for pharmacological treatment after confirmation of the diagnosis using evaluated diagnostic modalities.

3 Results

The resulting modeled values of lifetime costs and effects for all compared interventions assuming the basic scenario are shown in Table 4. DUS, the intervention with the lowest lifetime costs, is used as the baseline for comparisons (expressed as differences). The differences between the effects of the evaluated therapies are quite small, which is probably due to the comparable median survival of patients (around 8.51 years for all diagnostic modalities).

The DSA examination was the most expensive diagnostic modality, and it is also associated with the highest effects in the form of QALYs. CTA and MRA were comparable in terms of effects, but the CTA examination is less expensive than MRA. CTA has the lowest ICER value (EUR 2,167 per QALY). All ICER values are below SUKL's recommended cost-effectiveness thresholds (approx. EUR 48,700 per QALY).

If we compare the other diagnostic modalities with each other, the ICER for DSA compared to CTA is EUR 82,000 per QALY, and therefore DSA compared to CTA is not a cost-effective strategy. When comparing DSA with MRA, the ICER (EUR 34,500 per QALY) value is below the considered cost-effectiveness threshold. Since MRA and CTA bring the same effect, they can be compared only according to their price, which prioritizes CTA.

Figure 2 shows results of the probabilistic sensitivity analysis comparing CTA and DUS. In part A, we can see that the results of individual iterations are spread across all cost-effectiveness quadrants. Most of the iterations lie either in the upper right quadrant (the ICER values are below the cost-effectiveness threshold) or in the lower right quadrant, where CTA is more effective and less costly than DUS. The average cost difference between the compared strategies using 3% discounting is EUR 60 (95% CI EUR 50.5, 69.0). The average difference in effects is 0.0154 QALYs (95% CI 0.0116, 0.0192 QALYs), and the ICER value is EUR 3,881 per QALY. This value is close to the baseline scenario result. In part B of the figure, we can see that if the cost-effectiveness threshold was reduced to EUR 40,500 per QALY, around 65% of the results would still be cost-effective. The CTA curve does not rise further when the cost-effectiveness threshold is increased, because part of the iterations is in the upper left quadrant, where CTA

TABLE 4 Cost-effectiveness of evaluated diagnostic modalities, results of the base case scenario.

Diagnostic modality	Costs [EUR]	Cost difference [EUR]	Effects [QALY]	Effect difference [QALY]	ICER [EUR per QALY]
DUS	10,778	–	5.542	–	–
CTA	10,804	26	5.554	0.012	2,167
MRA	11,184	406	5.554	0.012	33,833
DSA	11,460	682	5.562	0.020	34,100

DUS, duplex ultrasonography; DSA, digital subtraction angiography; CTA, computed tomography angiography; MRA, magnetic resonance angiography; QALY, quality adjusted life years; ICER, incremental cost effectiveness ratio.

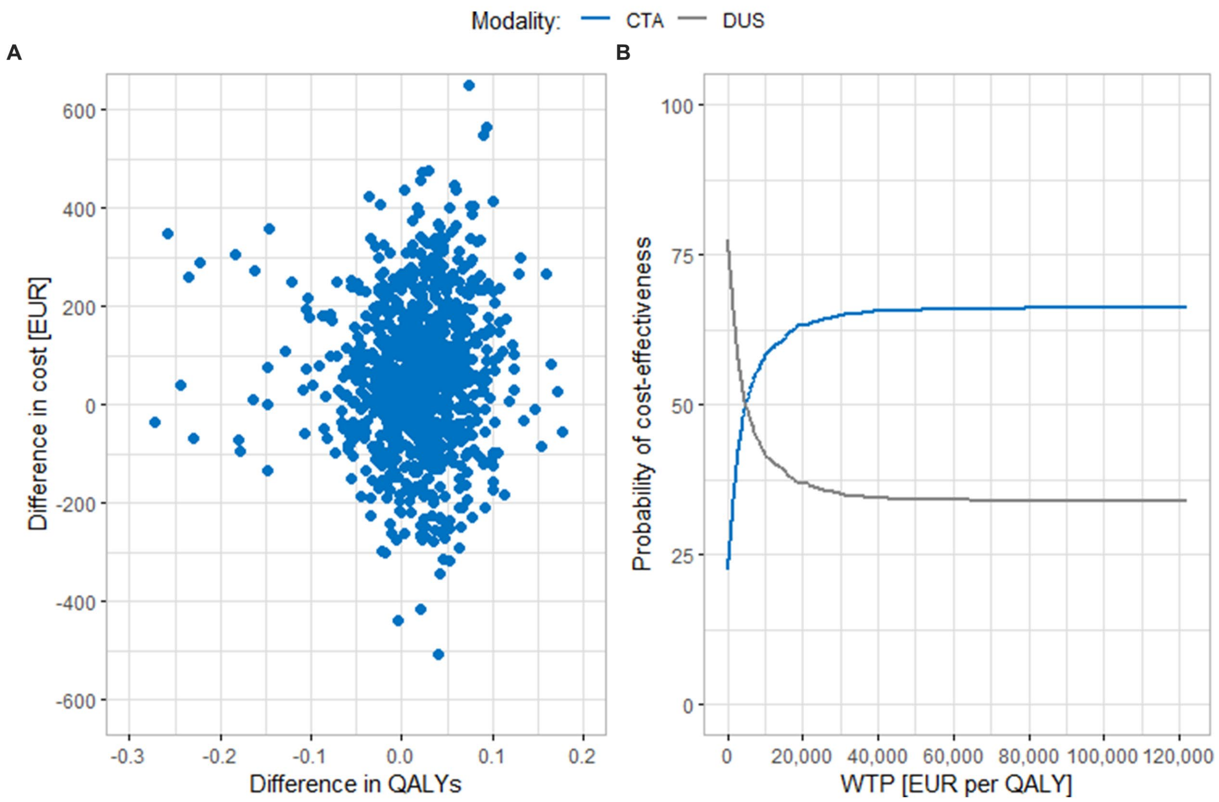

FIGURE 2
Results of the probabilistic sensitivity analysis comparing CTA and DUS. **(A)** Scatter plot of simulation results. **(B)** Cost-effectiveness acceptability curve. CTA, computed tomography angiography; DUS, duplex ultrasonography; QALY, quality adjusted life years; WTP, willingness to pay.

is a less effective and more costly modality and DUS is the dominant intervention.

Figure 3 shows results of a similar comparison of MRA and DUS. In this case, a large part of the results turn out to be in the upper right quadrant, where MRA is a more expensive, but also more effective diagnostic modality, and also in the upper left quadrant, where MRA is a more expensive and less effective strategy. This fact is also evident in part B of the figure; if the cost-effectiveness threshold is increased up to EUR 122,000 per QALY, only 63% of iterations are cost-effective. The average cost difference is EUR 270 (95% CI EUR 260.7, 279.9), and the average effect difference is 0.0078 QALY (95% CI 0.0042, 0.0113 QALYs). The value of the ICER is thus EUR 34,904 per QALY, which is below the cost-effectiveness threshold.

Figure 4 shows results of a comparison between DSA and DUS. Similar to MRA, most results are in the upper right or upper left quadrants. These findings also correspond to the results of the base scenario, MRA and DSA have similar ICER values. In part B of the figure, we can see that, like in the case of MRA, even if the WTP threshold increases, the curve does not rise further, and only around 65% of the results are cost-effective at the level of EUR 122,000 per QALY. In the sensitivity analysis, the average difference both in costs and in effects is lower than in the base scenario [EUR 392 (95% CI EUR 380.1, 404.2) and 0.0154 QALY (95% CI 0.0116, 0.0192 QALYs), respectively]. The value of the ICER is thus EUR 25,462 per QALY, which is also a lower value than in the base scenario.

When simulating a scenario where a part of the patients are treated with endovascular treatment as part of the DSA diagnostic examination, the total average cost per patient for this type of diagnosis decreases. This is because the cost of DSA is included in the cost of endovascular treatment for these patients. If 50% of

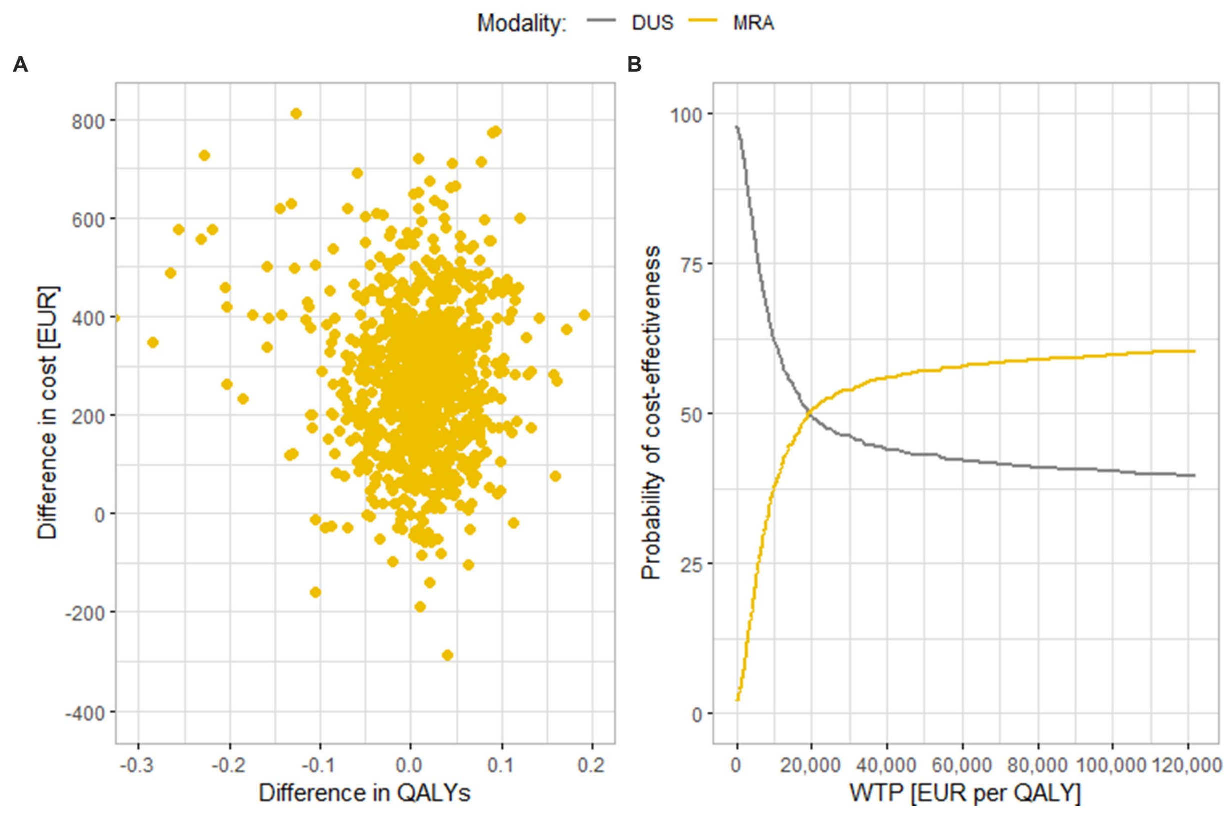

FIGURE 3
Results of the probabilistic sensitivity analysis comparing **(A)** Scatter plot of simulation results. **(B)** Cost-effectiveness acceptability curve. MRA and DUS. MRA, magnetic resonance angiography; DUS, duplex ultrasonography; QALY, quality adjusted life years; WTP, willingness to pay.

patients were treated with PTA or PTA/S right at the time of diagnosis, the DSA strategy would become the least costly and remain the most effective therapy as in the baseline scenario. In this case, the DSA is the dominant strategy over all other diagnostic modalities. If at least 25% of patients underwent a combined diagnostic and therapeutic procedure, the average costs would reach the level of average costs of MRA (EUR 11,165 vs. 11,184). The ICER value, when compared to DUS, would fall to EUR 19,350 per QALY, and compared to CTA to EUR 45,125, which is below the cost-effectiveness threshold of EUR 48,700 per QALY.

Considering alternative discount rates of 0 and 5% for sensitivity testing, the order of diagnostic modalities by costs remains the same. At the 0% discount rate, CTA is again a cost-effective diagnostic modality thanks to the ICER value of EUR 2,353 per QALY, while MRA and DSA can no longer be considered cost-effective (ICER values being EUR 61,618 per QALY and EUR 49,510 per QALY, respectively). In contrast, for MRA and DSA in particular, the 5% discount rate reduced the ICER values, and as in the baseline scenario with the 3% discount rate, the values are below the cost-effectiveness threshold. The scenario with indication of the pharmacotherapy only after a diagnostic examination with positive result had the effect of increasing the ICER values for all evaluated diagnostic modalities, but all ICER values stayed below the cost-effectiveness threshold. The increase in the ICER values is mainly due to the change in costs, where the largest decrease is for DUS, because this modality has the least sensitivity. The model values for individual scenarios are shown in Table 5.

4 Discussion

At present, various recommendations for selecting diagnostic modalities in symptomatic patients with atherosclerotic disease of the lower limb arteries are not uniform. In many cases, the choice between modalities is determined primarily by the physician's preference or the local availability of the technology (17). The ability to predict whether (and how much) a patient will benefit from the treatment can support the physician's decision on individual treatment. Improvements may occur through clinical outcomes or, for example, through reduction of unnecessary exposure to X-ray radiation or other adverse effects. In addition to monitoring clinical and patient outcomes, it is also necessary to evaluate the economic part of diagnostic technologies.

The use of modeling techniques appears to be a suitable approach for a comprehensive evaluation. Based on an analysis of published studies, the models appear to be often specifically aimed at solving particular research questions. When a model has been applied to a larger range of research problems, the published model has usually been adapted to address multiple research questions (18). In our study, a discrete event simulation (DES) model created to be used in solving several problems was applied to capture lifetime benefits and costs. The model was created based on the guidelines published by the

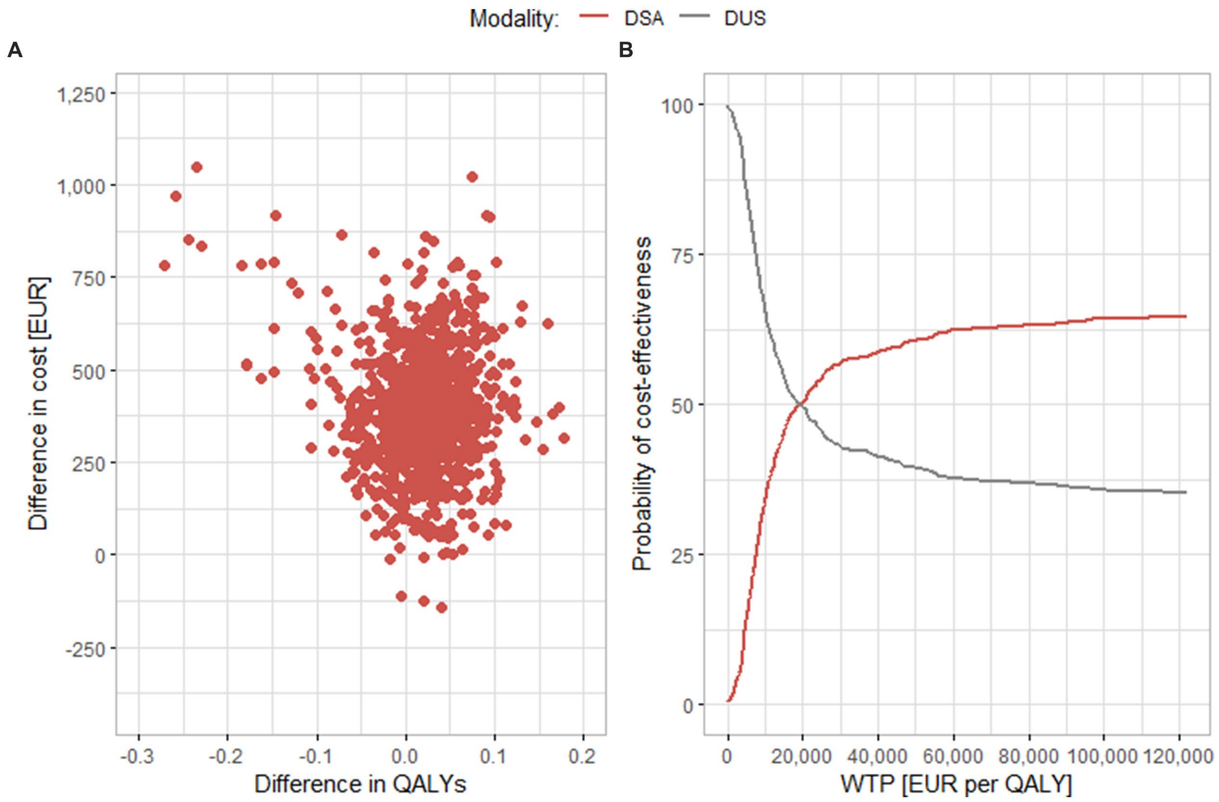

FIGURE 4
Results of the probabilistic sensitivity analysis comparing DSA and DUS. **(A)** Scatter plot of simulation results. **(B)** Cost-effectiveness acceptability curve. DSA, digital substraction angiography; DUS, duplex ultrasonography; QALY, quality adjusted life years; WTP, willingness to pay.

TABLE 5 Results of scenario analysis.

Diagnostic modality	Costs [EUR]	Cost difference [EUR]	Effects [QALY]	Effect difference [QALY]	ICER [EUR per QALY]
0% discount rate scenario					
DUS	11,889	–	6.467	–	–
CTA	11,905	16	6.474	0.0068	2,353
MRA	12,308	419	6.474	0.0068	61,618
DSA	12,597	708	6.481	0.0143	49,510
5% discount rate scenario					
DUS	10,200	–	5.061	–	–
CTA	10,239	39	5.075	0.014	2,786
MRA	10,601	401	5.075	0.014	28,643
DSA	10,870	670	5.083	0.023	29,130
Scenario with the indication of pharmacotherapy after a successful diagnostic examination					
DUS	10,618	–	5.548	–	–
CTA	10,734	116	5.560	0.012	9,667
MRA	11,109	491	5.560	0.012	40,917
DSA	11,410	791	5.568	0.019	41,684

DUS, duplex ultrasonography; DSA, digital subtraction angiography; CTA, computed tomography angiography; MRA, magnetic resonance angiography; QALY, quality adjusted life years; ICER, incremental cost effectiveness ratio.

societies ESC/ESVC and AHA/ACC and information from professional literature (4, 6). Our objective was to create a sufficiently complex model so that a broad spectrum of research questions can be solved, and so that there is no need to create individual (often incompatible) models for individual research questions.

The structure of the model and its assumptions were validated in collaboration with physicians from the Department of Cardiology and Angiology of the General University Hospital in Prague. The structure of the model was compared with the structure of published models focussing on diagnosis of lower limb PAD (19–23). The scripts created using the R programming language were checked as a part of the internal validity assessment by a co-author of the study. The model has already been used by the same team to evaluate the effectiveness of screening using the ABI–measurements in asymptomatic patients (8). The results of that study were compared with the results published by Vaidya et al. (24), Itoga et al. (25), and Lindholt and Søgaard (26).

Published cost analyses of diagnostic modalities in some cases focus on immediate or short-term outcomes and provide information on the costs of a correct diagnosis. However, long-term effects of a correct timely diagnosis are just as important. Hence, for diagnostic technologies, it is appropriate to analyse their effect on the entire therapeutic process, morbidity, mortality, other clinical outcomes, and (long-term) costs (18, 27, 28). For these reasons, the study evaluated cost-effectiveness of diagnostic modalities in symptomatic patients before intervention.

In the basic scenario, all evaluated diagnostic modalities (CTA, MRA, DSA) were cost-effective if compared with the cheapest option, i.e., the DUS examination with the lifetime costs of EUR 10,778. The ICER values of the analysed diagnostic modalities were below the cost-effectiveness threshold recommended by the Czech national authority [EUR 48,700 per QALY (14)]. The most expensive, but at the same time the most effective diagnostic modality is the angiographic examination (DSA). The CT examination has the lowest ICER value (EUR 2,167 per QALY), while ICER values of MRA and DSA are comparable (EUR 33,838 per QALY and EUR 34,100 per QALY, resp.). Comparing CTA with the more expensive modalities MRA and DSA found that DSA is not cost-effective if compared to CTA (EUR 82,000 per QALY), and MRA has similar results if compared to DUS. According to the results of the basic scenario, we can say that the examination using CTA seems to be the best option, as it is associated with a good efficiency at acceptable costs, and its ICER value is at a low level.

Robustness of the results was assessed using the probabilistic sensitivity analysis. In most cases, the resulting values, when simulating 1,000 iterations, were in all cost-effectiveness quadrants. Compared to DUS, the diagnostic modalities CTA and DSA performed better than MRA, where we could consider approximately 60–65% of iterations cost-effective for both modalities (they were either in the upper-right or lower-right quadrants of the cost-effectiveness plane). However, this level was still reached in CTA under the cost-effectiveness threshold of EUR 40,500 per QALY, whereas in DSA it was reached only around a high threshold of EUR 61,000 per QALY.

Last but not least, it is important to mention that if the diagnostic examination using DSA is performed together with the subsequent endovascular intervention, it becomes a cost-effective strategy. Even with the combination of diagnostic examination and endovascular intervention in 25% of patients, the value of DSA compared with CTA falls below the cost-effectiveness threshold.

A literary review found several studies evaluating cost-effectiveness of diagnostic methods for lower limb PAD using modeling techniques. Some modeling studies focused on subpopulations, typically patients with diabetes mellitus, however, they show a great heterogeneity in settings and parameters considered, which limits their applicability and comparability. None of the models used DES modeling technique to evaluate cost-effectiveness of diagnostic modalities. Simpson et al. (29) applied it to evaluate cost-effectiveness of therapeutic interventions.

Some cost comparisons were published. Yin et al. (19) compared MRA with DSA, where the diagnosis using MRA was a more costly strategy, which contradicts the conclusions of our work. This fact may be mainly due to the date of the study (1995), or the reason can be a shorter time horizon of the evaluation (2 years). Visser et al. published several studies (20–22) focused on an assessment of diagnostic modalities. Similarly to our study, they evaluated lifetime cost-effectiveness of MRA, DSA and DUS (20). In contrast to our study, however, they analysed costs from the societal perspective. As in our study, the DSA modality proved to be the most effective, and DUS the least effective. Unlike our study, MRA was less expensive than DUS, which may be due to the different perspective and different financing of health services. Another study by Visser et al. (21) is more difficult to compare with the results of our study, because the authors combined a diagnostic modality with a possible method of treatment. However, the strategy with DSA (combined with PTA, PTA/S or exercise therapy) is again associated with the greatest effect.

Collins et al. (23) compared MRA, DUS and CTA. The authors found that MRA is the cheapest strategy in a short-term perspective, but DUS in a long-term (in this case 1 year) perspective. The conclusions from the long-term evaluation are thus in agreement with our study, DUS being determined the least expensive diagnostic modality. They published similar conclusions regarding costs in their study comparing DUS and DSA (and their combinations). As well as our work, they identified DSA to be a more costly but also the most effective strategy.

It is important to mention that the presented results are valid for the femoropopliteal segment. The conclusions may differ in other segments of the lower limb. However, modifying the model to solve questions for other areas of the lower limb is not difficult. This would consist mainly in an adjustment of values simulating the effectiveness of diagnostic modalities and therapies. In the case of diagnostic modalities, this would be an adjustment of the sensitivity of the individual compared modalities.

An extension of the model can be a simulation of the occurrence of other cardiovascular events. The higher mortality of patients with PAD is captured in the model, if lower survival values have been simulated in patients with the disease (depending on the degree of disability), but the model does not simulate occurrences of such events as myocardial infarctions or cerebrovascular accidents, provided the patient has survived and is treated. If diagnostic interventions are being compared, this assumption does not have a significant effect on cost-effectiveness results. The occurrence of cardiovascular events is generally not included in simulation models for cost-effectiveness assessment (19–23, 29–31). This is because symptomatic patients are mostly simulated in these models, who are assumed to be already treated to reduce risk factors, and the imaging diagnostic methods affect the decision on the type of treatment, not the occurrence of such events.

This may cause a small bias, but the effect is usually more significant in simulations of screening cost-effectiveness. With a positive screening result, it is assumed that the patient will also be treated to prevent the occurrence of further cardiovascular events such as myocardial infarction. The cost-effectiveness results of the ABI screening examination could be even more favorable because patients with early diagnosed lower limb PAD will have a lower incidence of these events, as they are treated with, e.g., pharmacological treatment.

Another limitation may be the use of randomized controlled trials for setting model parameters. The effectiveness of the considered diagnostic modalities may be lower in real practice. This limitation is partly suppressed thanks to the DES modeling technique, where individual results from diagnostic modalities are simulated for each patient, and also thanks to the sensitivity analysis, which provides us with information about the robustness of results and conclusions.

A limitation of using the DES modeling technique and creating a model that captures the disease in the widest possible scope is that the simulations are more computer–intensive. The simulation of larger populations can take several minutes, and when simulating a large population in a probabilistic sensitivity analysis with many iterations, we can need up to hours of simulation time. This problem can be constrained by parallel computing methods.

The proposed model can also be used for the needs of early-stage HTA. Similarly to the study by Visser et al. (21), it is possible to determine minimum values of sensitivity and costs of a new diagnostic modality in order it was cost-effective. Because the same methodological basis will be used that has already proven itself in the evaluation of existing diagnostic modalities, we can assume that relevant information for an eventual implementation of the new technology can be obtained before the design and development phase of the device is completed.

5 Conclusion

Since the model simulates the lifelong evolution of the disease from the manifestations of intermittent claudication to the death of the patient, it is possible to carry out long-term evaluations, and thus capture all possible impacts of the evaluated technologies. When comparing diagnostic modalities, DUS examination was determined as the modality with the lowest costs and DSA modality with the highest costs. In terms of QALY, however, DUS generated the least effects and DSA the greatest effects. From the cost-effectiveness point of view, the CTA examination appears to be the optimum strategy. The results of the cost-effectiveness assessment of diagnostic modalities are associated with a large degree of uncertainty, which was analysed using the probabilistic sensitivity analysis. The resulting cost-effectiveness values depend mainly on the considered sensitivity values of the diagnostic modalities.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

VK: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. VR: Funding acquisition, Project administration, Visualization, Writing – review & editing. OG: Formal analysis, Software, Visualization, Writing – review & editing. GD: Formal analysis, Visualization, Writing – review & editing. BM: Data curation, Investigation, Writing – review & editing. MH: Data curation, Visualization, Writing – review & editing. AT: Project administration, Writing – review & editing.

Funding

The author(s) declare financial support was received for the research, authorship, and/or publication of this article. This research was supported by an internal grant from Czech Technical University in Prague No. SGS22/133/OHK4/2 T/17; SGS24/153/OHK5/3T/17.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2024.1367447/full#supplementary-material

References

1. Criqui MH, Aboyans V. Epidemiology of peripheral artery disease. *Circ Res.* (2015) 116:1509–26. doi: 10.1161/CIRCRESAHA.116.303849

2. Norgren L, Hiatt WR, Dormandy JA, Nehler MR, Harris KA, Fowkes FGR. Inter-society consensus for the Management of Peripheral Arterial Disease (TASC II). *J Vasc Surg.* (2007) 45:S5–S67. doi: 10.1016/j.jvs.2006.12.037

3. Fowkes FGR, Aboyans V, Fowkes FJI, McDermott MM, Sampson UKA, Criqui MH. Peripheral artery disease: epidemiology and global perspectives. *Nat Rev Cardiol.* (2017) 14:156–70. doi: 10.1038/nrcardio.2016.179

4. Gerhard-Herman MD, Gornik HL, Barrett C, Barshes NR, Corriere MA, Drachman DE, et al. 2016 AHA/ACC guideline on the Management of Patients with

Lower Extremity Peripheral Artery Disease: executive summary: a report of the American College of Cardiology/American Heart Association task force on clinical practice guidelines. *Circulation*. (2017) 135:e686–725. doi: 10.1161/CIR.0000000000000470

5. Martelli E, Enea I, Zamboni M, Federici M, Bracale UM, Sangiorgi G, et al. Focus on the Most common Paucisymptomatic Vasculopathic population, from diagnosis to secondary prevention of complications. *Diagnostics*. (2023) 13:2356. doi: 10.3390/diagnostics13142356

6. Aboyans V, Ricco JB, Bartelink MLEL, Björck M, Brodmann M, Cohnert T, et al. 2017 ESC guidelines on the diagnosis and treatment of peripheral arterial diseases, in collaboration with the European Society for Vascular Surgery (ESVS). *Eur Heart J*. (2018) 39:763–816. doi: 10.1093/eurheartj/ehx095

7. Pollak AW, Norton PT, Kramer CM. Multimodality imaging of lower extremity peripheral arterial disease: current role and future directions. *Circ Cardiovasc Imaging*. (2012) 5:797–807. doi: 10.1161/CIRCIMAGING.111.970814

8. Kamenský V, Rogalewicz V, Gajdoš O, Donin G. Discrete event simulation model for cost-effectiveness evaluation of screening for asymptomatic patients with lower extremity arterial disease. *IJERPH*. (2022) 19:11792. doi: 10.3390/ijerph191811792

9. RStudio Team. RStudio: Integrated development environment for R [internet]. Boston: RStudio, PBC (2021).

10. ČSÚ - Věková struktura. Sčítání (2021). Available at: https://scitani.gov.cz/vekova-struktura

11. Fontaine R, Kim M, Kieny R. Surgical treatment of peripheral circulation disorders. *Helv Chir Acta*. (1954) 21:499–533.

12. Corro Ramos I, Hoogendoorn M, Rutten-van Mölken MPMH. How to address uncertainty in health economic discrete-event simulation models: an illustration for chronic obstructive pulmonary disease. *Med Decis Mak*. (2020) 40:619–32. doi: 10.1177/0272989X20932145

13. Di Minno G, Spadarella G, Cafaro G, Petitto M, Lupoli R, Di Minno A, et al. Systematic reviews and meta-analyses for more profitable strategies in peripheral artery disease. *Ann Med*. (2014) 46:475–89. doi: 10.3109/07853890.2014.932618

14. SP-CAU-028 - W: Postup pro posuzování analýzy nákladové efektivity. Státní Ústav pro Kontrolu Léčiv; (2022). Available at:https://www.sukl.cz/file/97943_1_1/download/

15. Eddy DM, Hollingworth W, Caro JJ, Tsevat J, McDonald KM, Wong JB. Model transparency and validation: a report of the ISPOR-SMDM modeling good research practices task force–7. *Med Decis Mak*. (2012) 32:733–43. doi: 10.1177/0272989X12454579

16. Briggs AH, Weinstein MC, Fenwick EAL, Karnon J, Sculpher MJ, Paltiel AD. Model parameter estimation and uncertainty analysis: a report of the ISPOR-SMDM modeling good research practices task force working group–6. *Med Decis Mak*. (2012) 32:722–32. doi: 10.1177/0272989X12458348

17. Bertoldi EG, Stella SF, Rohde LEP, Polanczyk CA. Cost-effectiveness of anatomical and functional test strategies for stable chest pain: public health perspective from a middle-income country. *BMJ Open*. (2017) 7:e012652. doi: 10.1136/bmjopen-2016-012652

18. Tappenden P, Chilcott J, Brennan A, Squires H, Stevenson M. Whole disease modeling to inform resource allocation decisions in Cancer: a methodological framework. *Value Health*. (2012) 15:1127–36. doi: 10.1016/j.jval.2012.07.008

19. Yin D, Baum RA, Carpenter JP, Langlotz CP, Pentecost MJ. Cost-effectiveness of MR angiography in cases of limb-threatening peripheral vascular disease. *Radiology*. (1995) 194:757–64. doi: 10.1148/radiology.194.3.7862975

20. Visser K, Kuntz KM, Donaldson MC, Scott Gazelle G, Hunink MGM. Pretreatment imaging workup for patients with intermittent claudication: a cost-effectiveness analysis. *J Vasc Interv Radiol*. (2003) 14:53–62. doi: 10.1097/01.RVI.0000052291.26939.82

21. Visser K, Kock MCJM, Kuntz KM, Donaldson MC, Gazelle GS, Myriam Hunink MG. Cost-effectiveness targets for multi–detector row CT angiography in the work-up of patients with intermittent claudication. *Radiology*. (2003) 227:647–56. doi: 10.1148/radiol.2273020441

22. Visser K, de Vries SO, Kitslaar PJEHM, van Engelshoven JMA, Hunink MGM. Cost-effectiveness of diagnostic imaging work-up and treatment for patients with intermittent claudication in the Netherlands. *Eur J Vasc Endovasc Surg*. (2003) 25:213–23. doi: 10.1053/ejvs.2002.1838

23. Collins R, Cranny G, Burch J, Aguiar-Ibáñez R, Craig D, Wright K, et al. A systematic review of duplex ultrasound, magnetic resonance angiography and computed tomography angiography for the diagnosis and assessment of symptomatic, lower limb peripheral arterial disease. *Health Technol Assess*. (2007) 1:iii-iv, xi-xiii, 1-184. doi: 10.3310/hta11200

24. Vaidya A, Joore MA, ten Cate-Hoek AJ, ten Cate H, Severens JL. Screen or not to screen for peripheral arterial disease: guidance from a decision model. *BMC Public Health*. (2014) 14:89. doi: 10.1186/1471-2458-14-89

25. Itoga NK, Minami HR, Chelvakumar M, Pearson K, Mell MM, Bendavid E, et al. Cost-effectiveness analysis of asymptomatic peripheral artery disease screening with the ABI test. *Vasc Med*. (2018) 23:97–106. doi: 10.1177/1358863X17745371

26. Lindholt JS, Søgaard R. Clinical benefit, harm, and cost effectiveness of screening men for peripheral artery disease: a Markov model based on the VIVA trial. *Eur J Vasc Endovasc Surg*. (2021) 61:971–9. doi: 10.1016/j.ejvs.2021.02.039

27. Lord J, Willis S, Eatock J, Tappenden P, Trapero-Bertran M, Miners A, et al. Economic modelling of diagnostic and treatment pathways in National Institute for health and care excellence clinical guidelines: the modelling algorithm pathways in guidelines (MAPGuide) project. *Health Technol Asses*. (2013) 17:v-vi, 1-192. doi: 10.3310/hta17580

28. Tappenden P, Chilcott J, Brennan A, Squires H, Glynne-Jones R, Tappenden J. Using whole disease modeling to inform resource allocation decisions: economic evaluation of a clinical guideline for colorectal Cancer using a single model. *Value Health*. (2013) 16:542–53. doi: 10.1016/j.jval.2013.02.012

29. Simpson EL, Kearns B, Stevenson MD, Cantrell AJ, Littlewood C, Michaels JA. Enhancements to angioplasty for peripheral arterial occlusive disease: systematic review, cost-effectiveness assessment and expected value of information analysis. *Health Technol Assess*. (2014) 18:1–252. doi: 10.3310/hta18100

30. Hunink MG, Wong JB, Donaldson MC, Meyerovitz MF, de Vries J, Harrington DP. Revascularization for femoropopliteal disease. A decision and cost-effectiveness analysis. *JAMA*. (1995) 274:165–71. doi: 10.1001/jama.1995.03530020083037

31. Kearns BC, Thomas SM. Cost-effectiveness of superficial femoral artery endovascular interventions in the UK and Germany: a modelling study. *BMJ Open*. (2017) 7:e013460. doi: 10.1136/bmjopen-2016-013460

32. Zákony pro lidi. 428/2020 Sb. Vyhláška o stanovení hodnot bodu, výše úhrad hrazených služeb a regulačních omezení pro rok (2021). Available at:https://www.zakonyprolidi.cz/cs/2020-428

33. Státní ústav pro kontrolu léčiv. Available at: https://www.sukl.cz/modules/medication/search.php (Accessed May 29, 2022).

34. Janssen MF, Szende A, Cabases J, Ramos-Goñi JM, Vilagut G, König HH. Population norms for the EQ-5D-3L: a cross-country analysis of population surveys for 20 countries. *Eur J Health Econ*. (2019) 20:205–16. doi: 10.1007/s10198-018-0955-5

35. de Vries M, Ouwendijk R, Kessels AG, de Haan MW, Flobbe K, Hunink MGM, et al. Comparison of generic and disease-specific questionnaires for the assessment of quality of life in patients with peripheral arterial disease. *J Vasc Surg*. (2005) 41:261–8. doi: 10.1016/j.jvs.2004.11.022

36. Sculpher M, Michaels J, Mckenna M, Minor J. A cost-utility analysis of laser-assisted angioplasty for peripheral arterial occlusions. *Int J Technol Assess Health Care*. (1996) 12:104–25. doi: 10.1017/S0266462300009430

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 09 September 2024
DOI 10.3389/fpubh.2024.1476339

Check for updates

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Song Wang,
Northeastern University, China
Xueli Wang,
The University of Hong Kong, Hong Kong SAR, China

*CORRESPONDENCE
Chen Li
✉ lichen@sues.edu.cn

RECEIVED 05 August 2024
ACCEPTED 21 August 2024
PUBLISHED 09 September 2024

CITATION
Wu H and Li C (2024) The impact of economic agglomeration on China's urban public health.
Front. Public Health 12:1476339.
doi: 10.3389/fpubh.2024.1476339

The impact of economic agglomeration on China's urban public health

Honghua Wu[1] and Chen Li[2]*

[1]School of Economics, Wuhan Donghu University, Wuhan, China, [2]School of Management, Shanghai University of Engineering Science, Shanghai, China

Introduction: This study aims to explore the impact of economic agglomeration on the urban prosperity through economies of scale and agglomeration, it may also affect the public health of the agglomeration area.

Methods: This paper takes 280 cities in China as the research object, and explores the impact of economic agglomeration on public health through a two-way fixed effects model, instrumental variable method, and generalized moment estimation.

Results: The results indicate that: (1) the improvement of China's economic agglomeration can significantly promote urban public health, and economic agglomeration is a prerequisite for the improvement of urban public health, but there is no reverse causal relationship. (2) The enhancement of economic agglomeration in Northeast China has the greatest promotion effect on public health, followed by the eastern, western, and central regions; The economic agglomeration enhancement of the pilot medical group in closely connected cities has a greater promoting effect on public health than the pilot medical group in non-closely connected cities. (3) Empirical results based on micro sample data show that the improvement of economic agglomeration will also promote the increase of the number of public hospitals in cities.

Discussion: This study emphasizes the important role of economic accumulation in the improvement of urban public health and provides empirical support for future economic development policies and practices.

KEYWORDS

urban public health, economic agglomeration, bidirectional fixed effects model, pilot of tight city medical group, China

1 Introduction

The proportion of the global urban population has increased rapidly from 25% in 1950 to about 50% in 2020. But growth is expected to slow over the next 50 years, increasing to 58% in 2070. Since the reform and opening up, China has undergone the fastest and largest industrialization and urbanization process in the world. By the end of 1978, there were only 170 million permanent urban residents in China, and the urbanization rate of permanent urban residents was only 17.92%. By the end of 2022, the number of permanent urban residents had reached 920 million, 750 million more than that at the end of 1978, or an average annual increase of 17.04 million. The urbanization rate of permanent residents reached 65.2%, an increase of 47.28% points over the end of 1978. With the huge changes in urban environment and residents' lifestyles, many environmental risk factors and new health diseases pose a serious threat to national health. Under the influence of the global strategy for healthy cities, in order to address complex public health risks, China has continuously proposed health intervention strategies such as the "Guiding Opinions on the Construction of Healthy Cities and Healthy Villages (2016)" and the "Healthy China 2030'' planning outline, taking the construction of "healthy cities" as an important lever to promote the construction of "Healthy China." At the same time, thanks to the effective spatial agglomeration of economic activities, the Chinese economy has achieved sustained and rapid growth, and the spatial agglomeration process of economic activities is further strengthening. Cities are the core carriers of economic agglomeration development and promoting the construction of a healthy China. While economic agglomeration promotes urban prosperity through economies of scale and agglomeration effects, it may also directly or indirectly affect the public health of agglomeration areas through wealth creation, technological progress, resource supply, population mobility, environmental pollution, and other means (1–3). Therefore, how to integrate the concept of health intervention into the entire process of urban and rural planning, construction, and governance through the rational allocation of public health resources, promote the coordinated development of urban and people's health, and explore whether and how to "move toward health in agglomeration" from the urban scale is an urgent and significant issue in front of the academic community.

The essence of enhancing economic agglomeration is to fully leverage the leading, driving, and radiating role of large cities, and improve the level of public health resource agglomeration and the scope of urban spatial services (4). Therefore, economic gatherings can affect urban public health through the following three pathways. One is the agglomeration effect. With the continuous improvement of economic agglomeration, various types of public health factors are rapidly gathering in urban spaces, forming economies of scale effects. At the same time, the flow of a large number of specialized medical practitioners between cities also helps to disseminate implicit public health knowledge, promote knowledge spillover and technology transfer. Other hospitals and institutions within the agglomeration area can imitate and learn new technologies without having to invest in high research and development costs, thereby contributing to the improvement of urban public health (5–8). Therefore, the improvement of economic agglomeration will promote the level of public health agglomeration, thereby achieving externalities in knowledge production and promoting the improvement of public health. The second is cost-effectiveness. In the Internet era, there is a significant diminishing marginal cost effect in the production process of cities. With the increase of cities' position in the economic agglomeration system and production scale, the cost of public health will also decrease, thereby promoting larger scale specialization and division of labor (9, 10). Under the framework of monopolistic competition, it will lead to an increase in total output. The third is resource flow effect. Similar to traditional economic factors, public health resources also have the characteristics of scarcity and pursuit of maximizing their own value, and will flow from cities with low marginal returns to cities with high marginal returns. The different administrative levels of cities will to some extent affect the regional allocation of urban public health resources, especially the cross regional flow of high-end medical talents. In order to pursue the maximization of their own interests, high-end medical talents will migrate between cities through "voting with their feet," that is, they will move to cities with more development opportunities, better scientific research environment, and more generous welfare benefits (6, 11–14).

Currently, there are not many direct relevant literature on the public health effects of economic agglomeration, and similar results are mainly limited to the impact of a specific industry's spatial agglomeration process on a certain dimension of public health, which is quite different from the research topic (15, 16). However, by reviewing the literature, one can also find indirect theoretical evidence of the impact of economic agglomeration on public health. For example, economic agglomeration can improve residents' material living conditions, increase the supply of public health resources, and exacerbate haze pollution, which undoubtedly may further affect public health (4, 17–22). Although these studies have paid attention to the differences in public health among cities of different levels and sizes, they have not conducted in-depth research on the relationship between economic agglomeration and urban public health, nor have they revealed the mechanism of economic agglomeration on urban public health. Existing literature provides rich insights for research work, but the research is also quite inadequate. First, due to the continuous improvement of science and technology and medical and health conditions, the frequency of large-scale outbreaks of public health problems and their direct impact on macroeconomic growth is not high. Most scholars have not been able to predict that public health problems in today's era may also slow down economic development, and therefore have not conducted in-depth mechanism analysis and systematic empirical investigation into the economic drivers of public health problems. Secondly, when conducting relevant empirical research, most literature does not fully consider the possible bidirectional causal relationship between core explanatory variables and public health, which may lead to endogenous problems. It also fails to pay enough attention to the possible spatial correlation characteristics of public health (such as inter-city transmission of diseases), and does not thoroughly reveal the heterogeneity information of research objects in terms of economic agglomeration patterns, location characteristics, and urban hierarchy. This may result in biases in estimated parameters and real parameters, and prevent scientific and precise policy guidance for different regions based on local conditions. Thirdly, existing literature measuring public health often simply focuses on a single indicator to seek a proxy variable to characterize it, ignoring the multidimensional and comprehensive characteristics that public health itself should have. Such a simplistic approach cannot better fit the realities of public health. Therefore, the innovation of this paper is as follows: first, this paper explores the economic drivers of public health problems in depth, linking economic agglomeration with public health; Second, this paper fully considers the bidirectional causal relationship between the core explanatory variables and public health, as well as the spatial correlation characteristics of public health. Third, considering the multi-dimensional and comprehensive characteristics of public health, this paper constructs a comprehensive index of urban public health, rather than a single variable representation.

Obviously, public health is closely related to urban needs. Cities are the spatial carriers of high-quality production factors. High-quality public health resources are always concentrated in large cities, and then spill over to small and medium-sized cities. In addition, urban development itself has become an important source of public health needs (21). However, existing research has rarely addressed the relationship between economic agglomeration and public health. Does economic agglomeration pose a restrictive condition on public health? If so, what mechanism does it use to affect public health? Is there a nonlinear relationship between economic agglomeration and public health at different city sizes? Is there an optimal economic agglomeration that promotes public health improvement? In response to the above problems, this study will take 280 cities in China as the research object, conduct a systematic study on the relationship between economic agglomeration and public health, empirically analyze the impact of economic agglomeration on public health through a two-way fixed-effect model, and use instrumental variable two-stage least squares estimation (IV-2SLS), generalized method of moments estimation (GMM) and other methods to weaken the impact of endogenous factors on the estimation results.

2 Econometric model and variable selection

2.1 Econometric model

Based on the analysis above, this paper focuses on revealing the mechanism and degree of the impact of economic agglomeration on public health in the empirical part, and establishes the following panel least squares regression model:

$$Phealth_{it} = \beta_1 Urbh_{it} + \beta X_{it} + \beta_0 + T + \alpha + \alpha_{it} \tag{1}$$

In the formula, $Phealth_{it}$ represents urban public health, $Urbs_{it}$ represents economic agglomeration, X_{it} is the control variable, T is the time fixed effect, α is the individual fixed effect, ε_{it} is the random interference term, β, β_0, β_1 are the estimated coefficients.

2.2 Urban public health (*Phealth*)

Although the academic community generally believes that public mental health, social pressure, and moral quality are all important factors in public health, due to data availability constraints, existing research often seeks proxy variables from the dimension of public physical health to represent public health, and often uses a single negative measurement indicator (23–26). This approach is reasonable, as modern medicine has long established that mental health, social stress, and moral character significantly determine an individual's health level. Therefore, public health status is the most intuitive representation of public health, but using a single negative indicator to measure public health can be biased. Therefore, the paper is consistent with most literature, focusing on the health status of urban residents in terms of physical function, while taking into account both the necessary basic support conditions and the practical improvement of health performance when measuring public health, to construct a composite index of urban public health. On the one hand, the necessary public health foundation is the logical starting point and prerequisite for improving urban public health (27–30). Three indicators, namely the number of doctors per 10,000 people, *per capita* fiscal expenditure on medical and health care, and the number of beds in medical and health institutions per 10,000 people, are selected to characterize it from the perspective of "human, financial, and material" investment. On the other hand, the fundamental value pursuit of urban public health is to increase the "expected output" related to health as much as possible and reduce or eliminate the "undesired output" as much as possible under the established public health infrastructure support conditions. The incidence rate of population survival reflects the "expected output," while the incidence rate of infectious diseases reflects the "undesired output."From the perspective of history and reality, large-scale outbreaks of public health problems are more often presented in the form of infectious disease epidemics. The conflict between high population density brought about by economic agglomeration and the social distance required for infectious disease prevention and control often poses a greater risk of epidemic in the agglomeration area. The ability of the agglomeration area to prevent and control infectious diseases is also a direct reflection of its own public health governance capacity. Therefore, the incidence rate of infectious diseases is more suitable for fitting the current situation of urban public health than other negative indicators. This study is based on the incidence rate data of provincial-level Class A and B legally reported infectious diseases. The provincial data is weighted by the proportion of urban population size and the proportion of urban financial expenditure on medical and health care (reverse weight), respectively, to estimate the incidence rate of infectious diseases at the city level. The fixed-base range entropy weight method is used to calculate the urban public health composite index. The advantage of this method is that it can objectively assign corresponding weight values to different indicators with different levels of contribution, and fully reflect the spatial and temporal dual-dimensional and dynamic comparable characteristics of the evaluation object. For specific calculation steps, please refer to the literature.

2.3 Economic agglomeration (*Urbh*)

Drawing on the research of Wang et al. (31), an indicator evaluation system for economic agglomeration is constructed from the aspects of consumption scale, resource energy consumption level, degree of opening up to the outside world, manufacturing level, employment scale, and infrastructure level. Nine indicators are selected to evaluate economic agglomeration, including total retail sales of consumer goods in cities (in 10,000 yuan), total electricity consumption in the whole society (in 10,000 kWh), *per capita* electricity consumption (in kWh/person), actual utilization of foreign capital (in 10,000 US dollars), the proportion of actual utilization of foreign capital in the gross regional domestic product (%), the number of employees in the tertiary industry (in 10,000 people), the passenger volume of civil aviation (in 10,000 passengers), the proportion of passenger volume of civil aviation in the population (%), and the proportion of passenger volume of highway and waterway in the population (%). In addition to testing the correlation, it will also investigate whether economic agglomeration has a causal relationship with public health. Therefore, it is not enough to simply rank economic agglomeration after assigning values, but also to examine the impact of changes in economic agglomeration on public health. Comprehensive use of principal component analysis and entropy method to assign weights, and use least squares to minimize the deviation between the final determined weights and the two methods.

2.4 Control variables

Drawing on existing literature on the form of the health production function (32–34), Porter believes that the four stages of regional competitive advantage are: factor-driven, investment-driven, innovation-driven, and wealth-driven. The stage of urban development will affect urban public health, so we choose *per capita* GDP (*Gdpp*) and the proportion of the secondary and tertiary industries (*Ttsr*) as control variables to characterize the stage of urban development. The second is urban form, so we choose urban construction land area (*Urss*) and urban population density (*Urbd*) as control variables. The third is human capital (*Hcap*), which measures urban human capital using the number of college students per 10,000 people. Fourth, openness to the outside world (*Open*), which is characterized by travel activity (the ratio of total urban passenger traffic to the total urban population).

2.5 Data sources

This paper takes 280 cities in China as the research object, and the original data for the indicators are all taken from the corresponding years' "China Health Statistics Yearbook," "China City Statistical Yearbook," EPS data platform, Columbia University's Social Economic Data and Application Center. For individual missing data, trend prediction and moving average methods are used to fill in the gaps.

3 Empirical results and analysis

After conducting an F-test on the "city" dummy variable, it was found that individual effects exist at a 1% significance level, rejecting the null hypothesis that there are no individual effects. Considering that models with individual effects are divided into fixed-effect and random-effect models, after conducting a Hausman test, the *p*-value is close to 0, thus accepting the null hypothesis that the fixed-effect model is selected. In summary, the regression equation constructed in this paper is a two-way fixed effects model. The two-way fixed effect model can consider both individual and time dimensions of fixed effect, which improves the explanatory power of the model. Secondly, the model can deal with heteroscedasticity and sequence correlation problems, which improves the accuracy of estimation.

3.1 Benchmark regression results

First, we use least squares regression to measure the correlation between economic agglomeration and urban public health before and after adding control variables. By comparing the degree of dispersion and aggregation of variables, it is found that there is a significant positive correlation between economic agglomeration and urban public health. Columns (1, 2) of Table 1 present the regression results for the baseline model's bidirectional random effects and fixed effects, respectively; Due to the large variance of urban public health indicators, it is necessary to delete more extreme samples to ensure the robustness of the regression results. Column (3) of Table 1 shows the regression results after removing the top 10% samples of urban public health; Using the B-P test and (35) method, we tested for heteroskedasticity and cross-sectional correlation, respectively. The results showed that the equation had heteroskedasticity and cross-sectional correlation problems at a 1% significance level, which would reduce the authenticity and validity of the statistical results. Therefore, we selected the Driscoll-Kraay standard error, which addresses cross-sectional correlation and heteroskedasticity issues, instead of the standard *t*-test for significance testing. The results are shown in column (4) of Table 1.

In addition, as the improvement of urban public health level will promote economic agglomeration, economic agglomeration may in turn improve urban public health level. This endogenous problem caused by two-way causality needs to be solved using instrumental variable two-stage least squares regression and generalized method of moments estimation methods. First, we use instrumental variables to deal with endogenous problems, and select exogenous instrumental variables to deal with potential endogenous problems. GMM does not need to know the exact distribution information of the random error term, allowing the random error term to have heteroscedasticity and sequence correlation, so the obtained parameter estimators are more efficient than other parameter estimation methods. The ratio of the length to the width of the city is *Lrb*. The closer this value is to 1, the higher the degree of equilibrium in the spatial diffusion of the city around the city center point. It also represents a more homogeneous geographical environment around the city, with the potential to develop into a high-level city. This indicator does not necessarily have a direct causal relationship with public health, so this paper uses $(Lrb\text{-}1)^2$, a variable that measures the degree of urban equilibrium, as one of the instrumental variables, and uses *Lrb* as the other instrumental variable. These two instrumental variables passed the instrumental variable tests for the Cragg-Donald Wald F statistic, Sargan statistic, and Anderson canon. Corr. LM statistic. Column (5) of Table 2 shows the regression results of IV-2SLS. Secondly, we used the system GMM method and selected the lagged two and three periods of economic agglomeration as instrumental variables for two-stage least squares regression. The regression results are shown in column (6) of Table 2.

In the models (1–6) in Table 1, economic agglomeration has a significant promoting effect on public health levels. In models (1, 2, and 4), a 1% increase in economic agglomeration variables can improve urban public health by approximately 0.34 units. In models (3, 5, and 6), the positive and negative signs and significance of key explanatory variables in the regression results without extreme values and using instrumental variables remain unchanged, indicating that under different conditions, the role of economic agglomeration in improving urban public health is not covered by other influencing factors, that is, economic agglomeration is an important factor in improving urban public health. Economic factors are characterized by scarcity and profit-seeking, and will flow from areas with low marginal returns to areas with high marginal returns. This "selecting the best" mechanism will encourage economic factors to flow to higher-tier cities in order to increase their own value and marginal output efficiency, optimize the efficiency of urban public resource allocation, and thus have a positive impact on urban public health.

In terms of control variables, *per capita* gross domestic product (*Gdpp*) and human capital (*Hcap*) both significantly promote urban public health. This is mainly due to the fact that improving economic development and increasing human capital will inevitably attract more public health factors to gather, which is beneficial to the improvement of public health. The urban construction land area (*Urss*) and the proportion of the secondary and tertiary industries (*Ttsr*) have a suppressing effect on urban public health, indicating that the disorderly expansion of urban construction land area will reduce the efficiency of land resource allocation (26), while foreign investment will to some extent inhibit the improvement of urban public health. There is a non-significant positive correlation between urban

TABLE 1 Benchmark regression results.

Variables	(1) *Re*	(2) *Fe*	(3) Exclude extreme values	(4) *D-K*	(5) *IV*	(6) *GMM*
Urbh	38.660*** (19.26)	33.145*** (14.56)	14.678*** (15.34)	34.456*** (3.56)	153.43*** (23.45)	98.564*** (7.32)
Gdpp	3.45e-04***(5.36)	3.78e-04*** (5.67)	5.35e-05*** (5.65)	3.87e-04*** (8.76)	-3.77e-05 (−0.35)	7.76e-05*** (1.66)
Ttsr	−0.067* (−2.34)	−0.056 (−0.77)	−0.014** (−2.23)	−0.046*** (−8.56)	−0.023 (−0.65)	−0.015 (−0.56)
Urss	−8.065 (−1.12)	−6.344 (−0.87)	−2.543*** (−3.12)	−6.234*** (−3.56)	−10.134*** (−3.32)	−10.112*** (−2.54)
Urbd	1.354 (0.84)	0.675 (0.45)	0.267 (1.49)	0.723 (0.05)	0.343 (0.58)	−0.253 (−0.36)
Hcap	0.146 (0.85)	0.185 (1.03)	0.134*** (6.63)	0.187*** (3.24)	0.175*** (2.45)	0.154* (1.43)
Open	−0.232*** (−3.23)	−0.164** (−2.16)	0.002 (0.34)	−0.145 (−0.42)	−0.092*** (−3.12)	−0.054 (−1.24)
time effect	Control	Control	Control	Control	Control	Control
individual effect	Control	Control	Control	Control	Control	Control
constant	8.345*** (2.76)	3.894 (0.87)	0.588** (1.87)	0	0	0
R^2	0.4492	0.4678	0.4671	0.4772	0.7682	0.4123

The *t*-value is in parentheses, and ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.

TABLE 2 Results of robustness test.

Variables	(1) East China	(2) Central China	(3) West china	(4) Northeast China	(5) Medical Pilot City	(6) Non-medical pilot cities	(7) Lag one period	(8) Microdata
Urbh	45.654*** (11.43)	14.335*** (6.45)	34.564*** (15.54)	62.654*** (11.35)	31.64*** (7.54)	22.65*** (11.43)	30.675*** (15.65)	401.34*** (5.32)
Gdpp	2.29e-04*** (7.56)	3.68e-04*** (7.53)	−3.86e-05 (0.156)	1.83e-05 (0.43)	1.80e-05** (2.23)	1.62e-05** (9.54)	1.97e-05*** (9.34)	1.91e-03 (−0.76)
Tsr	−0.062* (−1.89)	−0.062*** (−3.18)	−0.038 (−2.65)	0.043* (1.86)	0.042 (0.52)	−0.052*** (−5.42)	−0.052*** (−3.86)	−1.542 (−0.72)
Urss	−10.872*** (−3.87)	−4.892 (−1.42)	−4.652*** (−1.36)	−2.672 (−0.38)	−14.89** (−2.16)	−3.173* (−1.78)	−6.472*** (−3.72)	−1.787** (−2.32)
Urbd	−0.887 (−1.43)	−0.198 (−0.38)	0.078 (0.15)	0.328 (0.56)	−2.127 (−1.53)	0.189 (−0.56)	0.016 (0.04)	−1.365 (−1.23)
Hcap	0.329*** (3.87)	0.187*** (3.53)	−0.087 (−1.53)	−0.032 (0.28)	0.128 (0.58)	0.112*** (3.43)	0.065* (1.54)	−4.234 (−0.26)
Open	0.058 (1.87)	0.051* (1.76)	−0.042** (−2.33)	−0.032 (−0.95)	0.018 (0.17)	−0.008 (−0.69)	0.011 (0.66)	−2.65e-04** (−2.45)
time effect	Control	Control	Control	Control	Control	Control	Control	Control
individual effect	Control	Control	Control	Control	Control	Control	Control	Control
constant	6.165** (2.43)	4.135** (2.16)	4.765*** (3.34)	−3.786* (−1.69)	−1.652 (−0.18)	4.886*** (5.36)	4.454*** (3.74)	132.8 (0.58)
R^2	0.5943	0.4015	0.5505	0.6006	0.6488	0.4082	0.4360	0.1228

The *t*-value is in parentheses, and ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.

population density (*Urbd*) and urban public health, indicating that most cities in China still need to increase the introduction of medical technicians to promote the improvement of public health through the increase of urban "doctor density." The impact of opening up on urban public health is not robust, possibly because the level of urban public health is mainly supported by local governments, and the correlation with opening up is not strong.

3.2 Robust test

This paper will test the robustness of the regression results from four perspectives: regional heterogeneity, policy impact of pilot cities for compact urban medical groups, lag effect, and micro-sample.

First, consider the impact of regional heterogeneity on the results. The robustness test was conducted using a sub-regional regression approach. Columns (1–4) in Table 2 present the regression results for the four major regions of eastern, central, western, and northeastern China. Through comparative analysis, it can be seen that although the impact coefficients of economic agglomeration on public health in the regression results of the four major sectors are all positive and the significance level is 1%, there is heterogeneity in the promotion effect of economic agglomeration on public health among the four major sectors.

Second, control the policy impact of pilot cities for closely controlled urban medical groups. Since 2013, China has gradually established pilot cities for the construction of compact urban medical groups. These groups are internally composed of leading hospitals and member units. In principle, the leading hospitals are municipal-level, district-level, and tertiary comprehensive hospitals (including traditional Chinese medicine hospitals). At least one-third of the outpatient number sources and one-fourth of the inpatient beds should be provided to family doctor contract service teams or grassroots medical and health institutions. Contracted residents who are referred by grassroots can have priority in treatment, examination, and hospitalization. The leading hospital focuses on providing diagnosis and treatment services for acute and critical illnesses and difficult and complex diseases, and is responsible for receiving patients transferred from other hospitals and referring patients who meet the criteria for transfer to member units in an orderly manner. In principle, member units should include at least a second-tier general hospital or a medical institution capable of providing common and chronic disease diagnosis and treatment, emergency and critical care rescue, and continuity of care for patients referred by leading hospitals. At the same time, the close-knit urban medical group will coordinate the construction of resource sharing centers for medical testing, medical imaging, electrocardiographic diagnosis, pathology, disinfection, and supply, etc., to achieve mutual recognition of inspection and testing results within the close-knit urban medical group, establish a telemedicine collaboration network covering all units of the medical consortium, and improve the efficiency of medical resource allocation and use. It is worth noting that most of the samples selected for the pilot cities of the compact urban medical group are high-level cities. Therefore, the non-randomness of the sample selection in this policy will lead to the improvement of urban public health not from the improvement of economic agglomeration, but from the consequences of the policy impact, resulting in a decrease in the credibility of the results. Therefore, in order to control the impact of the policy of pilot cities for compact urban medical groups, we will conduct a regression analysis between the pilot cities for compact urban medical groups and the pilot cities for non-compact urban medical groups. As shown in columns (5, 6) of Table 2, the promotion of economic agglomeration in both pilot cities of compact urban medical groups and pilot cities of non-compact urban medical groups has a significant positive impact on urban public health.

Third, consider the lag effect. The improvement of economic agglomeration may take some time before it has an impact on urban public health, and economic agglomeration reflects the long-term changes in urban development, while the level of urban public health reflects short-term fluctuations. There may be an effect estimation bias in the direct regression between the two. Therefore, in order to avoid this situation, all explanatory variables are regressed with a lag of one period. As shown in column (7) of Table 2, there is no fundamental change in the positive role of economic agglomeration in promoting urban public health.

Fourth, we use micro-sample data to verify. Match the database of public hospitals with urban panel data, and select the number of urban public hospitals as the dependent variable to conduct a regression analysis. The results are shown in column (8) of Table 2, which is consistent with the results of the benchmark regression. The increase in economic agglomeration will promote the increase in the number of urban public hospitals. In addition, the coefficients and significance of the control variables are basically consistent with the regression results in Table 1. It can be seen that the sign and significance of the key explanatory variables have not changed under different empirical model analyses using instrumental variables, indicating that under different conditions, the role of economic agglomeration in urban public health has not been covered by other influencing factors, that is, economic agglomeration is an important factor in improving public health.

3.3 Granger causality identification

The Granger causality test is one of the classic methods for testing causal relationships in time series models. Based on this, Dumiterescu and Hurlin (36) proposed an idea that is considered to extend the Granger causality test to panel models, which has been widely applied in empirical testing (36–39). This paper aims to study the causal relationship between economic agglomeration and urban public health, and the regression equation established is as follows:

$$Phealth_{it} = \sum_{i=1}^{N} \lambda_j L_j .Urbh_{it} + \sum_{j=1}^{N} \lambda_j L_j .Phealth_{it} + \lambda_0 + \zeta_{it} \tag{2}$$

Where j is the optimal lag order, and according to the principle of minimizing the AIC and BIC information criteria, two periods are selected as the lag order. The regression results are shown in Table 3. Columns (1, 2) are the ordinary panel VAR models, and columns (3, 4) are the regression results after taking the difference between the

TABLE 3 Granger causality results.

Variables	(1) *Inoe*	(2) *Urbh*	(3) *Inoe*	(4) *Urbh*	(5) *Inoe*	(6) *Urbh*
L.Inoe	1.192*** (41.66)	−0.002*** (−2.78)	0.287*** (11.98)	0.001 (1.06)	1.412*** (42.66)	−0.001 (−1.87)
L2.Inoe	−0.048 (−1.42)	0.007*** (9.87)	0.033 (0.62)	0.007 (1.32)	−0.098*** (−2.78)	0.004 (1.32)
L.Urbh	4.983*** (5.82)	0.453*** (21.54)	7.387*** (5.65)	−0.653*** (−22.46)	2.321*** (2.52)	0.531*** (23.43)
L2.Urbh	−2.872*** (−2.82)	0.378*** (16.87)	3.324** (2.32)	−0.282*** (−9.65)	−0.667 (−0.56)	0.427*** (14.87)
Time Trend	–	–	–	–	Control	Control
constant	0.054*** (3.78)	0.001*** (6.87)	0.119*** (9.18)	0.003*** (8.87)	0.398*** (12.53)	−0.001 (0.44)
R^2	0.8762	0.7253	0.1097	0.2098	0.9092	0.7562
Joint significance *P* value	Remarkable	Significance	Significance	Not significance	Significance	Not significance

The *t*-value is in parentheses, and ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.

independent variable and the dependent variable, aiming to reduce the possible impact of unit roots on the regression results. Columns (4, 5) are the results after controlling for the fixed effect of time, aiming to reduce the impact of time trends on the regression results. It can be found that although the urban public health and economic agglomeration in columns (1, 2) are Granger causes of each other at the 1% significance level. However, in columns (3–6) where the basic assumptions of no unit root and no time trend affecting the results are relaxed, economic agglomeration is a Granger cause of urban public health at the 1% significance level, but urban public health is not a Granger cause of economic agglomeration. Therefore, the improvement of economic agglomeration is a prerequisite for the improvement of public health, but the opposite is not true. It can be seen that although the improvement of urban public health will promote urban economic growth, it will also promote economic agglomeration. However, the improvement of urban public health level is not spontaneous, it requires the investment of capital and high-skilled medical workers, and both of them are improved with the increase of economic agglomeration. Therefore, the premise of improving urban public health is the accumulation of public health factors and the agglomeration of medical resources brought about by economic agglomeration.

4 Conclusions and policy recommendations

1. The improvement of China's economic agglomeration can significantly promote urban public health. The Granger causality test results show that economic agglomeration is a prerequisite for urban public health, but the converse is not true. This means that the prerequisite for a city to become a regional public health center is to first become a regional central city. Only large cities can better promote public health, and even increasing medical investment in small and medium-sized cities cannot effectively promote their economic agglomeration.
2. There is regional heterogeneity in the promotion effect of economic agglomeration on urban public health. The promotion effect of economic agglomeration in the northeast region on urban public health is the largest compared to other regions, followed by the eastern region, the western region, and the central region. What is more worth emphasizing is the population growth in the coastal cities of eastern China, as well as the population growth in the suburbs and new towns of cities, with a large number of immigrants as the main population. Due to the constraints of the household registration system and the associated social welfare system, these migrants do not have the same equal access to health and health services as local citizens. The vast majority of them do not enjoy medical insurance that urban residents have, and it is difficult for them to obtain high-quality health and health services that urban residents can obtain. The differential rights of migrant population in health and health services is a microcosm of their status in cities, and also undermines the public nature of urban health and public services. The promotion of pilot cities of close urban medical groups and non-close urban medical groups has a significant promoting effect on urban public health. The promotion of economic agglomeration in pilot cities of close urban medical groups has a greater promoting effect on public health than that in pilot cities of non-close urban medical groups. At the same time, empirical results based on micro-sample data show that the increase in economic agglomeration also promotes the increase in the number of urban public hospitals.
3. As an important part of patriotic health work in the new era, the construction of healthy cities is an important means to further implement the Healthy China strategy and promote the construction of a healthy China. A healthy city refers to an organic whole composed of healthy people, healthy environment and healthy society, with people's health as the center and the protection of the health of the general public as the focus, from urban planning, construction to management. In the future, we should take the construction of healthy cities as an important starting point for promoting the construction of a healthy China, ensure the demand for land for public facilities related to health, improve the relevant public facility systems, layouts, and standards, integrate health into the whole process of urban and rural planning, construction, and governance, and promote the coordinated development of cities and people's health. Efforts to provide universal health public services in the process of urbanization should become an important policy orientation to reduce urban internal differentiation and improve the quality of urban life.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: http://www.tjcn.org.

Author contributions

HW: Writing – review & editing, Writing – original draft. CL: Conceptualization, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This study was supported by the Project of Philosophy and Social Science of Shanghai "Study on the Role of Population Ageing on Economic Growth in the Yangtze River Delta Urban Agglomeration" (2023ZSH002).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

1. Zhang S, Deng Y. Effects of internal migrants' health on economic resilience in China's Yangtze River Delta urban agglomeration: moderating effects of basic public health services. *Front Public Health*. (2024) 12:1392657. doi: 10.3389/fpubh.2024.1392657

2. McKinnon K, Jaafar F, Alves-Bradford JM, Weinstein T, McKinnon AZ, Hughes E, et al. Sexual health services in urban, suburban, and rural outpatient mental healthcare settings in New York: findings from a survey of practices and gaps. *Sex Health*. (2023) 20:360–2. doi: 10.1071/SH22199

3. Ksibi A, Mhamdi H, Ayadi M, Almuqren L, Alqahtani MS, Ansari MD, et al. Secure and fast emergency road healthcare service based on Blockchain Technology for Smart Cities. *Sustain For*. (2023) 15:5748. doi: 10.3390/su15075748

4. Brulhart M, Sbergami F. Agglomeration and growth: cross-country evidence. *J Urban Econ*. (2009) 65:48–63. doi: 10.1016/j.jue.2008.08.003

5. Weng Z, Fan F, Yang B. Regional differences and drivers of patent transfer-in between Chinese cities: a city absorptive capacity perspective. *Tech Anal Strat Manag*. (2023) 5:1–15. doi: 10.1080/09537325.2023.2242509

6. Ravid M, Cohen N. Incremental urban citizenship-making: migrant serving organizations in Tel Aviv during COVID-19 and the politics of change in times of crisis. *Cities*. (2024) 153:105263. doi: 10.1016/j.cities.2024.105263

7. Kim KE, Yoon S, Jung US, Kweon SJ. Optimizing urban park locations with addressing environmental justice in park access and utilization by using dynamic demographic features derived from mobile phone data. *Urban For Urban Green*. (2024) 99:128444. doi: 10.1016/j.ufug.2024.128444

8. Rawat S, Sangam R, Shelke P, Gokhe SSB. A baseline cross-sectional study to assess patient satisfaction (18-60 years) toward Apli Chikitsa (free of cost medical laboratory tests) services provided at an urban health training center: a PPP model. *J Family Med Prim Care*. (2024) 13:2357–60. doi: 10.4103/jfmpc.jfmpc_1753_23

9. Li H, Lu J, Li B. Does pollution-intensive industrial agglomera-tion increase residents'health expenditure? *Sustain Cities Soc*. (2020) 56:102092. doi: 10.1016/j.scs.2020.102092

10. Ombengi ND. Development and implementation of a pharmacist-led, community engaged, health screening program in an underserved urban neighborhood. *J Pharm Care Health Syst*. (2021) 8:1–7.

11. Emerson A, Lipnicky A, Comfort M, Lorvick J, Cropsey K, Smith S, et al. Health and health service needs: comparison of older and younger women with criminal-legal involvement in three cities. *J Aging Health*. (2021) 34:60–70. doi: 10.1177/08982643211025443

12. Fan F, Yang B. The convergence mechanism and spatial spillover effects of urban industry-university-research collaborative innovation performance in China. *Tech Anal Strat Manag*. (2023) 34:1–17. doi: 10.1080/09537325.2023.2290169

13. Prabha L, Anna C. Challenges of conducting kidney health checks among patients at risk of chronic kidney disease and attending an urban aboriginal and Torres Strait islander primary healthcare service. *Aust J Prim Health*. (2022) 28:371–9. doi: 10.1071/PY21248

14. Jiang JW. The effects of urban neighborhood environmental evaluation and health service facilities on residents. *Int J Environ Res Public Health*. (2022) 19:4501. doi: 10.3390/ijerph19084501

15. Yanshuo H, Long M, Bei L. Urban public health education services, health status, and increased fertility intentions of the rural migrant population. *Reprod Health*. (2023) 20:108. doi: 10.1186/s12978-023-01648-2

16. Andrew P. Behavioral health services in urban American Indian health programs: results from six site visits. *J Commun Psychol*. (2023) 51:2618–34. doi: 10.1002/jcop.23035

17. Andrew P, Kawennison AF. Behavioral health services for urban American Indians and Alaska natives: a thematic analysis of interviews with 10 program directors. *Psychol Serv*. (2023) 20:962–72. doi: 10.1037/ser0000754

18. Kovacs N, Piko P, Juhasz A, Nagy C, Oroszi B, Ungvari Z, et al. Comparative analysis of health status and health service utilization patterns among rural and urban elderly populations in Hungary: a study on the challenges of unhealthy aging. *Gero Sci*. (2024) 46:2017–31. doi: 10.1007/s11357-023-00926-y

19. Emily LK. The effects of urban density on the provision of multiple health-related ecosystem services. *Urban Ecosyst*. (2023) 27:491–513. doi: 10.1007/s11252-023-01451-8

20. Thomas Y, Oni T, Ebikeme C, Mberu B. Research to address socio-environmental determinants of health and access to healthcare in urban Africa. *Cities Health*. (2022) 6:1–6.

21. Bai DM. Project HEAL: sustainability of a faith-based community health advisor training program in urban underserved communities in the USA. *J Relig Health*. (2021) 61:2527–38. doi: 10.1007/s10943-021-01453-w

22. Carolina A. Linking ecosystem services and human health in coastal urban planning by DPSIWR framework. *Ocean Coast Manag*. (2021) 210:105728. doi: 10.1016/j.ocecoaman.2021.105728

23. Li X, Xu Y, Yao X. Effects of industrial agglomeration on hazepollution: a Chinese city-level study. *Energy Policy*. (2021) 148:111928. doi: 10.1016/j.enpol.2020.111928

24. Roberto CA. Behavioral economics and public health. Oxford: Oxford University Press (2015).

25. Tseng HK. The U.S.health production function: evidence from 2001 to 2009. *Int J Health Econ Manage*. (2016) 16:51–64. doi: 10.1007/s10754-015-9180-2

26. Rui M, Zi F. Do migrant residents really achieve health equity by obtaining urban Hukou? A comparative study on health service utilization and urbanization in Central China. *Front Public Health*. (2022) 10:784066. doi: 10.3389/fpubh.2022.784066

27. Jacek K. Examining the spatial concentration of mental health calls for police Service in a Small City. *Policing J Policy Prac*. (2021) 15:1011–28. doi: 10.1093/police/paaa093

28. Vallejo AN, Raumer HGSV, Eisenberg B. The interplay of land-use and land-ownership as a key for urban greening management. *Urban For Urban Green*. (2024) 99:128442. doi: 10.1016/j.ufug.2024.128442

29. Wang X, Wang L. The spatiotemporal evolution of COVID-19 in China and its impact on urban economic resilience. *China Econ Rev*. (2022) 74:101806. doi: 10.1016/j.chieco.2022.101806

30. Fan F, Weng Z, Tian J. Impact of government support policies on regional economic resilience under the COVID-19 outbreak. *Technol Econ Dev Econ*. (2024) 30:74–106. doi: 10.3846/tede.2024.20397

31. Wang RY, Wang ZG. Financial agglomeration and urban hierarchy. *Econ Res*. (2019) 54:165–79.

32. Young C, Burgess L, Falster K, Zoega H, Banks E, Clapham K, et al. Mental health-related service and medicine use among a cohort of urban aboriginal children and young people: data linkage study. *Aust N Z J Psychiatry*. (2024) 6:00048674241248357. doi: 10.1177/00048674241248357

33. Wei L, Yong W. Spatiotemporal changes and driving forces of ecological security in the Chengdu-Chongqing urban agglomeration, China: quantification using health-services-risk framework. *J Clean Prod*. (2023) 389:136135. doi: 10.1016/j.jclepro.2023.136135

34. Wen JL. Determinants of intention with remote health management service among urban older adults: a unified theory of acceptance and use of technology perspective. *Front Public Health*. (2023) 11:1117518. doi: 10.3389/fpubh.2023.1117518

35. Pesaran MH. *Time series and panel data econometrics*. Oxford: Oxford University Press (2015) 1104.

36. Dumiterescu E, Hurlin C. Testing for granger non-causality in heterogeneous panels. *Econ Model*. (2012) 29:1450–60. doi: 10.1016/j.econmod.2012.02.014

37. Guo SH, Ze YW. Community public health safety emergency management and nursing insurance service optimization for digital healthy urban environment construction. *Front Public Health*. (2022) 10:1032758. doi: 10.3389/fpubh.2022.1032758

38. Pecina V, Juřička D, Galiová MV, Kynický J, Baláková L, Brtnický M, et al. Polluted brownfield site converted into a public urban park: a place providing ecosystem services or a hidden health threat? *J Environ Manag*. (2021) 291:112669. doi: 10.1016/j.jenvman.2021.112669

39. Zhai XQ, Sun CZ, Zou W, Hao S. Spatiotemporal characteristic and evolution of China's marine economic resilience. *Ocean Coast Manag*. (2023) 238:106562. doi: 10.1016/j.ocecoaman.2023.106562

frontiers | Frontiers in Public Health

TYPE Systematic Review
PUBLISHED 04 November 2024
DOI 10.3389/fpubh.2024.1439788

Check for updates

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Renata Linertová,
Canarian Foundation for Health Research, Spain
Martin Dlouhy,
Prague University of Economics and Business, Czechia
Alexandre Morais Nunes,
University of Lisbon, Portugal

*CORRESPONDENCE
Mélanie Lötscher-Stamm
✉ stmm@zhaw.ch

RECEIVED 28 May 2024
ACCEPTED 30 September 2024
PUBLISHED 04 November 2024

CITATION
Lötscher-Stamm M and Lenzin G (2024) Definition and understanding of "efficiency" in healthcare provision research: a scoping review.
Front. Public Health 12:1439788.
doi: 10.3389/fpubh.2024.1439788

Definition and understanding of "efficiency" in healthcare provision research: a scoping review

Mélanie Lötscher-Stamm[1,2]* and Golda Lenzin[1]

[1]Winterthur Institute of Health Economics, School of Management and Law, ZHAW Zurich University of Applied Sciences, Winterthur, Switzerland, [2]Faculty of Health Sciences and Medicine, University of Lucerne, Lucerne, Switzerland

Background: With rising healthcare costs over the last decades, the concept of efficiency has gained popularity in healthcare provision research. As efficiency can be understood and measured in many different ways, it is often unclear what is meant by "efficient health systems" or "efficient healthcare providers".

Objectives: This study aims to analyze and categorize the different definitions and understandings of "efficiency" used in healthcare provision research over time.

Methods: We searched five databases (Medline, Embase, CINAHL, Business Source Premier, and EconLit) to conduct a scoping review. Sources were screened independently by two researchers, using the online software Rayyan. Results are reported using PRISMA-ScR.

Results: Of 1,441 individual sources identified, 389 were included in the review. Most papers (77.3%) using the term "efficiency" do not include explicit definitions or explanations of their understanding of it. Almost all papers (99.0%) are interested in productive efficiency (vs. allocative efficiency) and more specifically technical efficiency, therefore comparing the number of inputs used and outputs produced. While many papers (70.4%) include some elements of quality of care or health outcomes in their discussion, few (30.3%) include aspects of quality in their measurement of efficiency. Over the last decades, Data Envelopment Analysis has become the main method to measure efficiency. We propose a broad categorization of efficiency definitions that could be used by researchers to improve the comprehensibility and comparability of their research. Key features are the general type of efficiency, inclusion of quality or outcome information, and inclusion of cost information.

Discussion: To allow for better comparability and comprehensibility, researchers in healthcare provision should state explicitly which type of efficiency they are studying. To do this, we propose to use combinations of the terms *productive efficiency*, *allocative efficiency*, *quality-inclusive efficiency*, and *cost efficiency*.

KEYWORDS

efficiency, definition, measurement, healthcare provision, quality-inclusive efficiency, scoping review

1 Introduction

Healthcare spending has increased in many countries over the past few decades, particularly in high-income countries (1). Policymakers and researchers are interested in understanding the underlying tendencies and finding more efficient ways to provide health care. The concept of efficiency has therefore received growing attention in healthcare provision research, leading to a variety of definitions and interpretations.

The concept of "efficiency" is rooted in economic theory. In economics, efficiency can be understood either as a productive or an allocative concept. *Productive efficiency* is interested in producing the *most* output with the least inputs (e.g., producing as many cars as possible with given materials) (2, 3). *Allocative efficiency* is interested in producing the *optimal mix* of outputs with given inputs, so that the outputs benefit society (or the company) the most, e.g., spending the available tax money on the right infrastructure renovations (3–5).

Productive efficiency can be further categorized into different subtypes. "Technical efficiency" examines the number of inputs used and outputs produced (6). Another subtype, "cost efficiency," assigns a monetary value to the inputs used to produce the highest number of outputs at the lowest costs (7). A third subtype, "scale efficiency," focuses on whether the analyzed economic unit (e.g., company) is the right size to produce with ideal scale effects (8, 9). Some papers applying Data Envelopment Analysis (DEA) also distinguish "allocative efficiency" as a fourth subtype of productive efficiency. In this understanding, "allocative efficiency" means using the right inputs to produce outputs with the highest possible monetary value (10), which means monetary value has to be assigned to all inputs and all outputs. In this review, these cases are assigned to the general category of productive efficiency, not allocative efficiency. Both general understandings of efficiency as well as all subtypes can also be applied to healthcare provision.

In healthcare provision research, efficiency can be analyzed from two main perspectives. Studies often either focus on health systems or healthcare providers. *Health systems* can be analyzed on an international, national, or subnational (e.g., state or regional) level. The efficiency goal of health system studies is often to provide a higher level of care with the same set of resources. Another perspective can be to provide the same level of care to a larger or older population with the same resources as before (11–13). Studies interested in *healthcare providers* often focus on one type of provider, such as hospitals, primary care centers, or nursing homes. The efficiency goal of healthcare provider studies is often to reduce costs by providing the same level of care with fewer resources (14–16).

Several systematic literature reviews and scoping reviews have been conducted on specific aspects of efficiency. These include reviews on efficiency in nursing homes (17), efficiency in primary care in high-income countries (18), and efficiency of health systems (19). Others have focused on the different methodologies of efficiency measurement, for example on the application of different frontier techniques (20) or specifically on the inputs and outputs used in efficiency models (21). Another review was conducted on different measures implemented to improve efficiency in health care (22).

The existing reviews have highlighted the diverse interpretations and understandings of the term "efficiency" being used in healthcare provision research. This diversity can sometimes be problematic: If research papers have different underlying understandings of efficiency, comparability between research on the topic might be very limited. Especially in healthcare provision research, where comparison between countries, regions, or providers is frequently performed, this ambiguity can be detrimental to the quality of research and the resulting policy recommendations. So far, there has been no review incorporating different settings and levels of interest, focusing on the concept of efficiency itself rather than on the most efficient ways to organize a specific setting (e.g., nursing homes) or on specific methodologies.

This paper therefore aims to answer the following questions:

(1) How has the term "efficiency" been defined and understood in the scientific literature on health care provision?
(2) Have the definitions and understandings changed over time?
(3) How can the definitions and understandings be broadly categorized for easier comparability?

By "definitions and understandings," we refer to both explicit definitions provided in sources and implicit definitions, where the underlying definition needed to be derived from the way efficiency was measured.

The study was designed using a scoping review approach. This type of review was chosen because the goal of the paper is to clarify a concept, which is one of the indications for a scoping review rather than a systematic literature review (23, 24). However, while the topic of this review lends itself to a scoping review, the methods used to identify, screen, and include or exclude articles for analysis are equivalent to a systematic literature review.

2 Materials and methods

This scoping review was conducted in accordance with the framework for scoping reviews by Arksey and O'Malley (25) and is reported under the Preferred Reporting Items for Systematic Reviews and Metaanalyses extension for Scoping Reviews (PRISMA-ScR; checklist available in the Supplementary Table 1). In some aspects, the guidelines of the Joanna Briggs Institute (JBI) methodology for scoping reviews (26) were followed for more detailed orientation. The research protocol for this review was not registered.

2.1 Identifying relevant studies

The authors conducted a systematic literature search in five literature databases (Medline, Embase, CINAHL, Business Source Premier, and EconLit). Results in English, French, and German were included. Only original research articles published in scientific journals were considered. No limits were set for the publication date of sources.

Preliminary search terms were developed by the research team. For the final design of the search strategy and the realization of the search, a scientific librarian of the medical library of the University of Zurich was consulted. The main keywords used included efficiency, inefficiency, and different keywords related to providers (hospital, primary care, health center, outpatient, etc.). To refine the search to studies that provide definitions or measurements of efficiency, supplementary terms such as defin*, measur*, or indicat* were added.

Boolean operators such as AND, OR, and NOT were applied. For full search terms, see Supplementary Table 2. The most recent search was executed on January 25th, 2022. The results of the search have been saved and managed in EndNote 20 (27).

While this study focuses on efficiency, the related term "inefficiency" was also searched for and is used in some of the included sources. Efficiency and inefficiency describe the two opposite facets of the same concept, e.g., studies searching for inefficient providers usually search for the least efficient ones. Studies might use "inefficiency" as a keyword but then provide definitions and measurements for "efficiency" [see for example (28, 29)] or give negative formulations of efficiency definitions for inefficiency [see for example (30, 31)]. This scoping review, therefore, also indirectly applies to research on inefficiency.

2.2 Selection of sources of evidence

The selection process involved (i) removal of duplicates, (ii) title/abstract screening, and (iii) full-text screening. Duplicates were removed automatically with the corresponding function of EndNote and an additional manual search for duplicates in the EndNote library. The screening was performed with the online software Rayyan (32).

For the title/abstract screening, sources were included or excluded based on pre-defined criteria. The screening guide is provided in Supplementary Table 3. The main criteria in this first screening stage were language, publication type, setting, and content. The "setting" criteria excluded studies on efficiency in dental care, military health care, and medical labs as these settings are or can be quite different from other healthcare provision settings. The "content" criteria excluded studies interested in other types of efficiency than economic efficiency, such as energy efficiency, treatment efficiency, imaging efficiency, etc. It also excluded medical studies focusing on a specific condition, screening, intervention, or medication, as this type of efficiency is not the focus of this review. A 93.4% agreement between the two screeners was reached in this first step of title/abstract screening. Disagreements were resolved by discussion.

For the full-text screening, a second screening guide was developed pre-screening (also provided in Supplementary Table 3). The criteria of the first stage were supplemented by criteria on "definition." Sources without an explicit or implicit definition of their understanding of efficiency were excluded. This mainly concerned studies using the term in the abstract but not in the body of the paper. Availability of the full text to the authors was another additional criterion. A 94.7% agreement between the screeners was reached after the first round of full-text screening. Conflicts were resolved by a separate, blinded re-screening of all contested articles by both MLS and GL. If the disagreement persisted, consensus was reached by discussion.

The results of the search and the study inclusion process are presented in Figure 1 in a PRISMA flow diagram (33). Reasons for the exclusion of sources at full-text screening are reported in the diagram.

2.3 Data extraction and analysis

Each author extracted information from half of the included sources into a charting template developed in Microsoft Excel (Excel 365, 2022). After charting, MLS conducted some quality control measures by searching the charting document for cells that had mistakenly not been filled. The missing information was then extracted directly from the corresponding source. Additionally, we ensured that, depending on the type of study, the correct cells were filled and/or left empty (e.g., when the method "DEA+" was selected, the cells on "inputs" and "outputs" should be filled, but the cell on "indicators" should be empty).

Extracted information included author, year, country of interest, level of interest (health system or health provider), study setting, direct or indirect definition of efficiency, type and subtype of efficiency studied, method used to quantify efficiency, input variables, output variables, indicators used, inclusion of quality of care or health outcomes in the discussion (yes/no), inclusion of quality of care or health outcomes in the efficiency definition (yes/no). Some categories were simplified for the analysis. One example concerns the countries of interest, which were categorized into the five UN world regions (34). The extracted data was handled and analyzed in Microsoft Excel and Stata (release 17) (35).

3 Results

3.1 Selection of sources of evidence

The initial search resulted in 2522 studies retrieved from the different databases, which were reduced to 1,441 studies after the removal of duplicates. After the screening of titles and abstracts, 589 studies were sought for full-text retrieval. 530 studies could be retrieved and were included in the full-text screening. Finally, 389 studies were included in the review. Reasons for exclusions at this stage are shown in Figure 1. All included sources are detailed in Supplementary Table 4.

Some of the included studies use multiple definitions or measurements of efficiency. This means that some analyses (e.g., general study characteristics) were conducted on the level of studies ($n = 389$). Other analyses (type of efficiency, method used, inputs and outputs used, etc.) are performed on the level of definition because two different versions can be used in one single study. Therefore, these analyses are performed on the slightly larger sample of definitions ($n = 405$). The Excel documents with the extracted characteristics are available in Supplementary Data Sheets 1, 2.

3.2 Results on the level of studies (n = 389)

3.2.1 General study characteristics

The included studies were published between 1974 and 2022. Table 1 summarizes the general study characteristics. 90.5% ($n = 352$) of the studies focus on a single country, while 9.5% ($n = 37$) are interested in multiple countries (globally or within a specific region). 32.7% ($n = 115$) of the studies interested in a single country focus on countries in Asia, 28.1% ($n = 99$) each on countries in the Americas and Europe, 8.5% ($n = 30$) on countries in Africa, and 2.6% ($n = 9$) on countries in Oceania.

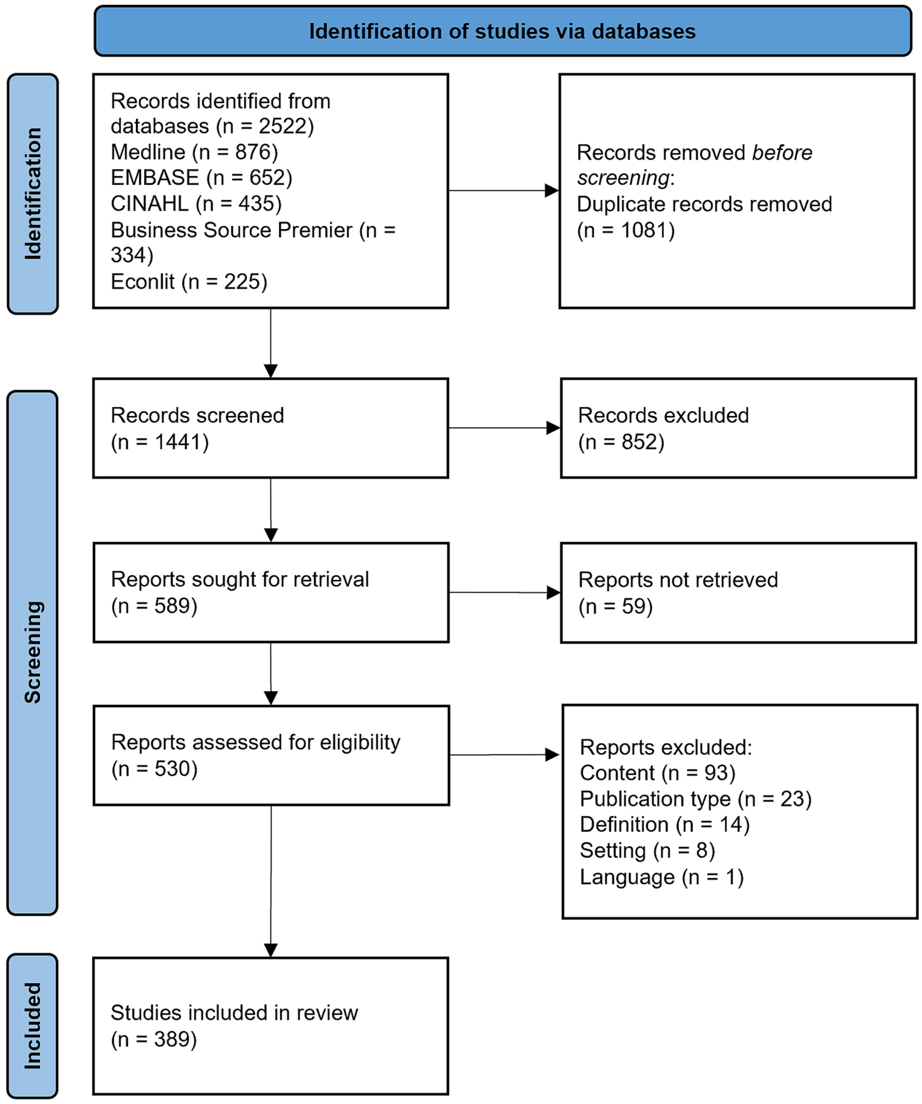

FIGURE 1
Results of the systematic search and screening process, using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram.

3.2.2 Levels and settings of interest

Most included studies analyze health providers (82%, $n = 321$), and only a minority analyze health systems (18%, $n = 69$). One study covers both provider and health systems and is included in the calculations for both settings. Regional variations exist: research concerning Africa, the Americas, Asia, and Europe mainly covers health providers (all over 88%). Studies focused on Oceania are more balanced between the levels, with 44.4% ($n = 4$) analyzing providers and 55.6% ($n = 5$) analyzing health systems. Studies done in an international setting are predominantly interested in health systems (81.1%, $n = 30$).

Of the studies analyzing providers, nearly 80% ($n = 255$) are interested in hospitals, 16.5% ($n = 53$) in primary care, and 4.1% ($n = 13$) in nursing homes, pharmacies, and other secondary care. Of the studies focusing on health systems, 46.4% ($n = 32$) conduct international analyses, 21.7% ($n = 15$) conduct analyses on a national, and 31.9% ($n = 22$) on a sub-national level.

95.9% ($n = 373$) of all papers use only one definition or measurement of efficiency.

3.2.3 Inclusion of quality of care or health outcomes

While there is no universal agreement on how to define or measure the quality of healthcare provision, we can generally divide healthcare quality into structural, process, and outcome quality (36). Most of the quality indicators used in the studies covered in this review focus on outcome quality (e.g., complication rates, unplanned readmission rates, or number of pressure ulcers). As we also cover health system analyses, more general health outcome measures (such as life expectancy or child mortality rates), which are far more comprehensive than the aforementioned examples of quality of care indicators, are also of interest.

We evaluated each source to determine whether any elements of quality of care or health outcomes were included in the discussion and

TABLE 1 General characteristics of included studies.

Variable		Frequency (%)
Year of publication	1970–1979	3 (0.8%)
	1980–1989	8 (2.1%)
	1990–1999	34 (8.7%)
	2000–2009	74 (19.0%)
	2010–2019	198 (50.9%)
	2020–2022	72 (18.5%)
Geographical focus	Single country	352 (90.5%)
	Multiple countries	37 (9.5%)
U.N. world regions (single country studies)	Africa	30 (8.5%)
	Americas	99 (28.1%)
	Asia	115 (32.7%)
	Europe	99 (28.1%)
	Oceania	9 (2.6%)
Level of interest	Health providers	321 (82.0%)
	Health systems	69 (18.0%)
Provider settings	Hospitals	255 (79.4% of provider studies)
	Primary care providers	53 (16.5%)
	Nursing homes	6 (1.9%)
	Secondary care (excl. hospitals)	4 (1.3%)
	Other	3 (0.9%)
Health system settings	International analyses	32 (46.4% of health system studies)
	National analyses	15 (21.7%)
	Sub-national analyses	22 (31.9%)
Quality of care and health outcomes	Quality included in the discussion	274 (70.4%)
	Quality included in the definition	118 (30.3%)

quantification of efficiency. This analysis was performed to understand whether "efficiency" is understood as a purely economic concept (number or cost of inputs and outputs) or whether healthcare provision researchers deem providers and health systems to be "most efficient" if they deliver health care with the fewest inputs and best health outcomes for the treated patients or population. For "quality included in discussion," statements as general as "quality of care is assumed to be equal in all analyzed hospitals" or "we wanted to include health outcomes, but there was no data available" were accepted. As a result, we created a broad indicator of whether quality of care or health outcomes were even slightly considered by the authors of the included sources. In contrast, we marked "quality included in definition" only when elements of quality of care or health outcomes were utilized in the calculation of efficiency.

70.4% ($n = 274$) of all included studies mention aspects of quality of care or health outcomes in their discussion. This share reaches 91.3% ($n = 63$) of studies covering health systems, while only 66.0% ($n = 212$) of provider-focused studies discuss aspects of quality of care or health outcomes.

However, only 30.3% ($n = 118$) of all studies include elements of quality of care or health outcome measures in their definitions or measurements of "efficiency." This represents 43.1% of the studies that discussed elements of quality or outcomes. Studies related to health systems more frequently incorporate quality of care or health outcomes into their efficiency definitions or measurements (73.9%, $n = 51$ vs. 21.2%, $n = 68$ for studies focusing on providers). This is expected as these analyses often involve population health outcomes such as life expectancy at birth or child mortality.

Figure 2 illustrates the differences in quality inclusion over time. Apart from the three studies published in the 1970s, all of which discussed aspects of quality of care or health outcomes, we can see an increase in the proportion of studies discussing such elements over time (37.5%, $n = 3$ in the 1980s, to 73.2%, $n = 145$, in the 2010s). Similarly, the proportion of studies including quality of care or health outcomes in their definition and measurement of efficiency increased from 12.5% ($n = 1$) in the 1980s to 34.8% ($n = 69$) in the last full decade analyzed (2010–2019).

3.3 Results on the level of definitions ($n = 405$)

3.3.1 Direct or indirect definitions

Table 2 summarizes the definitions and methods used in the included studies. Only in 22.7% ($n = 92$) of all cases is an explicit definition of "efficiency" included. The authors of the included studies typically do not provide a clear definition of the term, requiring the reader to analyze how efficiency is measured in the study to understand the intended meaning.

3.3.2 Type and subtype of efficiency

99.0% ($n = 401$) of the definitions are based on a productive understanding of efficiency. Only a small percentage (0.5%, $n = 2$ each) are based on an allocative understanding of efficiency or both types.

Most definitions and measurements of efficiency (84.7%, $n = 343$) use only one subtype of efficiency, while 13.6% ($n = 55$) of them include multiple subtypes such as technical, scale, and cost efficiency. Some definitions (1.7%, $n = 7$) do not include a subtype.

Among the definitions and measurements including only one subtype of efficiency, the vast majority (93.0%, $n = 319$) relies on technical efficiency, while only a few rely on cost efficiency (6.1%, $n = 21$) and even fewer rely on scale efficiency (0.6%, $n = 2$) or what the authors called "social efficiency" (0.3%, $n = 1$).

3.3.3 Methods used to quantify or measure efficiency

In most cases (74.1%, $n = 300$), efficiency is quantified by DEA or a DEA-based method [DEA (+)]. DEA is a non-parametric linear programming method used to determine and compare the efficiency of so-called "decision-making units," which in healthcare can be different types of providers or health systems. Units are compared based on the ratio of a weighted sum of the outputs of the unit to a weighted sum of its inputs (37). In some cases (10.1%, $n = 41$), efficiency is quantified by Stochastic Frontier Analysis (SFA) or SFA-based methods [SFA (+)]. SFA is a parametric method, calculating a best-practice frontier based

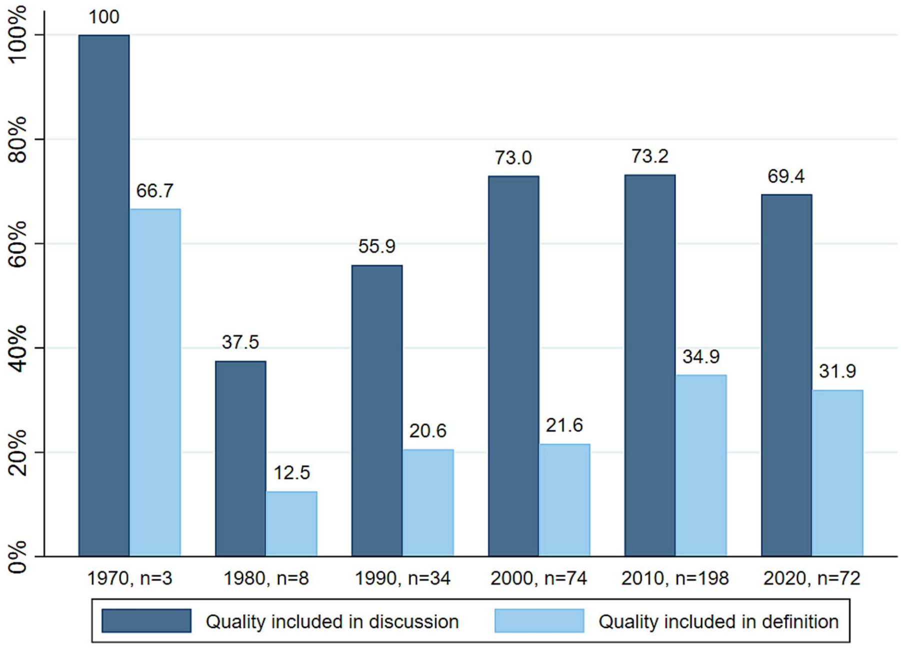

FIGURE 2
Proportion of studies including quality of care or health outcomes in their discussion and definition, per decade.

TABLE 2 Definitions and methods used in included studies.

Variable		Frequency (%)
Explicit definition of efficiency	Included	92 (22.7%)
	Not included	313 (77.3%)
Efficiency type	Productive efficiency	401 (99.0%)
	Allocative efficiency	2 (0.5%)
	Both	2 (0.5%)
Subtypes of productive efficiency	Technical efficiency	319 (93.0% of all studies with just one subtype)
	Cost efficiency	21 (6.1%)
	Scale efficiency	2 (0.6%)
	Social efficiency	1 (0.3%)
Method used	DEA (+)	300 (74.1%)
	SFA (+)	41 (10.1%)
	Indicators	41 (10.1%)
	Other (OLS models, Pabón Lasso models, etc.)	21 (5.2%)
	None	2 (0.5%)

on multiple inputs and a singular output using least squares methods (38, 39). Indicators are used quite frequently (10.1%, $n=41$), while alternative methods such as OLS models, mixed effect models, Pabón Lasso models, or order-m-estimators are used less frequently (5.2%, $n=21$). In two instances, a study proposed an explicit definition of efficiency without any quantification or measurement (0.5%, $n=2$).

Figure 3 shows that DEA has become the main method used to quantify efficiency in healthcare provision research.

3.3.4 DEA (+)

DEA models can generally be categorized as *input-oriented models*, trying to minimize inputs for constant outputs, or *output-oriented models*, aiming to maximize outputs for constant inputs. Among studies that employ DEA models, the majority (58.7%, $n=176$) use input-oriented models, while 25.3% ($n=76$) use output-oriented models, and 6% ($n=18$) use either both or non-oriented models. In 10% ($n=30$) of all DEA applications, information about the orientation of the model could not be extracted.

DEA applications at the provider level mostly use input-oriented models (62.8%, $n=153$ as opposed to 21.3%, $n=52$ output-oriented models), whereas DEA applications at the health system level use both input-oriented and output-oriented models with equal intensity (41.8%, $n=23$ each).

To analyze the inputs and outputs used in DEA papers, they were grouped into broad categories. Table 3 provides details on the inputs and outputs used. The input categories included labor, costs, supplies, services provided, capital, case complexity, and, exclusively for health systems, the number of medical institutions. Labor-related inputs (86.3% of all DEA papers, $n=259$), supply-related inputs (69.9%, $n=210$) such as hospital beds, and cost-related inputs (36.5%, $n=109$) were the most frequently used categories.

The outputs used in DEA papers were categorized into services provided, quality/outcomes, case complexity, revenue, and training. Services provided (86.0% of all DEA papers, $n=258$) and outcomes (25.1%, $n=76$) were the most frequently used output categories. The category of quality/outcomes covers many different variables, such as, for example, mortality rates, life expectancy, and percentage of births discharged alive, but also unplanned readmission rates or long-term complication rates.

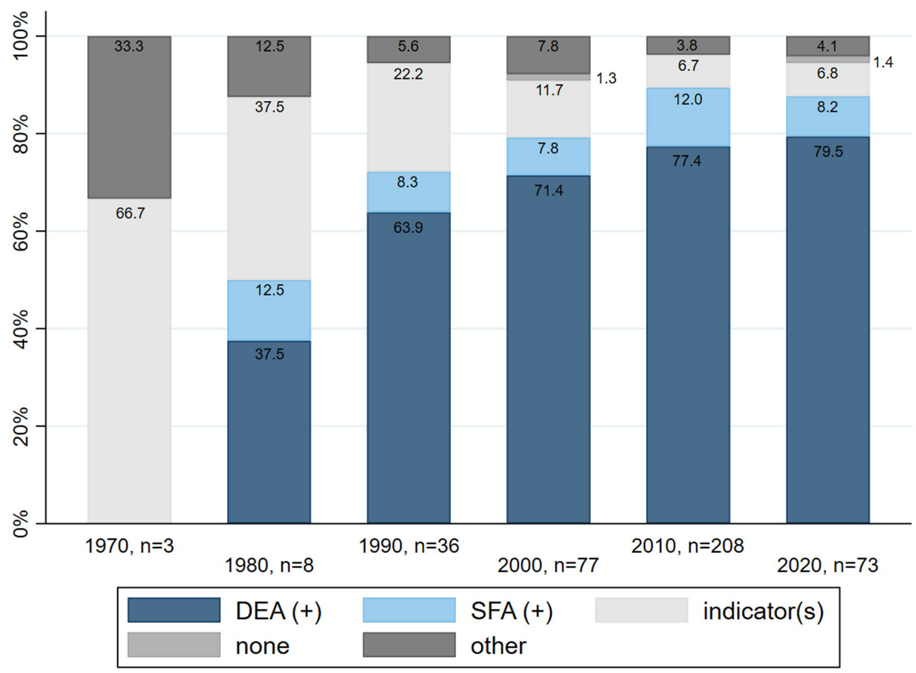

FIGURE 3
Relative frequency of methods used to quantify efficiency in the included studies, per decade.

TABLE 3 Categories of inputs and outputs used in DEA (+) studies.

	Provider (*n* = 244)	Health systems (*n* = 55)	Total (*n* = 299)
Inputs			
Labor	222 (91.0%)	36 (65.5%)	258 (86.3%)
Costs	80 (32.8%)	29 (52.7%)	109 (36.5%)
Supplies	178 (73.0%)	31 (56.4%)	209 (69.9%)
Services provided	15 (6.2%)	1 (1.8%)	16 (5.4%)
Capital	26 (10.7%)	4 (7.3%)	30 (10.0%)
Case complexity	12 (4.9%)	0 (0%)	12 (4.0%)
No of institutions	6 (2.5%)	5 (9.1%)	11 (3.7%)
Outputs			
Services provided	232 (95.1%)	25 (45.6%)	257 (86.0%)
Quality/outcomes	39 (16.0%)	36 (65.5%)	75 (25.1%)
Case complexity	34 (14.0%)	4 (7.3%)	38 (12.7%)
Revenue	20 (8.2%)	1 (1.8%)	21 (7.0%)
Training	11 (4.5%)	1 (1.8%)	12 (4.0%)

3.3.5 Ratios and indicators

Efficiency was measured using one or multiple indicators in 41 cases. 48.8% ($n = 20$) of those studies used cost indicators, while 41.5% ($n = 17$) used length of stay (LOS) indicators. Additional or other indicators were used in $n = 27$ cases. Studies focusing on health systems used additional indicators such as avoidable mortality rate, primary care coverage rate, or improvements in life expectancy. Studies focusing on providers utilized additional indicators such as staff per occupied bed, operations per month per operating room, or the bed occupancy rate.

3.4 Categorization of definitions

While a detailed analysis of the definition of efficiency used in healthcare provision research may not always be necessary, we believe that a broad categorization of definitions would facilitate comparability and comprehensibility of efficiency research. As such, one goal of this review was to propose a broad categorization of the definitions used in the healthcare literature over the last decades. We suggest that when designing efficiency studies or projects aimed at improving efficiency in health care, the underlying understanding of efficiency should be stated according to the key features presented in Figure 4.

The three key features of our categorization are the general type of efficiency (productive vs. allocative), the inclusion of quality of care or health outcome measures, and the inclusion of cost information. Although additional differences of methodological and other nature exist, we consider these three features to be the most distinctive. Figure 4 can be applied to different levels of analysis (health care systems vs. health care providers), different clinical settings, and different types of research. It could be used as a support tool both for designing efficiency studies and for communicating their results.

Communication is facilitated by the use of established and easily comprehensible terminology. The use of a specific term for each possible combination of the key features in Figure 4 would complicate, rather than simplify, the communication of efficiency studies and their results. Therefore, we propose to use combinations of well-known terms to effectively communicate the type of efficiency studied:

- *productive efficiency* and *allocative efficiency* for the general type of efficiency
- *cost efficiency* if cost information is included

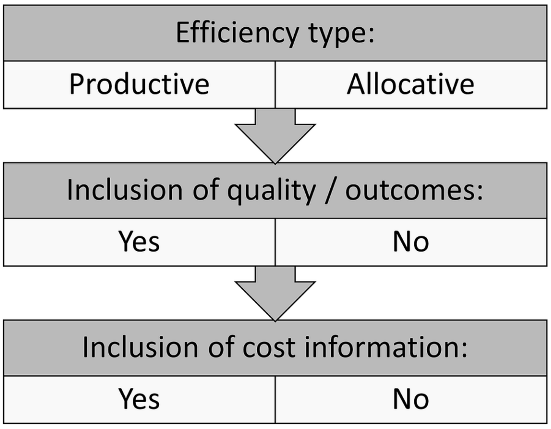

FIGURE 4
Gross categorization of efficiency definitions in healthcare provision research.

To the best of our knowledge, no such well-established term exists for efficiency which includes aspects of quality of care or health outcomes. We would therefore propose the following terminology:

- *quality-inclusive efficiency* if information on quality of care or health outcomes is included

Consequently, for studies including cost and/or quality information, two or even three terms would be applicable. To ensure the greatest clarity and comprehensibility, we would recommend using all applying terms in the respective manuscript, and potentially as keywords.

4 Discussion

4.1 Summary of results

The purpose of this study was to investigate how the term "efficiency" has been defined in the scientific literature on healthcare provision, how these definitions have changed over time, and how they can be categorized for better comparability.

Our analysis shows that most papers using the term "efficiency" in healthcare provision research fail to provide explicit definitions or explanations of the concept. As a result, readers need to infer the authors' understanding of efficiency based on the quantifications provided.

Most papers are interested in productive rather than allocative efficiency. This is true regardless of the level of interest (health systems or specific providers). Most papers focus on technical efficiency (the relation between the number of inputs and outputs), while only a few use cost efficiency, where cost information on inputs is needed. Efficiency is consistently understood as a comparative term, indicating that it is impossible to determine efficiency without one or more comparators. Comparators can consist of other countries, regions of the same country, or other providers. Although many papers discuss some aspects of quality of care or health outcomes, only a few include quality – as defined for this review—in their measurement of efficiency. Overall, efficiency is mostly understood as a concept that compares the ratio between the number of inputs used and outputs produced, not including quality measures or health outcomes, and only rarely including costs of the inputs.

One main change over time concerns the methodology used to quantify efficiency. Over the past 30 years, research on efficiency in health care has become strongly focused on applications of Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis (SFA). The use of efficiency indicators such as "length of stay" or "expenses per standard patient" on their own has decreased, even though these indicators are now commonly integrated as inputs or outputs in DEA applications. A further change over time includes the rise in the proportion of studies incorporating quality or outcome elements in their discussion and definition of efficiency. Excluding the three studies from the 1970s, which all incorporated quality of care elements, the proportion of studies doing so has continued to steadily increase from the 1980s to the last full decade analyzed (2010–2019). This could indicate that the quality aspect of health care is becoming more prominent and that efficiency is developing into a more comprehensive concept.

Our review results are consistent with other reviews conducted on efficiency in specific settings. In Neri et al.'s (18) study on primary care efficiency, all included studies focused on technical efficiency, with cost efficiency and other subtypes only rarely being investigated. Regarding the incorporation of quality and outcome considerations into efficiency discussions, Hussey et al. (22) discovered that almost none of the efficiency measures analyzed in their scoping review included quality of care. From their perspective, this means that efficiency measures only account for the cost of care but not for what they define as 'true efficiency', which would require the inclusion of both quality and cost (22). It should be noted that while many authors view quality of care as a component of efficiency, others consider efficiency and quality of care to be two concurrent concepts (40). A recently published review on healthcare quality in nonparametric efficiency studies goes into more detail on how exactly quality is incorporated in the calculation of efficiency scores (41). Regarding the methods used to measure the concept of efficiency, our study's findings are consistent with previous research conducted on health system efficiency. According to Mbau et al. (19), the most common method is DEA, followed by SFA. Hafidz et al. (42) similarly reported that DEA is the most commonly used method to measure efficiency in studies on healthcare facilities in low- and middle-income countries since the year 2000.

After the analysis of the included studies, we proposed a categorization of definitions and understandings of efficiency along three key features: general type of efficiency (productive vs. allocative), inclusion of quality of care or health outcome measures, and inclusion of cost information. We also proposed that researchers should use the following terms in combination to clearly communicate the type of efficiency analyzed in their research: *productive* vs. *allocative efficiency*, *quality-inclusive efficiency*, and *cost efficiency*.

As an example of the usefulness of our categorization, consider an efficiency study on primary care practices. Is the efficiency goal to reduce the number of inputs (e.g., GPs) with constant outputs (e.g., patients treated per week)? Or is the efficiency goal to improve patient outcomes (e.g., patient satisfaction) with the same cost of inputs (e.g., labor costs)? These two examples have vastly different understandings of efficiency and therefore different goals and implications. Findings from efficiency studies using technical efficiency without the inclusion of elements of quality of care or health outcomes (which, as we have shown, represent the majority of efficiency studies) might be less directly applicable to healthcare providers or political stakeholders who would include aspects of quality in their understanding of efficiency. An explicit statement of the general understanding of efficiency used in studies or projects according to the proposed key features and terms would facilitate the assessment of the comparability of studies as well as the practical applicability of study results. In addition, it would make the communication of results to non-scientific stakeholders and policymakers more precise and more comprehensible.

4.2 Limitations

Two limitations of this study should be noted. The first limitation results from the time that passed between the final database searches in January 2022 and the final submission of the paper in Spring 2024. Because of this delay, papers published after January 25th, 2022 were not considered in the review, resulting in the exclusion of the most recent papers on healthcare efficiency. As this scoping review is interested in long-term developments and covers five decades (1970 to 2020), we do not believe that re-running the search for two more years would add any substantial benefits compared to the additional effort. The authors do not expect this limitation to strongly influence the results of the paper. Nonetheless, efficiency studies published over the last two years are missing from this review [see for example (43–45)].

The second limitation stems from the lack of additional ways used to identify relevant sources. Although it was planned to search for further sources in the reference sections of included studies according to the JBI guidelines (26), it was not possible to do so due to the considerable number of included studies based on database searches alone. It is likely that our database search did not detect some sources of evidence that would fit our inclusion criteria and could have been found through manual reference searching. As the included studies from the database search alone cover five decades, many different countries, and topics, we do not believe that the lack of additional search methods strongly influences the results of this broad and conceptual scoping review. Other types of sources (reports, non-scientific articles, etc.) were not searched for as the research questions of this scoping review are specifically interested in scientific research.

5 Conclusion

This review has shown that many different definitions and understandings of "efficiency" have been used in the scientific literature on healthcare provision. Interestingly, many papers do not include an explicit definition of "efficiency." In most cases, efficiency is understood as a productive term, interested in the number of inputs used and the number of outputs produced. There is considerable variation in terms of whether quality of care and health outcomes are seen as part of efficiency and if so, how they are included in the quantification of efficiency. While different methods have been used to quantify efficiency over time, Data Envelopment Analysis has become increasingly dominant.

Since efficiency is often used without an explicit definition, we propose a broad categorization of efficiency definitions that could be used by researchers to improve the comprehensibility and comparability of their research. Key features are the type of efficiency, inclusion of quality information, and inclusion of cost information. Additionally, as quality of care is rarely incorporated in efficiency quantifications, this should be stated clearly by researchers when expecting their results to influence policy decisions.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ML-S: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Visualization, Writing – original draft, Writing – review & editing. GL: Data curation, Formal analysis, Writing – review & editing.

Funding

The author(s) declare financial support was received for the research, authorship, and/or publication of this article. ML-S has a PhD scholarship sponsored by Swiss universities (Swiss Learning Health System) and the ZHAW Zurich University of Applied Sciences. The funding bodies did not influence the design, realization or outcome of the study. Open access funding by Zurich University of Applied Sciences (ZHAW).

Acknowledgments

The authors want to thank Ms. Martina Gosteli, the scientific librarian of the medical library of the University of Zurich, for her help with the database search.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2024.1439788/full#supplementary-material

SUPPLEMENTARY TABLE 1
PRISMA-ScR Checklist.

SUPPLEMENTARY TABLE 2
Full search strategy.

SUPPLEMENTARY TABLE 3
Screening guide.

SUPPLEMENTARY TABLE 4
Full reference list.

SUPPLEMENTARY DATA SHEET 1
Extraction - level of papers.

SUPPLEMENTARY DATA SHEET 2
Extraction - level of definitions.

References

1. WHO. Global spending on health 2020: Weathering the storm. (2020). Report No.: 924001778X. Geneva: World Health Organization.

2. Farrell MJ. The measurement of productive efficiency. *J Royal Stat Soc Series A*. (1957) 120:253–81. doi: 10.2307/2343100

3. Bentley TG, Effros RM, Palar K, Keeler EB. Waste in the US health care system: a conceptual framework. *Milbank Q*. (2008) 86:629–59. doi: 10.1111/j.1468-0009.2008.00537.x

4. Allan T. Productive efficiency and allocative efficiency: why better water management may not solve the problem. *Agric Water Manag*. (1999) 40:71–5. doi: 10.1016/S0378-3774(98)00106-1

5. Hollingsworth B, Dawson PJ, Maniadakis N. Efficiency measurement of health care: a review of non-parametric methods and applications. *Health Care Manag Sci*. (1999) 2:161–72. doi: 10.1023/A:1019087828488

6. Atkinson SE, Cornwell C. Estimation of output and input technical efficiency using a flexible functional form and panel data. *Int Econ Rev*. (1994) 35:245–55. doi: 10.2307/2527100

7. Athanassopoulos A, Gounaris C, Sissouras A. A descriptive assessment of the production and cost efficiency of general hospitals in Greece. *Health Care Manag Sci*. (1999) 2:97–106. doi: 10.1023/A:1019023408924

8. Avkiran NK. Applications of data envelopment analysis in the service sector. In: Cooper WW, Seiford LM, Zhu J, editors. *Handbook on data envelopment analysis*. New York, NY: Springer (2011) 403–43.

9. Cooper WW, Seiford LM, Zhu J. Data envelopment analysis: history, models, and interpretations. In: Cooper WW, Seiford LM, Zhu J, editors. *Handbook on data envelopment analysis*. New York, NY: Springer (2011) 1–39.

10. Sheikhzadeh Y, Roudsari AV, Vahidi RG, Emrouznejad A, Dastgiri S. Public and private hospital services reform using data envelopment analysis to measure technical, scale, allocative, and cost efficiencies. *Health Promo Perspect*. (2012) 2:28–41. doi: 10.5681/hpp.2012.004

11. Zheng D, Gong J, Zhang C. Efficiency of medical service systems in the rural areas of mainland China: a comparative study from 2013 to 2017. *Public Health*. (2019) 171:139–47. doi: 10.1016/j.puhe.2019.04.003

12. Bonasia M, Kounetas K, Oreste N. Assessment of regional productive performance of European health systems under a metatechnology framework. *Econ Model*. (2020) 84:234–48. doi: 10.1016/j.econmod.2019.04.013

13. González E, Cárcaba A, Ventura J. Value efficiency analysis of health systems: does public financing play a role? *J Public Health*. (2010) 18:337–50. doi: 10.1007/s10389-009-0311-4

14. Piubello Orsini L, Leardini C, Vernizzi S, Campedelli B. Inefficiency of public hospitals: a multistage data envelopment analysis in an Italian region. *BMC Health Serv Res*. (2021) 21:1281. doi: 10.1186/s12913-021-07276-5

15. Ayiko R, Mujasi PN, Abaliwano J, Turyareeba D, Enyaku R, Anguyo R, et al. Levels, trends and determinants of technical efficiency of general hospitals in Uganda: data envelopment analysis and Tobit regression analysis. *BMC Health Serv Res*. (2020) 20:916. doi: 10.1186/s12913-020-05746-w

16. Walker DM. Does participation in health information exchange improve hospital efficiency? *Health Care Manag Sci*. (2018) 21:426–38. doi: 10.1007/s10729-017-9396-4

17. Tran A, Nguyen K-H, Gray L, Comans T. A systematic literature review of efficiency measurement in nursing homes. *Int J Environ Res Public Health*. (2019) 16:2186. doi: 10.3390/ijerph16122186

18. Neri M, Cubi-Molla P, Cookson G. Approaches to measure efficiency in primary care: a systematic literature review. *Appl Health Econ Health Policy*. (2021) 20:19–33. doi: 10.1007/s40258-021-00669-x

19. Mbau R, Musiega A, Nyawira L, Tsofa B, Mulwa A, Molyneux S, et al. Analysing the efficiency of health systems: a systematic review of the literature. *Appl Health Econ Health Policy*. (2023) 21:205–24. doi: 10.1007/s40258-022-00785-2

20. Worthington AC. Frontier efficiency measurement in health care: a review of empirical techniques and selected applications. *Med Care Res Rev*. (2004) 61:135–70. doi: 10.1177/1077558704263796

21. Imani A, Alibabayee R, Golestani M, Dalal K. Key indicators affecting hospital efficiency: a systematic review. *Front Public Health*. (2022) 10:830102. doi: 10.3389/fpubh.2022.830102

22. Hussey PS, De Vries H, Romley J, Wang MC, Chen SS, Shekelle PG, et al. A systematic review of health care efficiency measures. *Health Serv Res*. (2009) 44:784–805. doi: 10.1111/j.1475-6773.2008.00942.x

23. Munn Z, Peters MD, Stern C, Tufanaru C, McArthur A, Aromataris E. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC Med Res Methodol*. (2018) 18:1–7. doi: 10.1186/s12874-018-0611-x

24. Peters MD, Marnie C, Tricco AC, Pollock D, Munn Z, Alexander L, et al. Updated methodological guidance for the conduct of scoping reviews. *JBI Evid Synth*. (2020) 18:2119–26. doi: 10.11124/JBIES-20-00167

25. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. *Int J Soc Res Methodol*. (2005) 8:19–32. doi: 10.1080/1364557032000119616

26. Peters M, Godfrey C, McInerney P, Munn Z, Tricco A, Khalil H. Chapter 11: scoping reviews (2020 version). In: E Aromataris and Z Munn, editors. *JBI manual for Evidence Synthesis*. JBI (2020)

27. Team TE. EndNote. EndNote 20 ed. Philadelphia, PA: Clarivate (2013).

28. Burgess JF Jr, Wilson PW. Variation in inefficiency among US hospitals. INFOR: information systems and operational. *Research*. (1998) 36:84–102. doi: 10.1080/03155986.1998.11732348

29. Burney NA, Mohammad OE, Al-Ramadhan MA. Assessing the cost of inefficiencies: the case of the public health care system in Kuwait. *Int Soc Sci Rev*. (1999) 74:20–37.

30. Rosko MD, Mutter RL. Inefficiency differences between critical access hospitals and prospectively paid rural hospitals. *J Health Polit Policy Law*. (2010) 35:95–126. doi: 10.1215/03616878-2009-042

31. Ketabi S. Efficiency measurement of cardiac care units of Isfahan hospitals in Iran. *J Med Syst*. (2011) 35:143–50. doi: 10.1007/s10916-009-9351-0

32. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan—a web and mobile app for systematic reviews. *Syst Rev*. (2016) 5:1–10. doi: 10.1186/s13643-016-0384-4

33. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. *Ann Intern Med*. (2018) 169:467–73. doi: 10.7326/M18-0850

34. UN Statistics Division. *Standard country or area codes for statistical use (M49)*. New York NY: United Nationds Statistics Divisions (2024). Available from: https://unstats.un.org/unsd/methodology/m49/

35. StataCorp. Stata statistical software: Release 17. College Station, TX: StataCorp LLC (2021).

36. Donabedian A. Evaluating the quality of medical care. *Milbank Mem Fund Q*. (1966) 44:166–206. doi: 10.2307/3348969

37. Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. *Eur J Oper Res*. (1978) 2:429–44. doi: 10.1016/0377-2217(78)90138-8

38. Aigner D, Lovell CK, Schmidt P. Formulation and estimation of stochastic frontier production function models. *J Econ*. (1977) 6:21–37. doi: 10.1016/0304-4076(77)90052-5

39. Meeusen W, van Den Broeck J. Efficiency estimation from cobb-Douglas production functions with composed error. *Int Econ Rev*. (1977) 18:435–44. doi: 10.2307/2525757

40. Mennicken R, Kuntz L, Schwierz C. The trade-off between efficiency and quality in hospital departments. *J Health Organ Manag*. (2011) 25:564–77. doi: 10.1108/14777261111161897

41. Sommersguter-Reichmann M. Health care quality in nonparametric efficiency studies: a review. *CEJOR*. (2022) 30:67–131. doi: 10.1007/s10100-021-00774-1

42. Hafidz F, Ensor T, Tubeuf S. Efficiency measurement in health facilities: a systematic review in low-and middle-income countries. *Appl Health Econ Health Policy*. (2018) 16:465–80. doi: 10.1007/s40258-018-0385-7

43. Nunes AM, Ferreira DFC. Evaluating Portuguese public hospitals performance: any difference before and during COVID-19? *Sustainability*. (2022) 15:294. doi: 10.3390/su15010294

44. Zhou J, Peng R, Chang Y, Liu Z, Gao S, Zhao C, et al. Analyzing the efficiency of Chinese primary healthcare institutions using the Malmquist-DEA approach: evidence from urban and rural areas. *Front Public Health*. (2023) 11:1073552. doi: 10.3389/fpubh.2023.1073552

45. Yang Y, Zhang L, Zhang X, Yang M, Zou W. Efficiency measurement and spatial spillover effect of provincial health systems in China: based on the two-stage network DEA model. *Front Public Health*. (2022) 10:952975. doi: 10.3389/fpubh.2022.952975

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 19 November 2024
DOI 10.3389/fpubh.2024.1384474

Check for updates

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Roberto Alonso González-Lezcano,
CEU San Pablo University, Spain
Chen Li,
Shanghai University of Engineering Sciences,
China

*CORRESPONDENCE
Huaxing Wang
✉ wanghx@hzcu.edu.cn

RECEIVED 09 February 2024
ACCEPTED 31 October 2024
PUBLISHED 19 November 2024

CITATION
Peng X, Zeng Y, Chen Y and Wang H (2024) Dual assurance for healthcare and future education development: normalized assistance for low-income population in rural areas—evidence from the population identification.
Front. Public Health 12:1384474.
doi: 10.3389/fpubh.2024.1384474

Dual assurance for healthcare and future education development: normalized assistance for low-income population in rural areas—evidence from the population identification

Xiaoyan Peng[1], Yanzhao Zeng[2], Yanrui Chen[3] and Huaxing Wang[4,5]*

[1]School of Government, Sun Yat-sen University, Guangzhou, China, [2]School of Economics and Statistics, Guangzhou University, Guangzhou, China, [3]School of Public Administration, Guangzhou University, Guangzhou, China, [4]Institute of Urban Development and Strategy, Law School, Research Center for Digitalization and Rural Development, Hangzhou City University, Hangzhou, China, [5]School of Economics, Zhejiang University, Hangzhou, China

Introduction: This study aims to explore the relationship between healthcare and future education among the rural low-income population, using *J* City in Guangdong Province as the focal area. Addressing both healthcare and educational concerns, this research seeks to provide insights that can guide policy and support for this demographic.

Methods: Utilizing big data analysis and deep learning algorithms, a targeted intelligent identification classification model was developed to accurately detect and classify rural low-income individuals. Additionally, a questionnaire survey methodology was employed to separately investigate healthcare and future education dimensions among the identified population.

Results: The proposed model achieved a population identification accuracy of 91.93%, surpassing other baseline neural network algorithms by at least 2.65%. Survey results indicated low satisfaction levels in healthcare areas, including medical resource distribution, medication costs, and access to basic medical facilities, with satisfaction rates below 50%. Regarding future education, issues such as tuition burdens, educational opportunity disparities, and accessibility challenges highlighted the concerns of rural low-income families.

Discussion: The high accuracy of the model demonstrates its potential for precise identification and classification of low-income populations. Insights derived from healthcare and education surveys reveal systemic issues affecting satisfaction and accessibility. This research thus provides a valuable foundation for future studies and policy development targeting rural low-income populations in healthcare and education.

KEYWORDS

rural low-income population, healthcare, future education, target population identification, normalized assistance

1 Introduction

In modern society, healthcare and education development are closely intertwined, collectively shaping the future of society. Individuals in good health are more likely to access high-quality education, and well-educated people generally possess greater awareness and capabilities to maintain their health (1, 2). Therefore, a thorough exploration of the correlation between healthcare and future education is crucial for building a sustainable and thriving society.

Due to regional economic conditions and insufficient medical resources, the rural low-income population faces unique healthcare and education needs (3). Challenges for this group include poverty, unequal access to medical services, and a lack of educational opportunities (4, 5). Addressing the issues of the rural low-income population is crucial for individual survival and development and directly impacts the sustainable progress of the entire society.

Internationally, extensive research has shown that health directly influences individuals' learning abilities, career development, and social participation. For instance, Qiu et al. (6) reviewed the application, challenges, and future prospects of large artificial intelligence models in health informatics. They emphasized that the widespread application of these models in the healthcare domain directly influenced individuals' health conditions, thereby significantly impacting learning abilities, career development, and social participation. Shehab et al. (7) highlighted the latest machine learning methods in healthcare applications. The extensive application of these methods in the healthcare domain has enhanced the accuracy of medical diagnoses and profoundly impacted individuals' health and medical conditions. This influence extends to aspects such as learning, career, and social participation. Van Helden et al. (8), through a gender perspective, explored the impact of occupational shocks on career development. Gender differences and their association with career trajectories directly relate to individual learning and career development, highlighting the crucial role of gender in the professional domain. Jo et al. (9) found that the pressure of adapting to family culture directly influenced individual learning and career choices in the career development of multicultural adolescents from Korean families, revealing the significant impact of cross-cultural backgrounds on career development. Ronaldson et al. (10) discovered associations among multiple chronic conditions, depressive symptoms, and social participation in adults over 50. Health conditions directly influence individuals' social participation, affecting learning, career, and overall quality of life. Baeriswyl and Oris (11) found that social participation was a key factor in the learning and career development of older adults, highlighting the impact of social inequality on the lives of older people. Prieur Chaintré et al. (12) analyzed the impact of hearing loss on the social participation of older adults, demonstrating a direct correlation between hearing health and social participation in the older adult. A review of the above literature found that valuable lessons can be drawn from advanced countries in the research on the relationship between healthcare and education. By thoroughly investigating the role of population identification mechanisms in assistance, this work provides new theoretical and practical support for enhancing the precision and effectiveness of assistance efforts.

In conclusion, this work selects *J* City in Guangdong Province as the research context to explore the practical application and effectiveness of population identification mechanisms in assisting the rural low-income population. By delving into the advantages of such mechanisms, this work aims to gain a deep understanding of the healthcare and education conditions of the rural low-income population, providing robust support for the formulation of relevant policies.

The research innovation and contribution lie in the exploration of the correlation between healthcare and future education development while introducing the population identification mechanism to offer an innovative and more precise approach to assisting the rural low-income population. Through a comprehensive analysis of this mechanism's application, the work provides new insights and contributions for future policy formulation and societal practices.

2 Method

2.1 Analysis of the correlation between healthcare and future education for the rural low-income population

The healthcare and future education of the rural low-income population are two closely intertwined critical domains directly impacting their survival, development, and social participation (13–15). A comprehensive understanding of the specific conditions in these two domains can better grasp their correlation, providing strong support for subsequent research. Figure 1 illustrates the factors to be considered in the healthcare and future education of the rural low-income population.

Figure 1 illustrates the multiple challenges faced by the healthcare of the rural low-income population. Due to constraints in regional economic conditions and inadequate healthcare resources, this demographic often encounters issues such as unequal access to medical services, difficulty in obtaining health information, and a heavy burden of treatment costs. Common health problems may include the prolonged medication needs of chronic patients and a lack of basic medical facilities (16, 17). These factors directly impact the health status of the rural low-income population, potentially influencing their learning abilities, career development, and social participation.

In terms of education, the rural low-income population often faces challenges in future education due to economic difficulties and insufficient educational resources. This includes a lack of educational opportunities, heavy tuition burdens, and inconvenient transportation. As education is closely linked to career development, the educational level of the rural low-income population directly affects their future employment opportunities and career choices (18, 19). Therefore, addressing the healthcare and future education issues of the rural low-income population is crucial for their individual survival and development, and it holds significant importance for the overall sustainable progress of society.

2.2 Research design

The research design is a crucial step in ensuring the smooth implementation of the research and the comprehensive and systematic achievement of its objectives (20–22). This work focuses primarily on *J* City in Guangdong Province. A multi-stage research design is made to gain in-depth insights into the

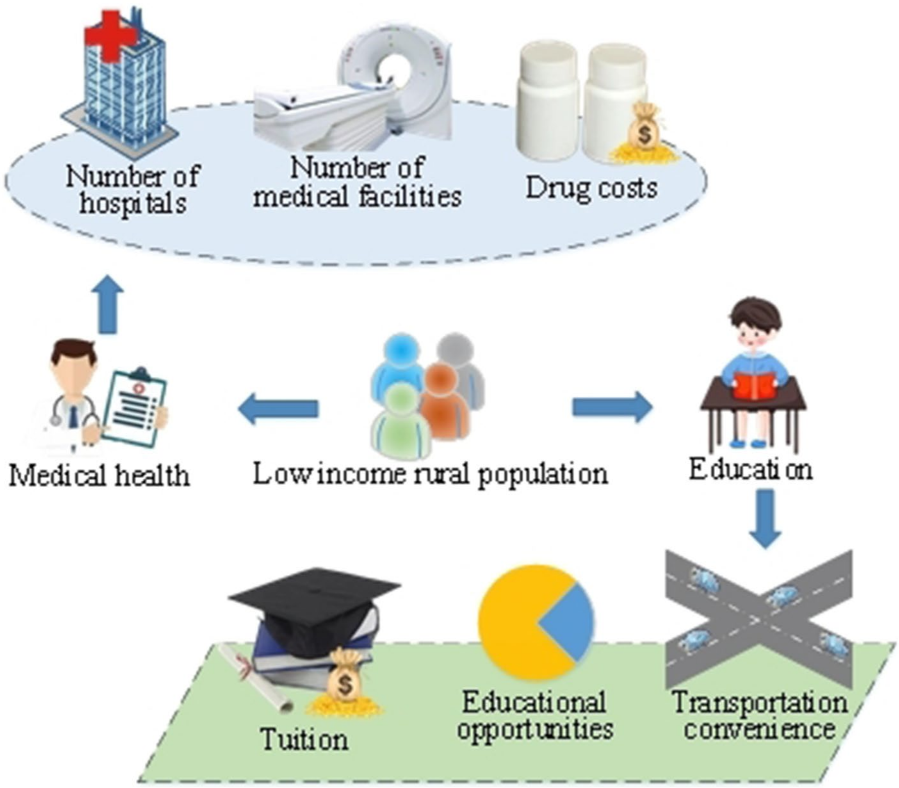

FIGURE 1
Illustration of factors influencing healthcare and future education for the rural low-income population.

FIGURE 2
Schematic diagram of the research design stage.

correlation between healthcare and future education for the rural low-income population. Figure 2 illustrates the stages of the research design.

In Figure 2, the first step involves specifying the research time and location. This work takes *J* City in Guangdong Province as the research area, selecting representative rural areas for investigation from March 1, 2023, to May 1, 2023, ensuring the research results have a certain degree of universality. A more comprehensive understanding of the similarities and differences in the healthcare and future education conditions of the rural low-income population can be obtained by conducting longitudinal and cross-sectional comparisons across different regions.

Next, the research objectives are defined. This work aims to gain in-depth insights into the correlation between healthcare and future education for the rural low-income population. Therefore, core questions that need to be addressed are clearly outlined, including the distribution of medical resources, tuition burdens, and disparities in educational opportunities. This contributes to ensuring the research's directionality and substance. In this research design, data are primarily collected through a questionnaire survey.

To ensure that the survey methods do not introduce bias in healthcare and future education, several measures are implemented to guarantee the fairness and accuracy of data collection. First, the questionnaire design is based on a comprehensive literature review, ensuring that the questions are thorough and neutral, thus avoiding leading questions and minimizing bias arising from poorly designed questions. Second, a five-point Likert scale is employed, which allows for a detailed capture of respondents' attitudes and opinions while reducing the likelihood of extreme responses, thereby enhancing the authenticity of the data. Additionally, all participants are involved in the survey on a completely voluntary basis and are explicitly informed of the research objectives and privacy protection measures before filling out the questionnaire, ensuring their informed consent. The anonymity and confidentiality of the data collection process are also maintained, further enhancing the credibility of the results. Through these measures, the impartiality of the survey methods is ensured. This prevents bias in the data collection processes related to healthcare and future education, thereby providing authentic and reliable data support for the research. Table 1 presents the questionnaire items.

Finally, the research framework is established. The research framework serves as the blueprint for the entire study, guiding the systematic data collection and analysis. This work uses a questionnaire survey to incorporate factors related to healthcare and future education, and clearly defines the relationships between these factors. The questionnaire covers healthcare-related issues, including the distribution of medical resources, medication costs for chronic patients, and the distribution of basic medical facilities (23). It also addresses core issues in future education, such as tuition burden, disparities in educational opportunities, and transportation conditions (24, 25). The questionnaire design process is primarily divided into three stages: literature review, initial draft design, expert consultation and revision, and final draft.

1) During the literature review, worldwide relevant literature on the healthcare and future education of rural low-income populations is comprehensively reviewed. The data are systematically organized and analyzed, providing a theoretical foundation for questionnaire design.
2) In the initial draft design of the questionnaire, based on the literature review results, a survey questionnaire covering multiple dimensions is constructed, including key issues in healthcare and future education. After completing the initial draft, academic experts in the field are invited to review it. Based on their feedback, relevant modifications are made, resulting in the first draft of the questionnaire.
3) Finally, the first draft of the questionnaire is further revised based on the feedback from experts, ensuring its content and structure are more logical and scientifically grounded.

This survey questionnaire uses the Likert five-point scale method, with response options categorized as strongly agree = 5, agree = 4, neutral = 3, disagree = 2, and strongly disagree = 1. The entire survey process strictly adheres to ethical principles and does not involve personal privacy. Participants are all 18 years old or older, and their participation is conducted with their consent. The questionnaire is not open to the public and is used solely for research purposes.

2.3 Ethical approval

This study was approved by the Academic Ethics Review Committee of Hangzhou City University, China, on November 15, 2023. Our study did not involve animal or human clinical trials and was not unethical. In accordance with the ethical principles outlined in the Declaration of Helsinki, all participants provided informed consent before participating in the study. The anonymity and confidentiality of the participant guaranteed, and participation was completely voluntary. Participants voluntarily click on the link to fill out the questionnaire. Before filling out the questionnaire, they have been informed of the research purpose and informed that "submitting answers" is considered informed consent. Participants can exit at any time during the questionnaire filling process.

2.4 Data collection and analysis

In order to ensure that this work obtains comprehensive and detailed data, a diversified set of data collection tools is employed.

First, extensive use of big data analysis and artificial intelligence technology. As one of the artificial intelligence technologies, deep learning, combined with big data analysis techniques, can accurately identify low-income rural populations when designing intelligent recognition and classification models for target population identification. By aggregating comprehensive and diverse datasets through big data analysis, the model can extract features relevant to low-income rural populations with high precision. The application of deep learning algorithms further enhances this capability, allowing the model to learn and adapt to the specific characteristics of the target population through training. Intelligent algorithms perform feature extraction, data cleaning, and noise reduction, ensuring the quality of data input into the machine learning model. The trained model can quickly and accurately determine whether individuals belong to the low-income rural group through prediction and classification. Figure 3 illustrates the process of target population identification and classification.

Figure 3 illustrates the use of big data analysis (26), and deep learning (27), algorithms for identifying the target population. First, through big data analysis, this work aggregates multidimensional information, including socioeconomic, medical, and educational data, from various sources to form a large and diverse dataset. Intelligent algorithms perform feature extraction on this basis, identifying potential features related to rural low-income individuals and ensuring data quality through cleaning and noise reduction. Next, artificial intelligence technology (28, 29) is employed to establish a machine learning model. Training enables the model to learn and adapt to the characteristics of the rural low-income population. Ultimately, through prediction and classification, the model can

TABLE 1 Items of questionnaire survey.

Dimension		Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Healthcare	Distribution of medical resources	A1: I believe the service quality of nearby medical institutions is high					
		A2: I believe that nearby medical institutions have well-equipped facilities					
		A3: Hospitals or clinics around me are very close to my home					
		B1: Treating chronic illnesses does not pose a significant economic burden on me					
		B2: I feel a heavy burden in treating chronic illnesses due to medication costs					
	Distribution of basic medical facilities	C1: There is a community health station or clinic near my home					
		C2: I feel that the services of the community health station or clinic are timely					
		C3: I am satisfied with the service quality of the community health station or clinic					
Future education	Tuition burden	D1: My family's monthly income is sufficient to cover my children's tuition					
		D2: The tuition fees for my children at school are relatively low					
		D3: I believe that the burden of my children's tuition fees imposes significant financial pressure on the family					
	Disparities in educational opportunities	E1: I feel that the schools in my area have teaching staff comparable to urban schools					
		E2: I believe that the schools in my area have relatively good facilities					
		E3: Whether children in the area can access better educational opportunities mainly depends on the family's economic situation					
	Transportation conditions	F1: The transportation method for my children to go to school is relatively convenient					
		F2: My children's transportation situation has a relatively minor impact on their academic performance					
		F3: The transportation situation for my children to go to school causes significant trouble for the family					

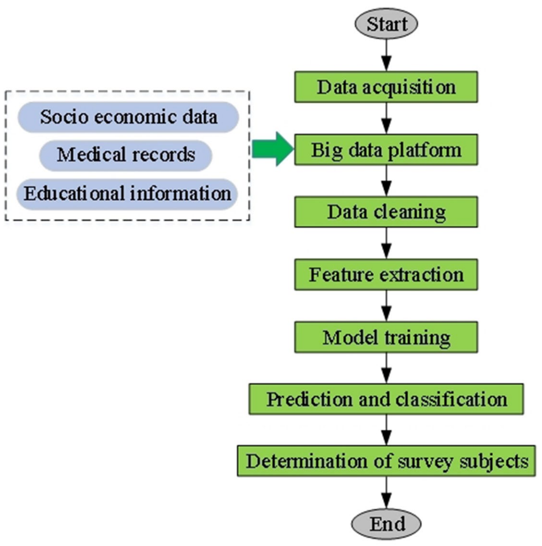

FIGURE 3
Flowchart of intelligent identification and classification process for the target population.

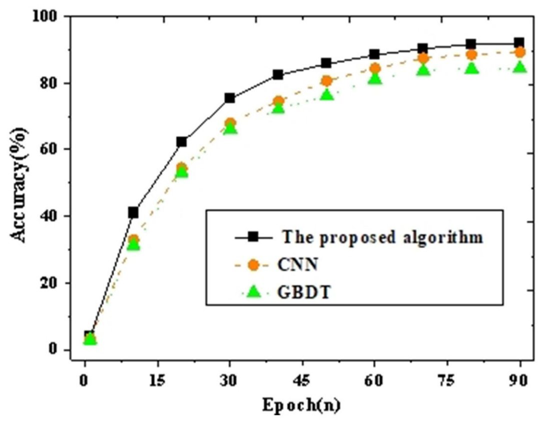

FIGURE 4
Accuracy curve graph compared with other neural networks.

rapidly and accurately determine whether individuals belong to the target group, ensuring the representativeness of the research sample and providing a reliable data foundation for this work.

Next, implementing a survey questionnaire is another crucial step for data collection. The questionnaire survey provides detailed data on participants' basic information, medical conditions, educational background, and other aspects. The questionnaire content is designed based on the research objectives, focusing on the correlation between healthcare and future education, and covering multiple dimensions to ensure a comprehensive understanding of the situation of rural low-income populations.

2.5 Statistical analysis of data

In order to analyze the proposed target population recognition mechanism, it is compared with other neural network algorithms, including convolutional neural network (30) and gradient boosting decision tree (GBDT) (31). The accuracy and F-score (F_1) values are used for population recognition accuracy evaluation. Equations 1, 2 present the calculation.

$$\mathrm{Acc} = \frac{\sum_{i=1}^{l} \frac{\mathrm{TP}_i + \mathrm{TN}_i}{\mathrm{TP}_i + \mathrm{FP}_i + \mathrm{TN}_i + \mathrm{FN}_i}}{l} \tag{1}$$

$$F_1 = \frac{2\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{2}$$

Where TP is the number of true positive samples predicted as positive; FP is the number of false positive samples predicted as positive; FN is the number of false negative samples predicted as negative; TN is the number of true negative samples predicted as negative. Accuracy (ACC) is employed to measure the overall classification accuracy, and the F-measure is the weighted harmonic mean of precision and recall. Recall (Rec) in Equation 2 measures the coverage of positive samples, that is, the proportion of correctly classified positive samples to the total number of positive samples; precision (Pre) refers to the proportion of examples classified as positive that are actually positive. Equations 3, 4 provide the specific equations:

$$\mathrm{Precision} = \frac{\sum_{i=1}^{l} \frac{\mathrm{TP}_i}{\mathrm{TP}_i + \mathrm{FP}_i}}{l} \tag{3}$$

$$\mathrm{Recall} = \frac{\sum_{i=1}^{l} \frac{\mathrm{TP}_i}{\mathrm{TP}_i + \mathrm{FN}_i}}{l} \tag{4}$$

When analyzing the questionnaire survey results, the questionnaires are distributed offline, reaching a total distribution of 487. Four hundred fifty-nine completed questionnaires are received, achieving a high response rate of 94.25%. This indicates the effectiveness of the survey. To further ensure the validity of the questionnaire survey, during the statistical analysis of the questionnaires, the 459 valid questionnaires are carefully reviewed. Any questionnaires with significant issues are excluded. Ultimately, 436 valid questionnaires are obtained, resulting in a questionnaire validity rate of 94.99%. Statistical analysis is conducted using Stata 16 software.

3 Results and discussion

3.1 Accuracy analysis of population identification under different algorithms

The intelligent identification classification model for the target population is analyzed for accuracy and F_1 value in comparison with CNN and GBDT. Figures 4, 5 present the results.

The results of accuracy and F_1 values validate the comparison of the proposed target population identification mechanism with CNN and GBDT. Figures 4, 5 depict the outcomes. It can be observed that

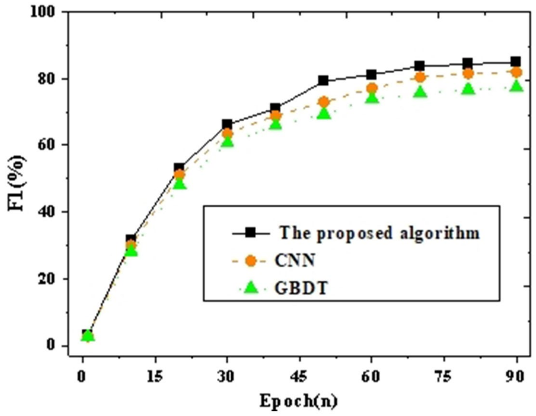

FIGURE 5
F_1 curve graph compared with other neural networks.

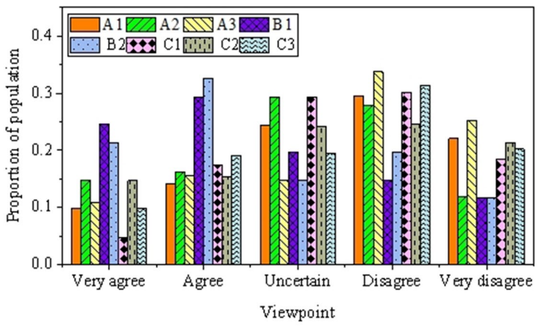

FIGURE 7
The survey results related to healthcare.

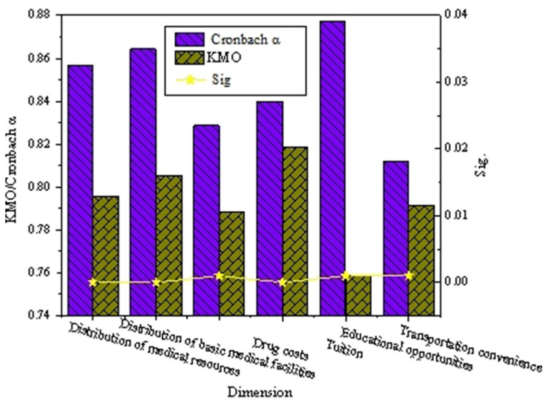

FIGURE 6
The diagram of the results of the reliability and validity test for the survey questionnaire.

with an increase in iteration cycles, the trend of accuracy and F_1 values initially experiences rapid growth, which stabilizes after reaching a certain value. Further comparative analysis reveals that the proposed method achieves an accuracy of 91.93% and an F_1 value of 84.94% after 90 iterations. This is at least 2.65% higher in accuracy compared to other baseline neural network algorithms (such as CNN and GBDT). To verify whether these differences are statistically significant, a t-test is further conducted. The proposed model's accuracy and F_1 scores are compared pairwise with those of other algorithms, as shown in Table 2.

Table 2 illustrates whether the differences in accuracy and F_1 scores between the proposed model and the CNN and GBDT algorithms are statistically significant. The t statistic indicates the magnitude of the difference, while the degrees of freedom reflect the sample size used to calculate the t statistic, minus one. The p-value represents the probability of observing the current or more extreme differences under the assumption of equal distributions. Generally, if the p-value is less than 0.05, the difference is considered statistically significant. Table 2 suggests that the differences in accuracy and F_1 scores between the proposed model and both CNN and GBDT are statistically significant (p-values are both less than 0.01). This further validates the superiority of the proposed model. Therefore, it is evident that the proposed target population identification mechanism exhibits superior precision in identifying low-income populations compared to other neural network algorithms, demonstrating significantly enhanced performance.

3.2 Analysis of survey statistical results

A reliability and validity test is conducted on the survey results, and Figure 6 shows the results.

Figure 6 suggests that the Cronbach's alpha values for each variable in the questionnaire are all greater than 0.800, KMO values are all greater than 0.259, and the significance (Sig.) values are all less than 0.050. This indicates that the survey questionnaire designed has significant internal consistency and stability, demonstrating high reliability. Therefore, the questionnaire used is considered rational and effective, forming a solid basis for further research.

Descriptive statistical analysis is conducted on the questionnaire results related to healthcare (distribution of medical resources, medication costs, distribution of basic medical facilities) and future education (tuition burden, differences in educational opportunities, transportation conditions). Figures 7, 8 present the results.

Figure 7 suggests that respondents opinions are relatively dispersed concerning the quality of service in nearby medical institutions, the completeness of service facilities, and the perceived distance to medical facilities. Regarding service quality, 29.59% of respondents express dissatisfaction with the quality of service in medical institutions. Similarly, 27.75 and 33.72% of respondents, respectively, indicate disagreement about the completeness of service facilities and the distance to medical facilities. Regarding the economic burden of treating chronic diseases and the cost of medication, a considerable proportion of respondents agree or strongly agree, indicating that some individuals find the economic burden of treating chronic diseases relatively manageable. However, a significant proportion of respondents express dissatisfaction concerning the existence of community health stations or clinics, the timeliness of service, and satisfaction with service quality. Specifically, 32.90% of respondents strongly disagree with the existence of community health services. Overall, there are certain issues in the field of healthcare, and respondents show relatively low satisfaction with some medical services.

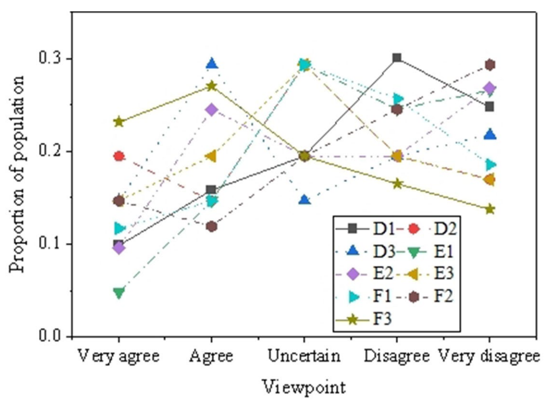

FIGURE 8
The survey results related to education.

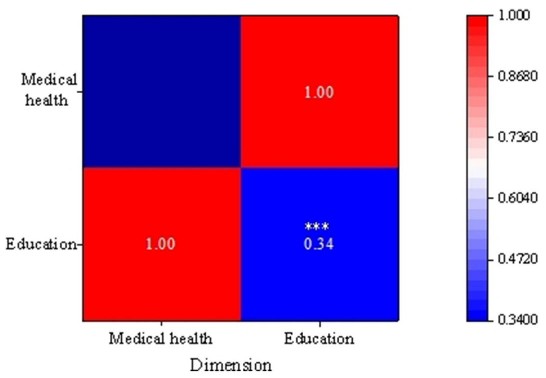

FIGURE 9
The correlation results between healthcare and education development.

Figure 8 displays the survey results reflecting respondents' perspectives and attitudes towards education, revealing a range of viewpoints related to family economic conditions, the ability to pay for children's education, school quality in the area, fairness in educational opportunities, and transportation for children's schooling. In terms of family finances, a significant proportion of respondents express concerns about their ability to pay for their children's education, with 30.05% considering their monthly income insufficient for tuition fees. Additionally, there is divergence among respondents regarding the perception of relatively lower tuition fees and the financial burden of tuition fees on the family economy, with 19.50 and 26.09% of respondents, respectively expressing strong disagreement. Regarding educational opportunities, the survey results indicate that 32.90% of respondents believe that schools in their area lack equivalent teaching staff, and 24.77% believe that school facilities in their area are inadequate. Furthermore, 43.67% of respondents agree that educational opportunities primarily depend on family economic conditions, indicating concerns about educational opportunities. A certain proportion of respondents consider transportation for children's schooling convenient. However, there is disagreement regarding the impact of transportation on academic performance and family life, with 43.27 and 32.11% of respondents, respectively expressing agreement or strong agreement. The diversity of these viewpoints highlights the concerns of low-income rural populations regarding future education issues.

TABLE 2 Results of the *t*-test.

Comparison algorithm	*t* statistic	Degrees of freedom	*p*-value
Proposed model vs. CNN	3.21	198	<0.01
Proposed model vs. GBDT	2.98	198	<0.01

3.3 The discussion and analysis of the correlation between healthcare and education development

Through the analysis of the questionnaire results on healthcare and future education, this work can delve into the correlation between healthcare and educational development. In terms of healthcare, the survey indicates that rural low-income populations express certain dissatisfaction with the quality of service, completeness of facilities, and distance to nearby medical institutions. Particularly, a significant proportion of respondents express dissatisfaction with community health services' existence, timeliness, and quality. This may suggest that factors such as inadequate healthcare resources, uneven service levels, and distance limitations could impact the healthcare experience of rural low-income populations. Meanwhile, regarding future education, respondents present diverse perspectives on issues related to family finances, the ability to pay children's school fees, the quality of schools in their area, fairness in educational opportunities, and the transportation of children to school. Figure 9 provides specific results of the correlation analysis.

Figure 9 reveals the importance of healthcare and future education among rural low-income individuals, indicating a positive correlation between them ($r=0.34$). This suggests that in the process of normalizing assistance for rural low-income populations, there is a correlation and mutual influence between healthcare and future education. For instance, health issues may impact the economic status of low-income rural families, affecting their ability to pay for their children's education. Simultaneously, the unfairness in educational opportunities may pose challenges for some families in accessing better healthcare services. Therefore, the complex relationship between health and education development can be better explored in future research to formulate more targeted policies and improvement measures, fostering the comprehensive development of rural low-income populations.

4 Discussion

Through analysis of the results, this work finds that the use of deep learning and big data analysis techniques for population identification achieves an accuracy of 91.93%, significantly outperforming the baseline algorithm of CNN. This finding aligns with the perspectives of Goel et al. (32) and Choi and Lim (33). Therefore, understanding the accuracy of the target population identification mechanism and the errors it generates is crucial for optimizing model performance and enhancing the precision of policy formulation. First, a highly accurate identification mechanism ensures that resources are more effectively allocated to rural low-income populations who truly need them, thereby improving the efficiency and effectiveness of aid programs. Then, by analyzing the sources of error, it is possible to identify and correct potential biases in the model, such as data collection bias, sample selection bias, or limitations inherent to the algorithm itself. This in turn enhances the fairness and reliability of the model. Additionally, the identification of errors can provide policymakers with insights into the current distribution of healthcare and educational resources, helping them to identify gaps and deficiencies in service provision, thus allowing for more targeted interventions. Finally, accurately identifying target populations is essential for assessing the impact of policies and evaluating their effectiveness. It provides a scientific basis for future policy adjustments and resource reallocation. This can ensure that policy formulation is grounded in actual data and objective analysis, thereby better serving rural low-income groups and promoting social equity and sustainable development. Therefore, a thorough understanding of the accuracy and errors in the target population recognition mechanism has significant benefits for enhancing the precision of aid programs, optimizing resource allocation, formulating effective policies, and promoting social justice.

Meanwhile, this work has explored the correlation between rural low-income populations in healthcare and future education, providing in-depth insights into the current situation of this specific demographic. Through the intelligent identification model developed using big data and deep learning algorithms, the work accurately identifies the target group. Moreover, it collects first-hand data through questionnaires on aspects such as healthcare resources, medication costs, satisfaction with basic healthcare facilities, educational burdens, disparities in educational opportunities, and transportation conditions. The analysis reveals that rural low-income populations exhibit low satisfaction with healthcare and have significant concerns regarding future education, primarily centered on economic burdens and inequalities in resource access. The work also uncovers a positive correlation between healthcare and education, indicating an interaction between health status and educational opportunities, which provides a basis for more targeted policy formulation. Furthermore, the intelligent identification model proposed outperforms existing algorithms in accuracy, offering a more precise tool for resource allocation and policy formulation. Thus, this work not only enhances the understanding of the needs of rural low-income populations but also provides valuable reference points for future research and policy formulation. It contributes to promoting equal opportunities in healthcare and education for these groups and fostering social equity and sustainable development.

Additionally, the research by Kadaei et al. (34) complements this work, as they proposed a new method to identify reverse logistics issues in smart buildings, with a particular focus on sustainable architecture. By integrating Kadaei's et al. (34) approach, a more comprehensive understanding and optimization of resource allocation for rural low-income populations in healthcare and education can be achieved while considering the sustainability of the construction industry. This interdisciplinary approach not only enhances awareness of the needs of rural low-income populations but also provides new perspectives for the future development of smart buildings and sustainable environments.

Finally, to address the challenges faced by rural low-income populations in the education sector, it is recommended that relevant authorities implement the following measures to strengthen the effectiveness of educational poverty alleviation policies. First, it is essential to increase educational investment in rural areas to improve basic education facilities, ensuring that schools have qualified teachers and essential teaching resources; second, tuition reduction and educational subsidy policies should be implemented to alleviate the financial burden on low-income families, enabling their children to complete their studies successfully; additionally, distance education and technology-assisted teaching should be promoted to provide rural students access to a broader range of knowledge and information resources; simultaneously, vocational education and skills training need to be strengthened to enhance the employability of rural youth and provide them with more career development opportunities; finally, it is essential to establish and improve student funding systems to ensure that impoverished students do not lose educational opportunities due to financial difficulties. Through these specific and targeted measures, the ability of rural low-income populations to access educational resources can be effectively enhanced, promoting educational equity and yielding long-term benefits for them and society as a whole.

5 Conclusion

This work delves into the correlation between healthcare and future education among rural low-income populations by employing advanced population identification mechanisms and diverse data collection tools. Through survey questionnaires and data analysis, it systematically reveals the problems and challenges faced by this group in terms of healthcare and education. It also introduces a targeted population intelligent recognition classification model and demonstrates its significant advantages in low-income population identification classification accuracy by comparing it with other baseline neural network algorithms. However, this work has some limitations, such as regional scope constraints and the locality of survey questionnaire design. Despite obtaining meaningful results, practical applications may face challenges related to technology and privacy. Future research can expand and refine this work by broadening the research scope, deepening correlation analysis, and continuously improving technology and privacy protection. In conclusion, this work provides profound insights into the current situation of rural low-income populations and serves as a valuable reference foundation for future research and policy formulation.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by Academic Ethics Review Committee of Hangzhou City University. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and institutional requirements. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

XP: Conceptualization, Data curation, Validation, Writing – review & editing. YZ: Conceptualization, Formal analysis, Investigation, Writing – review & editing. YC: Formal analysis, Methodology, Visualization, Writing – original draft. HW: Writing – original draft, Funding acquisition, Project administration, Resources, Software, Supervision.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This work was supported by Zhejiang Province Philosophy and Social Science Planning Research Methods Innovation Special Topic (Grant No. 23SYS07ZD), and Research Incubation Project Funding, Hangzhou City University (Grant Nos. 22FHXMO6 and Z2022037). This work was also supported by the Key Project of 2024 Special Fund for Science and Technology Innovation Strategy of Guangdong Province (Cultivation of Science and Technology Innovation for University Students) "Climbing Plan" (Grant No. pdjh2024a298), the Undergraduate Training Program for Innovation and Entrepreneurship of Guangzhou University (Project No. XJ202411078197), and the project of the 19th Challenge Cup, Guangzhou University (Project No. 2024TZBPHA0404).

Acknowledgments

Our heartfelt appreciation extends to the school teachers who assisted in experiment administration. Gratitude is also extended to all participants whose contributions enriched this study.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

1. Harvey M, Neff J, Knight KR, Mukherjee JS, Shamasunder S, Le PV, et al. Structural competency and global health education. *Glob Public Health*. (2022) 17:341–62. doi: 10.1080/17441692.2020.1864751

2. Wu H, Ba N, Ren S, Xu L, Chai J, Irfan M, et al. The impact of internet development on the health of Chinese residents: transmission mechanisms and empirical tests. *Socio Econ Plan Sci*. (2022) 81:101178. doi: 10.1016/j.seps.2021.101178

3. Coleman E, Radix AE, Bouman WP, Brown GR, de Vries ALC, Deutsch MB, et al. Standards of care for the health of transgender and gender diverse people, version 8. *Int J Transgender Health*. (2022) 23:S1–S259. doi: 10.1080/26895269.2022.2100644

4. Alowais SA, Alghamdi SS, Alsuhebany N, Alqahtani T, Alshaya AI, Almohareb SN, et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC Med Educ*. (2023) 23:689. doi: 10.1186/s12909-023-04698-z

5. Haleem A, Javaid M, Pratap Singh R, Suman R. Medical 4.0 technologies for healthcare: features, capabilities, and applications. *Internet Things Cyber-Phys Syst*. (2022) 2:12–30. doi: 10.1016/j.iotcps.2022.04.001

6. Qiu J, Li L, Sun J, Peng J, Shi P, Zhang R, et al. Large AI models in health informatics: applications, challenges, and the future. *IEEE J Biomed Health Inform*. (2023) 27:6074–87. doi: 10.1109/jbhi.2023.3316750

7. Shehab M, Abualigah L, Shambour Q, Abu-Hashem MA, Shambour MKY, Alsalibi AI, et al. Machine learning in medical applications: a review of state-of-the-art methods. *Comput Biol Med*. (2022) 145:105458. doi: 10.1016/j.compbiomed.2022.105458

8. Van Helden DL, Den Dulk L, Steijn B, Vernooij MW. Career implications of career shocks through the lens of gender: the role of the academic career script. *Career Dev Int*. (2023) 28:19–32. doi: 10.1108/CDI-09-2022-0266

9. Jo D, Woo S, Yang E. Role of family acculturation stress in career development among adolescents from multicultural families in Korea. *J Career Dev*. (2022) 50:901–16. doi: 10.1177/08948453221131362

10. Ronaldson A, de la Torre JA, Bendayan R, Yadegarfar ME, Rhead R, Douiri A, et al. Physical multimorbidity, depressive symptoms, and social participation in adults over 50 years of age: findings from the English longitudinal study of ageing. *Aging Ment Health*. (2023) 27:43–53. doi: 10.1080/13607863.2021.2017847

11. Baeriswyl M, Oris M. Social participation and life satisfaction among older adults: diversity of practices and social inequality in Switzerland. *Ageing Soc*. (2023) 43:1259–83. doi: 10.1017/S0144686X21001057

12. Prieur Chaintré A, Couturier Y, Nguyen THT, Levasseur M. Influence of hearing loss on social participation in older adults: results from a scoping review. *Res Aging*. (2023) 46:72–90. doi: 10.1177/01640275231174561

13. Gaffney AW, Hawks L, White AC, Woolhandler S, Himmelstein D, Christiani DC, et al. Health care disparities across the urban-rural divide: a national study of individuals with COPD. *J Rural Health*. (2022) 38:207–16. doi: 10.1111/jrh.12525

14. Khoury MJ, Bowen S, Dotson WD, Drzymalla E, Green RF, Goldstein R, et al. Health equity in the implementation of genomics and precision medicine: a public health imperative. *Genet Med*. (2022) 24:1630–9. doi: 10.1016/j.gim.2022.04.009

15. Abubakar I, Dalglish SL, Angell B, Sanuade O, Abimbola S, Adamu AL, et al. The Lancet Nigeria Commission: investing in health and the future of the nation. *Lancet*. (2022) 399:1155–200. doi: 10.1016/s0140-6736(21)02488-0

16. Cerchione R, Centobelli P, Riccio E, Abbate S, Oropallo E. Blockchain's coming to hospital to digitalize healthcare services: designing a distributed electronic health record ecosystem. *Technovation*. (2023) 120:102480. doi: 10.1016/j.technovation.2022.102480

17. Marwaha JS, Landman AB, Brat GA, Dunn T, Gordon WJ. Deploying digital health tools within large, complex health systems: key considerations for adoption and implementation. *npj Digit Med*. (2022) 5:13. doi: 10.1038/s41746-022-00557-1

18. Hanson K, Brikci N, Erlangga D, Alebachew A, De Allegri M, Balabanova D, et al. The Lancet Global Health Commission on financing primary health care: putting people at the centre. *Lancet Glob Health*. (2022) 10:e715–72. doi: 10.1016/s2214-109x(22)00005-5

19. Javaid M, Haleem A, Pratap Singh R, Suman R, Rab S. Significance of machine learning in healthcare: features, pillars and applications. *Int J Intell Netw*. (2022) 3:58–73. doi: 10.1016/j.ijin.2022.05.002

20. Duong CD. Exploring the link between entrepreneurship education and entrepreneurial intentions: the moderating role of educational fields. *Educ Train*. (2022) 64:869–91. doi: 10.1108/ET-05-2021-0173

21. Lacey AW, Chen W, Hao H. Experimental methods for inter-module joints in modular building structures—a state-of-the-art review. *J Build Eng*. (2022) 46:103792. doi: 10.1016/j.jobe.2021.103792

22. Sharma H. How short or long should be a questionnaire for any research? Researchers dilemma in deciding the appropriate questionnaire length. *Saudi J Anaesth*. (2022) 16:65–8. doi: 10.4103/sja.sja_163_21

23. Yao R, Zhang W, Evans R, Cao G, Rui T, Shen L. Inequities in health care services caused by the adoption of digital health technologies: scoping review. *J Med Internet Res*. (2022) 24:e34144. doi: 10.2196/34144

24. Jaca A, Malinga T, Iwu-Jaja CJ, Nnaji CA, Okeibunor JC, Kamuya D, et al. Strengthening the health system as a strategy to achieving a universal health coverage in underprivileged communities in Africa: a scoping review. *Int J Environ Res Public Health*. (2022) 19:587. doi: 10.3390/ijerph19010587

25. Curtis ME, Clingan SE, Guo H, Zhu Y, Mooney LJ, Hser YI. Disparities in digital access among American rural and urban households and implications for telemedicine-based services. *J Rural Health*. (2022) 38:512–8. doi: 10.1111/jrh.12614

26. Li X, Liu H, Wang W, Zheng Y, Lv H, Lv Z. Big data analysis of the internet of things in the digital twins of smart city based on deep learning. *Future Gener Comput Syst*. (2022) 128:167–77. doi: 10.1016/j.future.2021.10.006

27. Fathi M, Haghi Kashani M, Jameii SM, Mahdipour E. Big data analytics in weather forecasting: a systematic review. *Arch Comput Methods Eng*. (2022) 29:1247–75. doi: 10.1007/s11831-021-09616-4

28. Rehman A, Naz S, Razzak I. Leveraging big data analytics in healthcare enhancement: trends, challenges and opportunities. *Multimed Syst*. (2022) 28:1339–71. doi: 10.1007/s00530-020-00736-8

29. Kumar A, Alghamdi SA, Mehbodniya A, Haq MA, Webber JL, Navruzbek Shavkatovich S. Smart power consumption management and alert system using IoT on big data. *Sustain Energy Technol Assess*. (2022) 53:102555. doi: 10.1016/j.seta.2022.102555

30. Ren J, Wang Y. Overview of object detection algorithms using convolutional neural networks. *J Comput Commun*. (2022) 10:115–32. doi: 10.4236/jcc.2022.101006

31. Huang L, Chen C, Yun J, Sun Y, Tian J, Hao Z, et al. Multi-scale feature fusion convolutional neural network for indoor small target detection. *Front Neurorobot*. (2022) 16:881021. doi: 10.3389/fnbot.2022.881021

32. Goel A, Goel AK, Kumar A. The role of artificial neural network and machine learning in utilizing spatial information. *Spat Inf Res*. (2023) 31:275–85. doi: 10.1007/s41324-022-00494-x

33. Choi J-A, Lim K. Identifying machine learning techniques for classification of target advertising. *ICT Express*. (2020) 6:175–80. doi: 10.1016/j.icte.2020.04.012

34. Kadaei S, Nezam Z, González-Lezcano RA, Shokrpour S, Mohammadtaheri A, Doraj P, et al. A new approach to determine the reverse logistics-related issues of smart buildings focusing on sustainable architecture. *Front Environ Sci*. (2023) 10:1079522. doi: 10.3389/fenvs.2022.1079522

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 02 December 2024
DOI 10.3389/fpubh.2024.1514996

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Chen Li,
Shanghai University of Engineering Sciences, China
Song Wang,
Northeastern University, China

*CORRESPONDENCE
Qianrui Hwang
✉ alicehwang@stu.xust.edu.cn
Min Yao
✉ ymnxdx@nxu.edu.cn

RECEIVED 22 October 2024
ACCEPTED 07 November 2024
PUBLISHED 02 December 2024

CITATION
Hwang Q, Yao M, Li S, Wang F, Li Z and Liu T (2024) Research on occupational health and safety management in the context of big data.
Front. Public Health 12:1514996.
doi: 10.3389/fpubh.2024.1514996

Research on occupational health and safety management in the context of big data

Qianrui Hwang[1]*, Min Yao[1,2]*, Shugang Li[1], Fang Wang[3], Zheng Li[1] and Tongshuang Liu[1]

[1]College of Safety Science and Engineering, Xi'an University of Science and Technology, Xi'an, China, [2]State Key Laboratory of High-Efficiency Utilization of Coal and Green Chemical Engineering, Ningxia University, Yinchuan, China, [3]Ningxia Coal Industry Co., Ltd of China National Energy Group, Ningxia Hui Nationality Autonomous Region, Yinchuan, China

At present, with the rapid development of China's economy and industrial transformation, the situation of China's occupational health and safety is grim, and at this stage, there are still problems such as unsound laws and regulations and standard system, weak awareness of the primary responsibility of the enterprise, weak supervisory, technical capacity, and backward application of information technology. Based on the current situation of occupational health and safety management at home and abroad and relevant theories, this study adopts the method of systematic review and takes the evaluation of China's occupational health and safety management system as the theme and conducts a valuable exploration of the evaluation research of China's occupational health and safety management system, analyzes the current situation of occupational health and safety from the aspects of prevention and control of occupational diseases, prevention and control of safety accidents, and monitoring of the psychology of insecurity, and researches the two aspects of governmental regulation and social responsibility It analyzes the current situation of occupational health and safety from the aspects of prevention and control of occupational diseases, prevention and control of safety accidents and monitoring of unsafe psychology, and studies the current situation of post-performance evaluation of the development of OHS management system from the aspects of government supervision and social responsibility, aiming at providing countermeasure suggestions for the sustainable development of OHS management system in China. The research indicates that in the context of the new economic normal, effectively safeguarding workers' occupational health rights and interests, promoting sustainable and robust economic and social development, as well as enhancing the sustainability of China's occupational health and safety management system have emerged as challenging yet pivotal areas for comprehensive exploration.

KEYWORDS

occupational health and safety management system, big data, occupational disease prevention and control, safety management performance, sustainable development

With the continuous development, reform, and transformation of society and economy, "economic transformation" and "sustainable health" have become the themes of the era of economic transformation and development. Protecting workers' occupational health and safety has become an indispensable guarantee to promote industrial and economic transformation and development. However, the number of occupational diseases, injuries, and deaths remains large. This reflects that occupational health and safety needs to catch up to the pace of industrial economic construction. Occupational health and safety have become the fundamental guarantee for the economic development of all countries, and occupational health and safety management systems have also become an essential part of the economic legislation of many countries in the world. Western developed countries are leading in developing occupational health and safety management system theory and practice exploration. They have established and perfected the OHS management system, including government supervision, and created the achievement of "low or zero accident countries."

With the transformation and upgrading of China's economy and the integration of internationalized economic development, China's occupational health and safety has made significant progress compared to the past. However, a large gap exists between China and Western developed countries. The number of new cases of occupational diseases reported every year is still increasing, which reflects that safety accidents occur from time to time, the implementation of the primary responsibility of enterprises is not in place, the investigation of hidden dangers is only a formality, and the government supervision, especially the grass-roots supervision power and working capacity is relatively weak (1). This shows China's occupational health management work and occupational hazards are still severe. China is currently undergoing economic transformation, and occupational health and safety management "supporting the transformation and upgrading" has become an important issue of economic development that needs to be resolved. The government, society, and enterprises are increasingly prioritizing the management of occupational health and safety, which can effectively mitigate economic losses resulting from occupational health issues and alleviate pressure on the public healthcare system. This paper analyzes the research related to the safety status of occupational health management from three aspects of occupational diseases, safety accidents, and mental health through the study of domestic and foreign occupational health management methods, combines the research on government control of the performance of occupational health and safety management with the status quo of social responsibility, and puts forward suggestions for the scientific development of China's occupational health and safety management (2).

1 Introduction

The occupational health and safety management system (OHSMS) is a modern safety production management model that emerged internationally in the late 1980s. It is a systematic, procedural, and highly self-restraint, self-improvement scientific management system (3). In the late 1990s, under the influence of the integration of international occupational safety and health standards, the International Organization for Standardization (ISO) tried to develop and expand the occupational safety and health standardized management system so that it would become a standard similar to the ISO9000 and ISO14000 (4).

With the acceleration of trade and investment liberalization, global economic integration worldwide, and the development of technology, the number of occupational accidents and occupational diseases continues to rise in many developing countries (5–7). The rapid growth of occupational diseases in China is mainly due to insufficient awareness of occupational health and safety, inadequate supervision, and one-sided pursuit of economic efficiency (8). As can be seen from Table 1, statistics from China's Health Planning Commission show that by the end of 2023, there have established total 18,818 healthy enterprises across the country, and have included 185,000 enterprises in the scope of exceptional management of occupational disease hazards, and have carried out extraordinary management work. By the end of 2023, there were 1,297 technical service organizations for occupational health, 666 technical service organizations for radiation health, and 21 organizations for chemical toxicity assessment. A total of 5,670 occupational health inspection institutions reported 21.88 million cases of occupational health inspection, among which 368,000 cases of occupational contraindications and 9,000 cases of suspected occupational diseases were found. 620 occupational disease diagnostic organizations completed 27,740 occupational disease diagnoses. 829 pneumoconiosis rehabilitation stations (points) were built with funds transferred from the central government to local governments, and provided rehabilitation services to 1.2 million people. In 2023, a total of 12,087 new cases of various types of occupational diseases were

TABLE 1 Statistics of new cases of occupational diseases reported nationwide.

Types of occupational diseases	Number of new cases						
	2017	2018	2019	2020	2021	2022	2023
Occupational pneumoconiosis	22,701	19,468	15,898	14,367	11,809	7,577	8,051
Other respiratory diseases	89	56	49	41	68	38	54
Occupational ENT and oral diseases	1,608	1,528	1,623	1,310	2,123	1879	2,228
Occupational infectious disease	673	540	578	488	339	308	625
Occupational chemical poisoning	1,021	1,333	778	486	567	399	367
Occupational diseases caused by physical factors	399	331	264	217	283	749	577
Occupational dermatosis	83	93	72	63	83	10	65
Occupational tumor	85	77	87	48	79	71	67
Occupational eye disease	70	47	53	24	43	23	39
Occupational radiation sickness	15	17	15	10	5	11	7
Other occupational diseases	12	7	11	10	8	5	7
Total person	26,756	23,497	15,898	17,064	15,407	11,108	12,087

reported nationwide, among which there were 8,105 cases of occupational pneumoconiosis and other respiratory diseases (among which 8,051 cases were of occupational pneumoconiosis), 2,228 cases of occupational ear, nose, throat, mouth and oral cavity diseases, 625 cases of occupational infections, and 367 cases of occupational chemical poisoning, 577 cases of occupational diseases caused by physical factors, 65 cases of occupational skin diseases, 67 cases of occupational tumors, 39 cases of occupational eye diseases (including 1 case of radioactive cataract), 7 cases of occupational radiological diseases, and 7 cases of other occupational diseases (9). Regarding industry distribution, occupational disease cases are mainly concentrated in the mining, manufacturing, metallurgy, and building materials industries.

It is easy to see that China's occupational health and safety situation is still severe and restricts China's economic development. In the current transition stage of economic development, with the gradual improvement of the level of safety management and the emergence of new safety management concepts and methods, the key issues and research direction of China's occupational health and safety management system have shifted to improving the modern safety management level of enterprises and promoting a systematic and scientific occupational health and safety system in China.

2 Methodology

This study adopted the systematic review method in literature retrieval. Web of science (Web of Science Core Collection) and CNKI are chosen as the database in this study, as they cover a wide range of national and international journals. Search attributes and their values are presented in Table 2.

The scope of this study is limited to the research and application of occupational health and safety, as well as the performance of occupational health and safety management. Firstly, it focuses on a few relevant subject fields such as engineering, medicine, social science, and psychology. Secondly, only journal articles are considered for inclusion in this study; specifically, research papers, papers, and review papers are retained after preliminary review while book reviews and editorials are excluded. Based on the initial search results, a systematic review approach is adopted for further analysis by selecting journals related to occupational health and safety science. The secondary search process not only emphasizes the study of occupational health and safety management systems but also takes into account their current practical applications.

TABLE 2 Literature search methods.

Search attributes	Values used in the search
Database	Web of science(Web of Science Core Collection) or CNKI
Keywords	"Occupational health and safety" or "occupational health and safety management performance"
Search scope	Topic
Year published	From 2004 to present
Document type	Journal article
Language	English or Chinese

3 Literature review and current status of occupational health and safety in the context of big data

By searching the journal papers with the topic of "occupational health and safety" through web of science (Web of Science Core Collection) and CNKI from 2004 to 2024, there are 8,443 and 4,262 related papers were retrieved on web of science (Web of Science Core Collection) and CNKI, respectively. As shown in Figures 1, 2, the visual analysis of literature research on occupational health and safety shows that the research topics mainly focus on production safety, occupational health and occupational health. As shown in Figure 3, the research literature on occupational health and safety, both domestically and internationally, demonstrates a discernible upward trend, indicating the growing emphasis placed on this field in current times.

3.1 Current status and research on occupational diseases

Most research on occupational diseases in foreign countries focuses on industrial activities such as small and medium-sized enterprises. The categorization of occupational diseases varies from one industry to another, such as in the construction industry, where most of the occupational diseases are caused by employees suffering from shoulder pains, back pains, skin-related illnesses, problems with the eyes, and respiratory and noise irritation problems (10). Meanwhile, in small and medium-sized industries, it is found that the work-related occupational disease injuries suffered are different due to gender, monthly salary, age, work experience, and personal use (11). In addition, physical occupational hazards are positively associated with muscle, bone, or joint pain. The higher the exposure to physical hazards such as physical fatigue, adverse environmental factors, and repetitive exercise, the greater the likelihood of workers developing occupational diseases (12). Therefore, regulating occupational diseases requires official participation in managing the disease, as well as that of associations and civil organizations, which have highly dynamic forms of regulation and multifaceted regulatory content (13).

Domestic, occupational disease research is mainly focused on the industrial and mining industries with the highest incidence of occupational diseases, and the occupational diseases that are prone to incidence are dust-induced pneumoconiosis, noise-induced noise deafness, and toxic and hazardous gases-induced leukodystrophy. Therefore, combining safety assessment and occupational disease management will be the new direction of improvement. This new direction can improve the ability to manage preventive occupational disease and compose a new evaluation system of occupational health and safety management in order to improve the overall level of occupational health and safety management in China (14). In controlling and supervising occupational diseases, the government should take the primary responsibility for relief. In contrast, individual citizens' relief and public welfare organizations' relief are indispensable forces, and the focus of employees suffering from pneumoconiosis to fight for their rights and interests is their own individual awareness and group self-help (15).

FIGURE 1
Paper main topic distribution diagram on web of science.

3.2 Current status and research on security incidents

The accident causation chain is based on the view that all safety accidents are based on unsafe actions caused by human management negligence, and this view has become the typical representative of the accident causation chain. 1990, the "Swiss cheese" model view that the root causes of accidents are a combination of individuals, behaviors, and social relationships triggered by accidents has become the representative of the modern accident causation chain. This view has since become the modern representation of the accident causal chain (16). From the perspective of occupational safety climate, the correlation between safety climate and accidents in Denmark has been analyzed using a cross-adjusted regression model, which shows a gradual correlation between the number of safety climate problems and the ratio of accidents.

The research on domestic safety accidents started late and primarily focuses on industrial and mining industries where the most safety accidents occur. For coal mine safety accidents, the mathematical method of FAHP can be used to process the indicators of four aspects: mining personnel, machinery and equipment, working environment, and safety conditions, and to construct a safety early warning system for coal mines (17). Moreover, in order to prevent coal mine safety accidents, we should focus on reality and establish a long-term effective mechanism to find the root causes behind the safety accidents from the four aspects of people, machinery, environment, and management so as to provide strong evidence for the solution to the safety accidents (18, 19). The "2–4" model suggests that the root cause of accidents is the lack of an organization's safety management system, based on an analysis of China's current safety situation, individual behavior, and organizational factors (20).

3.3 Current status and research on mental health

In China, less attention has been paid to research on occupational mental health, the most common being the implementation and evaluation of EAP (Employee Assistance Program). The International Labor Office's research on this theory laid the foundation for this field, and this research is by far the most comprehensive research foundation. In addition to occupational and mental health, the ILO has also actively explored safety climate, job burnout, work stress, work environment, and other aspects. With the advancement of relevant research, it has been observed that due to unfavorable working conditions and a higher likelihood of accidents, workers exhibit lower levels of mental well-being compared to the general population. Consequently, psychological issues such as occupational stress resulting in tension, anxiety, depression, and other related problems have progressively emerged as significant concerns within the field of occupational health both domestically and internationally (21–23).

Mental health is a personal characteristic that can influence our behavior. It depends on the environment and personalities within and outside work and is related to job content, conditions, employment, and working relationships. The International Labor Office (ILO) 2000 introduced the concept of short-term mental health (e.g., mood and emotions, behaviors such as apathy, physiological reactions, etc.) and long-term mental disorders (e.g., exhaustion, post-traumatic stress disorder, depression, psychosis, cognitive disorders, drug use, etc.), arguing that in times of economic recession special attention needs to be given to the management of health and safety activities that occur in workplaces that are preventive of the mental health of the employees of a company (24). The concept of traumatic stress disorder is a critical component of the concept of mental health.

Research in the area of occupational health and mental health in China has been concerned with a relatively late period of time, and the breadth and depth of the areas covered have been limited. Usually,

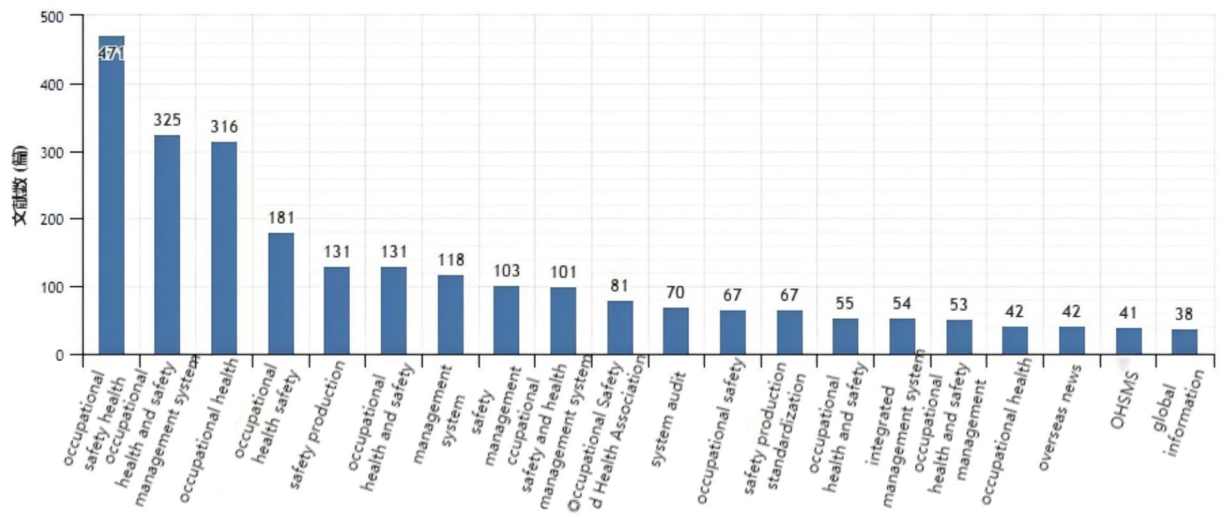

FIGURE 2
Paper main topic distribution diagram on CNKI.

researchers establish models of psychological elements (situational, defective, and endogenous) and, based on obtaining relevant data, analyze the influence relationship between unsafe psychological elements and such models according to the established safety psychometric models. Through the system dynamics model, the simulation of group factors and other influencing factors toward the coal mine employees' safety and mental health level of intervention strength, based on the service content and service mode of EAP (Employee Assistance Program), can form the best path to improve the level of employees' safety and mental health and the best intervention application strategy (25).

4 Literature review and current status of OHS management performance in the context of big data

By searching the journal papers with the topic of "occupational health and safety management performance" through web of science (Web of Science Core Collection) and CNKI from 2004 to 2024, there are 938 and 52 related papers were retrieved on web of science (Web of Science Core Collection) and CNKI, respectively. As shown in Figures 4, 5, the visual analysis of literature research on occupational health and safety shows that the research topics mainly focus on management system, standard mode, countermeasure analysis and management process. As shown in Figure 6, research literature on occupational health and safety management performance at home and abroad mainly shows an increasing trend but decreased after 2021. There is increasing attention on occupational health and safety management, and the research field categories are increasingly subdivided.

4.1 Current status and research on government regulation

For government control research earlier, foreign developed countries formed a theoretical system. Although these studies emphasize the effect of control, continuous adjustment and revision have formed a more complete system that can be adapted to the respective national conditions. In the United States, the central national occupational health regulatory agencies are the Occupational Safety and Health Administration (OSHA), the Mine Safety and Health Administration (MSHA), and the National Institute for Occupational Safety and Health (NIOSH) (26). The United Kingdom pioneered the Industrial Revolution, and poor working conditions led to an epidemic of occupational and infectious diseases. Therefore, in the 19th century, Britain enacted some laws such as the Factories Act, the Mines Act, the Public Health Act, and the Employers' Liability Act to protect workers' occupational health (27). In Germany, a highly industrialized country, occupational health management began in the 1850s. Because Germany has a large proportion of industrial workers, it is characterized by a dual model of occupational health management with government regulation and industry associations (28). The manufacturing industry in the United States between 1979 and 1998 is used as a case study to analyze examples of government regulation of occupational health and safety in the United States, and the results show that government regulation can be an excellent way to promote the performance of occupational health and safety management (29). An essential theme in developing the OHSAS regulatory system, "State-funded inspectorates to enforce and promote worker participation in the OHS legal system," traces the legal regulation of health, worker and other people's safety (30).

The research on domestic government regulation is based on analyzing countermeasures for coal mine safety regulations. Aiming at the series of problems of government regulation of coal mines in China, the study analyzes some problems and reasons of coal mine safety in government regulation. Therefore, the government regulation of safety in China's coal mining industry should strengthen the law enforcement, the self-discipline of enterprises, the construction of safety culture and the social publicity mechanism (31, 32). Moreover, China should strengthen its people-oriented management and realize the essential safety management of enterprises in the long-term mechanism of government supervision (33).

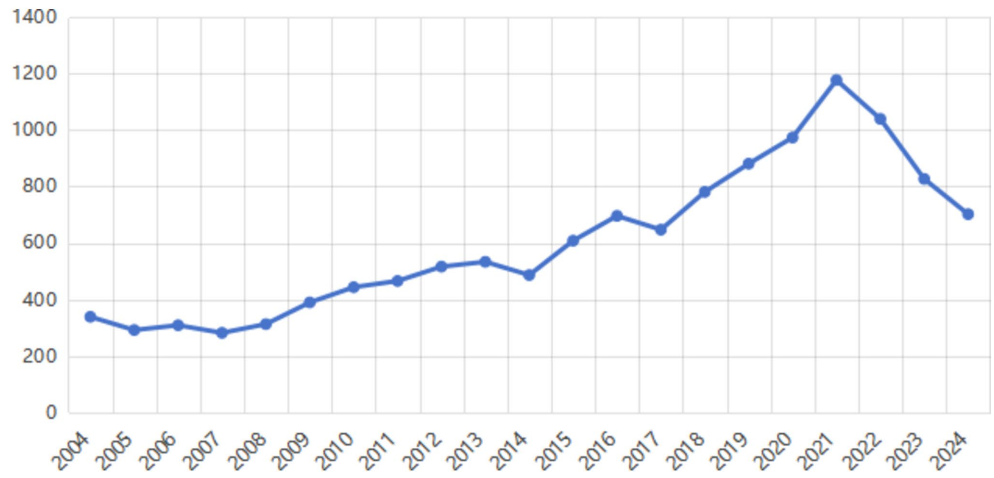

FIGURE 3
The fluctuation in literary output from 2004 to 2024.

FIGURE 4
Paper main topic distribution diagram on web of science.

4.2 Current status and research on social responsibility

OHS social responsibility involves an overview of OHS management, relevant employment information, welfare and health facilities, health education, accident statistics, OHS management and safety. The practical implementation of an OHS management system can be significantly improved by applying innovative OHS management systems that have been effectively implemented and measured in the EU, together with appropriate incentives.

At present, more studies at home and abroad are on whether corporate social responsibility (CSR) is positively correlated with financial performance, and they are mainly distributed in industrial and mining industries. The establishment of a mining enterprise social responsibility index evaluation system is of great significance for solving the problems of mining enterprises and carrying out research on mining enterprise social responsibility. The more influential international index systems for measuring CSR are the Dow Jones Sustainability Index (DJSI), Domini Socially Responsible Investment Index (KLD), Global Reporting Initiative (GRI), and Social Responsibility Guide (IS026000). We should further study and apply these index systems and continue to explore the CSR application mechanism, certification system development model, etc., suitable for China's OHS social responsibility (34). Based on studying the content of mining CSR and stakeholder relations, we should construct an evaluation index system to effectively solve China's OHS management problems, such as environmental and labor issues (35). The fulfillment of CSR by enterprises should also establish a research framework

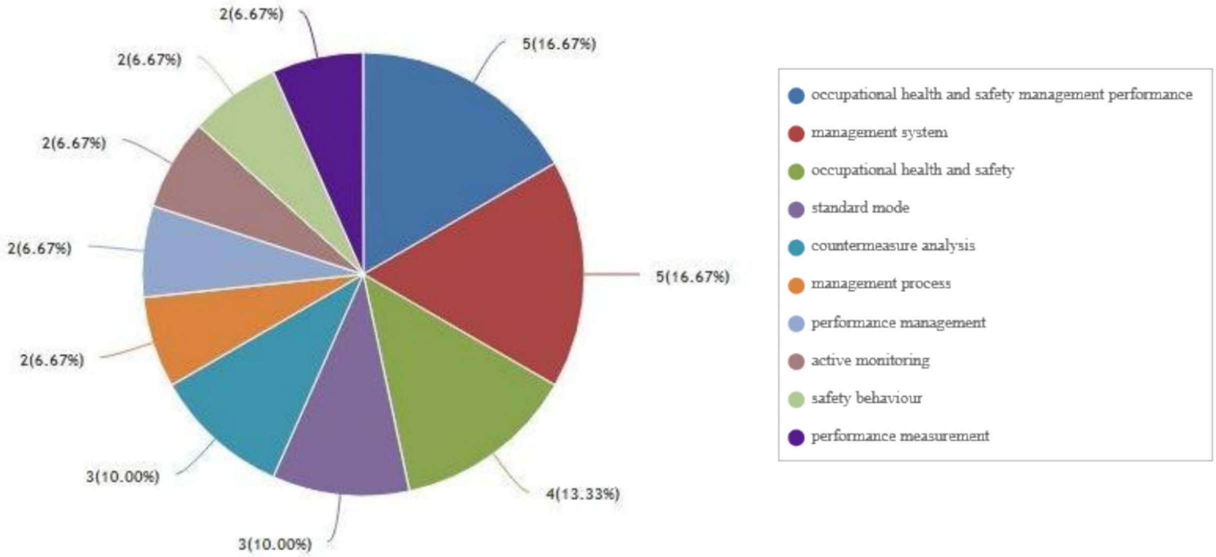

FIGURE 5
Paper main topic distribution diagram on CNKI.

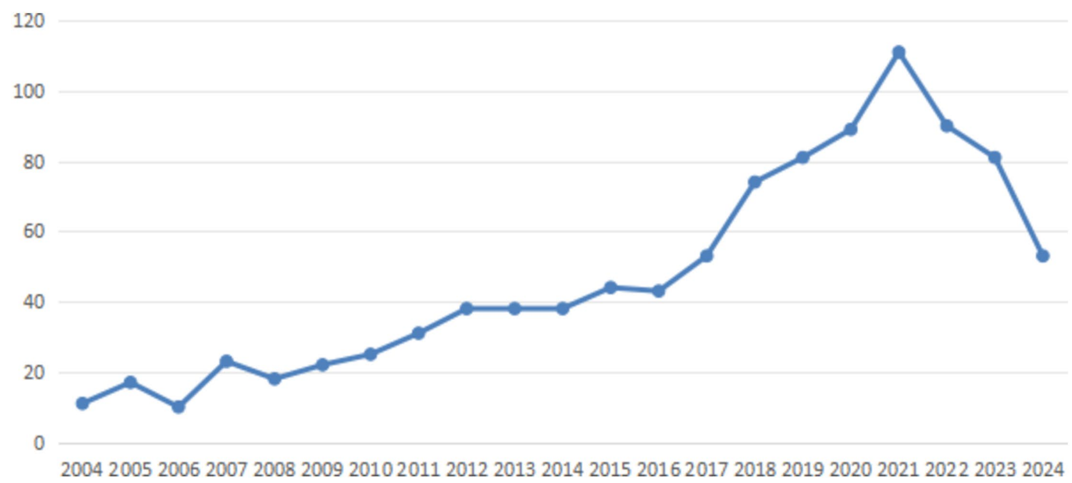

FIGURE 6
The fluctuation in literary output from 2004 to 2024.

suitable for CSR and values and drives suitable for China's economic characteristics and CSR, and pay attention to entrepreneurship, strategic research and development, etc. (36)

5 Discussion and illumination

Existing domestic and international literature provides new perspectives for studying occupational health and safety management systems. Domestic research on the contents of the OHS management system started late and is mainly based on the industrial and mining industries where safety accidents are frequent and the incidence of occupational diseases is high. Since there are fewer studies on other industries, this also requires us to study and evaluate the contents of OHSMS comprehensively. Due to the low awareness of governmental control by the managers of some business units and the insufficient investment by enterprises in the working environment, occupational health protection, and health check-ups of their employees, new safety problems and occupational disease hazards will continue to emerge with the wide application of new technologies, processes, equipment, and materials. This also poses new challenges to preventing and controlling occupational diseases and managing occupational health and safety. However, in foreign countries, as shown in Table 3, the regulatory aspects of OHS management include law enforcement regulation by government departments, assistance from relevant associations, and autonomous regulation by civil organizations. This is a highly dynamic form of regulation. For example, in developed countries such as the United Kingdom, Germany, and the United States, in terms of occupational health

10.3389/fpubh.2024.1514996

TABLE 3 Comparison of OHS between China and foreign countries.

Comparison content	Difference			
	China	Australia	Germany	Britain and America
Way	Volunteer	Volunteer	Force	Force
Supervise	Social regulation	The government and insurance agencies jointly supervise	The government and insurance agencies jointly supervise	The Work Environment Authority
Scope	Health and safety is mainly reflected in the body of employees	Health and safety are mainly reflected in the physical and psychological aspects of employees	Health and safety are mainly reflected in the physical and psychological aspects of employees	Health and safety are mainly reflected in the physical and psychological aspects of employees
Laws and regulations	Reflected in the overall framework	Reflected in the specific framework, and the enforcement	Reflected in the specific framework, and the enforcement	Reflected in the specific framework, and the enforcement
Educational training	Yes	Take education and training as the fundamental measure to prevent accidents	Take education and training as the fundamental measure to prevent accidents	Take education and training as the fundamental measure to prevent accidents
Role of industrial injury insurance institutions	Work-related injury compensation	Work consultation and supervision, work hazard investigation, analysis, testing, employee physical examination, formulation of relevant system documents, etc.	Work consultation and supervision, work hazard investigation, analysis, testing, employee physical examination, formulation of relevant system documents, etc.	Work consultation and supervision, work hazard investigation, analysis, testing, employee physical examination, formulation of relevant system documents, etc.
Health monitoring	Way of third-party supervision	Government and the insurance structure forced	The government forced	The government forced
Performance appraisal	Yes	Clear and definite	Clear and definite	Clear and definite

and safety management, although they emphasize the framework of occupational health and safety management system, to a certain extent, it is also consistent with the development of each country's economy, politics, culture and so on. The more economically developed countries are, the more importance they attach to managing safety accidents and preventing occupational diseases, which has resulted in outstanding performance, such as the world-famous domino model.

Based on this, China's OHS management system's operational status and management performance are comprehensively evaluated by drawing on domestic and international OHS management system-related research contents, perspectives, evaluation methods, etc. In implementing and developing the OHS management system in China, we should focus on the following aspects: Firstly, continuously improve the legal and regulatory system. The occupational health legislation of the United States, the United Kingdom and Germany was completed in the 1970s, and has been perfected after nearly half a century of continuous revision and development. China's occupational health laws and regulations are still at the stage of exploration and revision, especially the revision of laws and standards, which should be clearly defined as the central unit and department responsible, with deadlines set and the frequency of updating increased. The perfect bill not only is guarantee for the safety and health of workers, but also can make the overall management of occupational health more effective. Then, strengthen the government's supervision and monitoring efforts. In Sweden, occupational health and safety management is mandatory. In Germany and Australia, the government is multi-channel, large-scale supervision of the implementation of occupational health and safety management, and are actively involved in vocational skills training, accident investigation and other aspects. However, our government supervision of occupational health and safety management is minimal; only in the enterprise of more severe accidents does the role of government supervision appear. Therefore, China should moderately increase the strength of the government supervision and punishment, meanwhile, special inspect the duplication of problems to ensure that the scientific nature of supervision and monitoring means diversity, and ultimately enhance the importance of the enterprise to the management of occupational health and safety. Thirdly, strengthen the use of information technology. Informatization means should occupy an essential position in studying occupational health and safety management systems. Using extensive data collection to statistically analyze the occupational health and safety management data of industries and enterprises and form reports can effectively help the government and associations and provide strong support for diagnostic evaluation and early warning measures. Strengthen the interoperability and sharing of occupational health data among all relevant departments and establish a system for workers to lay the foundation for future informatization, data-based statistical analysis, and scientific research. Improve the occupational health and safety management system and realize the balanced and sustainable development of economic, environmental, and social benefits brought by the occupational health and safety management system (37).

6 Conclusion

In recent years, although the overall situation of occupational safety and health management in China has stabilized and improved compared with the past, safety accidents still occur from time to time. China is currently in a period of economic transition, which will inevitably bring about occupational health problems. By drawing on domestic and international research and development status, we will improve the occupational health and safety management system regarding government control and social responsibility in China. In a period of rapid industrial development and reform, this can better prevent safety accidents and combat occupational diseases and workers' mental health conditions at the root. Sustainable development emphasizes holistic development, which promotes economic development and coordinates the balanced development of the environment, society, and other aspects. Whether it is the comparative analysis of economic benefits and evaluation of environmental benefits in foreign countries or the perspective of sustainable development in China, we must treat economic, social, and environmental benefits holistically and systematically. Therefore, improving occupational health and safety management at this stage in China requires more social attention so that more workers can be aware of such issues. Supervisory authorities should also use more scientific and diverse methods to improve the quality of work so that enterprises can implement the primary responsibility to truly achieve the results of the occupational health-related level of protection of workers as the core of the enhancement of the level of occupational health because the adequate protection of the occupational health of employees is far greater than the pursuit of profit maximization brought about by the economic, social and environmental benefits (38, 39).

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

QH: Data curation, Writing – original draft, Writing – review & editing. MY: Funding acquisition, Writing – review & editing. SL: Conceptualization, Writing – review & editing. FW: Methodology, Writing – review & editing. ZL: Methodology, Writing – review & editing. TL: Conceptualization, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was funded by Provincial project funding for Key R&D programs of Ningxia Hui Autonomous Region (grant number 2022BEE02001). The APC was funded by Provincial project funding for Key R&D programs of Ningxia Hui Autonomous Region.

Acknowledgments

I thank all the participants who gave me suggestions and comments on this paper. In addition, I thank the reviewers for their valuable suggestions for improving the quality of the paper.

Conflict of interest

FW was employed by Ningxia Coal Industry Co., Ltd of China National Energy Group.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

References

1. Guan Z. Legal reflections on the incident of "open chest lung examination" [D]. *Lanzhou: Lanzhou University* (2011), pp. 5–11.

2. Magazzino C, Mele M, Leogrande A. Regional disparities and strategic implications of hydrogen production in 27 European countries. *Reg Sci Environ Econ*. (2024) 1:3–30. doi: 10.3390/rsee1010002

3. Xiao xu G, Longqing L, Xuewen L, Fengliang W. On the significance of establishing occupational safety and health management system in coal mining enterprises[J]. *Northwest Coal*. (2004) 1:49–52.

4. Qiquan W. The history of occupational safety and health management system and its development in China[J]. *Chin J Saf Sci*. (2003) 6:79–82.

5. Reese CD, Eidson JV. Handbook of OSHA Construction Safety& Health. Boca Raton: CRC/ Lewis Publishers (1999).

6. National Safety Council. Injury facts 2001 Edition,. Itasca, IL: National Safety Council (2000).

7. George R. Occupational safety and health in Australia: 25 years in review. *Prof Saf*. (2000) 45:39–41.

8. Zhang M, Tao L, Yunlin Z. Characteristics of acute occupational poisoning accidents and control measures in China. *Ind Hyg Occup Dis*. (2003) 29:203–5.

9. Statistical Bulletin on the Development of Health Care in the Country. Available at: http://www.nhc.gov.cn/guihuaxxs/s3585u/202408/6c037610b3a54f6c8535c515844fae96.shtml (2023).

10. Sharma HR, Appadurai S, Wubshet M, Tadess T. Occupational exposures and related health effects among construction workers[J]. *J Health Biomed Sci*. (2008) 1:41–6.

11. Molla GE, Salgedo WB, Lemu YK. Medicine prevalence and determinants of work related injuries among small and medium scale industry workers in Bahir Dar town, north West Ethiopia[J]. *Ann Occup Environ*. (2015) 27:34–43. doi: 10.1186/s40557-015-0062-3

12. Gulseren D. Physical hazards, musculoskeletal pain, and job control: multilevel results from the European social survey. *Saf Sci*. (2022) 156:105901. doi: 10.1016/j.ssci.2022.105901

13. Tafese A, Nega A, Kifle M, Kebede W. Occupational exposure to neck and shoulder in Ethiopia[J]. *Sci J Public Health*. (2014) 2:577–83.

14. Lin Z. Research on the integration of coal mine safety evaluation and occupational disease Hazard evaluation in China [D]. Taiyuan University of Technology (2011).

15. Chun D. Analysis of the rescue model for pneumoconiosis groups in China[J]. *China Hum Resour Dev*. (2016) 1:90–6.

16. Reason J. Human Error [M]. New York Cambridge: University Press (1990).

17. Ming Z. Research on coal mine safety early warning management and system [D]. Taiyuan University of Technology (2004).

18. Guohanfen. Economics analysis of coal mine safety accident causal factors and risk management method [D]. Ph.D., University of International Business and Economics (2007).

19. Haihui L. Research on safety management problems of Chinese coal mining enterprises [D]. Liaoning University (2006).

20. Gui F. Safety management-behavioral control methods for accident prevention [M]. Beijing: Science Press (2013): 57–69.

21. Xiaofan M, Hua G, Jiwen L. Investigation on mental health status of coal miners in Xinjiang [J]. *Occup Health*. (2018) 34:2892–5.

22. Li H, Jianhua Y. Investigation on the relationship between occupational stress and life quality of coal miners [J]. *Ind Hyg Occup Dis*. (2021) 47:206–8.

23. Xiaoguang L, Yang X, Fengsai D, Jingyun L, Kui M, Hanbin Y. Occupational stress of coal miners and its prevention and control measures [J]. *Chin J Preventive Med*. (2023) 24:1371–5.

24. International Labor Office. Encyclopedia of occupational health and safety. *Fourth Edition [M]* ed Beijing: China Labor and Social Security Press (2000).

25. Sai Z, Qinggui C, Hongguo J. The application research of EAP system to improve the safety psychology level of coal mine workers [J]. *China Coal*. (2016) 42:10–4.

26. Rongchang C, Minyan L, Bing H. Occupational health regulations, supervision and statistical system in the United States [J]. *Chinese J Saf Sci*. (2007) 3:100–4.

27. Ping'an Z. An analysis of occupational safety and health management in the UK[J]. *Shaanxi Coal*. (2015) 34:115–7.

28. Gao S. Occupational safety and health management in Germany[J]. *Saf Health*. (2012) 13:31–2.

29. Gray WB, John M. The declining effects of OSHA inspections on manufacturing injuries [J]. *Ind Labor Relat Rev*. (2005) 58:571–87. doi: 10.1177/001979390505800403

30. Johnstone R. Occupational health and safety, regulation of In: JD Wright, editor. International Encyclopedia of the Social & Behavioral Sciences (Second Edition). Amsterdam: Elsevier (2015). 141–6.

31. Fen Z.. Research on the problems of coal mine safety supervision in China-taking coal mine safety supervision in Shandong Province as an example [D]. Master of Shandong University (2010).

32. Xiao Z.. Effective regulation of coal mine safety in China: An example of coal mine safety regulation in Shanxi Province [D]. Nanjing Normal University (2008).

33. Yao S.. Exploration and analysis of coal mine safety supervision problems in China [D]. Sichuan University (2006).

34. Yuechun Z. A review of domestic and international researchers on corporate social responsibility [J]. *Manage Explor*. (2012) 11:9–11. doi: 10.17265/1537-1514/2012.11.009

35. Linlin M.. Research malefactor of mining enterprise social responsibility evaluation index system. China University of Geosciences (2010).

36. Xin J. Research on corporate social responsibility--a new theoretical framework and empirical analysis [D]. Shandong University (2009).

37. Fan F, Yang B, Wang S. The convergence mechanism and spatial spillover effects of urban industry-university-research collaborative innovation performance in China. *Tech Anal Strat Manag*. (2023) 9:1–17. doi: 10.1080/09537325.2023.2290169

38. Xu E, Fan F. The impact of innovation on intra-city economic disparity: a technological complexity perspective. *Appl Econ*. (2024) 1–16. doi: 10.1080/00036846.2024.2403781

39. Zhao L, Jiang J. Evolution and drivers of embodied energy in intermediate and final fishery trade between China and maritime silk road countries. *Reg Sci Environ Econ*. (2024) 1:104–27. doi: 10.3390/rsee1010007

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 06 January 2025
DOI 10.3389/fpubh.2024.1535932

Check for updates

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Song Wang,
Northeastern University, China
Fei Lu,
Southwestern University of Finance and Economics, China

*CORRESPONDENCE
Yaosen Qian
✉ 285864@whut.edu.cn

RECEIVED 28 November 2024
ACCEPTED 11 December 2024
PUBLISHED 06 January 2025

CITATION
Zhao L, Li C and Qian Y (2025) Research on the impact of urban innovation on public health.
Front. Public Health 12:1535932.
doi: 10.3389/fpubh.2024.1535932

Research on the impact of urban innovation on public health

Liang Zhao[1], Chen Li[2] and Yaosen Qian[3]*

[1]School of Tourism, Hubei University, Wuhan, China, [2]School of Management, Shanghai University of Engineering Science, Shanghai, China, [3]School of Naval Architecture, Ocean and Energy Power Engineering, Wuhan University of Technology, Wuhan, China

Introduction: This article explores the impact of innovation on urban public health, with a particular focus on panel data from 15 sub-provincial cities in China. The study aims to provide scientific evidence for policymakers by analyzing how technological innovation affects urban public health levels.

Methods: The study used a panel model for empirical analysis which based on panel data from 15 sub provincial cities across the country, using the number of doctors per 10,000 people and per capita financial medical and health expenditure as proxy variables for urban public health, and using the level of technological development as the core explanatory variable for regression analysis.

Results: The research results show that: (1) for public health quantified by the number of doctors per 10,000 people in cities, innovation does not have a significant promoting effect on urban public health; (2) Compared to the number of doctors per 10,000 people in a region, the per capita financial expenditure on healthcare can better measure the level of urban public health; (3) Innovation has a significant impact on urban public health, measured by per capita fiscal expenditure on healthcare.

Discussion: In order to transform technological innovation into a driving force for the development of urban public health, efforts must be made from multiple aspects. Currently, building a strong foundation for people's health relies on the support of science and technology, and enhancing innovation as a primary driving force is crucial. China urgently needs to improve the stability and competitiveness of its pharmaceutical industry and supply chain, break through key core technologies, and take the initiative in the future development of the pharmaceutical industry.

KEYWORDS

innovation, public health, number of doctors per 10,000 people, per capita fiscal expenditure on healthcare, Chinese cities

1 Introduction

The healthcare industry has always been closely linked with the overall national strategy and plays an important supporting role. People's health is an important symbol of China's modernization, and safeguarding people's health cannot be separated from technological support. On the new journey of comprehensively building a socialist modernized country and promoting the construction of a healthy China, it is necessary to further popularize healthy living, optimize health services, improve health guarantees, build a healthy environment, and develop the health industry. The Chinese government places the protection of people's health in a strategic position of priority development, accelerates the construction of a healthy China, and explicitly requires innovation to be "oriented towards people's lives and health." History and reality have fully proven that the development of the healthcare industry must rely on innovation to lead and promote, and ensuring human health cannot be separated from scientific development and technological innovation.

Science and technology are the most powerful weapons for humans to fight against diseases (1–3). The victory of humanity over major disasters and epidemics cannot be achieved without scientific development and technological innovation. Currently, the demand for a healthy lifestyle among the people is constantly increasing, and the status of the healthcare industry in the national strategy is also constantly rising. People's multi-level and diversified health needs will continue to grow rapidly, and the country will also put forward higher requirements for medical innovation (4–8). Compared to this, China's medical innovation system has not yet formed an overall advantage, and there are still shortcomings in key aspects such as the ability and output of medical innovation, the system and institutions, investment and support. Specifically, there is an urgent need to strengthen basic research capabilities and original innovation capabilities, improve the mechanism for coordinating scientific and technological resources and the independent and controllable innovation system, and enhance the guidance of medical innovation investment and direction. There is still a significant gap between China's medical technology and advanced countries in terms of overall innovation system and innovation capability, and there is still a long way to go to achieve the goal of providing strong support for building a world science and technology power.

There is a close and dynamic relationship between innovation and public health. At present, research progress in this field is reflected in multiple aspects. One is about innovating and improving the level of public health management. Through big data analysis and artificial intelligence technology, health data can be collected, stored, and analyzed more effectively, helping medical institutions understand the health status of a certain area, predict and monitor the spread of diseases (9–12). Big data technology can also be applied to evaluate the built environment related to public health, such as processing street view images through machine learning algorithms, identifying human scale information, and planning and designing healthy living environments. Artificial intelligence technology has made significant progress in medical diagnosis, treatment, and surgical planning, improving the accuracy and efficiency of diagnosis (13–18).

The second is to innovate and promote the optimization of public health services. With the continuous development of artificial intelligence technology, personalized medicine and health management have become possible (19–21). By analyzing patients' personal data and health records, personalized treatment plans and health management plans can be developed. Gene editing technologies such as CRISPR-Cas9 have also provided individuals with customized treatment plans, bringing revolutionary progress to medical technology. Medical robots have been widely used in fields such as surgery, rehabilitation, and nursing, improving the accuracy and stability of surgeries, reducing rehabilitation time, and enhancing rehabilitation outcomes (22–24). Bioprinting technology is an advanced technique that utilizes biomaterials and cells for directional printing in three-dimensional space to form tissues or organs. This technology has broad application prospects in the fields of tissue engineering and organ transplantation, providing the possibility for organ regeneration and transplantation.

The third is the challenges and response strategies faced by innovation. With the widespread application of big data and artificial intelligence technology, data privacy and security issues are becoming increasingly prominent (25–28). The response strategies include strengthening data encryption and access control, developing strict data privacy protection policies, and increasing public awareness and importance of data privacy. With the continuous advancement of technology, relevant laws, regulations, and ethical norms also need to be constantly improved. The response strategy includes strengthening the formulation and implementation of laws and regulations, establishing a reasonable ethical norm system, and enhancing international cooperation and sharing of experience. In addition, in the face of global public health challenges, international cooperation and sharing will become an important trend for future development. By strengthening international cooperation and sharing data resources, technological achievements, etc., we can jointly address global public health issues and improve the level of global public health (29–31).

In summary, innovation has made significant research progress in improving the level of public health management, promoting the optimization of public health services, and addressing challenges and response strategies. However, from the existing literature, research on the impact of innovation on public health is mostly interpreted from frameworks and concepts, with more qualitative research and less quantitative research. There is a lack of research literature on the impact mechanism of innovation on urban public health. Current research on the impact of innovation on public health is mostly interpreted at the framework and conceptual level, with more qualitative research and relatively less quantitative research. This means a lack of specific data analysis and empirical support to verify the actual effectiveness of innovation. In existing research literature, there is a lack of in-depth exploration of the specific mechanisms by which innovation affects urban public health. This limits our understanding of how innovation specifically affects the public health system, making it difficult to develop more effective policies and strategies. Although the application of big data analysis and artificial intelligence technology in public health management has been mentioned, existing research may still have shortcomings in providing practical data support. Lack of specific data analysis and case studies to demonstrate the practical application effects of innovative technologies.

In view of this, this article chooses innovation elements as the core explanatory variables, incorporates innovation and urban public health into a holistic research framework, focuses on measuring the level of public health development in 15 sub provincial cities in China, and explores the impact of innovation on urban public health. The article combines innovation, an important engine for regional economic development, with urban public health, a social welfare field, to explore the impact of innovation on the level of urban public health. This cross disciplinary perspective may not have been common in previous research, providing new ideas for understanding the social benefits of innovation. The article used panel data from 15 sub provincial cities across the country and systematically studied the relationship between innovation and urban public health through statistical methods such as regression analysis. This empirical research based on big data and statistical methods enhances the reliability and persuasiveness of the research results. When measuring the level of urban public health, the article not only considers the traditional indicator of the number of doctors, but also introduces the more comprehensive indicator of per capita fiscal medical and health expenditure. The innovation in variable selection enables research to more accurately capture the comprehensive impact of innovation on urban public health levels.

2 Variable selection and data explanation

2.1 Research on urban overview and data sources

This study selected 15 sub provincial cities across the country as research subjects. A sub provincial city is a provincial-level city under the administrative structure of sub provincial level in China, officially implemented in 1994. Its predecessor was a planned city. There are currently 15 sub provincial cities in China, namely Shenyang, Dalian, Changchun, Harbin, Nanjing, Hangzhou, Qingdao, Jinan, Ningbo, Xiamen, Wuhan, Chengdu, Xi'an, Guangzhou, and Shenzhen. Except for Dalian, Qingdao, Ningbo, Xiamen, and Shenzhen, all of these cities are provincial capitals. The reason for choosing sub provincial cities is that these cities have relatively good economic foundations, outstanding development, and special economic advantages that are different from mega cities. They also have coverage in the eastern, central, western, and northern and southern regions of the country, and therefore have certain representative significance. The relevant indicator data of each city mainly comes from the "China Urban Statistical Yearbook" (2008–2023) and the statistical yearbooks of each city.

2.2 Selection and explanation of variables

(1) Urban Innovation: Urban innovation refers to the integration of internal and external resources, the use of new knowledge, technologies, and methods to create new economic growth points, social service models, or cultural forms in a constantly changing environment, in order to promote the sustainable development and progress of urban economy and society. This article takes innovation as the explanatory variable, and for the measurement indicators of innovation, Sun Yu et al. (2008) selected 18 indicators including per capita GDP, patent applications per 10,000 people, patent authorizations per 10,000 people, and the proportion of scientific expenditure to total fiscal expenditure as indicators of urban innovation capability (32); Yu Liping (33) used provincial R&D investment data, including full-time equivalent R&D personnel, technology market transaction volume, and number of invention patents as innovation indicators (33); Fan Jie and Liu Hanchu (34) selected 11 representative indicators based on the connotation of regional innovation capability, including per capita financial science and technology funding and the number of patent applications accepted per 10,000 people (34); Zhou Ke et al. (35) used the number of domestic patent applications granted in each province over the years to measure innovation (35). From the construction of indicators by scholars, it can be seen that innovation variables have mostly chosen indicators such as patent application (authorization) volume and fiscal technology expenditure. Drawing on the indicators constructed by scholars and based on the needs of this study and the availability of data, this article uses the proportion of technology expenditure to urban fiscal expenditure and the number of patent authorizations per 10,000 people in the city to measure innovation indicators. Meanwhile, as James and Ron (36) pointed out, economic diversity is believed to affect regional public health and adaptability through various pathways (36). Therefore, factors such as employment form diversity, industrial diversification, and imports and exports associated with this can all be used as control variables. This article uses the proportion of urban private and individual employees to the total employed population to represent employment diversity, the proportion of the tertiary industry to urban GDP to represent industrial diversity, and the import and export variables are expressed as the ratio of the city's annual import and export volume to the city's GDP. The import and export volume is converted into RMB based on the exchange rate of the current year.

(2) The public health level of the city: Urban public health (Phenath). The article is consistent with most literature, focusing on the health status of urban residents in terms of physical function, while taking into account the necessary basic support conditions and practical health performance improvement when measuring public health to construct a composite index of urban public health. The necessary foundation of public health is the logical starting point and prerequisite for improving urban public health, represented by the number of doctors per 10,000 people and per capita financial medical and health expenditures.

3 Empirical analysis

3.1 Basic model

The basic research model of this article is established as follows:

$$Yit = \alpha it + \beta itXit + \theta itVit + \varepsilon it \quad (1)$$

In formula (1), Y_{it} is the dependent variable representing public health, and X_{it} is the core explanatory variable representing innovation indicators for each city in different years. These indicators are represented by the ratio of science and technology expenditure to fiscal expenditure (*texp*) and the number of patent authorizations per 10,000 people in each city. Vit represents control variables, including employment diversity (*empl*), industry diversity (*serind*), and the proportion of total import and export value to GDP (*imex*). Due to the fact that the dependent variable public health has two variables—the number of doctors per 10,000 people (*nodp*) and the per capita fiscal healthcare expenditure (*unem*), we constructed Model 1 and Model 2 for analysis, respectively (Table 1).

3.2 Construction and analysis of model 1

To confirm whether the panel model is suitable for a random effects model or a fixed effects model, the Hausman test method was used. The null hypothesis is that a random effects model should be established. According to the Hausman test results shown in Table 2, for the urban *grp* index, the value of the Hausman statistic is

TABLE 1 Hausman test results.

	Number of doctors per 10,000 people (*nodp*)	Per capita fiscal expenditure on healthcare (*pceh*)
Chi-Sq. Statisic	70.6271	1.0089
Chi-Sq. d.f.	5	5
Prob.	0.0000	0.9618

70.6271, the degree of freedom is 5, and the corresponding p-value is 0.0000, which is less than 0.05. This rejects the null hypothesis of the random effects model, so a fixed effects model should be chosen; For the unemployment rate indicator, the Hausman statistic has a value of 1.0089, a degree of freedom of 5, and a corresponding p-value of 0.9618, which is greater than 0.05. Therefore, the null hypothesis of the random effects model should be accepted, and the unemployment rate model should choose the random effects model.

According to whether the intercept and coefficient are variable, fixed effects models can be divided into constant parameter models with constant intercept and coefficient, variable intercept models with constant coefficient and variable intercept, and variable coefficient models with variable intercept and coefficient. To determine the specific form that an individual's panel fixed effects model should take, we construct two hypotheses:

> $H1$: The coefficients of the model are all equal, that is, the proportion of technology expenditure to fiscal expenditure, the number of patent authorizations per 10,000 people, industrial diversity, employment diversity, and the proportion of total import and export value to GDP have the same impact on urban public health.
>
> $H2$: The intercept of the model is equal, and the coefficients are also equal, assuming that the public health of each city is the same, and each indicator including the proportion of technology expenditure to fiscal expenditure, the number of patent authorizations per 10,000 people, industrial diversity, employment diversity, and the proportion of total import and export value to GDP have the same impact on urban public health.

Next, construct two F-statistics to test the above two hypotheses:

$$F1 = \frac{(S2 - S1)/\left[(N-1)k\right]}{S1/\left(NT - N(k+1)\right)} \sim F[(N-1)k, N(T-k-1]$$

$$F2 = \frac{(S3 - S1)/\left[(N-1)(k+1)\right]}{S1/\left(NT - N(k+1)\right)} \sim F\left[(N-1)(k+1), N(T-k-1)\right]$$

Through multiple regressions of grp, we can obtain S_1 (sum of squared residuals of variable coefficient model), S_2 (sum of squared residuals of variable intercept model), and S_3 (sum of squared residuals of constant parameter model) as follows:

$S_1 = 0.0146$, $S_2 = 0.0871$, $S_3 = 0.1447$.

So calculate F_1 and F_2 as follows:

$F_1 = 4.2458$, $F_2 = 6.3488$.

Firstly, test H_2. The F-distribution value $F_{0.05}(84, 60) = 1.4970$ compared to F_2 is smaller than F_2. Then, test H_1. The F-distribution value $F_{0.05}(70, 60) = 1.5160$ compared to F_1 is smaller than F_1. Therefore, for the public health indicator $nodp$, we should construct a fixed effects variable coefficient model, that is, formula (2) is:

$$nodp = \alpha_i + \beta_{1i} \cdot texpit + \beta_{2i} \cdot pateit + \beta_{3i} \cdot emplit + \beta 4i \cdot serind_{it} + \beta 5i \cdot imex_{it} + u_{it} \tag{2}$$

The regression results are as follows:

From Table 3, it can be seen that from the perspective of the impact of innovation on the public health indicator $nodp$, the impact of innovation on urban public health is not significant. However, in a few cities with significant impact, such as Xiamen, there is a negative relationship between technology investment (texp) and

TABLE 2 Model 1 regression results.

Explanatory variable	Proportion of technology investment in fiscal expenditure(*texp*)	Thousands of people have patents authorization quantity(*pate*)	Diversity in employment(*empl*)	Industrial diversity(*serind*)	Proportion of imports and exports(*imex*)
Shenyang	0.1989(0.0372)	−0.0220***(5.4004)	0.1334(0.5454)	−0.5449*(−1.8795)	0.0765(0.1630)
Dalian	5.7121(1.4886)	−0.0071(1.6617)	−0.5828(−1.6216)	−0.1634(−0.3392)	0.1330(0.9444)
Changchun	3.1766(0.6920)	−0.0198**(2.3232)	0.4521(1.1420)	0.7192(0.7472)	0.6555*(1.9421)
Haerbin	0.4474(0.0838)	−0.0068(1.1135)	0.1543(0.9687)	−0.4862(−0.3581)	−0.6866(−0.8948)
Nanjing	−2.0985 (0.6236)	0.0027(0.8580)	−0.2246(−0.8593)	−1.0878(−0.8750)	−0.0402(−0.2245)
Hangzhou	−4.3562(1.2761)	0.0009(0.8312)	0.3093(1.1204)	0.0415(0.1192)	0.0174(0.0868)
Qingdao	−1.8008(0.6966)	0.0012(0.3765)	−0.0793(−0.2288)	−0.6772(−0.4795)	0.0361(0.6619)
Jinan	−1.3587(0.3215)	−0.0010(0.4428)	−0.0437(−0.4638)	−0.5402(−0.7591)	0.1594(0.8771)
Ningbo	2.9456(1.3441)	−0.0001(0.3433)	−0.7259***(−2.7072)	0.6322(0.8174)	−0.0312**(−2.0627)
Xiamen	−11.0347**(2.2434)	0.0006(0.8303)	0.0521(0.1780)	−0.7464(−1.1729)	0.1140(0.7893)
Wuhan	−1.4258(1.2993)	0.0020(0.4531)	−0.3353(−0.8958)	−0.2439(−0.4834)	0.2082(0.7856)
Chengdu	−2.5262(1.1523)	−0.0033*(1.8285)	−0.0043(−0.0562)	1.0204(1.2441)	0.1570(1.0546)
Xian	0.9620(0.4029)	−0.0013(1.2444)	0.0262(0.1032)	−0.2376(−0.4346)	−0.1940(−0.6159)
Guangzhou	0.5018(0.6440)	0.0005(0.2299)	−0.2126(−1.1526)	−0.2120(−0.1776)	0.1021(0.7549)
Shenzhen	0.4439(1.3339)	0.0000(0.2430)	−0.0874(−0.4932)	−0.1560(−0.2074)	0.0346(1.0718)

The t-test is indicated in parentheses, with *, **, and ** representing significance levels of 10, 5, and 1%, respectively.

TABLE 3 Regression results of Model 2.

Variable	Coefficient	Standard deviation	T statistic	*p* value
C	0.0521	0.0098	5.2872	0.0000
TEXP?	−0.2349	0.0612	−3.8357	0.0002
PATE?	−0.0001	0.0000	−2.1437	0.0337
EMPL?	−0.0482	0.0078	−6.1484	0.0000
SERIND?	0.0117	0.0188	0.6228	0.5344
IMEX?	−0.0006	0.0017	−0.3410	0.7336

urban public health indicators, which seems counterintuitive. However, from another perspective, it is not difficult to understand that the process from technology investment to output itself has a time lag effect, and technology investment cannot immediately improve public medical resources. In addition, from the perspective of the proportion of technology investment to fiscal investment in each city, this value is very small. For example, in Harbin, the proportion of technology investment to fiscal expenditure in 2016 was only 0.87%. Even in Hangzhou, where technology investment is relatively high, technology investment only accounted for 5.33% of fiscal expenditure in 2016. Meanwhile, from the innovation indicator of the number of patents granted to 20,000 people, we can also see that in most cities, the number of patents granted is not significantly related to urban public health. Only Shenyang, Changchun, and Chengdu have a relatively significant impact on urban public health, but this impact is also relatively small and negative. For example, in Shenyang, for every one unit change in patent authorization, the public health sector will experience a reverse change of 0.02 units; For every unit change in patent authorization in Changchun, public health will experience a reverse change of 0.02 units; In Chengdu, for every 1 unit change in patent authorization, the public health sector experiences a reverse change of 0.003 units. Of course, these changes are relatively minor, and it can be said that the number of patent authorizations per 10,000 people has no significant impact on urban public health. The regional distribution of medical resources in China is very uneven, with the highest quality doctor resources concentrated in big cities such as Beijing, Shanghai, and Guangzhou, or in eastern coastal provinces. The density of doctors is high, and the corresponding supporting facilities are also good. However, in other regions, especially in the Midwest and rural areas, there is a relative scarcity of medical resources. This regional difference may lead to insignificant effects of innovation in increasing the number of doctors. There are significant differences in the allocation of medical resources between urban and rural areas, with urban areas having relatively abundant medical resources while rural areas have relatively scarce medical resources. This difference may lead to limited effectiveness of innovation in increasing the number of doctors in rural areas.

Of course, it may also be due to the large number of patent authorizations in Chinese cities, but the quality still needs to be improved, especially the invention patents that serve as the gold standard still need to be strengthened. In addition, it also indicates that the rate of patent conversion into production capacity in China is relatively low. Patents still mostly remain at the level of research and development. From other control variables, the impact of other factors on urban public health is also not the same. In Ningbo, both employment diversity and the proportion of imports and exports have a significant impact on the city's public health. Of course, the impact is negative, meaning that the more employment diversity increases, the lower the city's public health value; The larger the proportion of exports, the lower the public health value of the city, which may be related to the special geographical conditions of Ningbo. Ningbo is the world's third largest port city, and its own private commerce is also exceptionally prosperous. After the economy reaches a certain level, it may be weakened or even alienated by the diversity of employment and import and export factors.

3.3 Construction and analysis of model 2

Similarly, for Model 2, we can calculate that:
$S_1 = 0.0016$, $S_2 = 0.0044$, $S_3 = 0.0136$

$$F1 = \frac{(S2 - S1)/\left[(N-1)k\right]}{S1/\left(NT - N(k+1)\right)} \sim F[(N-1)k, N(T-k-1]$$

$$F2 = \frac{(S3 - S1)/\left[(N-1)(k+1)\right]}{S1/\left(NT - N(k+1)\right)} \sim F\left[(N-1)(k+1), N(T-k-1)\right]$$

So we can calculate $F_1 = 1.4179$, $F_2 = 5.1231$.

First, check H_2. Since $F_{0.05}(84, 60) = 1.4970$ is less than F_2, reject H_2. However, $F_{0.05}(70, 60) = 1.5160$ is greater than F_1. Therefore, a variable intercept model for random effects should be constructed, and the expression for formula (3) can be obtained as follows:

$$\begin{aligned} unemit &= \alpha + \alpha_i + \beta 1 \cdot texpit + \beta 2 \cdot pateit + \beta 3 \cdot emplit \\ &\quad + \beta 4 \cdot serind_{it} + \beta 5 \cdot imex_{it} + u_{it} \end{aligned} \tag{3}$$

The estimated values obtained are:

From the perspective of the impact of innovation on per capita fiscal healthcare expenditure (*unem*), innovation has a significant impact on urban public health. This indicates that providing strong technological support for "people's life and health" requires increased investment, which is comprehensive and includes not only economic investment but also investment in talent teams. It should be noted that the rapid development of medical technology in the world has increasingly significant impacts on people's health, economic development, and national security. These objective circumstances require our investment to be dynamic and continuous. In the future, a normalized national medical and health science fund can be established to focus on supporting clinical medicine, public health, translational medicine research, and basic scientific research work, further increasing the proportion of scientific and technological investment in the medical field in the overall national scientific and technological investment. The use of variable intercept in Model 2 means that although innovation has different impacts on various cities, the amount of change in innovation has the same impact on different regions. Every city can see the impact of innovation on its public health (Table 4).

TABLE 4 Estimated value ofα_i.

Number	City i	Estimated value of α	number	City i	Estimated value of α
1	Shenyang	0.0079	9	Ningbo	0.0023
2	Dalian	0.0096	10	Xiamen	−0.0100
3	Changchun	0.0073	11	Wuhan	0.0021
4	Haerbin	0.0012	12	Chengdu	−0.0100
5	Nanjing	−0.0012	13	Xian	0.0024
6	Hangzhou	−0.0121	14	Guangzhou	0.0147
7	Qingdao	−0.0028	15	Shenzhen	−0.0012
8	Jinan	−0.0102			

4 Conclusion and recommendations

This article uses a panel model to empirically test the impact of innovation on urban public health in 15 sub provincial cities in China. The conclusion is as follows: firstly, in terms of public health quantified by the number of doctors per 10,000 people in cities (*nodp*), innovative indicators have not shown a significant promoting effect, and some cities may even have a negative effect; Secondly, innovation has a significant impact on public health, which is quantified by per capita fiscal expenditure on healthcare (*unem*). The city's technology investment (*texp*) and patent authorization (*pate*) both have a positive effect on the city's public health. Of course, efforts need to be made from multiple aspects to better transform technology into momentum and maintain the development of urban public health. Now, more than ever before, building a strong foundation for people's health requires the support of science and technology, and the enhancement of innovation as the primary driving force. Make due contributions to building a national medical innovation system, leading and promoting the development of the health industry, and constructing a human health community, continuously advancing toward the breadth and depth of science and technology.

In recent years, countries have increasingly attached importance to the strategic position of the pharmaceutical industry, and the global industrial chain and supply chain have been rapidly reshaped. China also urgently needs to improve the stability and competitiveness of the pharmaceutical industry and supply chain. Promote key core technology breakthroughs and seize the initiative in the future development of the pharmaceutical industry. Concentrate efforts to carry out key core technology research and accelerate the resolution of bottleneck problems in a number of fields such as drugs, medical devices, medical equipment, vaccines, etc. (6–14). Only by achieving independent and controllable key core technologies can we firmly grasp the initiative of innovation and development in our own hands.

Continuously increasing investment in technology. Technology investment is an important guarantee for promoting innovation and an important indicator for measuring innovation level and capability. Cultivate and strengthen innovation platforms. Innovation platforms are important carriers for gathering various innovative resources and elements, which help promote innovation to expand into deeper fields and move toward higher levels. Accelerate the upgrading of industrial structure, enhance the stability and competitiveness of the pharmaceutical industry supply chain. Accelerate the implementation of a batch of major research and development projects. We will continue to promote the development of innovative products through breakthroughs in innovative technologies, focusing on the needs of industrialization and bottleneck technologies. We will also develop innovative drugs, new vaccines, new antibody drugs, cell therapy, and gene therapy products. At the same time, we will accelerate the localization and substitution research of raw materials and key instruments and equipment, and strive to solve the bottleneck problem of key core technologies and raw materials. Actively creating a source of original technology. The development and integration of cutting-edge technologies and the improvement of people's health awareness have promoted the rapid development of the global pharmaceutical industry, and also provided a broad space for China's pharmaceutical industry to seize the opportunities of a new round of technological revolution and industrial transformation.

To improve the layout of scientific research, it is necessary to integrate the best medical research resources in the country, adopt a "center network" construction method in accordance with national strategic needs, optimize combination and system integration, and achieve full coverage of important medical disciplines such as basic medicine, clinical medicine, preventive medicine, public health, nursing, pharmacy, biomedical engineering, health management and policy. Combine the construction of the national medical innovation system with the establishment of national laboratories in the medical field, and continue to tackle major scientific and technological issues around serving national goals. At the same time, we will persist in conducting long-term and high difficulty research, cultivating innovative strategic forces that are at the forefront of global medical technology and can undertake national missions.

Based on the data of per capita fiscal medical expenditure, adjust the structure of fiscal expenditure and increase investment in the medical and health field to ensure that urban residents can obtain sufficient medical security. In response to the problem of uneven distribution of medical resources, the government should take measures to promote the balanced distribution of medical resources, such as increasing investment in medical and health care in rural or underdeveloped areas, and narrowing the medical gap between urban and rural areas and regions. The government can detect and solve problems in the medical and health field in a timely manner by monitoring and analyzing per capita financial medical expenditures, ensuring the effective utilization of medical resources and continuous improvement of medical services.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://www.stats.gov.cn.

Author contributions

LZ: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing. CL: Software, Supervision, Writing – review & editing. YQ: Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

References

1. Schwartz R, Deber R. The performance measurement–management divide in public health. *Health Policy*. (2016) 120:273–80. doi: 10.1016/j.healthpol.2016.02.003

2. Lam WWT, Fielding R, Mcdowell I. Perspectives on family health, happiness and harmony(3H)among Hong Kong Chinese people:a qualitative study. *Health Educ Res*. (2012) 27:767–79. doi: 10.1093/her/cys087

3. Tseng HK, Olsen R. The U. S. Health production function: evidence from 2001 to 2009. *Int J Health Econ Manag*. (2016) 16:51–64.

4. Durand AM, Petticrew M, Goulding L, Eastmure E, Knai C, Mays N. An evaluation of the public health responsibility Deal: informants' experiences and views of the development, implementation and achievements of a pledge-based, public–private partnership to improve population health in England. *Health Policy*. (2015) 119:1506–14. doi: 10.1016/j.healthpol.2015.08.013

5. Di Ruggiero E, Cohen JE, Cole DC, Forman L. Public health agenda setting in a global context: the international labor Organization's decent work agenda. *Am J Public Health*. (2015) 105:e58–61. doi: 10.2105/AJPH.2014.302455

6. Zhao L, Jiang J. Evolution and drivers of embodied energy in intermediate and final fishery trade between China and maritime silk road countries. *Regional Sci Environ Econ*. (2024) 1:104–27. doi: 10.3390/rsee1010007

7. Fan F, Song T, Zhai X. Education, science and technology, and talent integrated development: evidence from China. *Regional Sci Environ Econ*. (2024) 1:60–77. doi: 10.3390/rsee1010005

8. Xu E. The impact of innovation on intra-city economic disparity: a technological complexity perspective. *Appl Econ*. (2024) 9:1–16. doi: 10.1080/00036846.2024.2403781

9. Fan F, Yang B, Wang S. The convergence mechanism and spatial spillover effects of urban industry-university-research collaborative innovation performance in China. *Tech Anal Strat Manag*. (2023) 12:1–17. doi: 10.1080/09537325.2023.2290169

10. Xu E, Xiao Z, Wang Z. Has the pilot project of innovative cities increased economic growth? An empirical study based on Chinese cities. *Regional Sci Environ Econ*. (2024) 1:31–45. doi: 10.3390/rsee1010003

11. Weng Z, Fan F, Yang B, Zhang H. Regional differences and drivers of patent transfer-in between Chinese cities: a city absorptive capacity perspective. *Technol Analysis Strat Manag, 2023*. (2023) 36:4113–27. doi: 10.1080/09537325.2023.2242509

12. Lindsay C, Commander J, Findlay P, Bennie M, Dunlop Corcoran E, van der Meer R. 'Lean', new technologies and employment in public health services: employees' experiences in the National Health Service. *Int J Hum Resour Manag*. (2014) 25:2941–56. doi: 10.1080/09585192.2014.948900

13. Sandström EB, Eriksson H, Norlander L, Thorstensson M, Cassel G. Training of public health personnel in handling CBRN emergencies: a table-top exercise card concept. *Environ Int*. (2014) 72:164–9. doi: 10.1016/j.envint.2014.03.009

14. Samarasundera E, Hansell A, Leibovici D, Horwell CJ, Anand S, Oppenheimer C. Geological hazards: from early warning systems to public health toolkits. *Health Place*. (2014) 30:116–9. doi: 10.1016/j.healthplace.2014.09.001

15. Donna S. Evaluating public health interventions: 4. The Nurses' health study and methods for eliminating Bias attributable to measurement error and misclassification. *Am J Public Health*. (2016) 106:1563–6. doi: 10.2105/AJPH.2016.303377

16. Mina AS, Debnath P, Hossain ZA, Hasan M, Azad AM. Screening and identification of multiple antibiotic- resistant genes containing *Salmonella Typhi* from drinking water: a severe public health concern in Bangladesh. *Heliyon*. (2024) 10:e40523. doi: 10.1016/j.heliyon.2024.e40523

17. Mechita N, Obtel M, Elmarnissi A, Lahlou L, Lyaghfouri A, Cherkaoui I, et al. Corrigendum to "decline in childhood respiratory-related mortality after the introduction of the pneumococcal conjugate vaccine in Morocco" [J infect public health 13 (march (3)) (2020) 402–406]. *J Infect Public Health*. (2021) 14:417–33. doi: 10.1016/j.jiph.2021.02.008

18. Ravid M, Cohen N. Incremental urban citizenship-making: migrant serving organizations in Tel Aviv during COVID-19 and the politics of change in times of crisis. *Cities*. (2024) 153:105263. doi: 10.1016/j.cities.2024.105263

19. Jiang JW. The effects of urban neighborhood environmental evaluation and health service facilities on residents. *Int J Environ Res Public Health*. (2022) 19:4501. doi: 10.3390/ijerph19084501

20. Bayor AA, da-Uri F, Gumah TA, Gyader G. Optimizing public health crisis communication: insights from technology-mediated COVID-19 messaging in rural Ghana. *J Health Commun*. (2024) 11:1–9. doi: 10.1080/10810730.2024.2431310

21. Dario M, Alessia A, Gino PB. Is mesothelioma unrelated to the lung Asbestos burden? Comment on Visonà et al. inorganic Fiber lung burden in subjects with occupational and/or anthropogenic environmental Asbestos exposure in Broni (Pavia, northern Italy). *Int J Environ Res Public Health*. (2021) 18:7177.

22. Akker DVA, Fabbri A, Bertscher A. Industry influence on public health policy formulation in the UK: a complex systems approach. *Health Promot Int*. (2024) 39:341–56.

23. Haque AM, Khatun B, Jewel SAM, Ara J, Islam MS, Hasan J. Assessment of water quality and heavy metal indices in a tropical freshwater river for aquatic life and public health standard. *Ecol Indic*. (2024) 169:112862. doi: 10.1016/j.ecolind.2024.112862

24. Arefin RM, Prouse C, Wittmer J. Making waves: a justice-centred framework for wastewater-based public health surveillance. *Water Res*. (2025) 268:122747. doi: 10.1016/j.watres.2024.122747

25. Lecouturier J, Kelly PM, Sniehotta FF. Reaching national Covid-19 vaccination targets whilst decreasing inequalities in vaccine uptake: public health teams' challenges in supporting disadvantaged populations. *Public Heal Prac*. (2024) 8:100551. doi: 10.1016/j.puhip.2024.100551

26. Korshever NG, Sidelnikov SA, Lipchanskaya MA. A scientific rationale for making changes to the law that governs cross-sectoral collaboration on the issues of public health. *Health Care of the Russian Federation*. (2021) 65:151–8. doi: 10.47470/0044-197X-2021-65-2-151-158

27. Minkler M, Salvatore AL, Chang C, Gaydos M. Wage theft as a neglected public health problem: an overview and case study from San Francisco's Chinatown District. *Am J Public Health*. (2014) 104:1010–20.

28. Shah H, Adler J, Ottoson J, Webb K, Gosliner W. Leaders' experiences in planning, implementing, and evaluating complex public health nutrition interventions. *J Nutr Educ Behav*. (2019) 51:528–38. doi: 10.1016/j.jneb.2019.02.005

29. Simeon WA. Palliative care for people living with HIV/AIDS: factors influencing healthcare workers' knowledge, attitude and practice in public health facilities, Abuja, Nigeria. *PLoS One*. (2019) 14:e0207499. doi: 10.1371/journal.pone.0207499

30. WFPHA. World federation of public health associations: Bettina Borisch and Marta Lomazzi, Federation's pages editors. *J Public Health Policy*. (2019) 40:266–70. doi: 10.1057/s41271-019-00162-9

31. Davies J, Sherriff N. Corrigendum to "assessing public health policy approaches to level-up the gradient in health inequalities: the gradient evaluation framework". *Public Health*. (2016) 133:129–9. doi: 10.1016/j.puhe.2016.02.006

32. Sun Yu, L, and Ma, R. Empirical study on the technological innovation capability of chinese cities [J]. *Nankai Economic Research*. (2008) 68–85.

33. Yu, L. Empirical study on the interactive relationship between inter provincial finance and technological innovation [J]. *Science and Technology Management*. (2013) 88–97.

34. Fan, J, and Liu, H. The impact and adaptation of technological innovation driven changes in china's regional development pattern during the 13th five year plan period [J]. *Economic Geography*. (2016) 1–9.

35. Zhou, K, Zhang, B, and Gu, Z. Empirical Study on the Impact of Technological Innovation on Industrial Upgrading [J]. *Industrial Technology and Economics*. (2016) 85–92.

36. James, S, and Ron, M. The economic resilience of regions: towards an evolutionary approach[J]. *Cambridge Journal of Regions,Economy and society*. (2009) 3, 27–43.

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 10 February 2025
DOI 10.3389/fpubh.2025.1549575

Check for updates

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Buyue Qian,
Xi'an Jiaotong University, China
Jiang Hua,
Capital University of Economics and Business, China

*CORRESPONDENCE
Aijing Luo
✉ luoaj@csu.edu.cn

RECEIVED 21 December 2024
ACCEPTED 24 January 2025
PUBLISHED 10 February 2025

CITATION
Wang Z, Chang W and Luo A (2025) A medical insurance fund operation performance evaluation system under the DRG payment mode reform.
Front. Public Health 13:1549575.
doi: 10.3389/fpubh.2025.1549575

A medical insurance fund operation performance evaluation system under the DRG payment mode reform

Zijian Wang[1,2,3], Weifu Chang[3,4] and Aijing Luo[1,3,5]*

[1]The Second Xiangya Hospital of Central South University, Changsha, China, [2]School of Public Administration, Central South University, Changsha, China, [3]Key Laboratory of Medical Information Research (Central South University), College of Hunan Province, Changsha, China, [4]The Third Xiangya Hospital of Central South University, Changsha, China, [5]Clinical Research Center For Cardiovascular Intelligent Healthcare in Hunan Province, Changsha, China

Background: An evaluation system for comprehensively measuring medical insurance fund operational performance under China's Diagnosis Related Groups (DRG) payment reform holds critical theoretical and practical significance, especially for enhancing the efficiency of medical insurance fund utilization and the quality of healthcare services. However, few studies undertake performance evaluations of medical insurance funds under DRG payments, especially those incorporating the Analytic Hierarchy Process (AHP)-Entropy Weight Method (EWM)- Fuzzy Comprehensive Evaluation (FCE) method model.

Methods: This study utilizes operational data from medical insurance funds across eight cities in S Province, China, from 2020 to 2022. It develops an innovative performance evaluation system for medical insurance funds utilizing the AHP-EWM-FCE evaluation method. Finally, it explores the key influencing factors by applying the Tobit regression model.

Results: As the reform of DRG payment methods has advanced, the operational performance scores related to the management, fundraising, utilization, and satisfaction of DRG medical insurance funds have consistently improved. Notably, the comprehensive indexes of QD and JN cities exhibit significant comparative advantages, resulting in higher performance evaluation scores for their medical insurance funds. Additionally, the performance scores assessed by the proposed evaluation system align closely with actual operational outcomes. Regression analysis further indicates that medical service capability is the key determinant influencing the operational performance of medical insurance funds.

Conclusion: This study develops a novel evaluation system for measuring medical insurance funds' operational performance. The insights can help proactively foster the high-quality development of these funds, and modernization of the medical insurance governance system and governance capabilities; stimulate the fund's productivity; and enhance the health and wellbeing of people.

KEYWORDS

medical insurance funds, AHP-EWM-FCE methodology, performance evaluation, DRG payment reform, Tobit regression model

Background

China has successfully established a universal basic medical insurance system. This system has achieved an impressive coverage rate of over 95% overall, which even approaches 100% in some cities (1). The urban employee medical insurance amount was raised to 5,737 yuan in 2022, while the urban–rural resident medical insurance increased to 1,029 yuan. The corresponding policy reimbursement rates stand at 84.2 and 68.3%, respectively (2). However, the current medical insurance funding system faces issues such as a large interest group in the field of medical services, information asymmetry, high technical barriers, and frequent policy risks. Consequently, a medical insurance service system that aligns with China's unique characteristics is needed (3). Indeed, in terms of medical insurance payment model reform, China's National Medical Security Administration has pioneered the implementation of the globally recognized scientific payment mode: DRG payment. Since 2019, this DRG payment model has been piloted in 30 cities across the country (4).

Capitalizing on the "law of large numbers" methodology, the DRG payment model offers a vital mechanism and management tool for macro-controls in modern medical insurance payment mode reforms. Here, an evaluation system for comprehensively measuring medical insurance fund operation performance, considering DRG payment, can be extremely useful in driving healthcare institutions to shift from "extensive" management to more "refined" approaches. For instance, such a performance evaluation system can promote the rational allocation of medical resources, reduce resource waste, and improve the quality and efficiency of medical insurance funds (5). In November 2021, the National Medical Security Administration released the Three-Year Action Plan for DRG/DIP Payment Mode Reform, which clearly stated that by 2025, DRG/Big Data Diagnosis-Intervention Packet (DIP) should be comprehensively implemented in four areas: overall planning, health care institutions, disease grouping, and medical insurance fund (6). This initiative aims to construct a robust health security network for the public, thereby serving as a powerful "stabilizer" for the steady progress of socialism with Chinese characteristics (7).

Still, a mature evaluation system for examining medical insurance fund operation performance is lacking both domestically and internationally. Currently, such an evaluation system considering the DRG payment mode reform has several shortcomings, including singularity, extensiveness, limitations in the dimensions and indicators considered, and the lack of comprehensive consideration for the medical insurance fund operations (8). Furthermore, due to the insufficient accumulation of historical data from the DRG payment model pilot cities in the early stages of implementation, it was unable to accurately analyze from the perspectives of institutional embedding, regulatory behavior, medical behavior, and social interaction (8). Consequently, constructing a rigorous and robust evaluation system of medical insurance fund operation performance under the DRG payment mode reform is a critical task.

The literature shows that the research focuses of foreign medical insurance funds are different. For example, Avedis Donabedian, the father of American medical management, divided medical insurance evaluation indicators into structure, process, and result evaluations, focusing on the efficiency and fairness of medical insurance fund allocation (9). British and Organisation for Economic Cooperation and Development (OECD) medical insurance emphasizes the fairness and accessibility of medical insurance but neglects efficiency evaluation (10–12). One study has used the content validity ratio to screen the identified factors to identify and rank critical factors affecting hospital performance using the best-worst method in Iran (13). In China, research on the performance evaluation system of medical insurance funds is still in the exploratory stage. An analysis of the medical insurance fund operation in Jiaxing City in 2019 used an evaluation system consisting of four dimensions and 10 indicators (14). Yu and Zhi empirically examined urban employee and rural resident basic insurance schemes in Yantai City, providing an initial overview of the status of the city's medical insurance fund operations (15). Meanwhile, research has also evaluated the performance system of public hospitals based on single balanced scorecard theory and the AHP, thereby establishing a model for the performance system of public hospitals (16, 17). However, the above studies have certain limitations in terms of the selection of horizontal indicators, vertical time range, methodology, and empirical research. Thus, they have failed to perform a comprehensive and dynamic evaluation of the actual operation of the medical insurance fund. Therefore, a rigorous performance evaluation system that encompasses comprehensive indicators and can dynamically evaluate the medical insurance fund operation is lacking.

Naturally, one may ask: How should we construct a comprehensive and dynamic performance evaluation system for medical insurance fund operation under the DRG payment method reform? One particular area can be using more rigorous and scientific research methods, which can enhance the focus ability and objectively evaluate the dynamic running differences of medical insurance funds. Among them, AHP can carry out step-by-step analysis and comprehensive evaluation of complex decision-making problems within a structured framework, thereby making more scientific and reasonable choices (18). AHP yields subjective weights, while the EWM yields objective weights. Then, the combination of EWM and AHP can be used to obtain and assign effective and true indicator weights (19). In addition, FCE can better handle the interaction between various complex factors, especially the performance evaluation of medical insurance funds, which has uncertainty, complexity, and dynamics (20–22). However, to the best of our knowledge, no studies have examined the comprehensive use of the AHP-EWM-FCE method for the performance evaluation of the medical insurance fund operation under the backdrop of DRG payments. Addressing this gap, this research uses operational data on medical insurance funds in eight cities in Province S of China over 3 years to construct a comprehensive and dynamic performance evaluation system for the medical insurance fund operation under the DRG payment method reform.

In summary, this study applies the AHP-EWM-FCE method to evaluate the operational performance of medical insurance funds within the context of the DRG payment system. Next, utilizing 3 years of operational data from medical insurance funds across eight cities in S Province, China, this study employs Tobit regression analysis to identify the key factors influencing the performance evaluation. The aim is to develop a comprehensive and dynamic performance evaluation system for medical insurance funds within the framework of the DRG payment reform.

Methods

Data sources and research methods

The literature and data for this study are sourced from both domestic and international databases, including the Web of Science, PubMed, China National Knowledge Infrastructure (CNKI), Wanfang Data Knowledge Service Platform, and VIP Chinese Journal Service Database. The statistical data for the indicator system mainly come from the National Tertiary Public Hospital Performance Appraisal Operation Manual, National Healthcare Security Diagnostic Related Groups (CHS-DRG) Grouping Plan, National Medical insurance Diagnostic Related Groups (CHS-DRG) Grouping and Payment Technical Specifications, Statistical Yearbook of S Province, Health Statistics Yearbook of S Province, Statistical Yearbook of Population and Employment Statistics of S Province, Statistical Yearbook of Civil Affairs of S Province, Social Statistics Yearbook of S Province, performance assessment data from some hospitals in eight cities of S province, and information from official hospital websites. To ensure the richness and authenticity of the data, field visits and semi-structured interviews were carried out to gather first-hand interview materials.

Preliminary determination of medical insurance fund indicators using the Delphi method

Expert selection

This study employs the Delphi expert consultation method. First, expert inquiry forms are disseminated via Questionnaire Star to recruit experts. Then, consultations or interviews with selected theorists and field experts affiliated with the domain of medical insurance fund operation management (such as medical insurance bureaus, health commissions, hospital medical insurance offices, and clinical medical staff) are conducted. Aggregating diverse viewpoints and professional knowledge from this expert sample ensures the professionalism and practicality of constructing evaluation models, and elicits more scientifically valid evaluation indicators and suggestions.

Construction of the performance evaluation system

Establishment of subjective weights for performance evaluation indicators by AHP

This study utilizes AHP to delineate the subjective weights of the constructed performance evaluation indicators via four main steps: building a hierarchical model, constructing a judgment matrix, calculating indicator weights, and testing consistency. Meanwhile, the concentration of expert opinions is measured by the mean and full score rate, while the coordination of expert opinions is measured via the dispersion coefficient (23, 24). Finally, the resulting index system is subjected to reliability and validity tests.

Establishment of objective weights for performance evaluation indicators by EWM

Operating data on 28 medical insurance fund operation performance indicators across eight sampled cities are used to assess matrix entropy values, and the randomness and disorder of the indicators. Next, the entropy value is employed to determine the degree of dispersion among the indicators. The degree of variation in the indicators is ascertained based on their weights, thereby eliminating subjective interference. EWM is subsequently used to determine the objective weights of each evaluation factor. To avoid the impact of singularity on the results of FCE, the subjective and objective weights of AHP-EWM are reconstructed using the geometric mean method to obtain new combined weights (25).

FCE evaluation

Determining evaluation factors and membership evaluation criteria

The comprehensive evaluation results are divided into five levels, each corresponding to different judgment values. Simultaneously, to obtain more authoritative results, 10 experts are invited for scoring. The membership degree of evaluation factors to comment level is determined through expert scoring and percentage statistics. The fuzzy evaluation set is then calculated by combining the membership and matrix.

Fuzzy evaluation of medical insurance performance results

As noted above, the fuzzy evaluation result is the product of membership and matrix, $C=B\cdot V^T$, which produces the fuzzy comprehensive evaluation of each criterion layer's corresponding indicator (26). This outcome allows for horizontal and vertical comparisons of the performance of the medical insurance fund in eight cities in S Province from 2020 to 2022 (Figure 1). Horizontal comparison refers to assessing the performance of the medical insurance fund and vertical comparison involves examining the performance of the medical insurance fund during 2020–2022. Next, the following Tobit regression model is employed to analyze the key factors influencing the performance evaluation.

$$Y_i^* = \beta_0 + \sum_{j=1}^{k} \beta_j X_{kj} + \varepsilon_i$$

$$Y_i = y_i^*, \text{if } y_i^* \in (0, +\infty)$$

$$Y_i = 0, \text{if } yi^* \in (-\infty, 0)$$

Here, the latent variable is expressed as Yi*.

The evaluation scores derived from the AHP-EWM-FCE method for the eight municipalities in S Province are used as the dependent variables, while eight secondary operational indicators serve as the independent variables. Stata 17.0 software has been used for the regression analysis.

Results

This study preliminarily constructs a comprehensive pool of 44 potential indicators through literature review and expert

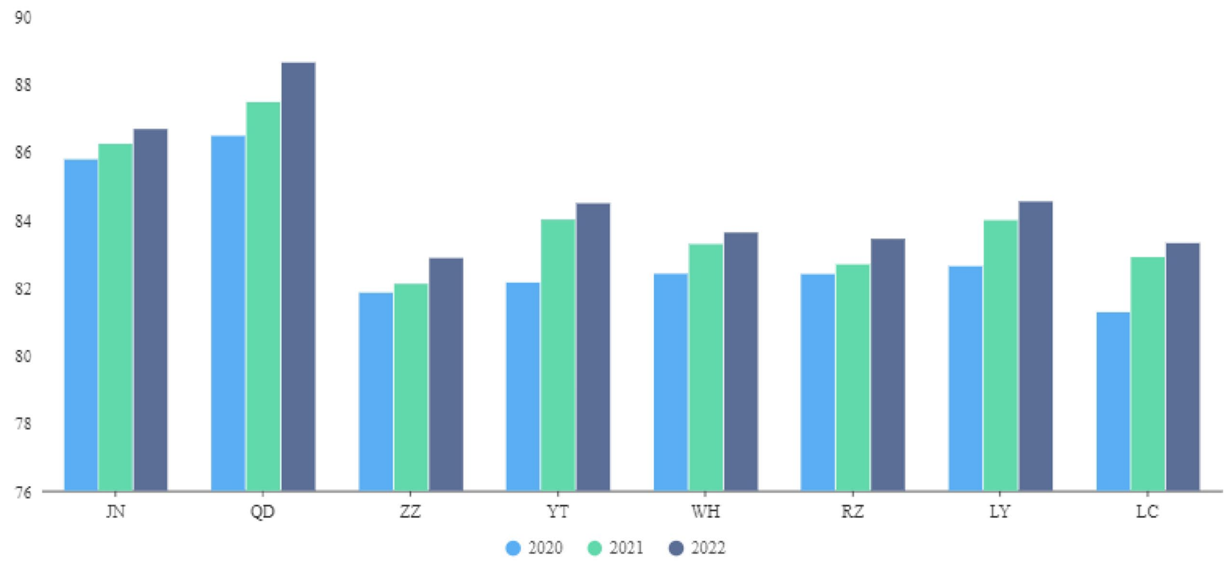

FIGURE 1
Horizontal and vertical comparisons of the performance of medical insurance fund.

consultation. Then, through an in-depth analysis of correlations and importance of these indicators, those with low correlation and high redundancy are eliminated. Simultaneously, new indicators intuitively reflecting medical insurance fund performance evaluation are introduced. Ultimately, 33 core indicators have been carefully selected and integrated after expert inquiry. And the 33 core indicators were further verified through reliability and validity tests with their validity and operability. We subject this evaluation indicator system to the empirical case of the eight cities in S Province in China. Finally, the Tobit regression model is employed to analyze the key factors influencing the performance evaluation.

Determining performance evaluation indicators using the Delphi method

Basic information about experts

This study has engaged 28 experts from domestic universities, medical institutions, and medical insurance management departments. The experts are between 30 to 65 years old, with 90.00% holding a bachelor's degree or above. In the two rounds of expert consultation, 28 and 22 questionnaires have been distributed, respectively, yielding effective recovery rates of 92.86 and 95.45%, respectively. The questionnaire recovery rate for both rounds is 94.00%, indicating that the experts have exhibited substantial enthusiasm in participating in the study.

Expert authority and opinion coordination degree

Table 1 shows that the authority coefficient of the experts is 0.865, indicating that this indicator aligns with the established standards. This supports the professionalism and authority of the evaluation process. The degree of expert coordination is depicted by Kendall's W coordination coefficient. In the two rounds, the p-value (<0.001) for the third-level indicators showed reliable results.

After two rounds of expert consultation, the first-level indicators include medical insurance fund management, medical insurance fund raising, DRG operation and use of medical insurance fund, and satisfaction with medical institutions. Second-level indicators include medical insurance fund policy, platform construction, medical insurance fund raising, expenditure and balance, medical service capability, expense control, reimbursement, and satisfaction with medical institutions. Finally, 28 indicators exist in the third level, including the number of participants in basic medical insurance, financial subsidy for resident medical insurance, growth rate of medical insurance fund income, proportion of recovery of medical insurance funds, growth rate of total fund expenditure over the previous year, current balance rate of medical insurance fund, number of months supported by the medical insurance fund balance and so on. Further the DRG group number refers to a diseases classification system and the number of diseases based on clinical symptoms.

Construction of performance evaluation system

Determination of AHP weight

The composite weights are then calculated using AHP. The highest weight is for the medical insurance fund information management at 0.1265. Satisfaction of medical staff and patients in medical institutions with the medical insurance fund system have weights of 0.1216 and 0.1204, respectively. The weights for financial subsidy for resident medical insurance, number of participants in basic medical insurance, growth rate of medical insurance fund income, and medical insurance fund participation rate are 0.052, 0.052, 0.0514, and 0.0514, respectively. Next, the proportion of recovery of medical insurance funds, medical insurance supervision and risk control measures, and where there is any publicity and education work on the medical insurance fund system have weights of 0.0499, 0.0418, and 0.0414, respectively (Table 2).

TABLE 1 Degree of expert consultation coordination.

	First round			Second round		
	W-value	χ^2-value	*p*-value	W-value	χ^2-value	*P*-value
First-level indicators and weights	0.136	8.561	0.036	0.17	13.286	0.004
Second-level indicators and weights	0.117	17.154	0.016	0.085	15.549	0.03
Third-level indicators and weights	0.052	29.648	0.33	0.089	73.696	<0.001

Determination of EWM weight

Next, EWM is employed to construct the judgment matrix and calculate the information entropy of the comprehensive evaluation indicators to determine objective weights. The highest weight for the proportion of recovered medical insurance funds is 0.1752. The weights for total weight value (number of discharged patients and number of operations), number of diseases, and number of hospitalizations are 0.1264, 0.1200, and 0.1002, respectively. The weights for number of participants in basic medical insurance, current balance rate of medical insurance fund, number of months of medical insurance fund balance support, inter-provincial direct settlement rate for out-of-town hospitalization expenses, and off-site reimbursement rate are 0.0648, 0.0603, 0.0566, 0.0416, and 0.0391, respectively (Table 3).

Determination of AHP-EWM combined weights

The geometric average method is used to reconstruct the AHP subjective and EWM objective weights, highlighting the importance of weights and disparity after reconstruction to obtain the combined weights. The weight of proportion of recovery of medical insurance funds is the highest at 0.1436. Next, the weights for number of participants in basic medical insurance, growth rate of medical insurance fund income, financial subsidy for resident medical insurance, current balance rate of medical insurance fund, and number of months of medical insurance fund balance support are 0.0891, 0.0687, 0.0656, 0.0547, and 0.0538, respectively (Table 3).

Evaluation index system construction and empirical research

Next, this article selects some designated medical institutions in the eight DRG payment pilot cities of S Province as case studies for the empirical research. According to the AHP-EWM-FCE evaluation results, the performance score of the medical insurance fund operation exhibits an upward trend across the sampled cities. The scores for JN and QD are relatively high between 2020 and 2022 at 85.76, 86.21, and 86.66, respectively, for JN, and 86.46, 87.46, and 88.62, respectively, for QD (Figure 1).

The Tobit regression analysis reveals that the two indices are significantly related to the medical insurance fund's operational performance. Specifically, medical service capacity, medical insurance fund raising, and expenditure and balance of the medical insurance fund exhibit a significant positive coefficient with the operational performance of the medical insurance fund (Table 4).

Discussion

In May 2019, QD of S Province was selected as a pilot city among the initial batch of 30 cities by the National Healthcare Security Administration to implement DRG payment reforms. In September of the same year, the Provincial Healthcare Security Administration of S Province was among the first to initiate DRG payment method reforms in 10 pilot cities in stages. However, extant research on the performance evaluation of medical insurance fund operation in the backdrop of the DRG payment method reforms has certain limitations in terms of indicator selection, time period, and methodology. Addressing this gap, this study draws on the AHP-EWM-FCE method to construct a rigorous evaluation system for examining the medical insurance fund operation performance under the DRG payment method reform over the 2020–2022 in S Province. It also performs an empirical case study using data from mainly large-scale tertiary general hospitals, thereby appropriately reflecting the diverse situations from hospital operation, referral, to off-site reimbursement, among others. Thus, the relevant conclusions offer valuable practical guidance.

Evaluation system indicators

Extant research shows that establishing comprehensive performance evaluation indicators for the medical insurance fund operation can not only better reflect the operations, but also promote the efficient use of medical insurance funds and improvement of medical service levels (27). Accordingly, this study combines extant research and the actual operation of DRGs to establish 44 potential indicators of medical insurance fund operation. This number is reduced to 28 after two rounds of expert consultation and correction. Among them, the number of participants in basic medical insurance, financial subsidy for resident medical insurance, growth rate of medical insurance fund income, proportion of recovered medical insurance funds, growth rate of total fund expenditure over the previous year, current balance rate of the medical insurance fund, and number of months supported by the medical insurance fund balance are closely related to the efficiency and effectiveness of the use of medical insurance funds. The number of DRG groups, CMI, the number of diseases, and the total weight value (number of discharged patients and volume of surgeries) are closely related to the reform of the DRG payment method. Therefore, the selected evaluation indicators can comprehensively reflect the medical insurance fund operation under the DRG payment method.

Indicator weights

This study is the first to use the AHP-EWM-FCE method to establish the weights of performance evaluation indicators for the medical insurance fund operation in the background of the DRG payment method reform. Among the indicators, the AHP-EWM

TABLE 2 Weight of indicators at each level.

First-level indicator	First-level weight	Second-level indicator	Second-level weight	Third-level indicator	Third-level weight	Combination weight
A1 Medical insurance fund management	0.2518	B1 Medical insurance fund policy	0.4975	C1 Whether to establish a medical insurance fund system	0.3366	0.0422
				C2 Whether there is medical insurance fund system publicity	0.3300	0.0414
				C3 Medical insurance supervision and risk control measures	0.3333	0.0418
		B2 Medical insurance fund service platform construction	0.5025	C4 Medical insurance fund information management	1.0000	0.1265
A2 Medical insurance fund raising	0.2567	B3 Medical insurance fund raising	1.0000	C5 Number of participants in basic medical insurance	0.2024	0.0520
				C6 Medical insurance fund participation rate	0.2004	0.0514
				C7 Financial subsidy for resident medical insurance	0.2024	0.0520
				C8 Growth rate of medical insurance fund income	0.2004	0.0514
				C9 Proportion of recovery of medical insurance funds	0.1944	0.0499
A3 DRG operation and use of medical insurance fund	0.2494	B4 Medical insurance fund expenditure and balance	0.2530	C10 Growth rate of total fund expenditure over the previous year	0.3232	0.0204
				C11 Current balance rate of medical insurance fund	0.3333	0.0210
				C12 Number of months of medical insurance fund balance support	0.3434	0.0217
		B5 Medical service capability	0.2555	C13 DRG group number	0.1231	0.0078
				C14 Case Mix Index (CMI)	0.1256	0.0080
				C15 Number of diseases	0.1256	0.0080
				C16 Total weight value (number of discharged patients and number of operations)	0.1281	0.0082
				C17 Average length of stay	0.1256	0.0080
				C18 Implementation of hierarchical diagnosis and treatment	0.1244	0.0079
				C19 Low risk average mortality rate	0.1231	0.0078
				C20 Number of hospitalizations	0.1244	0.0079
		B6 Medical expense control	0.2457	C21 Average hospitalization cost increase	0.3300	0.0202
				C22 Average outpatient cost increase	0.3267	0.0200
				C23 Proportion of medical service revenue	0.3432	0.0210
		B7 Medical insurance fund reimbursement	0.2457	C24 Off-site reimbursement rate	0.3333	0.0204
				C25 Inter-provincial direct settlement rate for out-of-town hospitalization expenses	0.3333	0.0204
				C26 Timely reimbursement rate of medical insurance fund	0.3333	0.0204
A4 Satisfaction	0.2421	B8 Satisfaction with medical institutions	1.0000	C27 Satisfaction of medical staff in medical institutions with medical insurance fund system	0.5025	0.1216
				C28 Satisfaction of patients in medical institutions with medical insurance fund system	0.4975	0.1204

10.3389/fpubh.2025.1549575

TABLE 3 Combined weight of third-level indicators.

Third-level indicators	AHP weight	EWM weight	Combined weight
C1 Whether to establish a medical insurance fund system	0.0422	0.0007	0.0082
C2 Whether there is medical insurance fund system publicity	0.0414	0.0008	0.0089
C3 Medical insurance supervision and risk control measures	0.0418	0.0008	0.0088
C4 Medical insurance fund information management	0.1265	0.0025	0.0276
C5 Number of participants in basic medical insurance	0.0520	0.0648	0.0891
C6 Medical insurance fund participation rate	0.0514	0.0016	0.0140
C7 Financial subsidy for resident medical insurance	0.0520	0.0351	0.0656
C8 Growth rate of medical insurance fund income	0.0514	0.0388	0.0687
C9 Proportion of recovery of medical insurance funds	0.0499	0.1752	0.1436
C10 Growth rate of total fund expenditure over the previous year	0.0204	0.0220	0.0325
C11 Current balance rate of medical insurance fund	0.0210	0.0603	0.0547
C12 Number of months of medical insurance fund balance support	0.0217	0.0566	0.0538
C13 DRG group number	0.0078	0.0097	0.0134
C14 Case Mix Index (CMI)	0.0080	0.0193	0.0191
C15 Number of diseases	0.0080	0.1200	0.0476
C16 Total weight value (number of discharged patients and number of operations)	0.0082	0.1264	0.0493
C17 Average length of stay	0.0080	0.0106	0.0141
C18 Implementation of hierarchical diagnosis and treatment	0.0079	0.0000	0.0009
C19 Low risk average mortality rate	0.0078	0.0091	0.0130
C20 Number of hospitalizations	0.0079	0.1002	0.0433
C21 Average hospitalization cost increase	0.0202	0.0376	0.0424
C22 Average outpatient cost increase	0.0200	0.0130	0.0248
C23 Proportion of medical service revenue	0.0210	0.0098	0.0221
C24 Off-site reimbursement rate	0.0204	0.0391	0.0434
C25 Inter-provincial direct settlement rate for out-of-town hospitalization expenses	0.0204	0.0416	0.0448
C26 Timely reimbursement rate of medical insurance fund	0.0204	0.0019	0.0096
C27 Satisfaction of medical staff in medical institutions with medical insurance fund system	0.1216	0.0013	0.0192
C28 Satisfaction of patients in medical institutions with medical insurance fund system	0.1204	0.0011	0.0174

TABLE 4 Tobit regression analysis results for influencing factors.

Second-level indicator	Regression coefficient	Standard deviation	*T*-value	*P*-value	Sig.
Medical insurance fund policy	0.033	1.34e-08	2440040.93	0	***
Construction of medical insurance fund service platform	0.018	1.88e-08	952141.98	0	***
Medical insurance fund raising	0.287	1.09e-08	26232752.12	0	***
Expenditure and balance of medical insurance fund	0.217	1.50e-08	14518224.56	0	***
Medical service capacity	0.401	1.88e-08	21318847.42	0	***
Medical cost control	0.102	7.31e-09	13952284.09	0	***
Medical insurance fund reimbursement	0.126	1.26e-08	9956651.29	0	***
Satisfaction of medical institutions	0.032	1.60e-08	2002835.78	0	***

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

combined weight of DRG operation and use of medical insurance fund is 0.529, the highest among all weights. This indicates that DRG operation and the use of medical insurance funds are closely related to the performance evaluation of medical insurance fund operation. According, efforts can focus on further improving the efficiency of medical insurance fund use, and standardize hospital diagnosis and treatment behaviors based on the indicators of DRG operation and use of medical insurance funds (28).

Next, the combined weight of the medical insurance fund raising indicator is 0.381, representing a relatively high weight. Research shows that an appropriate level and structure of financing for the medical insurance fund is key to promoting its accessibility, fairness, and sustainability (29). At present, China's medical insurance fund largely depends on government subsidies, which is increasing annually (30). In recent years, Chinese scholars have explored the improvement of the medical insurance fund financing mechanism and sustainability of funds. They suggest modifications to the frequency, timing, and extent of medical insurance fund raising, alongside the establishment of actuarial models to achieve "basic, bottom-line, and sustainable" medical insurance funds (31). As such, the government and relevant medical insurance departments should establish institutionalized and standardized dynamic adjustment mechanisms for medical insurance fund raising.

Next, experts demonstrate a high degree of recognition of "medical insurance informatization." This can assist in connecting medical information within designated medical insurance institutions and the real-time acquisition of patients' medical insurance information. On the one hand, such efforts can facilitate the real-time monitoring of big data pertaining to medical insurance funds, and help promptly detect and correct phenomena such as the abuse of medical insurance funds, medical misconduct, and unreasonable medical expenses. On the other hand, it can aid in the promotion of hierarchical diagnosis and treatment (3). Further, the DRG payment mode reform requires accurate accounting of disease costs, which also necessitates the support of hospital information system. For instance, based on big data, Liu conducted an in-depth analysis of disease costs using the principles of Boston Matrix Analysis to identify the root cause of cost controls. Therefore, medical insurance informatization is conducive to the efficient use of medical insurance funds and refined implementation of the DRG payment reform (32).

Empirical analysis

The performance score of the medical insurance fund operation in the eight sampled cities shows a clear growth trend over the 2020–2022 period. Among them, QD has embedded the DRG payment system into the reconstruction of its incentive structure.

Medical insurance fund raising

Among the third-level indicators, the participants in basic medical insurance of QD and LY remain at a high level, and the medical insurance fund participation rates of JN, QD, ZZ, YT, LY, and LC all exceed 96%. Notably, the overall insurance coverage level in the eight cities exceeds the national average. This may be related to the success of the medical insurance policy promotion and universal medical insurance expansion. However, China currently adopts a voluntary participation approach for basic medical insurance. Some new employees are missing from the scheme, while coverage for workers in small and micro enterprises is not yet complete. Therefore, there is room for improvement in medical insurance coverage (33). Thus, future efforts focus on increasing publicity by the government and medical insurance companies to reduce missing coverage, increase the coverage rate of micro and small enterprises, and achieve universal medical insurance.

Analysis of DRG operation and medical insurance fund use

Expenditure and balance of medical insurance funds

Under the DRG payment reform, the long-term benefits provided by the medical insurance fund to insured patients determine the integration and coordination between the medical insurance system and high-quality hospital development (34–36). In this study, JN and QD score the highest in the use of medical insurance funds. However, there is a relatively prominent imbalance in the revenue and expenditure of medical insurance funds in the eight cities. At present, China's medical insurance fund management adopts the principle of "vertical accumulation and actuarial balance." The imbalance between fund expenditures and balances, whether too high or too low, is not conducive to the functioning of medical insurance funds. According to Jia, the number of months for the balance payment of the medical insurance fund is an important factor its sustainability, and 6–9 months being an appropriate number (37). Specifically, if the medical insurance fund balance is paid for more (less) than nine (six) months, the fund accumulation is excessive (too low).

Meanwhile, the balances of eight cities in S Province are too small, indicating that the ability of medical insurance funds to resist risks is weak. Still, there was no cumulative deficit. Yet, the number of balance payment months in most cities is 0–1 month, and only a few cities have a balance of more than 1 month. This may be related to the fact that in the face of public emergencies in recent years, the National Medical Insurance Administration has promptly adjusted payment policies, expanded the scope of medical insurance payment, and dynamically adjusted payment and budget (38). Hence, the regulation of medical insurance funds is crucial. It is recommended to conduct horizontal risk control, avoid rough expenditures, and reduce the accumulation or deficit of medical insurance funds, thus promoting the smooth and efficient development of fund operations (39). Currently, most countries adopt diversified financing methods to balance the fund expenditures and balances (40). Irregularities and misuse of funds can be prevented by establishing effective monitoring mechanisms and auditing processes,

Medical service capabilities

The service capabilities of medical institutions can somewhat reflect the management level of medical insurance funds, governments, and medical institutions in the region. The survey sample comprises tertiary-A general hospitals, wherein the number of DRG groups in JN, QD, ZZ, and YT cities is relatively complete. Meanwhile, the number of DRG groups in RZ, LY, and LC is slowly increasing, indicating that the latter's DRG groups are becoming complete (41). The CMI values of QD and JN are higher than those of other cities, indicating that they have a relatively large number of highly weighted medical records. Compared with 2020, 70.5% of hospital departments significantly increased their CMI values in 2022. Thus, the tertiary-A general hospitals accurately position themselves in diagnosing and treating difficult cases. Moreover, the average length of stay in RZ and LY has dropped to 6.14 and 6.77, reflecting good control of hospital stays by medical institutions. However, shorter hospital stays do not necessarily mean better outcomes. For instance, blindly reducing hospital stays, and refusing difficult and complex patients will lead to a decrease in the CMI value (42).

Medical insurance fund reimbursement

Population mobility triggers off-site reimbursements from medical insurance funds. Owing to reasons such as education, employment, or relocation, young and transient populations might travel elsewhere. These groups are more likely to engage in activities like seeking medical treatment off-site (43). Indeed, the reimbursement indicators of medical insurance funds in the eight sampled cities in S Province have shown a significant increase. QD and RZ operate well in off-site reimbursements, with some areas achieving same-day reimbursement. Meanwhile, S Province continues to promote the national network of basic medical insurance and direct settlement of hospitalization expenses across provinces and places, which greatly facilitates the efficient use of medical insurance funds. Efforts should be made to increase the rate of same-day reimbursement off-site, which can not only meet the service needs of off-site medical treatment but also increase population mobility (44).

Conclusion

Based on operational data on medical insurance funds from eight cities in S province in China, this study comprehensively and dynamically evaluates the performance of the medical insurance fund under the DRG payment reform by constructing a rigorous performance evaluation system. This system can be used to improve the efficiency of using medical insurance funds and elevating the standard of medical services. This study is also the first to construct the evaluation system based on the AHP-EWM-FCE method. It identifies key indicators for the medical insurance fund operation, such as the DRG operation, use and management of medical insurance funds, fundraising, and satisfaction levels. Here, DRG operation and the use of medical insurance funds have the highest weights in the evaluation system. Furthermore, the performance of the proposed evaluation system is consistent with the actual operation and performance scores of the medical insurance fund across the eight cities. Overall, the proposed addresses the deficiencies in methodology, indicator system construction, and practical application with greater rigor, applicability, and promotability.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by the Second Xiangya Hospital of Central South University. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin.

Author contributions

ZW: Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. WC: Writing – review & editing, Data curation, Formal analysis, Software. AL: Conceptualization, Investigation, Project administration, Supervision, Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This study was supported by the Ethics Committee of the Second Xiangya Hospital of Central South University which number is LYEC2024-K0201.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

1. Tian W, Wu B, Yang Y, Lai Y, Miao W, Zhang X, et al. Degree of protection provided by poverty alleviation policies for the middle-aged and older in China: evaluation of effectiveness of medical insurance system tools and vulnerable target recognition. *Health Res Policy Syst*. (2022) 20:129. doi: 10.1186/s12961-022-00929-9

2. Qin Z, Liu S, Zhou M, Chen L, Huang W, Shen L. Impacts of unifying urban and rural residents' medical insurance on the hospitalisation expenses of rural patients in eastern China: an interrupted time series analysis. *BMJ Open*. (2023) 13:e067198. doi: 10.1136/bmjopen-2022-067198

3. Wu J, Qiao J, Nicholas S, Liu Y, Maitland E. The challenge of healthcare big data to China's commercial health insurance industry: evaluation and recommendations. *BMC Health Serv Res*. (2022) 22:1189. doi: 10.1186/s12913-022-08574-2

4. Yu L, Lang J. Diagnosis-related groups (DRG) pricing and payment policy in China: where are we? *Hepatobiliary Surg Nutr*. (2020) 9:771–3. doi: 10.21037/hbsn-2020-8

5. Kwak SH, Kim JH, Kim DH, Kim JM, Byeon HK, Kim WS, et al. Impact of the Korean diagnosis-related groups payment system on the outcomes of adenotonsillectomy: a single center experience. *Auris Nasus Larynx*. (2018) 45:504–7. doi: 10.1016/j.anl.2017.07.005

6. National Healthcare Security Administration. Notice of the National Healthcare Security Administration on issuing and issuing the three-year action plan on the reform of DRG/DIP payment method [EB/OL] no. 2021 48. Available at: http://www.nhsa.gov.cn/art/2021/11/26/art_37_7406.html.

7. Zhao C, Wang C, Shen C, Wang Q. Diagnosis-related group (DRG)-based case-mix funding system, a promising alternative for fee for service payment in China. *Biosci Trends*. (2018) 12:109–15. doi: 10.5582/bst.2017.01289

8. Shi Z, Zhang Q, Wang X. Does the disclosure of medical insurance information affect patients' willingness to adopt the diagnosis related groups system. *Front Public Health*. (2023) 11:1136178. doi: 10.3389/fpubh.2023.1136178

9. Donabedian A. Evaluating the quality of medical care. *Milbank Q*. (2005) 83:691–729. doi: 10.1111/j.1468-0009.2005.00397.x

10. Hone T, Macinko J, Millett C. Revisiting Alma-Ata: what is the role of primary health care in achieving the sustainable development goals? *Lancet*. (2018) 392:1461–72. doi: 10.1016/S0140-6736(18)31829-4

11. White J. Can performance measurement make health care systemsmore sustainable or at least more efficient? *OECD J Budg*. (2019) 19:118–24. doi: 10.1787/2b3d3059-en

12. Borges LC, Vaudelice MM, Almeida D, et al. Assessment of the quality of primary health care in Fortaleza, Brazil from the perspective of adult service users in 2019. *Ciencia Saude Coletiva*. (2021) 26:2083–96. doi: 10.1590/1413-81232021266.39722020

13. Shojaei P, Pourmohammadi K, Hatam N, Bastani P, Hayati R. Identification and prioritization of critical factors affecting the performance of Iranian public hospitals using the best-worst method: a prospective study. *Iran J Med Sci*. (2022) 47:549–57. doi: 10.30476/ijms.2021.91256.2237

14. Yu H, Shen L. The practical exploration of the construction of the performance evaluation system of the medical insurance fund in Jiaxing City. *Chin Med Insur*. (2020) 7:54–8. doi: 10.19546/j.issn.1674-3830.2020.10.012

15. Yu B, Zhi R. Performance evaluation model of medical insurance fund under uncertain information environment. *Chin J Manag*. (2018) 5:129–38. doi: 10.3969/j.issn.1672-884x.2018.12.014

16. Costa E, Climent E, Gawlitza K, Wan W, Weller MG, Rurack K. Optimization of analytical assay performance of antibody-gated indicator-releasing mesoporous silica particles. *J Mater Chem B*. (2020) 8:4950–61.

17. Bao HY. Performance evaluation and optimization research of public traditional Chinese medicine hospitals under the background of new medical reform. *Southwestern Univ Fin Econ*. (2023). doi: 10.27412/d.cnki.gxncu.2023.001496

18. Gehlot MR, Shrivastava S. An AHP based sustainability assessment of cement mortar with synergistic utilization of granite cutting waste. *J Build Eng*. (2024) 86:108794. doi: 10.1016/j.jobe.2024.108794

19. Wang SY, Yu SX, Yang X, Cui DZ, Fu XS, Wang QZ, et al. Evaluation of quality attributes of different parts of Poria cocos during stress sweating process based on AHP-EWM and RSM. *Ind Crop Prod*. (2024) 210:118047–53. doi: 10.1016/j.indcrop.2024.118047

20. Feng Q. Electromagnetic properties and structure of superconducting materials based on AHP-FCE model. *Appl Math Nonl Sci*. (2024) 9:110–9. doi: 10.2478/amns.2023.2.00075

21. Li Z, Wang S, Cao Y, Ding R. Dynamic risk evaluation method of collapse in the whole construction of shallow buried tunnels and engineering application. *Math Biosci Eng*. (2022) 19:4300–19. doi: 10.3934/mbe.2022199

22. Mousavi SM, Yazdanirad S, Althubiti S, Majdabadi MA, Najarian F, Sepehr P. Determination and prioritization of factors affecting the occurrence of needle stick injuries among healthcare workers using techniques of Delphi and fuzzy analytical hierarchy process (FAHP). *BMC Public Health*. (2023) 23:2009. doi: 10.1186/s12889-023-16969-x

23. Davies S, Romano PS, Schmidt EM, Schultz E, Geppert JJ, McDonald KM. Assessment of a novel hybrid Delphi and nominal groups technique to evaluate quality indicators. *Health Serv Res*. (2011) 46:2005–18. doi: 10.1111/j.1475-6773.2011.01297.x

24. Pathan AI, Girish A, Said S, et al. AHP and TOPSIS based flood risk assessment-a case study of the Navsari City, Gujarat, India. *Environ Monit Assess*. (2022) 194:509. doi: 10.1007/s10661-022-10111-x

25. Dolan JG. Shared decision-making--transferring research into practice: the analytic hierarchy process (AHP). *Patient Educ Couns*. (2008) 73:418–25. doi: 10.1016/j.pec.2008.07.032

26. Song H, Lu B, Ye C, Li J, Zhu Z, Zheng L. Fraud vulnerability quantitative assessment of Wuchang rice industrial chain in China based on AHP-EWM and ANN methods. *Food Res Int*. (2021) 140:109805. doi: 10.1016/j.foodres.2020.109805

27. Yan YH, Kung CM, Chen Y. The exploration of medical resources utilization among inguinal hernia repair in Taiwan diagnosis-related groups. *BMC Health Serv Res*. (2017) 17:708. doi: 10.1186/s12913-017-2665-6

28. Zhang Q, Li X. Application of DRGs in hospital medical record management and its impact on service quality. *Int J Qual Health Care*. (2022) 34:090. doi: 10.1093/intqhc/mzac090

29. Qiu X, Zhao T, Kong Y, Chen F. Influence of population aging on balance of medical insurance funds in China. *Int J Health Plann Manag*. (2020) 35:152–61. doi: 10.1002/hpm.2844

30. Manning WG, Marquis MS. Health insurance: the tradeoff between risk pooling and moral hazard. *J Health Econ*. (1996) 15:609–39. doi: 10.1016/s0167-6296(96)00497-3

31. Zhu K, Zhang L, Yuan S, Zhang X, Zhang Z. Health financing and integration of urban and rural residents' basic medical insurance systems in China. *Int J Equity Health*. (2017) 16:194. doi: 10.1186/s12939-017-0690-z

32. Luo AJ, Chang WF, Xin ZR, Ling H, Li JJ, Dai PP, et al. Diagnosis related group grouping study of senile cataract patients based on E-CHAID algorithm. *Int J Ophthalmol*. (2018) 11:308–13. doi: 10.18240/ijo.2018.02.21

33. Li Y, Li L, Liu J. The impact of health insurance on self-protection of Chinese rural residents. *Front Public Health*. (2022) 10:874619. doi: 10.3389/fpubh.2022.874619

34. Lyu Y, Xu Q, Liu J. Exploring the medical decision-making patterns and influencing factors among the general Chinese public: a binary logistic regression analysis. *BMC Public Health*. (2024) 24:887. doi: 10.1186/s12889-024-18338-8

35. Fourie C, Biller-Andorno N, Wild V. Systematically evaluating the impact of diagnosisrelated groups (DRG) on health care delivery: a matrix of ethical implications. *Health Policy*. (2014) 115:157–64. doi: 10.1016/j.healthpol.2013.11.014

36. Wishnia J, Goudge J. Impact of financial management centralisation in a health system under austerity: a qualitative study from South Africa. *BMJ Glob Health*. (2020) 5:e003524. doi: 10.1136/bmjgh-2020-003524

37. Jia HB. Research on the appropriate contribution rate of basic medical Insurance in China. *Liaon Univ*. (2007). doi: 10.19851/j.cnki.cn11-1010/f.2009.03.026

38. Yu ZQ, Chen LP, Qu JQ, Wu WZ, Zeng Y. A study on the sustainability assessment of China's basic medical insurance fund under the background of population aging-evidence from Shanghai. *Front Public Health*. (2023) 11:1170782. doi: 10.3389/fpubh.2023.1170782

39. Bi YN, Liu YA. The health insurance fund participates in controlling the epidemic: insights from german experience in dealing with the COVID-19 pandemic. *Risk Manag Health Policy*. (2023) 16:2391–404. doi: 10.2147/RMHP.S427717

40. Sato K, Ikeda T, Watanabe R, Kondo N, Kawachi I, Kondo K. Intensity of community-based programs by long-term care insurers and the likelihood of frailty: multilevel analysis of older Japanese adults. *Soc Sci Med*. (2020) 245:112701. doi: 10.1016/j.socscimed.2019.112701

41. Ockenga J, Freudenreich M, Zakonsky R, Norman K, Pirlich M, Lochs H. Nutritional assessment and management in hospitalised patients: implication for DRG-based reimbursement and health care quality. *Clin Nutr*. (2005) 24:913–9. doi: 10.1016/j.clnu.2005.05.019

42. Li X, Yuan L, Gao B, Chen W, Wang S, Xie Y, et al. Comparison of diagnosis-related group based reimbursement and case-mix index within hospitalized patients before and after modified malnutrition diagnosis. *Asia Pac J Clin Nutr*. (2023) 32:356–61. doi: 10.6133/apjcn.202309_32(3).0007

43. Xing Y, Tarimo CS, Ren W, Zhang L. The impact of health insurance policy on the fertility intention of rural floating population in China: empirical evidence from cross-sectional data. *Int J Environ Res Public Health*. (2022) 20:175. doi: 10.3390/ijerph20010175

44. Wei Z, Bai J. Measuring spatial accessibility of residents' medical treatment under hierarchical diagnosis and treatment system: multi-scenario simulation in China. *PLoS One*. (2023) 18:e0282713. doi: 10.1371/journal.pone.0282713

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 24 February 2025
DOI 10.3389/fpubh.2025.1496860

Check for updates

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Francesco Rosiello,
Sapienza University of Rome, Italy
Andrei Sleptchenko,
Khalifa University, United Arab Emirates

*CORRESPONDENCE
Xiao Lu
✉ 723478195@qq.com

RECEIVED 15 September 2024
ACCEPTED 11 February 2025
PUBLISHED 24 February 2025

CITATION
Zhang Y, Luo Y, Qiu L, Zhu Y and Lu X (2025) Design of an ultrasound appointment system based on a patient-centered real-time dynamic resource allocation strategy. *Front. Public Health* 13:1496860. doi: 10.3389/fpubh.2025.1496860

Design of an ultrasound appointment system based on a patient-centered real-time dynamic resource allocation strategy

Yong Zhang[1], Yan Luo[1], Li Qiu[1], Ying Zhu[2] and Xiao Lu[1]*

[1]Department of Medical Ultrasound, West China Hospital of Sichuan University, Chengdu, China, [2]Department of Thoracic Surgery, West China Hospital of Sichuan University, Chengdu, China

Introduction: The existing ultrasound appointment system faces multiple challenges, including a lack of diversity in its operation modes, sluggish efficiency, and limited flexibility. During emergency situations, such as disease outbreaks or severe disaster events, the demand for ultrasound examinations skyrockets, making it imperative to offer patients efficient and user-friendly ultrasound appointment services.

Methods: This study introduces the application of a patient-centered real-time dynamic resource allocation strategy in an ultrasound appointment system. This strategy focuses on the demand of patients, builds a multichannel and multimode ultrasound appointment system, and opens sets of parameters related to ultrasound appointments, such as examination room attributes, workload adjustments, and mutually exclusive rules of medical orders. The system can display patient appointment data in real time and carry out statistical analysis, and medical resources can be flexibly configured according to the patient appointment situation to fully meet the needs of patients. Moreover, the system interconnects the appointment data with the registration system and the examination room examination list to further optimize the medical service process.

Results: Data such as the proportion of appointment channels, appointment time, and the quality and efficiency of ultrasound examinations before and after the introduction of the appointment system were compared and analyzed. According to the statistics, the proportion of online bookings increased from 0% to 81.42%. The average appointment times of general ultrasound examination and specialist ultrasound examination were reduced by 90.7% and 78.86%, respectively. The appointment staff was saved by 4 people, the average waiting time of patients in the examination area was reduced from 42 min to 11 min, and the number of ultrasound examinations was increased by 11.5%, while the number of error reports was also significantly reduced.

Discussion: The results show that the application of this strategy in an ultrasound appointment system is feasible and efficient. Patients can participate more in the entire process of ultrasound appointment and examination, obtain reliable ultrasound medical services faster and more efficiently, improve the diagnosis and treatment environment and order of the hospital, and optimize the medical service process.

KEYWORDS

ultrasound appointment, patient-centered, dynamic resource, allocation strategy, real-time

Introduction

With the rapid development and popularization of ultrasound medical technology, ultrasound medical examination and diagnosis have been applied throughout the body, including the abdomen, superficial surface, blood vessels, musculoskeletal system, and heart. According to statistics, ultrasound examination is an important part of modern imaging examination, and it accounts for more than 30% of all imaging examinations (1, 2). The number of ultrasound patients is large, but ultrasound medical resources are limited, so ultrasound is often conducted by appointment (3). The appointment system has achieved certain results in many fields, including students' appointments in classrooms, trucks, and hotels (4–6). However, the appointment in the medical system is relatively more complicated; in addition to issuing medical orders, payments, etc. (7), there are other restrictions on various examinations in the hospital, such as fasting, defecation, etc., and there may be restrictions and conflicts between different examinations, such as that abdominal ultrasound examination cannot be performed within 2 days after gastroenteroscopy (8). Although many medical systems have designed a variety of ultrasound appointment systems, most of them are still only for medical personnel, and patients need to make an appointment at the ultrasound appointment window after opening the examination application form and paying (9). This approach not only requires patients to queue several times but also requires multiple trips to and from the hospital, which is inefficient (10). When patients cannot attend appointments due to other matters, there is also a lack of effective modification channels, which may cause patients to miss appointments, further increasing the time of ultrasound appointments and wasting valuable medical resources (11, 12). To obtain a more suitable time when making an appointment, patients often arrive at the hospital many hours in advance to carry out an inspection as early as possible, wasting patients' time and causing a crowded hospital environment and difficulty maintaining order (13). When patients need more than one test, it is even less efficient and even ineffective because of inadequate preparation or conflicts between tests (14, 15). During disease outbreaks, like the COVID-19 pandemic, ultrasound appointment services can experience even greater delays (16, 17). In emergency scenarios such as floods, earthquakes, and other catastrophic events, the need for ultrasound examinations spikes significantly, hospitals are focusing on how to swiftly adapt to fluctuations in patient numbers, minimize fatalities, and uphold societal wellbeing (18, 19). Consequently, there's an urgent necessity to revise the current ultrasound appointment procedures and methodologies, as well as ultrasound resource allocation strategies. This is not only to address issues such as frequent patient visits, extended appointment times, and inconveniences, but also to enhance preparedness for a variety of diseases and disasters (20, 21). Many scholars have also conducted studies on the problems encountered in the ultrasound appointment system, including the cause of patient absenteeism, online appointment design, and cohort optimization (22, 23). These studies have achieved some results, but there are still some problems, such as insufficient channel smoothness, poor statistical and analytical utilization of data, inflexible configurations, and poor interactions between appointment data and other systems (24, 25).

In this study, we describe the application of a patient-centered real-time dynamic resource allocation strategy in an ultrasound appointment system. The strategy is built around the actual needs of patients and provides patients with online and offline multichannel and multimode ultrasound appointment selection. The system has a built-in ultrasound examination room, doctor's orders, a workload, mutually exclusive rules and other attributes. In accordance with the real-time appointment data of patients, the dynamic adjustment of ultrasound medical resources is carried out to meet the needs of patients. Moreover, the data of the appointment system are connected with the registration system, examination room work list, and self-service printing system to optimize the whole process of ultrasound diagnosis and treatment so that patients can obtain efficient and high-quality ultrasound medical services in time.

The rest of this article is organized as follows. In the "Materials and methods" section, we describe in detail the demand analysis, the architecture of the system and the design of the various functional modules. In the "Results" section, we compare the data before and after the introduction of the appointment system, including the proportion of appointment channels, appointment time, quality and efficiency of ultrasound examination, etc. In the Discussion section, we discuss the results in terms of accelerating patient access to reliable ultrasound, increasing patient participation, optimizing the diagnosis and treatment environment, and protecting patient privacy. In the last section, we present our conclusions and outline the future work of the system.

Materials and methods

Analysis of demands

The purpose of this study was to improve patient satisfaction and sense of medical gain by allowing patients to travel less and information to travel more and to improve the efficiency of the ultrasound department through the dynamic allocation of ultrasound appointment resources (26). Our building objectives include the following:

1) Communication and dynamic management of ultrasound resources. Unified and comprehensive management of resources in each examination room, real-time updates, and subdivisions of resource allocation are achieved.
2) Multiple appointment channels. We made full use of network information technology to realize ultrasound appointments through various channels, such as manual appointment windows, patient self-service device terminals, mobile phone applications and WeChat public accounts.
3) Intelligent appointment rules. Flexible allocation of resources in the examination room, establishment of mutually exclusive rules for inspection items, management of medical order appointment rules, and automatic recommendation of appointment plans.
4) Automatic registration triage call, visual waiting screen, secondary triage. Patients should be triaged to ensure the treatment environment.

Most of our needs come from patients and hospitals. For patients, the main demands are as follows:

1) Shorten the waiting time for medical treatment, including the waiting time for appointment, the waiting time for examination, etc.
2) Medical costs, travel times and unnecessary accommodation costs are reduced.
3) Active participation in the examination, including self-appointment of examination time, being informed of matters needing attention in advance, self-registration for examination on time, checking progress in time, self-printing, etc., is needed.

For hospitals, the main needs are as follows:

1) Efficient resource utilization, real-time resource update, unified allocation.
2) The government should allocate medical resources rationally, improve equipment utilization, and reduce labor costs.
3) To develop a patient-centered diagnosis and treatment process and improve the quality and efficiency of diagnosis and treatment.

System architecture

Through the detailed demand analysis of the system, we designed the overall architecture of the ultrasound appointment system, as shown in Figure 1, which includes mainly the databases and server layers, interface layers, application layers and user layers.

The main functions of each module are as follows:

Databases and server layer: This layer includes all the databases and servers related to the ultrasound appointment system, including obtaining ultrasound order information from the HIS and pushing the appointment list to the ultrasound information system (UIS). The ultrasound appointment system also obtains other examination appointment information from other information systems to avoid examination conflicts. The data of the appointment system are stored in the database and synchronized with the waiting call system for data and status.

Interface layer: The interface layer includes all the database and server interfaces that need to interact with the ultrasound appointment system, including the HIS, UIS, SMS platform, mobile app, waiting and calling system, etc.

The application layer includes the application hardware and software related to the ultrasound appointment system, which

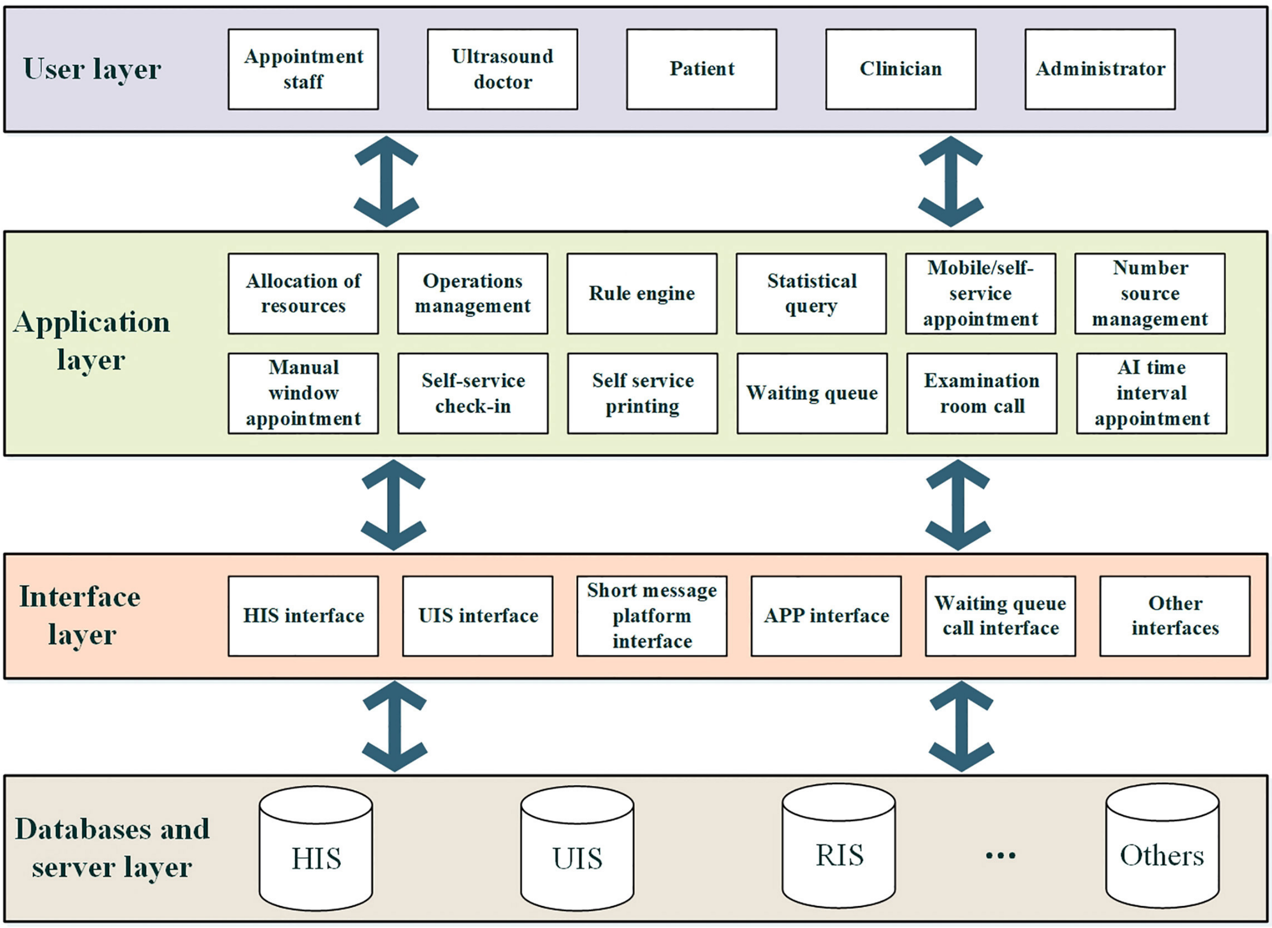

FIGURE 1
Appointment system architecture diagram.

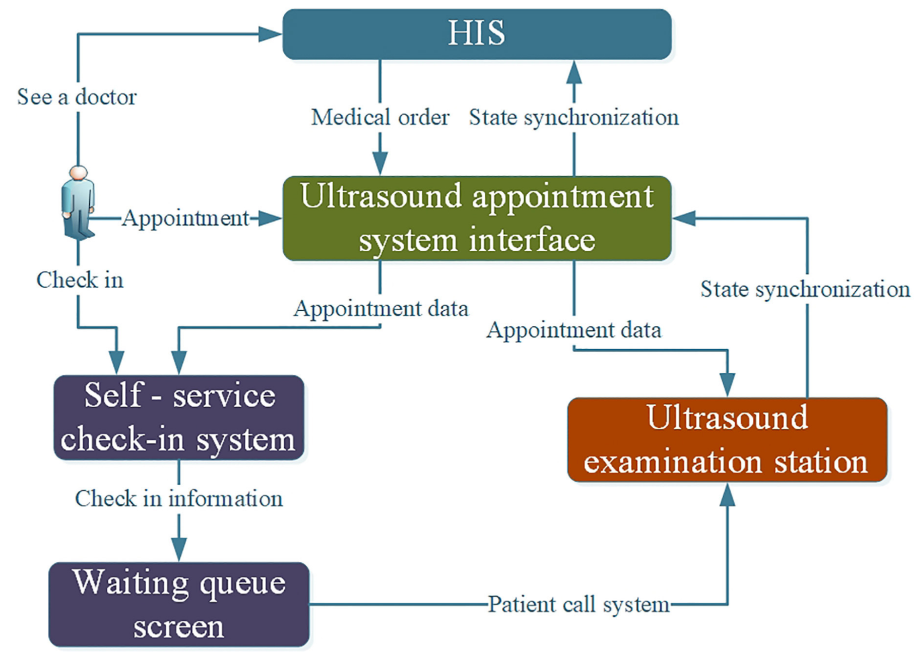

FIGURE 2
Appointment system interface design diagram.

can perform medical resource allocation, operation management, appointment rule configuration, manual intelligent time-division appointment, appointment statistical analysis, number source management, self-service appointment system, self-service check-in, self-printing, triage waiting list, and examination room number calling system on the appointment system.

User layer: The users of the ultrasound appointment system mainly include appointment staff, ultrasound doctors, patients, clinicians, and administrators.

Interface design

With the rapid development of hospital informatization and intelligence, hospitals require all kinds of systems to realize interconnections to avoid the formation of information islands; thus, interface design is important in the design of ultrasound appointment systems (27). An HIS is an information management system covering all the business and the whole process of the hospital, and it is the main line of information construction of the hospital. The ultrasound appointment system needs to conduct data interaction with the hospital's HIS system to obtain the patient's ultrasound medical order from the HIS system. The main information includes patient ID, basic patient information, medical order items, prescribing individuals, billing departments, clinical diagnoses, cost information, etc. The ultrasound appointment system also needs to conduct interface data interactions with the ultrasound information system, which mainly includes synchronizing the appointment information to the ultrasound examination workstation and retrieving state synchronization information. The interface design of the appointment system is shown in Figure 2.

Appointment workflow design

The ultrasound appointment system in this study adheres to the patient-centered concept. Through mobile apps and self-service terminals, patients are allowed to participate in appointments, registrations and examinations as much as possible, which makes the appointment- and examination-related processes simpler and more friendly. The main workflow is shown in Figure 3.

After completing the registration of the electronic medical card, patients can complete the application and pay for the ultrasound doctor's advice online or through self-billing. Then, they can choose the time to complete the online appointment and obtain the electronic ultrasound appointment form. According to the date, time and place on the electronic appointment form, they arrive at the examination area, complete the registration and wait for the examination call at the self-service terminal. Finally, the ultrasound examination was completed to obtain an electronic report, or a paper report could be printed through the self-service terminal.

Patient-centered design

With the deepening of medical reform, patient-centered approaches have become increasingly popular, which is also the core idea of this study (28). Let patients run less, information run more, and improved patient satisfaction and sense of access to medical treatment are the core goals of this study. As shown in Figure 4, the patient-centered ultrasound appointment system was carefully designed, and data were collected throughout the entire process before, during and after ultrasound examination. Before ultrasound examination, patients can make an ultrasound

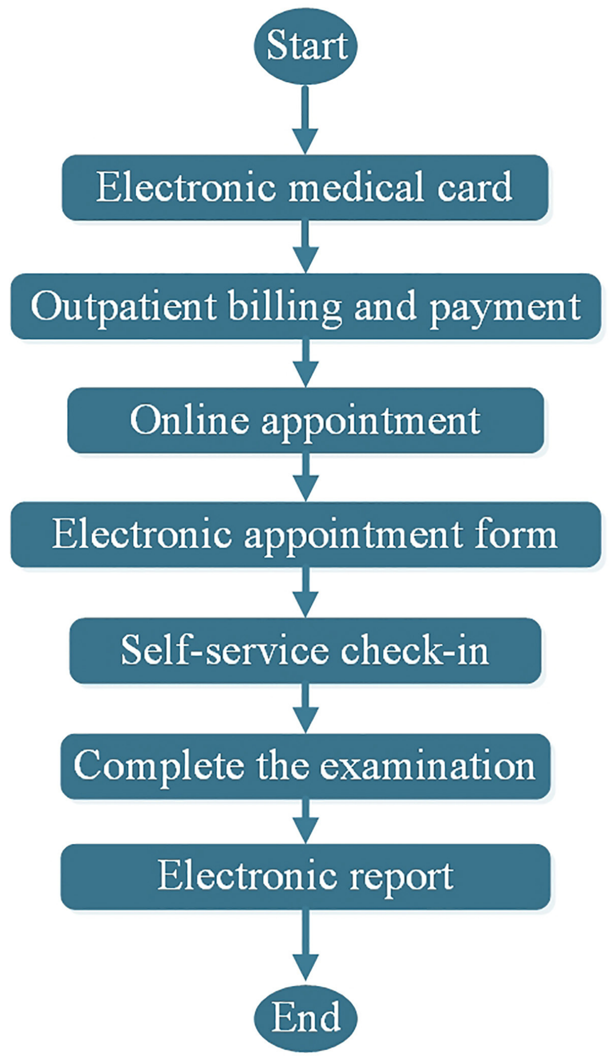

FIGURE 3
Flow chart related to the ultrasound appointment system.

medical order through an online outpatient service or self-billing function and then make an appointment through multiple appointment channels, such as mobile phone applications and WeChat public accounts. At the same time, the appointment system provides patients with multiple appointment mode options, including the shortest time, the least round trip, and self-selected time. The appointment data of the appointment system are updated synchronously in real time, and patients can modify the appointment through the appointment system, but the modification is limited; for example, the modification should be completed 1 day before the appointment time to avoid wasting medical resources caused by temporary cancellation of the appointment. When the patient completes the appointment, the appointment system provides the patient with detailed precautions and explanations to ensure that the patient can be prepared for the examination in advance. These designs can reduce the time and cost of patients traveling to and from the hospital and improve the efficiency of appointments. During the ultrasound examination, the ultrasound appointment system pushes the patient's appointment information of the current time period of the day to the triage registration system and the work list of the ultrasound examination room, and the patient first arrives at the waiting area according to the appointment time and location. Upon completion of the patient check-in, the patient's name is displayed in the waiting queue for the examination room call. After the patient enters the examination room, the examination list can be automatically matched by scanning the appointment information. These designs increase patient participation in the ultrasound process, reduce wait time, and reduce patient and information mismatch. After the ultrasound examination, the patient can visit the self-service printer to print the super report through the appointment information of the appointment system. Moreover, the ultrasound results will also be synchronized to the patient's mobile application, forming a list of examination records and providing appropriate follow-up suggestions for the patient. These designs can effectively protect patient privacy, reduce waiting times for printed reports, and effectively organize patient test results to improve patient satisfaction.

Appointment system management and real-time dynamic resource allocation strategy

Authority management

As shown in Figure 1, the ultrasound appointment system faces different users, and different users are configured with different user permissions. For example, patients only have the right to make an appointment and view their own ultrasound examination on a mobile phone or self-service terminal, and the ultrasound department appointment staff have the right to make an appointment on a computer terminal and the right to view appointment data. The administrator has all the rights of the system, including log management and rule configuration.

Dynamic rule configuration

To improve the flexibility of the system, all the parameter configurations are open and can be flexibly configured. For example, different branches can be configured to meet the ultrasound appointment needs of different branches (29). The information of the ultrasound examination room can be flexibly configured, such as adding, deleting, modifying, and booking the opening days of the examination room. Ultrasound medical order configurations include medical order codes, combination rules and exclusion rules, workload settings, special medical order binding examination rooms, etc. The properties of the ultrasound examination room can be dynamically deployed according to the actual needs of patients (30, 31). For example, when the appointment time of a specialist ultrasound examination is long, the general examination room can be set as a specialist examination room, and the corresponding medical order configuration can be carried out according to needs, which can shorten the appointment time of a specialist ultrasound examination.

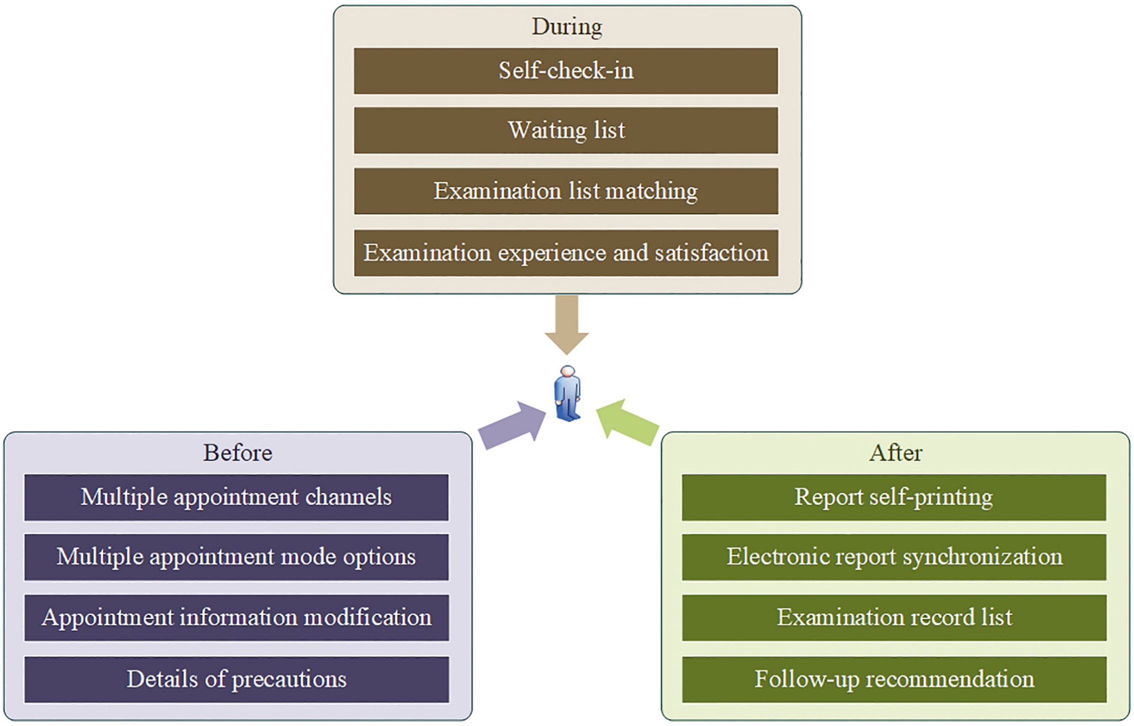

FIGURE 4
Design of a patient-centered ultrasound appointment system before, during and after ultrasound examination.

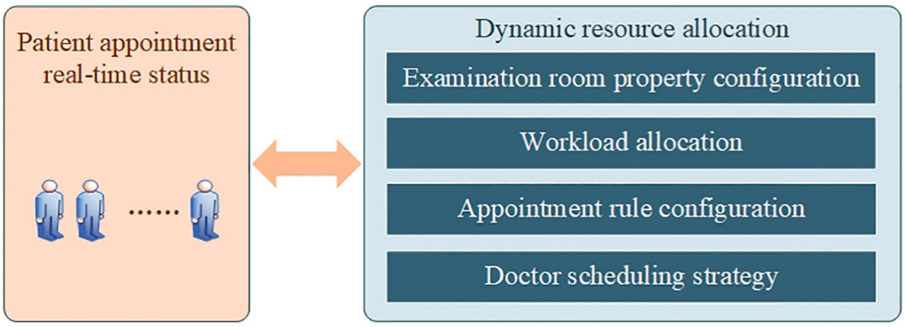

FIGURE 5
Real-time dynamic resource allocation strategy of the ultrasound appointment system.

Real-time resource allocation

Another advantage of the system is the visualized real-time configuration of resources. The ultrasound appointment system can provide real-time and multidimensional data analysis for department managers, including the appointment volume and trend, proportion of different appointment methods, non-attendance rate, resource utilization rate, and appointment workload statistics. These data are presented as visual reports, such as curves and pie charts. The appointment system calculates the position to be booked in each time period according to the set time period and the set number of people and displays it in a visual interface. Different appointment methods, such as self-service appointments and window appointments, are distinguished by different symbols. Administrators and ultrasound appointment staff can also intuitively see the appointment of each examination room, each time period, and position through this interface and can also lock and leave a number for each position in advance. The resources of the examination room are updated in real time, and the appointment information of various channels is summarized to the appointment system and displayed in real time. Administrators can flexibly allocate ultrasound resources according to the appointment situation, as shown in Figure 5.

For example, when the number of ultrasound appointments for patients increases, the workload configuration of the examination room can be appropriately increased as needed, or the number of examination rooms can be increased. In contrast, the number of examination rooms should be appropriately reduced. The statistical analysis of multidimensional appointment data will also provide data support for the real-time resource allocation of departments. This helps to realize the rational allocation and efficient utilization of ultrasound medical resources and improve the quality and efficiency of patient ultrasound examinations.

Online appointment

Through the mobile internet, the online appointment function was designed for patients (32). Patients can complete online ultrasound examination appointments through the mobile app and enjoy a more convenient and efficient appointment experience. After the patient completes the payment of the doctor's order for ultrasound examination, the system will push the information of the ultrasound examination appointment to be made. After the appointment interface is entered, there are generally two options: an intelligent appointment and a self-selected appointment. If an intelligent appointment is chosen, the system automatically obtains the doctor's order of all the ultrasound examination appointments to be made and recommends the most recent appointment plan for the patient according to the set appointment rules and other appointment information of the patient. If you do not like the recommended appointment plan, you can choose the method of self-selected appointment, and the system will list all the appointment dates that can be selected for the patient. The ultrasound appointment system integrates the rules of all ultrasound examinations. For example, abdominal color Doppler ultrasound can only be booked until the morning, and contrast-enhanced ultrasound or intervention can only be booked in the corresponding contrast-enhanced specialist examination room and intervention specialist examination room. There are not only internal appointment rules for ultrasound but also possible interactions between ultrasound and other examinations. For example, abdominal ultrasound usually takes 3 days to perform after gastrointestinal endoscopy or enhanced CT. The ultrasound appointment system can automatically obtain the patient's other examination information through the HIS, which can automatically avoid examination conflicts and cause unnecessary waste of time. At the same time, to further shorten the waiting time of patients for examination, we also adopt the subperiod appointment method, which subdivides half a day into different time periods, usually half an hour (33, 34). In accordance with the order of patients' appointments, different arrival time periods are suggested on patients' electronic appointment forms. In addition to the appointment period, the electronic appointment form displays the full information of the appointment examination room, appointment number, and precautions. The precautions are based on the patient's different ultrasound advice, with different precautions, including fasting, bladder filling, etc., to ensure that the examination can be carried out smoothly.

Appointment record traceability mechanism

The appointment system in this study has a perfect record traceability mechanism, including the appointment method, executor, IP address, and operation time of each appointment record, which are stored in the database. This is of practical importance for the management of the appointment system, appointment workload statistics, problem traceability, etc. In addition, ultrasound departments often encounter situations in which patients need temporary plus sign examinations. To avoid medical risk caused by the plus sign, this study standardizes the plus sign mechanism to support a reasonable plus sign and avoid reselling the plus sign. Usually, the application is initiated by a clinical doctor with a plus sign, indicating the applicant, the application department, and the reason for the application, and the application is sent to the ultrasound doctor. If consent is obtained, the ultrasound appointment staff performs the plus sign registration and sends it to the ultrasound doctor's examination room, and all the application information is also bound to this examination order for subsequent tracking.

Self-service check-in and waiting module design

Patient satisfaction is closely related to patient participation in the treatment process and the openness and transparency of waiting. Therefore, this study designed a self-service check-in and printing system to improve patient participation and designed a visual waiting system and voice call system to improve the openness and transparency of waiting. The appointment data are synchronized with the self-service check-in system. After patients arrive at the ultrasound department according to the appointment date and time period on the electronic appointment sheet, they scan the QR code to check and register on the self-service machine. All the registered information is displayed on a large screen in the waiting area, and patients can intuitively see their queuing position. Patients who do not arrive at the examination area in time after calling will be treated as over-registered and will be reregistered. This not only allows patients to clearly see the fairness of the queue but also ensures the smooth flow of the ultrasound examination and a quiet examination environment. After completion of the examination, the ultrasound report is synchronized to the mobile app, and the patient can also pick up the paper ultrasound report from the self-service machine with the examination QR code.

Results

Comparison of appointment methods

Before the establishment of the appointment system, window appointments accounted for almost 100% of all appointments. After the appointment system is established, the mobile terminal online appointment function and the hospital multifunction terminal appointment function are added, which greatly reduces the pressure of manual window appointment. However, the manual appointment window has not been completely replaced. One reason is that some people do not have smartphones or do not know how to use them, so they need a manual window to help them complete the appointment. Another reason is that some ultrasound appointments can be made only after the review of window staff, such as ultrasound intervention. We calculated the data 1 month after the establishment of the appointment system, as shown in Table 1. The proportion of manual window appointments decreased from 100% to 23.72%, and with the continuous improvement in appointment rules and the increase in patients' self-appointment awareness rate, this proportion still decreased.

Comparison of appointment time

The length of the appointment time between the completion of the ultrasound appointment and the execution of the ultrasound examination is one of the key indicators we pay attention to, which is related to whether patients can undergo ultrasound examination in a timely manner to provide ultrasound image data for the clinic and then obtain timely diagnosis and treatment. Ultrasound examinations are usually divided into general ultrasound examinations and specialist ultrasound examinations, and the average waiting time (days) 1 month before and after the introduction of the appointment system is reported in Table 2. Before the introduction of the appointment system, the average number of appointment days for general ultrasound examination and specialized ultrasound examination was 8.6 and 12.3 days, but it decreased to 0.8 and 2.6 days after the introduction of the appointment system, with decreases of 90.7% and 78.86%, respectively.

Comparison of ultrasound quality and efficiency

For hospitals and departments, in addition to shortening the appointment time of patients, quality and efficiency are also indicators that need to be focused on, including the quality assurance and efficiency improvement of ultrasound appointments, ultrasound waiting and examination execution. We compared the relevant indicators before and after the introduction of the ultrasound appointment system. As shown in Table 3, the number of window appointment staff was reduced from 5 to 1, the average waiting time for patients (from the time they arrived at the waiting area to the start of ultrasound examination) was reduced from 42 to 11 min, and the number of ultrasound examinations in a month increased from 87,931 to 98,045. The number of error reports decreased from 28 to 9.

TABLE 1 Comparison of appointment methods.

Ultrasound appointment channels	Appointment number	Proportion (%)
Mobile terminal appointment	79,827	81.42
Self-service terminal appointment	7,635	7.79
Manual window appointment	10,583	10.79

TABLE 2 Comparison of appointment time before and after the introduction of the appointment system.

Type	Before (days)	After (days)	Decline (days)	Decline (%)
General examination	8.6	0.8	7.8	90.7
Specialist examination	12.3	2.6	9.8	78.86

Discussion

Patient-centered design is the original intention of this system design so that patients can obtain reliable and effective medical services as soon as possible. The patient-centered real-time dynamic resource allocation strategy is multifaceted in optimizing the ultrasound appointment system.

Accelerate the appointment and examination process to ensure timely access to high-quality and reliable ultrasound medical services for patients

This study proposes a patient-centered real-time dynamic resource allocation strategy to optimize ultrasound appointment systems. This strategy dynamically allocates examination rooms and medical resources by analyzing patients' ultrasound appointments in real time and improves the effectiveness of appointments by setting mutually exclusive rules and doctor's order appointment rules. In addition to providing multiple appointment channels, multiple appointment modes are set for patients to flexibly choose according to their actual needs. These measures significantly shorten the appointment time of patients for ultrasound examinations. As shown in Table 2, the average waiting days for general ultrasound examination and specialist ultrasound examination decreased by 90.7% and 78.86%, respectively. This significant reduction in wait time ensures that patients can access ultrasounds in a more timely manner, thereby improving the efficiency and reliability of healthcare delivery. In addition, the appointment system further reduces the inconvenience caused by examination conflicts by automatically assigning the optimal appointment scheme and limiting mutually exclusive rules. For example, the system can automatically avoid

TABLE 3 Comparison of ultrasound quality and efficiency.

Items	Before	After
Appointments staff	5	1
Waiting time (min)	42	11
Amount of examination	87,931	98,045
Error reports	28	9

time conflicts between abdominal ultrasound and examinations such as gastroenteroscopy or enhanced CT. The docking of the ultrasound appointment system with the triage calling system and examination room work list also improves the fluency of ultrasound examination, and sonographers can focus more on the ultrasound examination and diagnosis of patients, improving the efficiency of ultrasound examination. As shown in Table 3, owing to the detailed data interface design between the ultrasound appointment system and each system, the number of ultrasound examinations increased by 11.5%, whereas the number of error reports also decreased significantly, which fully indicates that the introduction of the appointment system has improved the quality and efficiency of ultrasound examinations and that patients have obtained more reliable ultrasound medical services.

Enhancing patient participation and satisfaction

Allowing patients to participate in the whole process of ultrasound examination is one of the measures used to improve patient satisfaction (35). The design of this ultrasound appointment system focuses on the sense of patient participation. Through various channels, such as mobile apps and self-service terminals, patients can choose and adjust their appointment time independently, which enhances the initiative and convenience of patients. According to their needs and actual situation, patients can choose a variety of appointment modes, such as the shortest time, the least number of round trips or the optional time, which improves patient satisfaction. After the appointment is completed, the appointment system prompts you to prepare for the ultrasound examination. After patients arrive at the examination area, through the self-service check-in system and visual waiting screen, patients can know their own examination progress and waiting situation in real time, improve the transparency of the queuing system, and further enhance the sense of participation and experience of patients. After the examination is completed, the patient will print the ultrasound report as needed, while the ultrasound results will be synchronized to the patient's mobile app and provide the patient with appropriate explanations and follow-up recommendations. These user-friendly designs of the ultrasound appointment system allow patients to fully participate in the whole process of ultrasound examination while respecting patients' independent choices, thus improving patient satisfaction.

Optimization of the treatment environment and improvement of the order

The effective triage of patients is an important measure for building an optimized treatment environment. As shown in Table 1, the proportion of online appointments is large, and patients can make ultrasound doctor orders and ultrasound examination appointments online, which can greatly reduce the number of patients returning to the hospital, improve the effectiveness of patients arriving at the hospital, and reduce the flow of patients in the hospital. The hospital treatment environment should be optimized. Moreover, the ultrasound appointment system calculates the patient's expected examination time according to the patient's appointment sequence number through statistical analysis of the average examination time of each doctor's order, and the patient can reach the waiting area according to the prompt time of the ultrasound appointment sheet. As shown in Table 3, the time from the arrival of patients in the waiting area to the start of the ultrasound examination was reduced from 42 to 11 min, which greatly reduced the number of patients in the waiting area and ensured a relatively quiet examination environment for the ultrasound doctors. Furthermore, by visualizing the waiting screen and the secondary triage system, patients can see the queue clearly and transparently, avoiding conflicts caused by unclear queues. These measures are very effective in optimizing and improving the environment and order of medical treatment.

Privacy protection and humanistic care

Patient privacy protection and humanistic care are also the focus of this ultrasound appointment system. The appointment system ensures the security and privacy of patient information through permission management to avoid the risk of information disclosure. The system provides a variety of appointment modes and detailed examination precautions so that patients can choose and prepare according to their actual situation and needs, reflecting attention to and respect for the individual needs of patients. In addition, various designs that allow patients to participate in the whole process of ultrasound examination, including dynamic adjustment of ultrasound resources to shorten the appointment time, self-service registration, and self-service printing, also reflect the emphasis on humanistic care.

Comparison of different appointment strategies

At present, there are a variety of studies on appointment strategies for ultrasound and other medical examinations at home and abroad, including independent appointments, overbooking, classified appointments, free ride appointments by carpools, intelligent appointments, etc. Independent appointments are among the easiest and most commonly used strategies to implement. In this appointment strategy, the appointment of the ultrasound department is relatively independent from that of the radiology department and other medical examination departments, which is conducive to the internal resource allocation of the ultrasound department, simplifying the appointment process, and improving the appointment efficiency (36–38). The greatest drawback of the ultrasound department is that it cannot be combined with other medical examinations, which usually leads to patients returning to the hospital multiple times to complete different examinations. Sometimes there are even conflicts between test items that cause invalid appointments, thus extending the overall time of the patient's visit. Overbooking is another common appointment strategy, which involves making more appointments on the basis of the original appointment workload (39, 40). This

TABLE 4 Advantages and disadvantages of different current appointment strategies.

Strategy	Advantages	Disadvantages
Independent appointment	Simplify the ultrasound appointment process and improve the appointment efficiency	Inability to coordinate with other medical tests leads to multiple trips to the hospital for different examinations
Overbooking	Avoid the waste of medical resources caused by some patients missing appointments	Increase the workload of the doctor and the quality of the examination is difficult to guarantee
Classified appointment	Ensure emergency patients have priority access to ultrasound	The classification criteria were controversial and did not improve routine patient appointments
Carpool appointment	Improve the timeliness of appointment for a small number of patients with transportation difficulties	Implementation was difficult, costly and failed to reduce missed appointments
Intelligent appointment	Optimize the allocation and utilization of medical resources	High technology dependence, potential data security risks, model generalization

strategy is used to avoid the waste of medical resources caused by some patients missing appointments. However, its disadvantages are also obvious because the absence of patients is difficult to predict; when patients do not miss appointments, the workload of doctors increases, and the quality of ultrasound examination is difficult to guarantee. The classification of patient appointments is another appointment strategy. Under this strategy, patients are divided into emergency patients and routine patients to ensure that patients in urgent need of treatment can have priority access to ultrasound examination resources (13). However, the classification standard is controversial to some extent; sometimes, there are cases of fake emergency treatment, and the appointment of routine patients has basically not improved. A small number of studies have examined ride-sharing services or offering free rides to reduce missed appointments, a strategy that can be effective for a small number of patients with transportation difficulties and can improve the immediacy of appointments but does not significantly reduce missed appointments (41, 42). An intelligent appointment system can analyze historical data to optimize the allocation and utilization of medical resources, but it has several problems, such as high technical dependence, potential data security risks, and poor generalizability of the model (43). The advantages and disadvantages of different current appointment strategies are shown in Table 4.

The patient-centered real-time dynamic resource allocation strategy in this study combines the advantages of multiple appointment strategies while minimizing their disadvantages. This study is expected to provide a positive reference for existing research on ultrasound and other medical appointment systems. This strategy has many advantages, through the establishment of a unified database with other medical examinations and a mutually exclusive medical order association system, the overall appointment efficiency of patients can be improved while reducing the transportation cost and time cost associated with patients returning to the hospital multiple times. Through the design of online and offline combinations of multichannel and multimode appointments, the appointment process can be simplified. Through the combination of outpatient “people may take breaks, but the machines continue running” and emergency and hospitalization service modes, doctors’ shifts can be flexibly adjusted according to patients’ appointment conditions in the limited ultrasound examination space, which can improve the efficiency of equipment use and effectively shorten the appointment time of patients. Through machine learning analysis and deep mining of historical appointment data, the time required for various ultrasound examinations can be budgeted, and the estimated examination time of patients can be calculated according to the order of patient appointments. The system makes time-sharing appointments for patients, thus further shortening the time for patients to wait for examinations, ensuring a good medical environment and avoiding medical chaos. Through real-time statistical analysis, the missed appointment data can be supplemented in time to make full use of valuable medical resources and avoid overbooking. By combining the ultrasound appointment system with the self-service registration system, waiting system and self-service printing system, the participation and satisfaction of patients can be improved, and the spirit of humanistic care can be reflected while protecting the privacy of patients. By designing a visualization system to display appointment data in real time and combining information technology with data mining technology, the system’s ease of use, interpretation, traceability and generalizability can be improved.

Conclusion

The application of a patient-centered real-time dynamic resource allocation strategy in an ultrasound appointment system is introduced in this work. This study comprehensively analyzed patients’ demand for ultrasound appointments; designed the system architecture, function modules, data interfaces and workflows on the basis of patients’ demand; and integrated online and offline data, diversified appointment modes, automated medical order attributes and mutually exclusive rules, visualized appointment data, and integrated data between systems. The real-time appointment data of patients are used to make dynamic allocations of resources to the ultrasound appointment system. Through comparative analysis of the data before and after the introduction of the appointment system, the system effectively accelerated the process of patient appointment and examination, shortened the time of ultrasound appointment and improved the quality and efficiency of ultrasound examination. The ultrasound appointment system under this strategy can enhance the participation of patients in the whole process of ultrasound appointment and examination and improve the hospital treatment environment and order. Patient privacy is effectively protected, and patient satisfaction is greatly improved. These patient-centered designs reflect the hospital’s emphasis on humanistic care and patient-centered philosophy, while also improving the hospital’s ultrasound medical service performance in extreme disaster events and disaster preparedness for various emergency situations. In the next step, high-tech technologies such as artificial intelligence and data mining will be gradually introduced to continuously innovate and optimize ultrasound appointment and diagnosis and treatment models to better serve patients.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YZha: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. YL: Conceptualization, Data curation, Writing – review & editing. LQ: Formal analysis, Funding acquisition, Writing – review & editing. YZhu: Investigation, Supervision, Validation, Writing – review & editing. XL: Conceptualization, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Funding

The author(s) declare financial support was received for the research, authorship, and/or publication of this article. This research was supported by the 1 · 3 · 5 project for disciplines of excellence, West China Hospital, Sichuan University.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

1. Lai CH, Lu YJ, Chen PS. Using data-driven techniques to predict outpatient ultrasound examination time for the multi-clinic outpatient appointment scheduling problem. *Commun Statistics Simulat Comput.* (2024) 2024:1–19. doi: 10.1080/03610918.2024.2349168

2. Zhang Y, Luo Y, Qiu L, Lu Q, Lu X. Remote ultrasound real-time consultation and quality control system. *Int J Imaging Syst Technol.* (2023) 2023:1–14. doi: 10.1002/ima.22969

3. Kitema GF, Morjaria P, Mathenge W, Ramke J. The appointment system influences uptake of cataract surgical services in Rwanda. *Int J Environ Res Public Health.* (2021) 18:743. doi: 10.3390/ijerph18020743

4. Xu B, Liu X, Yang Y. Optimization for a multi-constraint truck appointment system considering morning and evening peak congestion. *Sustainability.* (2021) 13:1181. doi: 10.3390/su13031181

5. Torkjazi M, Huynh NN. Design of a truck appointment system considering drayage scheduling and stochastic turn time. *Transp Res Rec.* (2021) 2675:342–354. doi: 10.1177/03611981211029643

6. Wibowo B, Fransoo J. Joint-optimization of a truck appointment system to alleviate queuing problems in chemical plants. *Int J Product Res.* (2021) 59:3935–9350 doi: 10.1080/00207543.2020.1756505

7. Liu D, Shin WY, Sprecher E, Conroy K, Santiago O, Wachtel G, et al. Machine learning approaches to predicting no-shows in pediatric medical appointment. *NPJ Digital Med.* (2022) 5:50. doi: 10.1038/s41746-022-00594-w

8. Pousson JE, Jusot F, Silberzan L. Social inequalities in medical appointment cancellations and reschedulings at the onset of the COVID-19 epidemic in France. *Eur J Public Health.* (2024) 34:652–659. doi: 10.1093/eurpub/ckae101

9. Ala A, Chen F. Appointment scheduling problem in complexity systems of the healthcare services: a comprehensive review. *J Healthc Eng.* (2022) 2022:5819813. doi: 10.1155/2022/5819813

10. Kuiper A, de Mast J, Mandjes M. The problem of appointment scheduling in outpatient clinics: a multiple case study of clinical practice. *Omega.* (2021) 98:102122. doi: 10.1016/j.omega.2019.102122

11. Suk MY, Kim B, Lee SG, You CH, Hyun Kim T. Evaluation of patient no-shows in a tertiary hospital: focusing on modes of appointment-making and type of appointment. *Int J Environ Res Public Health.* (2021) 18:3288. doi: 10.3390/ijerph18063288

12. Hu M, Xu X, Li X, Che T. Managing patients' no-show behavior to improve the sustainability of hospital appointment systems: exploring the conscious and unconscious determinants of no-show behavior. *J Clean Prod.* (2020) 269:122318. doi: 10.1016/j.jclepro.2020.122318

13. Simmons K, Sada YH, Song MM. Reducing delays in oncology clinic appointment scheduling for inpatients: a quality improvement project at a Veterans Affairs medical center. *JCO Oncol Pract.* (2023) 19:328. doi: 10.1200/OP.2023.19.11_suppl.328

14. Zhao J, Liu X, Gu G. Application of the cycle management model in improving outpatient appointment services. *INQUIRY.* (2022) 59:00469580221081407. doi: 10.1177/00469580221081407

15. Fan X, Tang J, Yan C. Outpatient appointment scheduling problem considering patient selection behavior: data modeling and simulation optimization. *J Comb Optim.* (2021) 42:677–699. doi: 10.1007/s10878-019-00487-x

16. Nguyen K, Nguyen K, Lekshmi D, Corlin L, Niska R. Delays in children's preventive health services during the COVID-19 pandemic. *Fam Med.* (2022) 54:350–361. doi: 10.22454/FamMed.2022.922801

17. Woodward CA, Hertelendy AJ, Hart A. Emergency medical services preparedness in dual disasters: war in the era of COVID-19 in Armenia. *Prehosp Disaster Med.* (2022) 37:749–754. doi: 10.1017/S1049023X22002163

18. Na Y, Hassell K, Oni G. PatientPatientatientservices preparedness in dual disasters: war in the eraA crosssectional questionnaire study. *Int J Clin Pract.* (2021) 75:e14446. doi: 10.1111/ijcp.14446

19. Liu C, Yang Y, Liu H. Agent-based modeling for estimating the performance of medical service systems in disaster scenarios. *Int J Disaster Risk Reduct.* (2025) 2025:105183. doi: 10.1016/j.ijdrr.2025.105183

20. Rahiminia M, Shahrabifarahani S, Mojaradi Z. A queueing-inventory model to control the congestion of patients and medical waste in the medical centers, a case study. *J Manage Analyt.* (2023) 10:416–445. doi: 10.1080/23270012.2023.2211073

21. Filyo L, Hansen K, Khazan E. Reducing heart failure readmissions through a shared medical appointment. *J Card Fail.* (2020) 26:S6. doi: 10.1016/j.cardfail.2020.09.025

22. Mateo CM, Johnston PR, Wilkinson RB. Sociodemographic and appointment factors affecting missed opportunities to provide neonatal ultrasound imaging. *J Am College Radiol.* (2022) 19:112–121. doi: 10.1016/j.jacr.2021.09.012

23. Safdar KA, Emrouznejad A, Dey PK. An optimized queue management system to improve patient flow in the absence of appointment system. *Int J Health Care Qual Assur.* (2020) 33:477–494. doi: 10.1108/ijhcqa-03-2020-0052

24. Par0 G, Raymond L, Castonguay A. Assimilation of medical appointment scheduling systems and their impact on the accessibility of primary care: mixed methods study. *JMIR Med Inform.* (2021) 9:e30485. doi: 10.2196/30485

25. Ala A, Alsaadi FE, Ahmadi M. Optimization of an appointment scheduling problem for healthcare systems based on the quality of fairness service using whale optimization algorithm and NSGA-II. *Sci Rep.* (2021) 11:19816. doi: 10.1038/s41598-021-98851-7

26. Valenzuela-Ntion of Latorre-Ntorre-Na-Ntion of an appoinmedical appointment scheduling: optimization, machine learning and overbooking to enhance resource utilization. *IEEE Access.* (2024) 12:7551–7562. doi: 10.1109/access.2024.3349953

27. Zhang X, Ma L, Ma Y. Mobile information systems usage and doctorappointment scheduling: optimization, machine learnin*Mobile Inform Syst.* (2021) 2021:6684448. doi: 10.1155/2021/6684448

28. Subramaniam Kalianan R, Woon YL, Hing YL, et al. Appointment structure in Malaysian healthcare system during the COVID-19 pandemic: the public perspective. *BMC Health Serv Res.* (2022) 22:141. doi: 10.1186/s12913-021-07456-3

29. Chen PS, Chen GYH, Liu LW. Using simulation optimization to solve patient appointment scheduling and examination room assignment problems for patients undergoing ultrasound examination. *Healthcare.* (2022) 10:164. doi: 10.3390/healthcare10010164

30. Pan X, Geng N, Xie X. Appointment scheduling and real-time sequencing strategies for patient unpunctuality. *Eur J Oper Res.* (2021) 295:246–260. doi: 10.1016/j.ejor.2021.02.055

31. Srinivas S, Ravindran AR. Designing schedule configuration of a hybrid appointment system for a two-stage outpatient clinic with multiple servers. *Health Care Manag Sci.* (2020) 23:360–386. doi: 10.1007/s10729-019-09501-4

32. Xie H, Prybutok G, Peng X. Determinants of trust in health information technology: an empirical investigation in the context of an online clinic appointment system. *Int J Hum Comp Interact.* (2020) 36:1095–109. doi: 10.1080/10447318.2020.1712061

33. Srinivas S, Choi SS. Designing variable-sized block appointment system under time-varying no-shows. *Comp Indus Eng.* (2022) 172:108596. doi: 10.1016/j.cie.2022.108596

34. Akintomide AO, Ukweh ON, Efanga SA. An audit of the appointment booking system and patient waiting time in an ultrasound unit in Nigeria: a need to eliminate congestion in our public hospitals. *J Family Med Primary Care.* (2019) 8:2055–2060. doi: 10.4103/jfmpc.jfmpc_235_19

35. Bagheri F, Behnam F, Galavi Z. The use of various appointment systems among patients visiting academic outpatient centers in Kerman and the evaluation of patientstientsentsive and satisfaction. *BMC Health Serv Res.* (2022) 22:1344. doi: 10.1186/s12913-022-08635-6

36. Kuiper A, Mandjes M, Mast J, Brokkelkamp R. A flexible and optimal approach for appointment scheduling in healthcare. *Decision Sci.* (2023) 54:85–100. doi: 10.1111/deci.12517

37. Harris SL, May JH, Vargas LG, Foster KM. The effect of cancelled appointments on outpatient clinic operations. *Eur J Oper Res.* (2020) 284:847–860. doi: 10.1016/j.ejor.2020.01.050

38. Zou Y, Guo P, Zhu X, Liu X, Xin N. Internet appointment has more advantages than traditional appointment in the nursing service of dry eye patients. *Medicine.* (2023) 102:e36348. doi: 10.1097/MD.0000000000036348

39. Chen Y, Kuo YH, Fan P, Balasubramanian H. Appointment overbooking with different time slot structures. *Comp. Indus. Eng.* (2018) 124:237–248. doi: 10.1016/j.cie.2018.07.021

40. Valenzuela-N1EngoverLatorre-Ntorre-NaEspinosa FT. Smart medical appointment scheduling: optimization, machine learning and overbooking to enhance resource utilization. *IEEE Access.* (2024). 2024:49953. doi: 10.1109/ACCESS.2024.3349953

41. Whorms DS, Narayan AK, Pourvaziri A, Miles RC, Glover M, Herrington J, et al. Analysis of the effects of a patient-centered rideshare program on missed appointments and timeliness for MRI appointments at an academic medical center. *J Am College Radiol.* (2021) 18:240–247. doi: 10.1016/j.jacr.2020.05.037

42. Chaiyachati KH, Hubbard RA, Yeager A, Mugo B, Lopez S, Asch E, et al. Association of rideshare-based transportation services and missed primary care appointments: a clinical trial. *JAMA Intern Med.* (2018) 178:383–389. doi: 10.1001/jamainternmed.2017.8336

43. Yang Y, Madanian S, Parry D. Enhancing health equity by predicting missed appointments in health care: machine learning study. *JMIR Med Inform.* (2024) 12:e48273. doi: 10.2196/48273

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 28 February 2025
DOI 10.3389/fpubh.2025.1535218

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Hagen Wenzek,
GI Digital Inc., United States
Sung-Ho Kim,
Cheongju University, Republic of Korea
Emmanouil Spanakis,
Foundation for Research and Technology Hellas (FORTH), Greece

*CORRESPONDENCE
Lin Liang
✉ linliang@csu.edu.cn

RECEIVED 27 November 2024
ACCEPTED 11 February 2025
PUBLISHED 28 February 2025

CITATION
Liang L (2025) How is patient trust transferred from online medical platforms to offline? *Front. Public Health* 13:1535218.
doi: 10.3389/fpubh.2025.1535218

How is patient trust transferred from online medical platforms to offline?

Lin Liang[1,2]*

[1]Business School, Central South University, Changsha, China, [2]Xiangya Hospital, Central South University, Changsha, China

Introduction: The function of the internet medical platform has expanded from online consultation to offline diagnosis and treatment appointment, forming a complete service process combining online and offline, improving the patient's medical experience and promoting the transfer of online trust to offline. However, the existing studies pay insufficient attention to the dynamic and multi-stage characteristics of online medical trust, especially the lack of in-depth discussion on the trust transfer of patients from online to offline.

Methods: This study builds a patient trust transfer model based on relevant theories, and analyzes the influence mechanism of online reputation feedback on patients' online and offline trust combined with text mining technologies such as sentiment analysis. The research adopts the multi-dimensional analysis method, comprehensively considers the online and offline scenarios, and reveals the key drivers of trust transfer through large-scale data analysis.

Results: The study found that doctors' online reputation feedback and interaction quality were important factors affecting patients' trust transfer. Positive online interaction and high-quality reputation feedback significantly enhanced patient trust and promoted the transfer of online trust to offline. The trust transfer process is dynamic and multi-stage, and the influencing factors of different stages are different. The study also revealed the significant difference in trust mechanism between online medicine and traditional medicine.

Discussion: This study revealed the formation and transfer mechanism of trust in online health care by building a trust transfer model, filling the gap in related research. The results provide practical guidance for the online medical platform to optimize the service process and enhance the trust of patients. In the future, we can further explore the trust transfer mechanism under different cultural backgrounds to promote the globalization of Internet medicine.

KEYWORDS

online healthcare, patient online trust, patient offline trust, reputation mechanism, trust transfer

1 Introduction

Online healthcare, as a new form of medical consultation in modern society, has won the favor of a large number of users due to its convenience and efficiency since its inception, and has maintained a stable growth momentum (1). Online medical platforms provide various communication methods such as text, images, and videos, making communication between doctors and patients more comprehensive and convenient. Meanwhile, doctors can utilize fragmented time for online diagnosis and treatment, improving work efficiency and providing patients with more medical options (2). In other words, online healthcare has improved the accuracy and personalization of medical services through technologies such as big data and artificial intelligence, thereby enhancing the quality of medical services.

At the same time, online medical platforms have broken the limitations of geography and time through digital means, enabling patients to access medical services more conveniently. On the one hand, it has increased the coverage of medical services. Online medical platforms enable patients in remote areas or with limited mobility to access high-quality medical resources, improving the coverage of medical services. On the other hand, it reduces the waiting time for patients. Patients do not need to go to the hospital in person, they can obtain doctors' consultation and advice through online platforms, thereby reducing waiting time for treatment (3).

In addition, online medical platforms play an important role in reducing patient medical expenses and improving medical efficiency (2). One is to reduce medical expenses. Online medical platforms reduce additional costs for patients, such as transportation and accommodation, by providing remote consultation, online diagnosis and treatment services. Secondly, it has improved medical efficiency. Digital medical methods enable doctors to have a more accurate understanding of patients' conditions, thereby developing more precise treatment plans, reducing unnecessary examinations and drug use, and lowering medical costs. Thirdly, some platforms also provide financial services such as medical insurance and installment payments, further enhancing patients' medical experience.

However, we also need to be aware that the development of online medical platforms still faces many challenges and problems. For example, aspects such as medical quality and safety, doctor-patient trust, technology and privacy protection need to be further improved and optimized.

In summary, as an important component of the modern healthcare system, online medical platforms provide patients with convenient and efficient medical services, while also offering doctors a more flexible way of working. However, the issue of doctor-patient trust has always been one of the key challenges in the development of online healthcare platforms. One is the issue of data security and privacy protection. Despite the various data security measures taken by online medical platforms, once a data breach occurs, it will cause huge harm to patients and seriously damage the reputation of medical institutions. In addition, some platforms have shortcomings in privacy protection, such as collecting, using, or leaking personal information without the patient's consent, leading to a decrease in patient trust. Secondly, the quality of service varies greatly. Due to differences in internal management and personnel quality within medical institutions, some patients may encounter situations such as indifferent service attitudes and non-standard diagnosis and treatment during the medical process, leading to a breakdown of trust. The third issue is poor communication. In the actual diagnosis and treatment process, due to unequal information and insufficient communication skills between doctors and patients, patients often find it difficult to fully understand their condition and treatment plan, resulting in doubts and concerns, which affects the establishment of trust between doctors and patients (4). Therefore, to truly establish a stable doctor-patient trust relationship, it requires joint efforts from various aspects such as the platform, doctors, patients, and the government.

Moreover, in the process of providing medical services on online medical platforms, due to spatial barriers and the particularity of the medical industry, the reputation feedback mechanism of the platform has become a key factor in establishing trust between users and doctors (5). The solution to this problem plays a crucial role in enhancing the trust of online medical platforms among users and promoting the further development of online healthcare. Although online healthcare has experienced rapid development in the context of online consumption, its characteristics differ significantly from online consumption. Online healthcare mainly provides professional services rather than property transactions, which makes users have higher expectations for doctors' professional abilities and service quality. Meanwhile, the high-frequency real-time user demands driven by mobile technology also make trust building and risk perception in online medical processes more complex and variable (6).

With the continuous expansion of medical and health platform and website functions, online consultation and offline diagnosis and treatment appointment have formed a complete Internet medical service process. When patients consult online, they can have in-depth communication with doctors to understand their condition and treatment plan; when offline medical treatment is needed, it can be easily scheduled through the platform, achieving seamless integration between online consultation and offline medical treatment (7). This process not only greatly improves the patient's medical experience, but also promotes the transfer of patient trust from online to offline. In the environment provided by online medical platforms, real-time interaction between patients and doctors has become possible. Patients can understand the service quality or personal characteristics of doctors through the platform reputation feedback mechanism, and these signals serve as important clues that will directly affect the formation of patient trust (8). Therefore, how to better utilize these signals and improve the trust of online medical platforms has become an important issue that urgently needs to be addressed.

By systematically reviewing the historical evolution of doctor-patient trust and the current research status of doctor-patient trust by domestic and foreign scholars, we can clearly see that online healthcare, as an innovative model that integrates information technology and medical services, is gradually changing the traditional medical landscape (9–12). From the initial exploration of technological applications to the current in-depth attention to the needs of users and patients, research in the field of online healthcare is constantly expanding and deepening. However, although scholars have begun to pay attention to issues such as online health platforms and online health information, there is still insufficient attention to the core issue of doctor-patient trust, especially the transfer of trust between patients on online medical platforms from online to offline.

Current research focuses more on the antecedents and consequences of trust in specific scenarios, neglecting the dynamic and multi-stage nature of trust. Trust is complex and multidimensional, evolving over time and space, and requires a deeper exploration of its evolutionary patterns and influencing factors beyond a single stage analysis (13). As a new medical service model, online healthcare differs from traditional healthcare in terms of doctor-patient interaction and trust mechanisms. It has characteristics such as anonymity, remote access, and immediacy, and requires specialized research on its trust evolution mechanism (2). The trust issue in online healthcare involves temporal and spatial transformation. Trust may be established online first, and then consolidated and improved through offline medical services, requiring a comprehensive consideration of various factors both online and offline. Therefore, a comprehensive and systematic research method is needed, including multidimensional considerations and comprehensive consideration of online and offline scenarios, to accurately grasp the essence and laws of doctor-patient trust, optimize doctor-patient relationships, improve the quality of medical services, and help understand and solve the crisis of doctor-patient trust both online and offline.

2 Theory

2.1 Online healthcare

2.1.1 Concept of online healthcare

Internet medicine is the product of the combination of network communication technology and the field of medical and health care. Institutions and personnel with medical qualifications provide medical and health services through electronic communication technology, computers, mobile terminals and other information tools. This field developed early in foreign countries. The U.S. government started research on "telemedicine" related policies in 1976 and first proposed the concept of "telemedicine" the following year. In the 1990s, other developed countries and regions also actively participated in the construction of regional medical and health informatization. For example, the European Union launched the "European e-health action plan" in 2004, while the UK launched the national health informatization project (npfit) in 2002. Since then, smart phones, PDAs and other mobile terminals have been widely used in the medical field, which not only helps the efficient collection and management of hospital data, but also greatly improves the convenience of users to obtain medical services and significantly optimizes the efficiency of medical services (14).

2.1.2 Difference between online healthcare and traditional healthcare

There are many differences between online health care and traditional health care systems. These differences are mainly reflected in medical channels, diagnosis and treatment methods, data storage and management, medical services and expenses (15).

First, access to medical treatment. Online health care uses the Internet as the medium to realize the storage, transmission, communication and support of medical services through digital and information technology. Patients only need to register, consult and pay on their mobile phones to obtain diagnosis, treatment and consulting services, eliminating the tedious process of queuing, waiting and registration. Traditional medical treatment is mainly carried out through offline medical institutions such as hospitals, clinics and community health service centers. Patients need to fill in medical records, queue up, register, and then accept the diagnosis and treatment of doctors. The process is relatively cumbersome and may need to wait for a long time. The second is the diagnosis and treatment method. Patients in the online medical platform can communicate with doctors through online video, graphics and other forms. This "cloud medical" method greatly reduces the problems of difficult and expensive medical treatment, and can also solve the situation that some patients cannot go to the hospital at home. Traditional medicine relies on professional equipment and doctors' examination, auxiliary diagnosis and treatment methods, such as electrocardiogram, B-ultrasound, surgery, etc. Third, medical services. Online medicine can provide round the clock online consultation and diagnosis services, as well as online prescription, drug purchase and distribution services. Online consultation is no longer limited by time and space, extending the time span of medical services. Traditional medicine usually needs to be treated at a fixed time and place. Although the diagnosis and treatment experience and academic accumulation are well-known, the service flexibility and convenience are relatively weak. Fourth, expenses. Online medical costs are relatively low, because there is no need to rely on large medical institutions, nor need to pay the human costs of hospitals and other institutions. The cost of traditional medical treatment is relatively high, especially when it comes to high-end examination and treatment. Fifth, risk management. There are great differences in the quality of medical students on the online medical platform. Some doctors may not have a practicing doctor certificate or have a low level of knowledge, causing risks to the treatment of patients. At the same time, the risk of personal privacy disclosure is high, because patients need to input personal information into the Internet system. There is a risk of misdiagnosis, because doctors cannot diagnose patients face-to-face, nor can they use actual equipment for examination. Although traditional medicine also has the risk of misdiagnosis, it is relatively low, because doctors can diagnose and treat face-to-face. The risk of data leakage is relatively low, because the traditional medical data storage and management methods are relatively safe.

To sum up, online health care and traditional health care systems have their own advantages and disadvantages. How to effectively combine the two to form a multi-party coexisting health care system is an urgent problem for us to solve.

2.1.3 Current status of online medical research

At present, the related research of Internet medicine mainly focuses on patients (users), and the research topics mainly cover three aspects. One is user health information behavior in the Internet environment. Study how users collect, evaluate and use health information. Users mainly obtain the information they need through health information search, and will evaluate the quality of the information, which is affected by factors such as information sources, communication channels, etc. Ultimately, users will make decisions based on information (16). The second is the impact of online medical and health communities and social media on health. Online medical and health communities not only provide health information, but also provide social support, including information support, emotional support and companionship. Social media also enriches users' sources of medical and health information and provides users with a platform to express their health concepts. These platforms help users form a mutually supportive patient friend network and improve health (17). Third, health privacy and trust research. Users are worried about the privacy protection of personal health information, which will affect their acceptance of online medical and health services. Privacy concerns will negatively affect user trust, and then affect the adoption of mobile health care. Strengthening privacy protection and security regulations can alleviate this negative effect, and also help build trust in online health information interaction (18).

2.2 Trust theory

2.2.1 Concept of trust theory

Trust, as a multidimensional and interdisciplinary concept, has presented different research perspectives and definitions in various fields. In the field of social psychology, trust is regarded as a comprehensive reflection of individual psychology, personality traits, and behavioral performance. It focuses on the trust relationship between people and its impact on individual behavior. Scholars in this field, such as Deutsch, have revealed the central role of trust in interpersonal relationships by exploring the role of trust in conflict resolution (19). Rotter and Julian have also provided many explanations regarding trust between individuals and organizations, among which the expectation given to a particular individual or organization is what we call trust (20). Brahm and Kunze proposed that trust is a feeling, expectation, or belief of a person (21).

Management regards trust as an important mechanism within an organization, which helps to reduce uncertainty and risk and improve management performance. Driscoll believes that trust is the belief of decision makers that implementing a certain behavior will result in a beneficial outcome for themselves (22). Mayer et al.'s (23) study emphasizes the important role of trust in decision-making, cost reduction, and relationship regulation. Hwang et al. proposed that trust is conducive to promoting the formation and stability of cooperative relationships between individuals and between individuals and organizations (24).

2.2.2 Research on trust transfer

Doney and Cannon proposed and explained trust transfer, which refers to the transfer of trusted things or people to unknown people or things, thus forming certain special relationships (25). The foundation of trust is an important source of trust, but it also requires the joint action of other factors to truly generate trust. Many factors, such as the environment in which the trust target is located, can affect the trust subject's perception and evaluation of the target (26). Trust transfer is an important component of the trust formation process. Xu found through research that online comments attract tourists' attention, which is influenced by both positive and negative comments. Among them, positive comments promote the establishment and strengthening of user trust. According to relevant research, trust objects can be transferred, and these transfers are all influenced by the source of trust (27). For example, Flaherty pointed out in her research that when a trusted third party proves that a stranger is trustworthy, they largely decide to trust the stranger (28). Plavini summarized the impact of online trust in retail enterprises based on the theory of trust antecedents, and found that there is a significant positive relationship between retail performance and online trust level, and product type also affects the trust relationship (29). In the online environment, people often rely on the experiences of others, such as online comments, to reduce their doubts and uncertainties, thereby establishing trust in unfamiliar targets. This is the process of trust transmission (30).

There are various psychological processes involved in building trust, and many analyses have been conducted based on trust transmission models. For example, foreign scholars Doney and Cannon proposed a trust process model, which is divided into five processes: computation, prediction, ability, intention, and transmission (25). Among them, transmission refers to the evaluation and judgment of trust in organizations or individuals. The organization or individual can assign trustworthy characteristics to the authenticated person. This also indicates that when consumers have little or no knowledge of the trust object used as a basis for judgment, trust can be transferred from high trust sources to the target object, such as third-party networks, authentication and evaluation by trust assessment agencies, etc. They will transfer trust to the corresponding online merchants. Scholars represented by McKnight have identified three methods for building trust from the perspectives of institutions, knowledge transfer, and trust transfer. Firstly, trust can be transmitted in different processes (31). For example, the trust of the principal during the communication process may be directly affected by the third party or target party involved in the trust transfer (32). Yang et al. (33) found through empirical research that users' trust in suppliers' offline stores can be transferred to their online stores. Zhao et al. provided a detailed summary of the implementation of trust transfer and proposed a trust transfer mechanism, pointing out that trust transfer cannot be separated from the scope of trust. They also analyzed two types of trust: functional trust and recommendation trust (34).

2.2.3 Current status of trust theory research

Trust plays an important role in the medical and health system, and the medical services provided by doctors are regarded as a unique trust commodity. With the rise of online medical services, scholars at home and abroad began to explore the trust problem in this new situation. At present, the research on trust in online medical context is mainly carried out in three areas: online medical and health information, online medical and health websites, and mobile medicine. Its core is to analyze the influencing factors of trust and its results.

The Internet has become the main way for people to obtain health information. However, the medical and health information on the Internet is rich and complex, and it is easy to be misled by wrong information for users who lack medical knowledge. Therefore, it is particularly important to build a trust relationship between doctors and patients, which can not only help users screen information more effectively, but also further promote the harmony of doctor-patient relationship. The empirical study of Harris et al. revealed multiple influencing factors of online trust, including the quality and neutrality of online health information, as well as users' perceived threats and new confirmations. These factors have a significant positive impact on users' online trust, and then affect their willingness to accept suggestions (35).

Online medical and health websites provide users with diverse medical and health services. In this context, scholars have conducted in-depth research on trust. Ko et al. divided trust into cognitive trust and emotional trust, and constructed the corresponding trust model to explore the establishment mechanism of user trust in online medical communities (36). Seckler et al.'s research found that user interface, demand satisfaction, responsiveness, security and other factors have a significant impact on user trust. At the same time, trust will further affect user satisfaction and loyalty (37).

In addition, some scholars have also explored the issue of trust in the field of mobile medicine. Guo et al. (38) analyzed the trust and adoption of mHealth services by users at different ages from the perspective of privacy and personalization. Kesharwani et al. (39), combined with the technology acceptance model, explored the influence of trust, risk, ease of use and usefulness on the use of mobile health applications by AIDS patients. Akter et al. (40), taking low-income people as the research object, constructed a model of continuous use of mobile health care, and found that user trust has a significant impact on their willingness to continue to use.

2.3 Reputation mechanism

The reputation mechanism, as an indispensable part of social communication, carries different meanings and values in different fields. In the field of online markets, the definition of reputation is more specific and important: it represents the conditional probability of a person acting in a specific way and becomes one of the key factors for the success of online transactions or services (41). The online reputation feedback mechanism has just taken advantage of the two-way communication characteristics of the Internet and the huge amount of information to establish a reputation information network dedicated to providing communication and feedback for online trading parties (42). This mechanism effectively prevents the occurrence of moral hazard and mitigates the potential harm caused by adverse selection by designing clever reward and punishment mechanisms and information learning mechanisms, thereby greatly improving the efficiency and security of online transactions (43). In multiple fields, online reputation feedback mechanisms have played a crucial role. In the field of e-commerce, reputation feedback mechanism has become the core of website management. It not only ensures the stability of online transactions and effectively prevents online fraud, but also establishes a solid trust relationship between buyers and sellers, greatly improving market efficiency (42). In the medical field, with the rise of online medical services, the online reputation feedback mechanism has also become an important reference for patients to obtain doctor service information and make reasonable medical decisions (44).

In traditional offline environments, reputation measurement is often difficult due to the difficulty of obtaining and disseminating information. But with the emergence of various social platforms and new media, measuring online reputation has become particularly important (45). Online reputation facilitates communication and decision-making between users and platforms, creating favorable conditions for cooperation between both parties. In the field of online healthcare, the improvement of doctor-patient trust and information asymmetry issues, as well as the transmission of service quality, largely depend on online reputation (46). Practice has shown that the higher the reputation level, the lower the uncertainty and perceived risk of users (47). In the medical field, the problem of information asymmetry between doctors and patients is particularly prominent, and online medical service platforms exacerbate this issue. However, with the development of the Internet, patients are increasingly inclined to search and understand the reputation of doctors through online platforms. The formation of doctors' online reputation mainly relies on patients' online evaluations, feedback, sharing, and promotion by medical institutions. This information quickly spreads through online platforms and has a profound impact on other patients' medical decisions.

2.4 Research review

Through the systematic review of domestic and foreign scholars' research on online health care, trust theory, reputation mechanism, and trust in the context of online health care, we can clearly observe the rapid development trend of online health care and its potential optimization space. At the same time, the core role of doctor-patient trust in optimizing the doctor-patient relationship has been widely recognized (10). However, the current research on doctor-patient trust in online medicine still faces several key issues that need to be further explored.

(1) The development and research status of online medicine shows that the field is undergoing a shift from simple technology application to in-depth attention to the needs of users and patients. However, despite the significant progress made in online health care, scholars have focused more on online health communities and online health information related issues, while the discussion on doctor-patient trust is relatively rare. In fact, reasonable service selection and the improvement of doctor-patient trust are the key elements for the sustainable development of online health care. As an important cornerstone of the stable operation of society, trust has been faced with a crisis of trust in the offline environment, and the complexity and anonymity of the Internet environment exacerbate the difficulty of building doctor-patient trust. Due to the particularity of medical services, people tend to rely more on traditional face-to-face offline medical services, which further highlights the seriousness of the problem of doctor-patient trust in the Internet environment. However, at present, the research on doctor-patient trust at home and abroad is mostly limited to offline environment, and the research on doctor-patient trust in online medical context is obviously insufficient.

(2) When integrating the formation and evolution of doctor-patient trust and trust research in the online medical context, we found that although scholars paid high attention to trust issues in the Internet context, these studies were relatively scattered and lack of systematicness. The existing research

focuses more on the antecedents and outcomes of trust in a single stage in different scenarios, and rarely incorporates the dynamic and multi-stage characteristics of trust into the analysis framework. Therefore, at present, the research on doctor-patient trust in online medical environment is still relatively single, and there is a lack of comprehensive and systematic research on the formation and evolution of doctor-patient trust, which limits our in-depth understanding of the construction and evolution of doctor-patient trust in online medical environment.

(3) The lack of trust between doctors and patients and the distrust between doctors and patients are one of the most serious problems in the doctor-patient relationship. Although there have been in-depth studies on the dimensions, system evaluation, influencing factors and results of doctor-patient trust in the traditional medical model, there is still a relative lack of research on the doctor-patient trust in the innovative medical model of online medicine. There are significant differences between the doctor-patient interaction mode in online medicine and the traditional medical model, so the influencing factors, trust dimensions and trust results of doctor-patient trust will also be different. In addition, the evolution process of trust in the online medical environment has become more complex, which not only involves the evolution of different time periods, but also spans online and offline. Therefore, it is of great significance to systematically study the construction and evolution of doctor-patient trust in online medical environment, and to explore the formation and evolution mechanism of doctor-patient trust, in order to promote the healthy development of doctor-patient relationship and improve the quality and efficiency of online medical services.

3 Hypothesis

3.1 Trust transfer

Trust transfer is a unique and important mechanism in building user trust. When we delve deeper into this mechanism, we will find that it is essentially a complex cognitive process (26). In this process, people often transfer their trust in a familiar target to another relatively unfamiliar target based on some kind of correlation between the targets (48). This transfer is not limited to trust exchange between entities, it also involves the transfer of trust in different contexts. This article focuses on the transfer of trust between channels, specifically transferring trust from one channel or context to another. We have seen many examples of this in e-commerce platforms. For example, the research of Naseri et al. (49) revealed how users' trust in traditional offline banks significantly affects their trust in corresponding online banks. This trust transfer has expanded from offline channels to online channels, proving that even in a digital environment, users' trust in traditional institutions still has strong continuity. Similarly, scholars such as Gao and Waechter (50) have also pointed out in their research that users' trust in mobile payments is directly influenced by their trust in online payments, which is actually the process of trust transfer between the network and mobile environments. In the medical field, this phenomenon of trust transfer is also worthy of attention. With the rise of Internet medicine, more and more patients begin to communicate and consult with doctors through online platforms. This online interaction provides patients with a convenient and efficient medical service experience, while also establishing a preliminary trust relationship between them and doctors. However, when patients require further treatment or examination, they may still need to go to the hospital for face-to-face communication with doctors. In this situation, whether the trust of patients in doctors online can be smoothly transferred to offline has become a worthwhile research question.

We know that in the field of Internet medicine, online trust is usually established based on a number of factors, including platform reputation (platform popularity, reputation and user evaluation, etc.), doctor qualifications (doctor's education, professional title, professional experience, etc.), interactive experience (online communication quality and response between patients and doctors, etc.), and information security (patient's personal information protection and data security, etc.), which together constitute the basis for patients to trust doctors or platforms in the online environment.

When patients require further treatment or examination, they often hope to transfer the trust established online to the offline environment. The demand for this transfer stems from patients' expectations for offline medical services, including confirmation of professional abilities, development of treatment plans, and establishment of emotional connections. However, the process of transferring trust from online to offline is not simply a continuation, but is based on a series of complex causal mechanisms. These mechanisms include: consistency of information, consistency of service experience, satisfaction of patient expectations, social identity and sense of belonging, etc. Specifically, patients will pay attention to whether the information provided by doctors in online and offline environments is consistent, including disease diagnosis, treatment plans, etc., whether the quality, attitude, professionalism, etc. of online and offline services are consistent, whether offline services can meet patients' expectations and needs, such as treatment effectiveness, communication quality, etc., and whether patients can gain a sense of social identity and belonging through communication with doctors in offline environments.

Based on the above analysis, we can see that the establishment of online trust provides a preliminary trust foundation for patients. This foundation is established based on factors such as doctors' professional competence, communication skills, and the convenience and safety provided by the platform. When there is a correlation between online and offline environments, patients are more likely to transfer online trust to the offline environment. This correlation is mainly reflected in the consistency of doctor identity, continuity of information, and coherence of service experience. The quality and experience of offline services further consolidate the trust established online. When consistency is maintained between online and offline environments, patients are more likely to transfer online trust to the offline environment.

Therefore, this article makes the following assumptions:

H1: Patients' offline trust will be positively influenced by their online trust.

3.2 Reputation feedback

On e-commerce platforms, reputation mechanisms are crucial for the survival and development of merchants. Under the influence of online reputation, consumers and merchants from different geographical locations can quickly connect. Posting feedback information such as digital ratings and text comments is the most traditional reputation mechanism. After the system summarizes and organizes the feedback information, it will be included in the reputation files of merchants and consumers, providing a basis for user decision-making. Similarly, the influencing factors of offline trust also include reputation mechanisms. Racherla and Friske (51) conducted in-depth analysis on the role of reputation from both online and offline markets, revealing the commonalities and differences of reputation in different environments. The reputation mechanism can also affect users' trust in online medical platforms. In order to attract users and encourage more users to choose the platform, medical service platforms will regulate their own medical behavior, continuously improve the level and quality of medical services, and gain a good online reputation. As an intangible asset of traders, reputation can effectively constrain their behavior, greatly reducing the likelihood of moral hazard and adverse selection. Through research, scholars represented by Noort have found that managing reputation is not easy, but once lost, the impact can be profound. Consumers are more susceptible to the impact of negative transactions (52). Many studies have confirmed that the higher the credibility of a business, the higher the trust of consumers in it. In any field and market, reputation is one of the key factors in winning trust (53). For doctors, as a special service provider, their online reputation can also affect patients' trust in them. This impact is not only reflected in online consultation and interaction, but also extends to the offline medical process. Therefore, doctors need to value their online reputation and win the trust and respect of patients by providing high-quality services and positive interactions. Therefore, this article makes the following assumptions:

H2: Patients' online trust will be positively influenced by doctors' online reputation.
H3: Patients' offline trust will be positively influenced by doctors' online reputation.

The transfer of trust between multiple contexts is not a simple psychological transfer, but a complex process. Only with specific characteristics or structures can trust be transferred in different contexts. If there are common factors that provide guarantees for different situations, the transfer of trust will become more natural and smooth (54). For example, if the trust relationship in one context is based on professionalism, reliability, and transparency, and these factors also exist in another context, then individuals are more likely to transfer trust from one context to another. This phenomenon of trust transfer provides us with a window into the essence of trust (55). In the process of trust transfer, reputation plays a crucial role as an observable signal. Reputation is not only an evaluation of a target's past behavior, but also a signal that indicates that the target possesses certain advantages or traits (56). In the medical field, if a doctor has established a good reputation on online platforms, patients are more likely to extend this trust to offline environments (57). On the one hand, reputation can reflect a doctor's level of service ability, providing patients with objective information about the doctor's professional competence and service quality. On the other hand, reputation can also promote the reduction of uncertainty in patients' use of the platform. When patients are faced with numerous choices, they often tend to choose doctors with higher reputations because these doctors can provide them with more reliable and professional services. Based on the above discussion, we make the following assumptions:

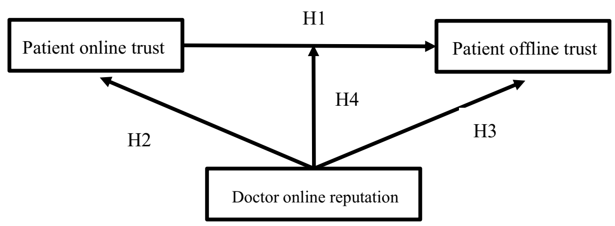

FIGURE 1
Research model.

H4: The relationship between patient trust online and offline will be positively moderated by the online reputation of doctors.

3.3 Research model

We have constructed an online and offline trust model for patients based on the assumptions mentioned above, as shown in Figure 1.

4 Method

4.1 Variables

4.1.1 Dependent variable and independent variable

(1) Patient offline trust

This variable is the main dependent variable in this study, as it reflects the patient's decision to ultimately choose a doctor for offline treatment. Trust, as a complex social psychological phenomenon, is often difficult to quantify directly, but we can infer patients' level of trust from their behavior (58). In this study, we assume that the behavior of patients choosing specific doctors for offline consultations is a direct reflection of their trust in doctors. To quantify patients' offline trust, we chose the total number of offline appointments received by doctors as the measurement indicator. This is because only when patients have a high level of trust in the doctor's professional ability, service attitude, patient evaluation, and other aspects, will they choose this doctor for offline treatment when needed. The number of offline appointments not only represents the actual behavioral choices of patients, but also indirectly reflects their level of trust in the doctor.

The offline appointment volume of patients on online medical platforms refers to the behavior of patients agreeing with doctors through online platforms to receive face-to-face diagnosis and treatment services at specific times and locations during a specific time period. This behavior usually occurs when the patient has a preliminary understanding or experience of the doctor's services and decides to further receive their professional treatment or health guidance. In the Good Doctor Medical Platform, the total number of consultations on this front line is automatically calculated and displayed to users on the platform's webpage. This indicator can be directly obtained through the online medical platform webpage.

(2) Patient online trust

Patient online trust plays an important role in this study, serving as both the dependent variable in the early stages and a significant factor influencing patient offline trust. On online medical platforms like "Good Doctor," patients can gain a preliminary understanding of doctors by browsing their personal information, historical evaluations, professional expertise, and other information, and establish trust in doctors based on this information (58). When a patient chooses to initiate an online consultation with a doctor, this behavior itself can be seen as a manifestation of the patient's trust in the doctor online. The more online consultations there are, the more patients choose this doctor for consultation, indirectly reflecting the popularity of doctors on online platforms and the level of trust among patients. In order to quantify patients' online trust, we chose the total number of doctors' online consultations as the measurement indicator.

The online consultation volume of patients on an online medical platform refers to the total number of patient consultations received by a doctor on the platform during a specific time period. The "online consultation" referred to here includes all online medical behaviors such as disease consultation, health guidance, and online consultation. This quantity reflects the level of patient acceptance of a certain doctor's service in online healthcare. In the Good Doctor Medical Platform, the total number of consultations on this front line is automatically calculated and displayed to users on the platform's webpage. This indicator can be directly obtained through the online medical platform webpage.

(3) Doctor's online reputation

Patient online comments reflect the true experience and satisfaction of patients, which is an important indicator for measuring the quality and reputation of doctors' services (59). Patients share their medical experiences through online platforms such as medical forums, health communities, or specialized doctor evaluation websites, and evaluate the doctors' service attitude, professional level, treatment effectiveness, and other aspects. These comments are not only a direct reflection of patients' real experiences and satisfaction, but also provide valuable reference information for other patients, thereby affecting their trust and choice of doctors (60). The importance of doctors' online reputation is self-evident. If a doctor has numerous positive and detailed online reviews, it often means that he has gained recognition and trust from a large number of patients (61). The wide coverage and real-time nature of online comments are its unique advantages in measuring doctors' online reputation. With the popularity of the Internet, the real-time nature of online comments enables doctors' reputation to quickly update and reflect the latest patient evaluations, providing timely and accurate data for research. Therefore, this study measured the online reputation of doctors using the content of patients' online comments.

4.1.2 Control variables

In order to more accurately study the relationship between patient trust and doctors' online reputation, we need to effectively identify and control other factors that may affect patient trust (62). In this study, there are two variables: hospital level and doctor title. The title of doctor is an important criterion for measuring the professional level and experience of doctors. In this study, we mainly focused on the clinical titles of doctors and divided them into four levels: chief physician, associate chief physician, attending physician, and resident physician. Meanwhile, as the vast majority of doctors are at the level of chief physician and associate chief physician, and the proportion of physicians at other levels in the sample is extremely low, we focus on chief and associate chief physicians (Title1 = associate chief physician, Title2 = chief physician, measured using 0–1 variables). Hospital level is another important control variable. In China, hospital levels are usually divided into Grade 3, Grade 2, and Grade 1 (Grade 1 = Grade 1 hospital, Grade 2 = Grade 2 hospital, Grade 3 = Grade 3 hospital, with corresponding measurement values of 0, 1, and 2). Table 1 shows the meanings and measurement methods of different variables.

Among the seven variables mentioned above, the four variables of patient offline trust, patient online trust, doctor title, and hospital level can be relatively easily obtained from online medical platforms through direct data statistics. Specifically, patient offline trust can be quantified by the number of offline appointments obtained by doctors; Patient online trust can be measured by counting the number of online consultations received by doctors; the doctor's professional title and hospital level can be directly obtained from the doctor's personal page information. However, the three variables of professional competence, service attitude, and treatment effectiveness are not so easily obtained directly. In this study, we extracted and measured online comment texts through analysis and mining. This is because patient reviews often include multiple aspects of their evaluation of the doctor, including the accuracy of the doctor's diagnosis, the rationality of the treatment plan, surgical skills, communication methods, service attitude, etc.

In the following research, we will provide a detailed introduction to the feature mining and mapping methods of online user comments. The main purpose of this method is to extract features related to doctors' professional abilities, service attitudes, and treatment outcomes from a massive amount of patient comments. Specifically, we will use natural language processing (NLP) and text mining techniques to perform segmentation, part of speech tagging, sentiment analysis, and other processing on comment texts, in order to extract keywords, phrases, or sentences related to professional competence, service attitude, and treatment effectiveness (63). Then, we quantify these extracted features, such as calculating the frequency of keywords or phrases, emotional tendencies, etc., to evaluate the performance

TABLE 1 Variable description and measurement.

Variable	Describe	Symbol	Measure
Patient offline trust	Patient offline trust behavior	OFT	Number of patients who make offline appointments with doctors
Patient online trust	Patient online trust behavior	ONT	Number of patients who consult doctors online
Professional competence	Extract content from comment texts	PC	Mentioning this feature: 1, otherwise 0 Extract the sum of features
Service attitude	Extract content from comment texts	TE	Mentioning this feature: 1, otherwise 0 Extract the sum of features
Treatment effect	Extract content from comment texts	SA	Mentioning this feature: 1, otherwise 0 Extract the sum of features
Doctor's title	Doctor's clinical title	Title	Title 1 and Title 2 represent the deputy director and chief physician, respectively, with a measurement variable range of [0, 1]
Hospital level	The level of the hospital where the doctor is located	Grade	Grade 1 = First level hospital Grade 2 = Second level hospital Grade 3 = Third level hospital, Variable range of [0–2]

of doctors in these areas. In this way, we can transform the three variables of professional competence, service attitude, and treatment effectiveness that were originally hidden in the comment text into observable and quantifiable indicators, thereby more comprehensively evaluating the performance of doctors and the trust level of patients.

4.2 Feature mining and mapping methods

4.2.1 Feature mining

The latent Dirichlet distribution reveals the similarity between elements in observed data sets (such as document sets) by introducing hidden layers (i.e., latent themes or topics) (64). As an unsupervised machine learning method, it has been widely applied in natural language processing. The core idea of LDA is to assume that each document is a mixture of multiple potential topics, and each topic is composed of a series of words in the vocabulary according to a certain probability distribution. When faced with a large amount of online user comment data, LDA can help us effectively mine the implicit topic features in the comments. These thematic features often reflect users' overall evaluation and focus on a certain product or service. In order to better utilize LDA for feature mining of comments, we need to preprocess the original comment text. The first step in preprocessing is to convert the comment text into a Bag of Words (BOW) pattern (65). When converting comment text into bag of words mode, we first need to segment the text. Due to the lack of clear separators between Chinese words, word segmentation is an essential step in Chinese text processing. Through word segmentation, we can divide continuous Chinese text into discrete word units, laying the foundation for subsequent text representation and analysis. After the word segmentation is completed, we need to further clean the text data. The purpose of this step is to remove noisy information from the text, such as stop words (common but meaningless words like "de" and "is"), special characters, HTML tags, etc. Through data cleaning, we can improve the quality of text and enable LDA models to more accurately capture thematic information in the text. After processing the comment text collection through a word segmentation tool, a valuable set of text words w_{ij} is formed.

$$x_i = \{w_{i1}, ...w_{ij}, ...\} \quad (1)$$

For example, as shown in Figure 2, given an online review of a coronary heart disease patient, if the content of the review posted by the reviewer x_1 = "Due to discomfort, I underwent a follow-up examination. Thanks to Director Liu's strong professional ability and accurate judgment, I was able to detect the narrow area that was almost missed in the first place. I guided the team to perform a difficult intervention treatment, which perfectly solved the hidden problem. At the same time, it was rechecked and found that the stent was in good condition a year ago. Thank you to Director Liu's team for your superb medical skills, which enabled me to effectively recover and fill my future life with sunshine." We can intuitively see that multiple characteristic words are mentioned in this comment, so we can conclude that x_1 = {Strong professional ability, accurate judgment, timely detection, high difficulty intervention treatment, perfect solution to hidden worries, good condition, superb medical skills, effective rehabilitation}.

Then, we analyze the set of comment data $X = \{x_i\}$ Using latent topic model LDA algorithm for feature content mining, generating a series of feature sets $T = \{T_j\}$:

$$T_j = \{t_{j1}, ...t_{jk}, ...\} \quad (2)$$

Among them, t_{jk} is the feature word associated with the feature T_j. Table 2 presents the extracted features and examples of feature words.

4.2.2 Mapping method

When dealing with massive online user comments, directly applying data mining algorithms for feature mining often faces the challenge of data sparsity. Data sparsity is a common

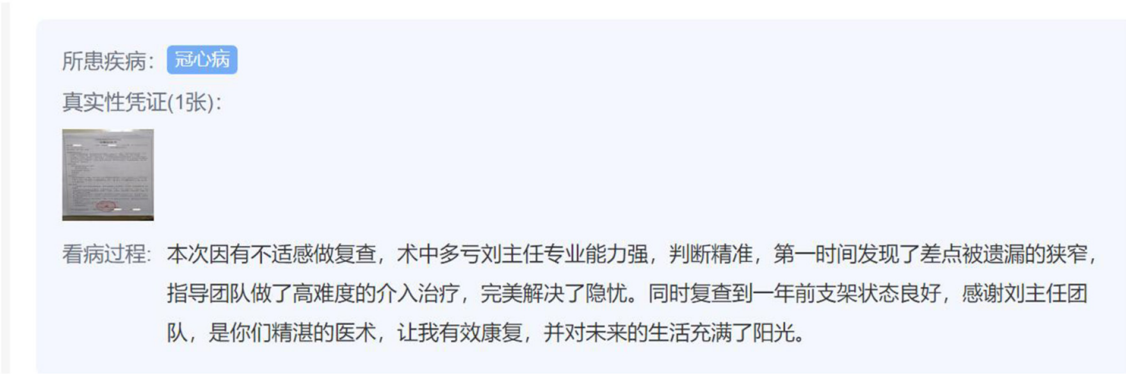

FIGURE 2
Example of online user comment retrieval page.

TABLE 2 Features and related vocabulary.

T_j	Feature	Related feature words
T_1	Professional competence	For example: strong professional ability, accurate judgment, superb medical skills, high difficulty intervention therapy
T_2	Service attitude	For example, discovering at the first time
T_3	Treatment effect	For example: perfectly resolved hidden concerns, in good condition, and effectively recovered

issue, especially in the field of text processing, which is mainly caused by the following factors: firstly, due to the diversity of commenters' backgrounds, their educational level, motivation for posting comments, and personal habits can all affect their word choice. This leads to a diversity of word expressions in the comment text, which in turn makes the distribution of features sparse (66). For example, for the same service or product, different reviewers may use completely different vocabulary to describe their experiences and feelings. Secondly, there are a large number of synonyms or synonyms in language, which, although expressing similar meanings, are regarded as different features in the text. This further exacerbates the sparsity of feature data. This situation is particularly evident in online medical reviews, as reviewers may use different vocabulary to describe the same medical experience or emotion. Furthermore, online user comments, as a form of emotional expression, typically have a more free and colloquial writing style. Although this expression is intuitive and easy to understand, it also leads to a large amount of non-standard vocabulary and expressions in the text. At the same time, due to the medical field involved in the comments, it is inevitable to involve some professional terms, such as disease types, surgical names, and medication situations. The emergence of these professional terms further increases the complexity of feature data.

In order to address the lack of feature reflecting data in massive comments, we adopted the method of mapping features through comments. Its core lies in achieving the transformation from text to feature set based on the semantic distribution of words. Regarding the dataset $\cup\{x_i\}$, If the conditions are met $|T_j \cap x_j| \geq 0$, it is believed that features were mentioned in the comment text x_i.

For example, as shown in Figure 3, given a comment text x_2 = "Dr. Zhang's diagnosis was accurate, the surgery was performed quickly, and the postoperative feeling was good. Thank you to Dr. Zhang. Dr. Zhang has been tracking the recovery situation after the surgery, reviewing the results of the follow-up examination, and providing detailed responses. Thank you very much," By using the "comment feature" mapping method, then x_1 can be expressed as: x_1 = {Accurate diagnosis, fast surgery, good postoperative feeling, continuous tracking of recovery after surgery, detailed response}. Based on the above method, we obtain a feature set that includes service attitude, treatment effectiveness, and professional competence. Based on the feature set, we can convert text statements into comment feature vectors.

4.3 Data collection

The data sample of this article comes from "Haodafu," the largest online medical platform in China. The platform not only provides online services such as graphic and textual consultations, but also offers offline appointment functions, which allows us to simultaneously examine the trust status of doctors both online and offline. We can calculate online trust by counting the number of patients received by doctors online, and predict offline trust based on the number of appointments with doctors offline. This dual dimensional trust assessment method can more comprehensively and accurately reflect the trust relationship between doctors and patients.

In order to ensure the accuracy and completeness of the data, we have adopted a web data scraping program (crawler) to automatically collect relevant information from the online website of Good Doctor. By programming specific rules and parameters, crawlers can simulate user browsing behavior, automatically capture and organize the data we need, such as doctor information

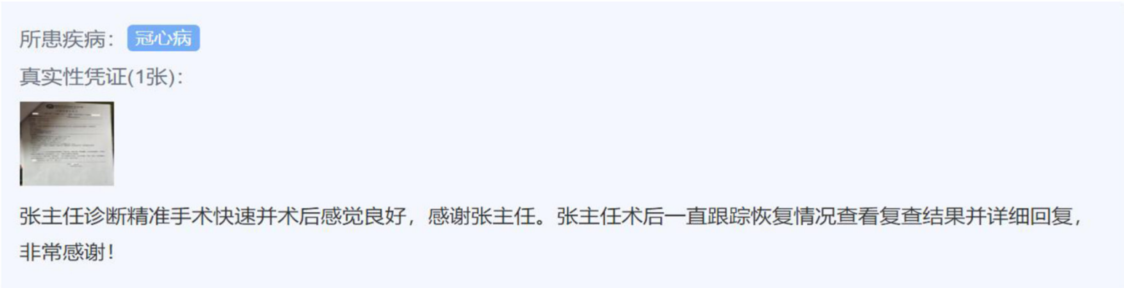

FIGURE 3
Example of online user comment retrieval page.

and patient evaluations. It is worth noting that although the platform provides both online and offline medical services, the number of offline consultations is much lower compared to online consultations. These doctors usually conduct related medical activities online while conducting offline diagnosis and treatment. We should focus on these types of doctors as the main research subjects. This choice helps us to have a more comprehensive understanding of the trust status of doctors in different service scenarios, as well as the correlation and differences between these trust statuses.

As shown in Figure 4, the above picture is the online comment interface of Good Doctor that we randomly captured. Here, X represents the collection of captured comments, and $x_i \epsilon X, (i = 1, ..., |X|)$ represents the comment of i.

When conducting this study, we initiated the collection of doctor data on July 1, 2022. Based on the specific needs of the research, we first collected the website links of all doctors who provided online appointment services on that day. Subsequently, we used these URLs to automatically access the doctor's homepage and extracted their homepage information. Next, we conducted a detailed screening based on the completeness of the homepage information and whether it contained user comment text, to ensure that the final obtained doctor data was comprehensive and met our research standards.

4.4 Distribution

When processing and analyzing raw comment texts captured from the "Good Doctor" online medical platform, we face a difficult challenge, which is that these comment data do not have clear labels or clues to directly identify the key features of user discussions. However, the rich information contained in these comments is crucial for understanding patients' needs, doctors' service quality, and the trust relationship between doctors and patients. In order to extract valuable information from a massive amount of comment texts, we used a Java version based on LDA (Latent Dirichlet Allocation) to extract features from 597,623 comments. LDA is an unsupervised machine learning algorithm used to discover hidden themes or features from a collection of texts (67). However, a major limitation of LDA is the need to pre-set two key parameters before running: "number of features" and "number of associated words for each feature."

In traditional LDA method applications, the setting of these two parameters usually depends on the researcher's experience or experimental attempts. In this study, a series of experiments were conducted to ensure that the mined features fully reflect the essence of the comment data. We set multiple feature numbers ranging from 1 to 20 and used the perplexity metric to evaluate the performance of the LDA model under different parameters. Confusion is an indicator that measures the degree to which a model fits text data, with a smaller value indicating better model performance. After multiple repeated experiments, we found that when the number of features is set to 3, the perplexity of the LDA model reaches its lowest level, which means that the model can best capture hidden features in the comment data. Therefore, we chose 3 as the most suitable number of features.

However, relying solely on unsupervised LDA algorithms to mine features in comments may have limitations. In order to further improve the accuracy and completeness of feature mining, we introduced a semi supervised method (68). Specifically, we used a word vector based representation method that can capture the semantic relationships between words. By calculating the semantic similarity between the feature related words mined by LDA and other words, we can select words that are similar to these feature words, thereby expanding the range of feature related words. In order to ensure that each feature is sufficiently complete, we utilized manual adjustment to further improve the feature related words, and achieved the transformation from text to feature word set through mapping. If there are words with associated features in the comments, set the value corresponding to that feature to 1; otherwise, set it to 0. Through this approach, we can quantitatively evaluate the level of mention of each feature in each comment. Finally, we accumulated and summarized the feature word frequencies of all doctors, and obtained the total numerical values of each doctor on each feature. This step not only helps us understand the performance of doctors in different aspects, but also provides an important data foundation for subsequent analysis and evaluation. Table 3 presents the characteristics of online user comment content and typical characteristic words used to express this feature.

FIGURE 4
Example of capturing user comments from good doctor online.

TABLE 3 Features mentioned in online comment texts.

Feature	Typical characteristic words (top 5)
Professional competence	Highly skilled, accurate in judgment, exquisite, professional, efficient
Service attitude	Responsible, meticulous, patient, caring, respectful
Treatment effect	Recovery, rehabilitation, restoration of health, stability, improvement of condition

5 Data

5.1 Statistical analysis

We also collected and analyzed data related to the personal pages of doctors on the Good Doctor online platform. Table 4 shows the specific analysis results.

When conducting statistical analysis on the dataset, we noticed that the data distribution presented in Table 4 exhibits skewness. In order to ensure the accuracy and effectiveness of data analysis, we have decided to implement logarithmic processing on all variables involved to correct this skewed distribution. Logarithmic processing is a commonly used data conversion method that can effectively reduce data skewness, making the originally skewed data closer to a normal distribution, thereby making subsequent data analysis more accurate and reliable. To evaluate whether the logarithmically transformed variables are affected by multicollinearity, we calculated the variance inflation factor (VIF) for each variable. VIF is an important indicator for measuring the severity of multicollinearity, and it is generally believed that multicollinearity problems are not significant when the VIF value is <10. According to our calculations, the VIF values of all variables are below 10, indicating that the issue of multicollinearity between variables is not severe after logarithmic transformation and will not have a significant impact on our research (69).

5.2 Model

Patient online and offline trust are the focus of this study, as they are continuous dependent variables. Based on this, we chose multiple linear regression method for data analysis. In order to explore in depth how the independent variable and a potential moderating effect affect these two dependent variables, we constructed three models with the following specific formulas:

$$\begin{gathered} \ln ONT = \alpha_0 + \alpha_1 Grade1 + \alpha_2 Grade2 + \alpha_3 Grade3 \\ +\alpha_4 Title1 + \alpha_5 Title2 + \alpha_6 \ln PC + \alpha_7 \ln SA + \alpha_8 \ln TE + \varepsilon \end{gathered} \tag{3}$$

$$\begin{gathered} \ln OFT = \beta_0 + \beta_1 Grade1 + \beta_2 Grade2 + \beta_3 Grade3 \\ +\beta_4 Title1 + \beta_5 Title2 + \beta_6 \ln PC + \beta_7 \ln SA + \beta_8 \ln TE \\ +\beta_9 \ln ONT + \mu \end{gathered} \tag{4}$$

$$\begin{gathered} \ln OFT = \gamma_0 + \gamma_1 Grade1 + \gamma_2 Grade2 + \gamma_3 Grade3 \\ +\gamma_4 Title1 + \gamma_5 Title2 + \gamma_6 \ln PC + \gamma_7 \ln SA \\ +\gamma_8 \ln TE + \gamma_9 \ln ONT + \gamma_{10} \ln PC \times \ln ONT \\ +\gamma_{11} \ln SA \times \ln ONT + \gamma_{12} \ln TE \times \ln ONT + \theta \end{gathered} \tag{5}$$

Model 1: In this model, we focus on the dependent variable—patient online trust. To more accurately predict patient online trust, we included several key variables. Firstly, professional competence, service attitude, and treatment effectiveness are set as explanatory variables, which directly reflect the performance of doctors in medical services. In addition, we also considered hospital level and

TABLE 4 Descriptive statistical analysis of variables.

Variable	Minimum value	Maximum value	Mean value	Standard deviation	Median
OFT	0	17,065	426.54	587.25	206
ONT	2	49,342	2,768.86	3,986.12	1,428
PC	0	6,232	42.56	142.48	27
SA	0	8,965	71.24	205.32	19
TE	0	10,324	608.45	827.65	249

doctor title as control variables, which may affect patients' trust in doctors' online services.

Model 2: Similar to Model 1, Model 2 also explores the relationship between doctor performance and patient trust. However, in this model, we shifted our focus to patient offline trust. In addition to the three explanatory variables of professional competence, service attitude, and treatment effectiveness, we also specifically included patients' online trust as an explanatory variable to examine the impact of online trust on offline trust. Hospital level and doctor's professional title are still included as control variables.

Model 3: This model is a further extension of Model 2. In addition to the original explanatory and control variables, we have also added corresponding interaction terms, which are composed of the multiplication of professional competence, service attitude, treatment effectiveness, and online trust variables. The design of interaction items aims to explore the possible interactions between these factors and how they collectively affect the level of patient offline trust.

5.3 Result analysis

Table 5 shows the specific results of regression analysis. Patient trust model 1 only has control variables, while model 2 has added explanatory variables. After adjustment, the latter $R^2 = 0.689$, that is to say, patients' online trust can be explained 68.9% by controlling for variables and independent variables. In patient offline model 1, there are only control variables. In model 2, explanatory variables have also been added. In model 3, in addition to control and explanatory variables, we have also added interaction terms. The results showed that the adjusted values R^2 for models 2 and 3 were 0.597 and 0.648. That is to say, patient offline trust can be explained 59.7% by controlling for variables and independent variables, and adding interaction terms on this basis, patient offline trust can be explained 64.8%. The above models all have good fit and interpretability.

Observing the Table 5, it can be seen that Model 2 of online trust has a significant regression coefficient, and professional competence, service attitude, and treatment effectiveness all have a significant impact on patients' online trust. It is worth noting that the impact of treatment effect is the greatest ($\beta = 0.596$, $p < 0.001$), which strongly indicates that treatment effect is the most important factor for patients to evaluate doctors online. In contrast, the influence of professional competence is the smallest ($\beta = 0.053$, $p < 0.001$), indicating that professional competence also has a significant impact on patients' online trust, but its degree of influence is relatively small. It is interesting that the influence of service attitude ($\beta = 0.198$, $p < 0.001$) even exceeds professional competence. This finding reveals that in the modern medical environment, patients have very high expectations and requirements for doctors' service attitude, which greatly affects patients' online trust in doctors.

According to the explanatory power of offline trust model 2, it can be found that patients' offline trust is directly affected by the treatment effect of doctors and online trust, especially the influence value of offline trust has reached 0.634, indicating a particularly significant impact. This means that patients often form initial trust in doctors through online channels before engaging in offline communication, which will directly affect the effectiveness of offline communication and patient satisfaction. In addition, besides the insignificant effect of professional competence on patients' offline trust, service attitude has a significant impact on patients' offline trust ($\beta = 0.102$, $p < 0.01$), and treatment effectiveness also has a significant impact on patients' offline trust ($\beta = 0.131$, $p < 0.001$). This indicates that the service attitude of doctors is an important factor for patients to consider when evaluating offline trust. A good service attitude can increase patients' comfort and trust, thereby improving their satisfaction and trust in doctors' offline services. Meanwhile, the treatment effect remains one of the most concerning aspects for patients, as it directly affects their health and recovery. When the doctor's treatment effect is significant and can effectively solve the patient's health problems, patients will naturally have higher trust and satisfaction with the doctor. Therefore, the treatment effect is also an important factor that patients cannot ignore when evaluating offline trust.

In Model 3 of patient offline trust, we specifically focused on the impact of interaction terms to reveal possible interactions between different factors. Firstly, it is worth noting that in addition to professional competence, service attitude ($\beta = 0.012$, $p < 0.01$) and treatment efficacy ($\beta = 0.029$, $p < 0.01$) both showed significant positive effects in the interaction terms of Model 3. This indicates that when patients perceive doctors to have a positive and friendly service attitude, they are more likely to trust doctors in the offline environment. The enhancement of this sense of trust not only comes from patients' online trust, but is also deeply influenced by doctors' service attitude. Similarly, the therapeutic effect plays a crucial role in the formation of offline trust among patients. Patients often use the treatment effect as a key indicator to evaluate the ability of doctors and the quality of medical services. When the treatment effect is significant, patients are more likely to trust doctors and are willing to continue receiving their offline medical services. In addition, the explanatory power of Model 3 has improved compared to previous models, mainly due to the introduction of interaction terms. The introduction

TABLE 5 Results of multiple linear regression.

Variable	Patient online trust		Patient offline trust		
	Model 1	Model 2	Model 1	Model 2	Model 3
Constant	5.379*** (0.078)	3.295*** (0.054)	4.512*** (0.091)	−1.093*** (0.157)	−0.64*** (0.283)
Third level hospital (Grade 1)	0.242*** (0.062)	0.151*** (0.024)	0.341** (0.059)	0.339** (0.046)	0.237*** (0.054)
Second level hospital (Grade 2)	0.124** (0.059)	0.158** (0.024)	0.119*** (0.048)	0.258** (0.042)	0.160** (0.051)
First level hospital (Grade 3)	−0.063** (0.067)	−0.144** (0.035)	−0.285* (0.076)	−0.200 (0.063)	−0.197** (0.058)
Chief Physician (Title 1)	0.164** (0.085)	0.158*** (0.034)	0.149*** (0.087)	0.413*** (0.064)	0.436*** (0.064)
Deputy Chief Physician (Title 2)	−0.045 (0.078)	−0.148 (0.038)	0.291* (0.093)	0.286* (0.061)	0.276*** (0.061)
Patient online trust (ONT)				0.634*** (0.027)	0.564*** (0.043)
Professional competence (PC)		0.053*** (0.008)		0.032 (0.064)	0.051 (0.048)
Service attitude (SA)		0.198*** (0.008)		0.102** (0.015)	0.115** (0.015)
Treatment effect (TE)		0.596*** (0.008)		0.131*** (0.012)	0.218*** (0.012)
PC × ONT					0.009 (0.038)
SA × ONT					0.012** (0.008)
TE × ONT					0.029** (0.008)
N	4,526	4,526	4,526	4,526	4,526
Adjusted R^2	0.012	0.689	0.034	0.597	0.648
F	3.56***	707.13***	37.40***	423.60***	381.87***

*p< 0.05.
**p < 0.01.
***p < 0.001.

of interaction terms enables us to comprehensively consider the interactions between different factors, thereby more accurately predicting changes in patient offline trust. This discovery not only validates some hypotheses about the moderating effect of doctors' online reputation, but also provides us with a comprehensive understanding of the mechanism of patient trust formation. By comparing the regression results of different models, we can see more clearly the impact and mechanism of each factor on patient trust, providing useful references for future medical services and patient trust management. Table 6 details the hypothesis test results proposed in this paper.

TABLE 6 Regression coefficients and hypothesis testing results.

Hypothetical relationship	Results
Patient online trust → patient offline trust	Accept
Professional competence → patient online trust	Accept
Service attitude → patient online trust	Accept
Treatment effect → patient online trust	Accept
Professional competence → patient offline trust	Reject
Service attitude → patient offline trust	Accept
Treatment effect → patient offline trust	Accept
Professional ability × patient online trust → patient offline trust	Reject
Service attitude × patient online trust → patient offline trust	Accept
Treatment effect × patient online trust → patient offline trust	Accept

*p < 0.05.
**p < 0.01.
***p < 0.001.

5.4 Robustness test

In the initial data collection, we only obtained cross-sectional data at the same time point. Although these data revealed key factors affecting patient trust, the characteristics of cross-sectional data made it difficult for us to accurately evaluate the dynamic effects of these influencing factors over time. In order to gain a more comprehensive understanding of the long-term impact of these factors on patient trust, we collected sample data again on August 1, 2022, 1 month after the initial data collection. The doctors who provide offline diagnosis and treatment appointment services may change at different times. In order to ensure that the two rounds of data can match each other, we have processed the data appropriately. After screening, we successfully retained the data of 4,235 doctors corresponding to the first round of data. In order to more accurately evaluate the changes in the quality of doctor services and patient trust in a short period of time, we calculated the increment of online consultations and offline appointments during the month as a unit time. This indicator can intuitively reflect the improvement or decline of doctor service quality, as well as the trend of changes in patient trust. After incorporating these two incremental dependent variables into the model for the second round of analysis, we obtained the results shown in Table 7.

According to the analysis results, it can be found that the of model is at a high level, with strong explanatory power, and

TABLE 7 Results of robustness test.

Variable	Patient online trust		Patient offline trust		
	Model 1	Model 2	Model 1	Model 2	Model 3
Constant	5.418*** (0.078)	3.385*** (0.057)	4.632*** (0.091)	−1.087*** (0.164)	−0.83*** (0.292)
Third level hospital (Grade 1)	0.265*** (0.067)	0.184*** (0.032)	0.335** (0.054)	0.341** (0.052)	0.242*** (0.062)
Second level hospital (Grade 2)	0.136** (0.061)	0.162** (0.026)	0.121*** (0.052)	0.262** (0.044)	0.154** (0.063)
First level hospital (Grade 3)	−0.059** (0.063)	−0.156** (0.025)	−0.292* (0.074)	−0.208 (0.059)	−0.199** (0.064)
Chief Physician (Title 1)	0.174** (0.079)	0.161*** (0.032)	0.152*** (0.085)	0.425*** (0.068)	0.454*** (0.078)
Deputy Chief Physician (Title 2)	−0.049 (0.081)	−0.157 (0.036)	0.302* (0.094)	0.292* (0.065)	0.252*** (0.056)
Patient online trust (ONT)				0.641*** (0.024)	0.572*** (0.038)
Professional competence (PC)		0.053*** (0.009)		0.045 (0.029)	0.009* (0.015)
Service attitude (SA)		0.201*** (0.009)		0.112** (0.012)	0.134** (0.012)
Treatment effect (TE)		0.572*** (0.009)		0.129*** (0.012)	0.225*** (0.012)
PC × ONT					0.012 (0.032)
SA × ONT					0.018** (0.009)
TE × ONT					0.030** (0.009)
N	4,235	4,235	4,235	4,235	4,235
Adjusted R^2	0.397	0.678	0.402	0.502	0.552
F	3.62***	710.23***	37.40***	433.51***	383.84***

*p < 0.05.
**p < 0.01.
***p < 0.001.

can effectively predict changes in patient trust and doctor service performance. We found that in the second round of analysis, the impact of professional competence on patients' offline trust changed from insignificant to significant ($\beta = 0.009$, $p < 0.05$). This change may indicate that as time goes on and interaction between patients and doctors deepens, patients begin to pay more attention to the professional abilities of doctors. The improvement of professional skills can enhance patients' trust in doctors, thereby promoting an increase in the number of offline appointment registrations. The impact of other independent variables on patient trust and doctor service performance, apart from professional competence, remains consistent with the results of the first round of analysis. This result validates the robustness of our previously proposed hypothesis and model, demonstrating that the impact of these factors on patient trust is consistent across different time periods. Therefore, the robustness of the results of this study has been validated.

6 Discussion

6.1 Research conclusion

In the context of rapid development of digital healthcare, the interaction mode between patients and doctors is undergoing profound changes, and online medical consultation and services have become an important channel for patients to obtain medical information and treatment advice. However, the uncertainty brought by the online environment and the problem of information asymmetry between doctors and patients make it more complex to establish trust between doctors and patients online (70). This study conducted an in-depth analysis of the important factors that affect patients' online and offline trust, as well as the mechanism of trust transfer. The main conclusions are as follows:

Firstly, online healthcare provides patients with an unprecedented medical experience due to its convenience and immediacy. However, this virtual communication method also brings challenges in building trust (71). This study found that although there are many uncertainties in the online environment, the trust established by patients online can still significantly affect their trust in offline doctors, which reflects the practical significance of trust transfer theory. This discovery emphasizes the importance of online healthcare platforms in maintaining patient trust. In order to promote trust transfer, online medical platforms should strive to improve service quality, ensure accuracy and transparency of information, and strengthen professional training and certification of doctors to enhance patient confidence.

Secondly, the presentation of professional abilities in online healthcare differs from traditional offline healthcare. In the online environment, patients mainly perceive the professional abilities of doctors through their written descriptions, video consultations, and other means (72). Therefore, doctors need to pay more attention to improving their online communication skills and expression methods in order to effectively showcase their professional knowledge and experience in the online environment. Meanwhile, due to the time lag effect of establishing online trust on the perception of professional competence, online medical platforms can consider assisting patients in forming a comprehensive understanding of doctors' professional competence through patient evaluation, professional certification, and other methods.

Thirdly, service attitude also plays a crucial role in online healthcare. Online medical platforms should encourage doctors to demonstrate a positive and patient service attitude, and improve patient satisfaction and trust through instant replies, detailed answers, and other methods (73). In addition, online medical platforms can optimize service processes and improve service efficiency through technological means such as intelligent customer service and appointment reminders, thereby further enhancing patient trust.

Fourthly, treatment effectiveness, as a core element in building trust between doctors and patients, has shown significant impact in both online and offline healthcare. In order to improve the treatment effect, doctors need to continuously enhance their professional skills and medical level, while paying attention to communication and interaction with patients, understanding their needs and expectations. Online medical platforms can assist doctors in developing more personalized and accurate treatment plans by providing remote monitoring, data analysis, and other services, thereby improving treatment effectiveness and patient satisfaction (74).

In summary, there are significant differences between online healthcare and traditional offline healthcare in establishing trust between doctors and patients, but the two share commonalities in the core elements of trust building. This study provides useful suggestions for online medical platforms and doctors by analyzing the complex mechanisms of trust building between doctors and patients in both online and offline environments. In the future, with the continuous development and improvement of digital medical technology, online medical platforms should continue to explore how to better integrate online and offline resources, optimize medical service quality, enhance patient satisfaction, and establish a more stable doctor-patient trust relationship. At the same time, the government and regulatory agencies should strengthen supervision and guidance of online medical platforms to ensure the safety and effectiveness of online medical services, and provide patients with better quality medical services.

6.2 Theoretical contributions

Firstly, this study fills the gap in research on trust transfer mechanisms in the field of online healthcare by analyzing in depth the process of trust formation in patients' online medical platforms and how this trust is transferred to offline diagnosis and treatment activities. This discovery not only deepens our understanding of the dynamic evolution of trust, but also provides theoretical support for how online medical platforms can effectively promote trust transfer.

Secondly, this study not only focuses on a single path of trust transfer, but also comprehensively explores online and offline trust transfer from multiple dimensions, such as trust mechanisms, influencing factors, and conversion paths. This multidimensional analysis approach helps us to have a more comprehensive understanding of the complexity and diversity of trust transfer, providing new perspectives and methods for future research.

Furthermore, this study applies trust transfer theory to the emerging field of online healthcare platforms, which not only enriches the research content of trust in the medical field, but also provides new practical scenarios and theoretical support for the expansion of trust theory in the medical field.

6.3 Practical implications

The proposed integration model of online and offline services, online reputation management mechanism for doctors, and user feedback mechanism in this study provide specific practical guidance for online medical platforms on how to optimize service experience and enhance patient trust. These measures will help online medical platforms better meet the needs of patients and achieve seamless integration of online and offline medical services.

Specifically, we propose the following suggestions for policy makers:

Firstly, formulate policies for the integration of online and offline services. Promote the formulation of relevant policies, encourage the deep integration of online and offline medical services, and ensure that patients can enjoy continuous, consistent, and high-quality medical services across different service channels. Establish special funds or subsidies to support medical institutions in technological transformation and process optimization for the integration of online and offline services.

Secondly, establish an online reputation management system for doctors. Develop unified standards and methods for online reputation evaluation of doctors to ensure fairness and accuracy of the evaluation. Encourage third-party organizations to participate in the evaluation and certification of doctors' online reputation, and improve the transparency and credibility of reputation management.

Thirdly, improve the user feedback mechanism. Establish a sound mechanism for collecting, analyzing, and processing user feedback to ensure timely response and improvement of patient opinions. Making user satisfaction one of the important indicators for evaluating medical institutions and doctors, and linking it with medical insurance payments, professional title evaluations, etc.

Fourthly, strengthen Internet medical supervision. We will improve laws and regulations related to Internet medicine, clarify the responsibilities and obligations of all parties, and protect the rights and interests of patients. Strengthen the daily supervision and regular inspection of the Internet medical platform to ensure its compliance operation (75).

On the other hand, we offer the following suggestions to platform developers:

Firstly, optimize the online medical service experience. Utilize technologies such as big data and artificial intelligence to enhance the intelligence and convenience of online consultation, appointment registration, remote diagnosis and treatment services. Design a simple and intuitive user interface and operation process to lower the threshold for patients to use.

Secondly, strengthen the online reputation management function for doctors. Develop an online reputation display and evaluation system for doctors, allowing patients to evaluate and score doctors based on their real experiences. Introducing algorithms to dynamically update and rank the reputation of doctors, ensuring that high-quality doctors can stand out.

Thirdly, establish an efficient user feedback system. Develop multi-channel user feedback collection tools, including online questionnaires, customer service hotlines, social media, etc., to ensure the comprehensiveness and timeliness of feedback. Utilizing natural language processing and other technological means to intelligently analyze and classify user feedback, providing data support for improving services (76).

Fourthly, ensure data security and privacy protection. Strengthen data encryption and access control to ensure the security of patient personal information and medical data. Comply with relevant laws and regulations, clearly inform patients of the purpose and scope of data use, and obtain patient consent. The fifth is to promote technological innovation in the integration of online and offline services. Explore the use of technologies such as the Internet of Things and 5G to achieve seamless integration and collaboration of online and offline medical services. Develop intelligent medical devices that support remote monitoring, diagnosis, and treatment to improve the efficiency and accuracy of medical services (77).

In conclusion, this study reveals the key role of patient trust in the development of Internet medicine, and the importance of online and offline trust transfer mechanism. These findings will help policymakers and industry participants better understand and understand the development law of Internet medicine, so as to formulate more scientific and reasonable policies and management measures, and promote the healthy development of Internet medicine.

7 Research limitations and future prospects

Although we have made substantial progress in exploring the issue of patient trust on online medical platforms, revealing the phenomenon of patients transferring from online trust to offline trust in online medical platforms, we still face some research limitations, as follows:

(1) Method gap and model optimization

Although we employed text mining techniques for robust analysis, this study did not use qualitative methods such as patient interviews or focus groups to triangulate the results. This may affect the comprehensiveness and accuracy of our verification of trust transfer models. To make up for this deficiency, we plan to further conduct qualitative research in subsequent studies, through patient interviews and focus groups, to explore in depth the process of establishing and transferring patients' trust in online medical platforms, in order to more comprehensively validate and optimize our trust model.

(2) Contextual externalities and data acquisition

Due to limitations in data acquisition, this study may not fully reflect the changes and impacts of all relevant external factors. For example, certain policy shifts or technological adoption may have varying impacts in different regions or time periods. Future research can more accurately evaluate the effects of these external factors through broader data collection and analysis.

(3) Generalizability challenges and global perspective

The trust model proposed in this study may have limited applicability in different socio-cultural and regulatory environments. There are systemic differences in the global healthcare service system, including medical regulations, cultural backgrounds, patient behavior patterns, and other factors that may affect patients' trust building and transfer process toward online healthcare platforms. Therefore, we recognize that trust models may need to be adjusted and optimized accordingly in different environments. In order to meet this challenge, we plan to further investigate the impact of different social cultures and regulatory environments on trust models in future research, explore the trust transfer mechanism in the cross-cultural context, and how to adjust and optimize trust models in different environments to ensure their wide applicability.

In summary, by comprehensively considering issues such as method gaps, contextual externalities, generalization challenges, and deepening the understanding and strategy development of trust transfer mechanisms, we expect to achieve more comprehensive and in-depth results in future research, providing more effective support for trust building and patient trust transfer in online medical platforms. At the same time, we also look forward to collaborating with more researchers to jointly promote the development of this field.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

LL: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

References

1. Jie-Mein Goh GG, Agarwal R. The creation of social value: can an online health community reduce rural-urban health disparities? *MIS Q.* (2016) 40:247–63. doi: 10.25300/MISQ/2016/40.1.11

2. Jun G, Ninghao L, Mark L, Xia H. An interpretable classification framework for information extraction from online healthcare forums. *J Healthc Eng.* (2017) 2017:2460174. doi: 10.1155/2017/2460174

3. Song X, Jiang S, Yan X, Chen H. *Collaborative Friendship Networks in Online Healthcare Communities: An Exponential Random Graph Model Analysis*. Cham: Springer International Publishing (2014). doi: 10.1007/978-3-319-08416-9_8

4. Zhang Y, Qiu C, Zhang J. A research based on online medical platform: the influence of strong and weak ties information on patients' consultation behavior. *Healthcare.* (2022) 10:977. doi: 10.3390/healthcare10060977

5. Mahmut A, Mustafa A, Özgün Ü, Saba SE. The mediating role of hospital reputation in the effect of doctor reputation on patients loyalty. *Int J Healthc Manag.* (2023) 16:12–8. doi: 10.1080/20479700.2022.2062853

6. Yingli G, Hongwei W, Qiangwei X, Lijuan Z, Yunxiang S. Factors that determine a Patient's willingness to physician selection in online healthcare communities: a trust theory perspective. *Technol Soc.* (2021) 64:101510. doi: 10.1016/j.techsoc.2020.101510

7. Wu H, Lu N. Online written consultation, telephone consultation and offline appointment: an examination of the channel effect in online health communities. *Int J Med Inf.* (2017) 107:107–19. doi: 10.1016/j.ijmedinf.2017.08.009

8. Pollak F, Svetozarovova N, Malinak B. Multifactor analysis of online reputation as a tool for enhancing competitiveness of selected tourism entities. *Glob Bus Econ Rev.* (2018) 20:231–47. doi: 10.1504/GBER.2018.10010228

9. Hall MA, Dugan E, Zheng B, Mishra AK. Trust in physicians and medical institutions: what is it, can it be measured, and does it matter? *Milbank Q.* (2001) 79:613–39. doi: 10.1111/1468-0009.00223

10. Leape L, Berwick D, Clancy C, Conway J, Gluck P, Guest J, et al. Transforming healthcare: a safety imperative. *Qual Saf Health Care.* (2009) 18:424–8. doi: 10.1136/qshc.2009.036954

11. Yang TW, Wu YJ. A study on the influence of patient participation on patient trust-based on sample survey in China. *Front. Psychol.* (2018) 9:2189. doi: 10.3389/fpsyg.2018.02189

12. Zhang Z, Bickmore TW, Paasche-Orlow MK. Perceived organizational affiliation and its effects on patient trust: role modeling with embodied conversational agents. *Patient Educ Couns.* (2017) 100:1730–7. doi: 10.1016/j.pec.2017.03.017

13. Chang SE, Liu AY, Shen WC. User trust in social networking services: a comparison of facebook and linkedin. *Comput Human Behav.* (2016) 69:207–17. doi: 10.1016/j.chb.2016.12.013

14. Tucker JD, Wong B, Nie JB, Kleinman A. Rebuilding patient–physician trust in China. *Lancet.* (2016) 388:755–755. doi: 10.1016/S0140-6736(16)31362-9

15. Lyu Z, Wu S, Cai Z, Guan X. Patient–physician trust in china: health education for the public. *Lancet.* (2016) 388:2991–2991. doi: 10.1016/S0140-6736(16)32521-1

16. Thom DH, Wong ST, Guzman D, Wu A, Penko J, Miaskowski C, et al. Physician trust in the patient: development and validation of a new measure. *Ann Fam Med.* (2011) 9:148–54. doi: 10.1370/afm.1224

17. Calnan RM. Trust relations in health care—the new agenda. *Eur J Public Health.* (2006) 16:4–6. doi: 10.1093/eurpub/ckl004

18. Wang W, Zhang H, Washburn DJ, Shi H, Chen Y, Lee S, et al. Factors influencing trust towards physicians among patients from 12 hospitals in China. *Am J Health Behav.* (2018) 42:19–30. doi: 10.5993/AJHB.42.6.3

19. Deutsch M. Cooperation and trust: some theoretical notes. In: Jones MR, editor. *Nebraska Symposium on Motivation Nebraska Symposium on Motivation.* Lincoln, NE: University of Nebraska Press (1962), p. 275–319.

20. Rotter JB. Generalized expectancies for interpersonal trust. *Am Psychol.* (1971) 26:443–52. doi: 10.1037/h0031464

21. Brahm T, Kunze F. The role of trust climate in virtual teams. *J Manag Psychol.* (2012) 27, 595–614. doi: 10.1108/02683941211252446

22. Driscoll JW. Trust and participation in organizational decision-making as predictors of satisfaction. *Acad Manag J.* (1978) 21:44–56. doi: 10.2307/255661

23. Mayer RC, Davis JH, Schoorman FD. An integrative model of organizational trust. *Acad Manag Rev.* (1995) 20:709–34. doi: 10.5465/amr.1995.9508080335

24. Hwang P, Burgers WP. Properties of trust: an analytical view. *Organ Behav Hum Decis Process.* (1997) 69:67–73. doi: 10.1006/obhd.1996.2673

25. Doney PM, Cannon JP. An examination of the nature of trust in buyer-seller relationships. *J Mark.* (1997) 61:35–51. doi: 10.1177/002224299706100203

26. Stewart KJ. Trust transfer on the world wide web. *Organ Sci.* (2003) 14:5–17. doi: 10.1287/orsc.14.1.5.12810

27. Xu X. How do consumers in the sharing economy value sharing? Evidence from online reviews. *Decis Support Syst.* (2020) 128:1–13. doi: 10.1016/j.dss.2019.113162

28. Flaherty KE, Pappas JM. The role of trust in salesperson—sales manager relationships. *J Pers Sell Sales Manag.* (2000) 20:271–8. doi: 10.1080/08853134.2000.10754247

29. Punyatoya P. Effects of cognitive and affective trust on online customer behavior. *Mark Intell Plann.* (2019) 37:80–96. doi: 10.1108/MIP-02-2018-0058

30. Lu Y, Yang S, Chau PYK, Cao Y. Dynamics between the trust transfer process and intention to use mobile payment services: a cross-environment perspective. *Inf Manag.* (2011) 48:393–403. doi: 10.1016/j.im.2011.09.006

31. McKnight DH, Choudhury V, Kacmar C. Developing and validating trust measures for e-Commerce: an integrative typology. *Inf Syst Res.* (2002) 13:334–59. doi: 10.1287/isre.13.3.334.81

32. Sarkar S, Chauhan S, Khare A. A meta-analysis of antecedents and consequences of trust in mobile commerce. *Int J Inf Manage.* (2020) 50:286–301. doi: 10.1016/j.ijinfomgt.2019.08.008

33. Yang S, Chen Y, Wei J. Understanding consumers' web-mobile shopping extension behavior: a trust transfer perspective. *J Comput Inf Syst.* (2015) 55:78–87. doi: 10.1080/08874417.2015.11645759

34. Zhao J, Huang J, Su S. The effects of trust on consumers' continuous purchase intentions in C2C social commerce: a trust transfer perspective. *J Retail Consum Serv.* (2019) 50:42–9. doi: 10.1016/j.jretconser.2019.04.014

35. Harris LC, Goode MMH. The four levels of loyalty and the pivotal role of trust: a study of online service dynamics. *J Retail.* (2004) 80:139–58. doi: 10.1016/j.jretai.2004.04.002

36. Ko J, Chang BH. Effects of AI speaker's cognitive and emotional decision-making on ai trust. *Int J Contents.* (2023) 19:28–38. doi: 10.5392/IJoC.2023.19.2.028

37. Seckler M, Heinz S, Forde S, Tuch AN, Opwis K. Trust and distrust on the web: user experiences and website characteristics. *Comput Human Behav.* (2015) 45:39–50. doi: 10.1016/j.chb.2014.11.064

38. Guo X, Zhang X, Sun Y. The privacy–personalization paradox in mhealth services acceptance of different age groups. *Electron Commer Res Appl.* (2016) 16:55–65. doi: 10.1016/j.elerap.2015.11.001

39. Kesharwani A, Bisht SS. The impact of trust and perceived risk on internet banking adoption in India: an extension of technology acceptance model. *Int J Bank Market.* (2012) 30:303–22. doi: 10.1108/02652321211236923

40. Akter S, Ray P, D'Ambra JG. Continuance of mHealth services at the bottom of the pyramid: the roles of service quality and trust. *Electron Mark.* (2013) 23:2947. doi: 10.1007/s12525-012-0091-5

41. Jøsang A, Ismail R, Boyd C. A survey of trust and reputation systems for online service provision. *Decis Support Syst.* (2005) 43:618–44. doi: 10.1016/j.dss.2005.05.019

42. Judith K, Rense C, Arnout R. Trust, reputation, and the value of promises in online auctions of used goods. *Ration Soc.* (2023) 35:387–419. doi: 10.1177/10434631231170342

43. Amutha B, Gupta P, Kumar H. Website reputation system. *Int J Innov Technol Explor Eng.* (2019) 8:1228–33. doi: 10.35940/ijitee.K1248.09811S19

44. Gupta R, Ponnuru K, Kumar A, Trivedi SK. Factors identification of online reputation and relationship with trust: a study of generation Y. *Int J Bus Inf Syst.* (2017) 26:151–65. doi: 10.1504/IJBIS.2017.086326

45. Hyeon J. What drives recommendation intention and loyalty of online for offline (O4O) consumers? *Sustainability.* (2023) 15:4775. doi: 10.3390/su15064775

46. Yi MY, Yoon JJ, Davis JM, Lee T. Untangling the antecedents of initial trust in Web-based health information: the roles of argument quality, source expertise, and user perceptions of information quality and risk. *Decis Support Syst.* (2013) 55:284–95. doi: 10.1016/j.dss.2013.01.029

47. Casaló L, Flavián C, Guinalíu M. The role of perceived usability, reputation, satisfaction and consumer familiarity on the website loyalty formation process. *Comput Human Behav.* (2007) 24:325–45. doi: 10.1016/j.chb.2007.01.017

48. Wang N, Shen XL, Sun Y. Transition of electronic word-of-mouth services from web to mobile context: a trust transfer perspective. *Decis Support Syst.* (2013) 54:1394–403. doi: 10.1016/j.dss.2012.12.015

49. Naseri S, Taimouri A, Zare R, Emamisaleh K. Recognising the factors affecting customer trust in online banking services among Iranian banks. *EuroMed J Manag.* (2022) 4:298–314. doi: 10.1504/EMJM.2022.127442

50. Gao L, Waechter KA. Examining the role of initial trust in user adoption of mobile payment services: an empirical investigation. *Inf Syst Front.* (2017) 19:525–48. doi: 10.1007/s10796-015-9611-0

51. Racherla P, Friske W. Perceived 'usefulness' of online consumer reviews: an exploratory investigation across three services categories. *Electron Commer Res Appl.* (2012) 11:548–59. doi: 10.1016/j.elerap.2012.06.003

52. Noort GV, Willemsen LM, Kerkhof P, Verhoeven JWM. *Webcare as an Integrative Tool for Customer Care, Reputation Management, and Online Marketing: A Literature Review*. London: Palgrave Macmillan UK (2015).

53. Dellarocas C, Fan M, Wood CA. *Self-Interest, Reciprocity, and Participation in Online Reputation Systems*. New York, NY: Social Science Electronic Publishing (2004), p. 195–244.

54. Levin ZD, Cross R. The strength of weak ties you can trust: the mediating role of trust in effective knowledge transfer. *Manag. Sci.* (2004) 11:1463–613. doi: 10.1287/mnsc.1030.0136

55. Xiao L, Zhang Y, Fu B. Exploring the moderators and causal process of trust transfer in online-to- offline commerce. *J Bus Res.* (2019) 98:214–26. doi: 10.1016/j.jbusres.2019.01.069

56. Chang HH, Wong KH, Ho PW. The determinants of trust transfer on mobile shopping decision: flow experience as a moderator. *Int J Mob Commun.* (2019) 17:1. doi: 10.1504/IJMC.2019.10011897

57. Meng F, Guo X, Peng Z, Lai KH, Zhao X. Investigating the adoption of mobile health services by elderly users from a trust transfer perspective (preprint). *JMIR mhealth uhealth.* (2018) 7:e12269. doi: 10.2196/preprints.12 269

58. Lee V. Transparency and trust - online patient reviews of physicians. *N Engl J Med.* (2017) 376:197–9. doi: 10.1056/NEJMp1610136

59. Greaves F, Ramirez-Cano D, Millett C, Darzi A, Donaldson L. Use of sentiment analysis for capturing patient experience from free-text comments posted online. *J Med Internet Res.* (2013) 15:e239. doi: 10.2196/jmir.2721

60. Kanouse DE, Schlesinger M, Shaller D, Martino SC, Rybowski L. How patient comments affect consumers' use of physician performance measures. *Med Care.* (2015) 54:24. doi: 10.1097/MLR.0000000000000443

61. Jingfang L, Xin Z, Jun K, Liangyu W. The impact of teammates' online reputations on physicians' online appointment numbers: a social interdependency perspective. *Healthcare.* (2020) 8:509. doi: 10.3390/healthcare8040509

62. Yang W, Hong W, Xueqin L, Jingxuan S, Zhanchun F. The influence of doctors' online reputation on the sharing of outpatient experiences: empirical study. *J Med Internet Res.* (2020) 22:e16691. doi: 10.2196/16691

63. Guizhe S, Degen H, Zhifeng X. A study of multilingual toxic text detection approaches under imbalanced sample distribution. *Information.* (2021) 12:205. doi: 10.3390/info12050205

64. Jelodar H, Wang Y, Yuan C, Fen X, Jiang X, Li Y, et al. Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. *Multimed Tools Appl.* (2019) 78:15169–211. doi: 10.1007/s11042-018-6894-4

65. Soumya GK, Shibily J. Text classification by augmenting bag of words (BOW) representation with co-occurrence feature. *IOSR J Comput Eng.* (2014) 16:34–8. doi: 10.9790/0661-16153438

66. Wei CP, Chen YM, Yang CS, Yang C. Understanding what concerns consumers: a semantic approach to product feature extraction from consumer reviews. *Inf Syst e-Bus Manag.* (2010) 8:149–67. doi: 10.1007/s10257-009-0113-9

67. Khandani AE, Kim AJ, Lo AW. Consumer credit-risk models via machine-learning algorithms. *J Bank Finance.* (2010) 34:2767–87. doi: 10.1016/j.jbankfin.2010.06.001

68. Yu H, Yang J. A direct lda algorithm for high-dimensionaldata – with application to face recognition. *Pattern Recognit.* (2001) 34:2067–70. doi: 10.1016/S0031-3203(00)00162-X

69. O'Brien RM. A caution regarding rules of thumb for variance inflation factors. *Qual Quant.* (2007) 41:673–90. doi: 10.1007/s11135-006-9018-6

70. Gal-Oz N, Yahalom R, Gudes E. Identifying knots of trust in virtual communities. *Int Confer Trust Manag.* (2011) 358:67–81. doi: 10.1007/978-3-642-22200-9_8

71. Moore S. Towards a sociology of institutional transparency: openness, deception and the problem of public trust. *Sociology.* (2018) 52:416–30. doi: 10.1177/0038038516686530

72. Gefen D. E-commerce: the role of familiarity and trust. *Omega.* (2000) 28:725–37. doi: 10.1016/S0305-0483(00)00021-9

73. Morgan RM, Hunt SD. The commitment-trust theory of relationship marketing. *J Mark.* (1994) 58:20–38. doi: 10.1177/002224299405800302

74. Kangning W, Yuzhu L, Yong Z, Jing M. Trust, risk and transaction intention in consumer-to-consumer e-marketplaces. *Ind Manag Data Syst.* (2019) 119:331–50. doi: 10.1108/IMDS-10-2017-0489

75. Glaeser EL, Laibson DI, Scheinkman JA, Soutter CL. Measuring trust. *Q J Econ.* (2000) 119:811–46. doi: 10.1162/003355300554926

76. Hibbitt K, Jones P, Meegan R. Tackling social exclusion: the role of social capital in urban regeneration on merseyside — from mistrust to trust? *Eur Plann Stud.* (2001) 92:141–61. doi: 10.1080/09654310124536

77. Grimen H. Power, trust, and risk: some reflections on an absent issue. *Med Anthropol Q.* (2009) 23:16–33. doi: 10.1111/j.1548-1387.2009.01035.x

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 04 March 2025
DOI 10.3389/fpubh.2025.1561060

Check for updates

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Bingquan Lin,
East China Normal University, China
Quanen Guo,
Nanchang University, China

*CORRESPONDENCE
Chen Li
✉ lichen@sues.edu.cn

RECEIVED 15 January 2025
ACCEPTED 11 February 2025
PUBLISHED 04 March 2025

CITATION
Li X and Li C (2025) Promoting Healthy Aging: Physical Activity and Its Dual Effects on Physical Health and Cognitive Function in Chinese Older Adults.
Front. Public Health 13:1561060.
doi: 10.3389/fpubh.2025.1561060

Promoting Healthy Aging: Physical Activity and Its Dual Effects on Physical Health and Cognitive Function in Chinese Older Adults

Xing Li and Chen Li*

School of Management, Shanghai University of Engineering Science, Shanghai, China

Background: With the acceleration of societal aging, the physical health and cognitive function issues of seniors have increasingly garnered widespread attention. This article explores the impact of physical activity on the physical health and cognitive performance of seniors, aiming to provide a theoretical basis for health management and related policy formulation for seniors, which holds significant academic value and social significance.

Methods: This study constructs an ordered logit regression model to analyze the effects of physical activity on the physical health and cognitive performance of seniors, serving as the baseline model, and conducts a parallelism test to verify the model's applicability. To ensure the robustness of the results, various methods were employed for testing, including model substitution, replacement of independent and dependent variables, and the use of propensity score matching analysis. Through these methods, the marginal effects of physical activity on the physical health and cognitive performance of seniors were revealed, and further analysis was conducted on the heterogeneity of physical health and cognitive performance among different groups and regions of seniors.

Results: (1) Physical activity has a significant promoting effect on the physical health and cognitive performance of seniors. Seniors who engage in physical activity demonstrate markedly better physical health and cognitive abilities compared to those who do not participate in physical activity, indicating that physical activity has a positive effect on improving the physical health and cognitive performance of seniors. (2) Physical activity exhibits notable marginal effects on the physical health and cognitive performance of seniors. The probability of seniors who participate in physical activity experiencing improvements in physical health and cognitive performance significantly increases, while those who do not engage in physical activity show the opposite trend, with a decrease in the probability of improvement. (3) There is significant heterogeneity in the effects of physical activity on the physical health and cognitive performance of different senior groups. Specifically, seniors who are female, married, or living in urban areas exhibit more pronounced improvements in health and cognition after engaging in physical activity, indicating that the benefits of physical activity are particularly prominent in these groups.

Discussion: Seniors who participate in physical activity demonstrate significantly better physical health and cognitive abilities compared to those who do not engage in physical activity, suggesting that physical activity not only helps to delay physical aging but also effectively slows cognitive decline. Future policies should focus on enhancing the promotion and implementation of physical activity among seniors, especially within groups with differentiated needs, to advance the process of healthy aging and further enhance the overall well-being of the senior population.

KEYWORDS

physical activity, physical health, cognitive performance, seniors, ordered logit model

1 Introduction

With the acceleration of global aging, the physical health and cognitive function issues of the older adults population have become a significant challenge in the field of global public health. According to the World Health Organization's definition, health is not merely the absence of disease or infirmity, but a complete state of physical, mental, and social well-being. Therefore, improving the overall health level of the older adults population, particularly in terms of physical function and cognitive ability, has become an important issue in health policies across countries worldwide. In 2020, the World Health Organization released the "Global Guidelines on Physical Activity for Older Adults," advocating that regular participation in physical activities helps older adults improve their physical health, enhance muscle strength, and increase balance, while also promoting mental health and cognitive function, thereby reducing the risk of depression and anxiety. China's "Healthy China 2030 Planning Outline" also clearly states that the health of the older adults is a key component in achieving the Healthy China strategy, emphasizing that physical activity should be an effective means to promote the health of older adults, capable of preventing chronic diseases, delaying physical decline, and improving cognitive function.

According to existing research, the main factors influencing the health status of the older adults can be categorized into five major categories: natural attributes, socio-economic status, lifestyle, health conditions, and psychological factors (1). Among these five factors, lifestyle is a crucial determinant of health throughout the entire life course. Lifestyle generally includes smoking, alcohol consumption, physical activity, and participation in various activities. Among these, physical activity has become an internationally recognized strategy for promoting health in middle-aged and older adults due to its low cost and ease of participation (2). However, the proportion of older adults individuals participating in physical activities is currently low in many countries around the world, with a preference for moderate to low-intensity activities. Moreover, a common trend is that the level of participation in physical activities gradually declines with age (3–8). Therefore, there is an urgent need to encourage more older adults individuals to engage in physical activities, promote the implementation of healthy aging, and overall enhance the physical and mental health levels of the older adults population.

Currently, research on physical activity and the physical health and cognitive performance of seniors mainly focuses on the following aspects.

Firstly, the duration, intensity, and type of physical activity have an impact on the physical health and cognitive performance of the older adults. The benefits of physical activity for the physical health and cognitive performance of older adults are undeniable (1, 9). Existing research has found that physical activity is significantly positively correlated with both subjective and objective health; the higher the frequency of participation in physical activities, the better the subjective and objective health status (3). However, the "frequency" of physical activity does not adequately explain the "duration, intensity, and type," which requires further investigation. Chen classified physical activity intensity into vigorous, moderate, and light levels, and the propensity score matching results showed that participating in moderate activities could increase the probability of healthy aging for seniors by 0.76–0.78%, while vigorous and light physical activities had no significant impact on healthy aging (10). The research by Uchida indicated that low-intensity physical activity could improve lung function and physical condition, and is recommended for promoting the health of seniors (11). Other studies found that physical-cognitive dual-task physical activity games had the best intervention effects, followed by physical-cognitive combined activity games, and lastly, single physical or cognitive training. The frequency of physical activity game interventions was generally three times per week, with a duration primarily of 12 weeks, and intervention times ranging from 18 to 90 min, with each session gradually increasing from less to more, ultimately reaching 30 or 50 min (12–14). Carta verified through randomized controlled trials the effectiveness of moderate-intensity physical activity on the cognitive performance of seniors, indicating that moderate-intensity exercise could improve seniors' cognitive performance, particularly in memory and visual–spatial skills (15).

Secondly, the impact and mechanisms of physical activity on the physical health and cognitive performance of seniors. Physical activity can enhance the physical, mental, and social functions of the research subjects, improve the physical condition of seniors, and increase their immune system strength. For seniors with certain chronic diseases, it helps alleviate or maintain their conditions, thereby improving their physical condition and promoting physiological health. Svobodová et al. found that physical activity could improve seniors' aerobic capacity and endurance, with seniors engaging in physical activity showing significant improvements in indicators such as the 10-meter walking test and the 6-min walking test, indicating that endurance training helps enhance seniors' muscle strength and endurance, as well as improve coordination and balance, thus enhancing walking ability (16). Fang Guoliang et al. found that high-intensity interval training could significantly improve seniors' short-term memory, reaction speed, and resistance to interference in

Abbreviations: phyh, physical health; cog, cognitive performance; ac, physical activity; lightac, light physical activity; moderac, moderate physical activity; intenac, intensity physical activity; gender, gender; age, age; agesqr, age squared; marry, marry; edu, education; lninc, logarithm of household income; lnfacom, logarithm of household consumption per capita; lnfinasu, logarithm of children's financial support for parents; urban, urban; ADL, activities of daily living; IADL, instrumental activities of daily living; memory, contextual memory; mentim, mental image.

cognitive functions, although its effect on improving attention was not significant (17). Although there is no direct research indicating specific mechanisms through which physical activity affects seniors' cognitive functions, physical activity can improve cardiovascular function, increase blood supply and oxygen delivery to the brain, and sufficient blood and oxygen supply can maintain normal metabolism and function of neurons, enhancing the synthesis and transmission efficiency of neurotransmitters, thereby contributing to improved cognitive abilities.

Thirdly, there are differences in the impact of physical activity on the physical health and cognitive performance of older adults individuals with different characteristics. Among those who engage in regular physical activity, the probability prediction values for both subjective and objective health for middle-aged and older men are higher than those for middle-aged and older women. Regular physical activity has a greater positive effect on the health levels of middle-aged and older men who have experienced famine. Additionally, urban older adults individuals who have experienced famine and participate in physical activity occasionally or regularly have higher health probability prediction values than their rural counterparts with the same physical activity habits and famine experience (3). Research by Gonçalves A K and others found that physical fitness improves with training, but the effects vary across different age groups: physical training has a positive impact on the 60–69 and 70–79 age groups, while it has no significant effect on those aged 80 and above (18).

It is evident that the consensus in academia is that physical activity can enhance the physical health and cognitive abilities of the older adults, although the focus varies slightly by country. Some studies in European countries pay more attention to the effects of physical activity on brain structure and neural plasticity, while research in developing countries tends to emphasize the prevention and control of common chronic diseases through physical activity. Some findings are particularly novel and thought-provoking; for example, in Indonesia, physical activity can increase bone density, reduce fat accumulation, improve body mass index, lower the risk of musculoskeletal system damage, influence dopamine levels and changes in neurotrophic factors, and suppress cognitive decline and dementia. In Malaysia, physical activity is associated with cognitive function in the older adults, with walking improving cognitive abilities. In developed countries, physical activity is considered essential for maintaining physical function in older adults, improving quality of life, and preventing chronic diseases, with dance potentially having the greatest impact on enhancing cognitive abilities in healthy older adults. In China, physical exercise has been shown to significantly improve cognitive function in sedentary older adults patients with diabetes (19–26). However, there are still disagreements in academia regarding the intensity of physical activity, and research on the differences in the impact of physical activity on the physical health and cognitive performance of older adults individuals with different characteristics remains incomplete. Currently, there is no evidence to suggest that longer durations of physical activity, more frequent activities, or higher intensity levels lead to greater functional improvements (27). The optimal intensity of physical activity for enhancing the physical health and cognitive performance of the older adults still needs to be explored. Questions remain, such as whether higher intensity physical activity can lead to better health outcomes for older adults, whether there are marginal effects of physical activity on older adults health, and whether the impact of physical activity varies among different age groups, genders, and regions. There is currently no comprehensive and unified perspective in academia on these issues.

In light of the above issues, this paper aims to verify the impact of physical activity on the physical health and cognitive performance of seniors by constructing an ologit model. Based on this, it will explore the marginal effects of physical activity on seniors with different levels of physical health and cognitive performance, the differences in the effects of light, moderate, and vigorous physical activity on seniors of different age groups, as well as the heterogeneity in terms of gender, marital status, and urban–rural differences. Finally, combined with empirical findings, this study attempts to provide a scientific basis for health management and policy formulation for seniors, thereby promoting the overall improvement of societal health levels. This research not only has theoretical significance but also provides practical guidance for addressing public health challenges in an aging society.

Compared to existing research, the potential marginal contributions of this paper are as follows. First, this paper further verifies the positive impact of physical activity on the physical health and cognitive performance of seniors based on the ologit model, with robust results. Second, it explores the marginal effects of physical activity on seniors with different levels of physical health and cognitive performance. Third, it investigates the differences in the effects of light, moderate, and vigorous physical activity on seniors of different age groups, as well as the heterogeneity in terms of gender, marital status, and urban–rural differences, thereby supplementing existing evidence.

2 Data and methods

2.1 Data sources and variable selection

2.1.1 Data sources

The data for this study comes from the China Health and Retirement Longitudinal Study (CHARLS). CHARLS is a large-scale household survey led by the National School of Development at Peking University, which is nationally representative and covers 150 counties and 450 villages across 28 provinces (autonomous regions and municipalities) in China. In terms of survey content, the CHARLS questionnaire includes a wealth of individual and family information about middle-aged and seniors, encompassing their physical and mental health status represented by chronic diseases, disability levels, depression, and cognitive abilities, as well as demographic variables such as gender, age, marital status, and education level. This information provides data support for exploring the causal relationship between physical activity and the physical health and cognitive performance of seniors. Therefore, based on the research objectives, this study utilizes the latest fifth wave (2020) national follow-up data, which was officially released to the public on November 16, 2023. After data cleaning, samples of seniors aged 60 and above were retained, resulting in a final valid sample of 11,473.

2.1.2 Variable selection

2.1.2.1 Dependent variables

This article uses physical health and cognitive performance to reflect the health level of seniors, constructing the following indicators based on these two metrics:

First, physical health is composed of 12 categorical variables, including whether the individual has hypertension, diabetes, cancer, lung disease, heart disease, has had a stroke, arthritis, abnormal blood lipids, liver disease, kidney disease, stomach disease, or asthma. This article distinguishes the health status of the older adults based on the number of illnesses using Hu's method (28). Using the recode command in Stata software, physical health is categorized into five levels: very poor health, poor health, average health, good health, and very good health.

Second, cognitive performance indicators are constructed from two aspects: situational memory and mental memory. Situational memory is represented by phrase memory, which consists of immediate phrase recall and delayed phrase recall. Mental memory is represented by cognitive completeness, which includes date recognition, calculation, and drawing ability. The former is scored from 0 to 10, with higher scores being better, while the latter is scored from 0 to 11, also with higher scores being better. The combined cognitive performance score ranges from 0 to 21, with higher scores indicating better performance. This is based on Hu's analysis of cognitive function in the older adults from the CHARLS database (29). Using the recode command, cognitive performance is categorized into five levels: very poor, poor, average, good, and very good.

2.1.2.2 Core explanatory variable

The core explanatory variable is a binary variable indicating whether seniors aged 60 and above participate in physical activities, where 0 represents non-participation and 1 represents participation.

2.1.2.3 Control variables

Control variables include gender, age, age squared, marital status, education level, the logarithm of family income, the logarithm of per capita family consumption, and the logarithm of financial support from children to parents.

2.1.2.4 Other variables

For alternative variables, ADL and IADL are selected as substitutes for the dependent variable of physical health, while situational memory and mental memory are used as substitutes for cognitive performance. Light physical activities (primarily referring to walking, including moving from one place to another while working or at home, as well as other walking for leisure, exercise, or entertainment), moderate-intensity physical activities (activities that make the respondent breathe faster than usual, such as carrying light objects, cycling at a regular pace, mopping, practicing Tai Chi, or brisk walking), and high-intensity physical activities (intense activities that cause the respondent to breathe heavily, such as carrying heavy objects, digging, farming, aerobic exercise, fast cycling, or cycling with cargo) are selected as alternative variables for the core explanatory variable. For heterogeneity analysis, urban–rural status (0 indicates living in a rural area, 1 indicates living in an urban area), gender (0 indicates female, 1 indicates male), and marital status (0 indicates unmarried, 1 indicates married) are chosen as covariates for the heterogeneity analysis.

2.1.3 Descriptive statistics of the data

Table 1 shows the descriptive statistics of the variables.

In terms of the dependent variables, the average scores for physical health and cognitive performance are 2.90 and 3.22, respectively, indicating that the average score for cognitive performance is slightly higher than that for physical health. Based on the values assigned to physical health and cognitive performance, the health status of the surveyed seniors is at a moderate level. The standard deviation for physical health is 1.30, while the standard deviation for cognitive performance is 1.17, suggesting that the variability in physical health is greater. Both variables have a range of 4, indicating significant health disparities within the old people group.

TABLE 1 Descriptive statistics of variables.

Variables	*N*	Mean	sd	Min	Max
phyh	11,473	2.900	1.295	1	5
cog	7,142	3.219	1.173	1	5
ac	11,450	0.861	0.346	0	1
lightac	11,449	0.752	0.432	0	1
moderac	11,450	0.497	0.500	0	1
intenac	11,450	0.305	0.460	0	1
gender	11,473	0.482	0.500	0	1
age	11,473	70.046	7.201	60	120
agesqr	11,473	4,958.238	1,056.908	3,600	14,400
marry	11,473	0.774	0.418	0	1
edu	11,473	1.865	1.057	1	4
lninc	10,120	7.001	4.312	0	14.982
lnfacom	8,318	9.391	0.929	0	13.116
lnfinasu	11,473	7.087	3.026	0	13.065
urban	11,473	0.598	0.490	0	1
ADL	11,448	4.422	1.077	1	5
IADL	11,447	4.384	1.130	1	5
memory	9,526	3.166	1.239	1	5
mentim	7,239	3.166	1.123	1	5

Regarding different levels of physical activity, the proportions of surveyed seniors who have participated in light physical activity, moderate physical activity, and intense physical activity are 75.20, 49.70, and 30.50%, respectively, indicating that as the intensity of exercise increases, the participation rate among seniors decreases.

In terms of control variables, males constitute 48.20% of the surveyed seniors, indicating a relatively balanced gender distribution. The average age of the respondents is 70.05 years, with a minimum age of 60 years and a maximum age of 120 years. Regarding marital status, the proportion of those who are married reaches 70.05%, while nearly 30% of the senior respondents are not married, including widowed, unmarried, and divorced individuals.

In terms of educational attainment, 52.29% of the respondents have an education level of elementary school or below, 20.23% have completed elementary school, 16.20% have completed junior high school, and 11.28% have completed high school or higher, indicating that the overall educational level of the respondents is not high. The means for the logarithm of household income, the logarithm of household consumption per capita, and the logarithm of children's financial support for parents are 7.00, 9.39, and 7.09, respectively.

Regarding other variables, 51.00% of the surveyed seniors live in urban areas, while 49.00% reside in rural areas, indicating a relatively balanced urban–rural distribution among the respondents. Looking at activities of daily living (ADL) and instrumental activities of daily living (IADL), the mean scores after reverse coding are 4.42 and 4.38, respectively, indicating that most seniors do not require assistance with ADL and IADL and can generally manage their daily lives independently. In terms of contextual memory and mental imagery, both have a mean score of 3.17, suggesting that the cognitive performance of seniors is slightly above average.

2.2 Research methods

The dependent variables of seniors' physical health and cognitive performance are classified as ordinal variables, and an ologit regression can be used to estimate the impact of physical activity on seniors' physical health and cognitive performance. The equation of the ologit model can be expressed as:

$$\log\left[\frac{p(y\le 1)}{1-p(y\le 1)}\right]=\tau_1-b_1x_i \tag{1}$$

$$\log\left[\frac{p(y\le 2)}{1-p(y\le 2)}\right]=\tau_2-b_2x_i \tag{2}$$

$$\vdots$$

$$\log\left[\frac{p(y\le j-1)}{1-p(y\le j-1)}\right]=\tau_{j-1}-b_{j-1}x_i \tag{3}$$

$$\log\left[\frac{p(y\le j)}{1-p(y\le j)}\right]=\tau_j-b_jx_i \tag{4}$$

In Equations 1–4, $p_{(y\le j)}$ represents the cumulative probability of the dependent variable being less than or equal to option j, while the denominator $1-p_{(y\le j)}$ represents the probability of being greater than option j. The expression $\log\left[\frac{p(y\le j)}{1-p(y\le j)}\right]$ is the logit of the cumulative probability. On the right side of the equation, there is no constant term a_j; instead, it is replaced by cutting points τ_j. b_j represents the regression coefficients of the independent variables. From the above equation, it can be seen that the ologit model is not a single model, but rather j models; the ologit model actually estimates *j*-1 effective models (where *j* is the number of ordered categories of the dependent variable).

3 Results and analysis

3.1 Benchmark regression and diagnostic testing

3.1.1 Benchmark regression

The ologit model uses the maximum likelihood estimation method for parameter estimation, and the interpretation of its regression results is similar to that of the binary logistic model. We will present the odds ratios from the ologit model and explain the baseline models for the dependent variables of physical health and cognitive performance. Models (1) and (2) represent the baseline regression models for physical health, while Models (3) and (4) represent the baseline regression models for cognitive performance.

After four iterations and final convergence, Models (1), (2), (3), and (4) all passed the significance tests (Table 2).

Model (1) shows that the coefficient of the core explanatory variable, physical activity, is statistically significant, with a *p*-value less than 0.05, indicating that there are significant differences in the physical health of seniors. Specifically, seniors who participate in physical activities have noticeably better physical health compared to those who do not. Model (2) indicates that when controlling for variables such as gender, age, agesqr, education, lninc, lnfacom, and

TABLE 2 Ologit model estimating the health influencing factors for seniors.

Var	Model (1)	Model (2)	Model (3)	Model (4)
	phyh	phyh	cog	cog
ac	0.205***	0.280***	0.554***	0.325***
	(0.048)	(0.061)	(0.076)	(0.092)
gender		0.330***		0.053
		(0.043)		(0.054)
age		−0.323***		0.384***
		(0.046)		(0.080)
agesqr		0.002***		−0.003***
		(0.000)		(0.001)
marry		−0.036		0.344***
		(0.054)		(0.073)
edu		−0.035		0.741***
		(0.021)		(0.027)
lninc		0.007		−0.016*
		(0.005)		(0.006)
lnfacom		−0.147***		0.200***
		(0.023)		(0.031)
lnfinasu		−0.010		0.003
		(0.007)		(0.009)
cut1	−1.514***	−14.843***	−1.972***	14.025***
	(0.049)	(1.698)	(0.080)	(2.871)
cut2	−0.061	−13.361***	−0.441***	15.692***
	(0.046)	(1.697)	(0.073)	(2.873)
cut3	0.793***	−12.496***	0.863***	17.270***
	(0.046)	(1.696)	(0.074)	(2.875)
cut4	1.977***	−11.322***	2.131***	18.717***
	(0.050)	(1.695)	(0.077)	(2.876)
N	11,450	7,758	7,142	5,073
pseudo R^2	0.000	0.008	0.002	0.077

Standard errors in parentheses.
$^*p < 0.05$, $^{***}p < 0.001$.

lnfinasu, the significance level of the core explanatory variable, physical activity, remains unchanged, with a *p*-value still less than 0.05, further confirming the significant differences in the physical health of seniors. The odds ratio (OR) of the core explanatory variable is 0.205, which is a positive number, reflecting that seniors who participate in physical activities are more likely to have a higher ranking in the dependent variable and better physical health compared to those who do not participate in physical activities (the reference group). In other words, seniors who engage in physical activities are healthier than those who do not. Controlling for other variables, the OR of physical activity is 0.280, indicating that, while keeping other variables constant, seniors who participate in physical activities are increasingly likely to have a higher ranking in the dependent variable. Model (2) further reveals that seniors who engage in physical activities are healthier than those who do not.

Model (3) shows that the coefficient of the core explanatory variable, physical activity, is statistically significant, with a *p*-value less than 0.05, indicating that there are significant differences in the cognitive performance of seniors. Specifically, seniors who participate in physical activities exhibit noticeably better cognitive performance compared to those who do not. Model (4) indicates that when controlling for variables such as gender, age, agesqr, education, lninc, lnfacom, and lnfinasu, the significance level of the core explanatory variable, physical activity, remains unchanged, with a *p*-value still less than 0.05, further confirming the significant differences in the cognitive performance of seniors. The OR of the core explanatory variable is 0.554, which is a positive number, reflecting that seniors who participate in physical activities are more likely to have a higher ranking in the dependent variable and stronger cognitive abilities compared to those who do not participate in physical activities (the reference group). In other words, seniors who engage in physical activities demonstrate better cognitive performance than those who do not. Controlling for other variables, the OR of physical activity is 0.325, indicating that while the likelihood of seniors who participate in physical activities having a higher ranking in the dependent variable has somewhat diminished, Model (4) reveals that seniors who engage in physical activities exhibit stronger cognitive performance compared to those who do not.

3.1.2 Parallelism test

The baseline regression model explains two facts: that engaging in physical activities offers more benefits for seniors, at least in terms of meeting health requirements and enhancing cognitive performance. However, due to the assumption in the ologit model that the proportional odds hold, meaning the effect of the independent variable on the dependent variable remains constant across the categories of the dependent variable, it is necessary to conduct a score test for the proportional odds assumption. This test examines whether the impact of different values of the independent variable on the dependent variable is consistent across the various regression equations. The null hypothesis of the score test for the proportional odds assumption is that the model satisfies parallelism. If the *p*-value is greater than 0.05, it indicates that the model accepts the null hypothesis, thus meeting the parallelism test; conversely, if the p-value is less than or equal to 0.05, the null hypothesis is rejected, indicating that the model does not satisfy the parallelism test. Since parallelism is a prerequisite for using the ologit model, if it cannot be satisfied, it is preferable to use the mlogit model.

After running the ologit regression model, execute the brant command to output the results of the parallelism test for the ologit model. The parallelism test consists of two parts: one part tests the overall model, represented by the row corresponding to "All," which checks whether all variables together violate the parallelism assumption, while the other part assesses whether the individual effects of each independent variable violate the parallelism assumption.

As indicated in Table 3, regarding the baseline regression model for physical health, both the overall model test and the tests for each independent variable yield relatively small Chi2 values, and the parallelism tests for all variables, including ac, gender, age, agesqr, edu, lninc, lnfacom, and lnfinasu, are not significant, which means that the baseline regression model for physical health fully satisfies the parallelism assumption. In the case of the baseline regression model for cognitive performance, the Chi2 value for the overall model test is relatively large, and the overall model test is significant, indicating that the baseline regression model for cognitive performance does not satisfy the parallelism assumption. Therefore, since the cognitive performance baseline regression model violates the parallelism assumption, how should we address this issue? Given the complexity of social phenomena, it is not uncommon for the ologit model to be used for statistical estimation of qualitative variables in quantitative social science research, even when the parallelism assumption is violated. If it is found that the model violates the parallelism assumption after testing, different measures should be taken based on the specific situation. If the variable that violates the assumption is not a core explanatory variable in the study but rather a control variable, it may not be necessary to be overly concerned about this issue, as long as the effect of the core explanatory variable does not violate the parallelism assumption, indicating that its estimates for the dependent variable are reliable (30). However, if the core explanatory variable violates the parallelism assumption, the ologit model cannot be used for estimation; in this case, the mlogit model can be chosen for estimation. In Table 3, the Chi2 value for the core explanatory variable ac is relatively small, and its parallelism test is not significant, indicating that the core explanatory variable does not violate the parallelism assumption, and the baseline regression model for cognitive performance still possesses explanatory power.

TABLE 3 Brant test of parallel regression assumption.

	Phyh			Cog		
	Chi2	p > chi2	df	Chi2	p > chi2	df
All	29.48	0.338	27	74.00	0.000	27
ac	3.06	0.382	3	3.52	0.318	3
gender	2.73	0.435	3	23.52	0.000	3
age	5.94	0.115	3	12.09	0.007	3
agesqr	5.77	0.124	3	11.10	0.011	3
marry	1.49	0.685	3	1.51	0.680	3
edu	1.53	0.675	3	15.44	0.001	3
lninc	4.83	0.185	3	0.74	0.864	3
lnfacom	2.92	0.405	3	0.85	0.837	3
lnfinasu	0.12	0.989	3	0.35	0.950	3

3.2 Marginal effects analysis

Based on the baseline regression and parallelism test, in order to make the analysis results more quantifiable and precise, we run the margins command to measure the health marginal effects of participation in sports activities among different categories of seniors.

First, we examine the marginal effects of participation in sports activities on physical health among the old people (Table 4). We select the probabilities of having very poor physical health (score of 1), poor physical health (score of 2), average physical health (score of 3), good physical health (score of 4), and very good physical health (score of 5) based on participation in sports activities. Holding other variables constant, the probabilities of having very poor physical health for those who do not participate in sports activities and those who do are 19.50 and 15.51%, respectively; the probabilities of having poor physical health are 31.54 and 28.68%; the probabilities of having average physical health are 19.91 and 20.78%; the probabilities of having good physical health are 17.68 and 20.55%; and the probabilities of having very good physical health are 11.37 and 14.48%. This indicates that the probability of having better physical health with participation in sports activities is increasing, while the probability of having better physical health without participation in sports activities is decreasing. The two show a polarized difference, proving that participation in sports activities is beneficial for the physical health of seniors, and the marginal effect on physical health from participating in sports activities is significant.

Second, we examine the marginal effects of participation in sports activities on cognitive performance among the old people (Table 5). We select the probabilities of having very poor cognitive performance (score of 1), poor cognitive performance (score of 2), average cognitive performance (score of 3), good cognitive performance (score of 4), and very good cognitive performance (score of 5) based on participation in sports activities. Holding other variables constant, the probabilities of having very poor cognitive performance for those who do not participate in sports activities and those who do are 9.63 and 7.27%, respectively; the probabilities of having poor cognitive performance are 22.85 and 19.35%; the probabilities of having average cognitive performance are 31.95 and 31.41%; the probabilities of having good cognitive performance are 21.94 and 24.57%; and the probabilities of having very good cognitive performance are 13.62 and 17.41%. This indicates that the probability of having better cognitive performance with participation in sports activities is increasing, while the probability of having better cognitive performance without participation in sports activities is decreasing. The two show a polarized difference, proving that participation in sports activities is beneficial for the cognitive performance of seniors, and the marginal effect on cognitive performance from participating in sports activities is significant.

3.3 Robustness test

To verify that the results of the benchmark regression model analysis are more convincing, the study conducts robustness tests using methods such as sampling replacement models, replacing independent variables, replacing dependent variables, and propensity score matching analysis.

TABLE 4 Marginal effects of physical activity on the physical health of seniors.

	Margin	Std. err.	z	P > |z|	95% conf. Interval	
1#no	0.1950	0.0095	20.61	0.0000	0.1764	0.2135
1#yes	0.1551	0.0042	36.91	0.0000	0.1469	0.1634
2#no	0.3154	0.0073	43.03	0.0000	0.3010	0.3298
2#yes	0.2868	0.0052	55.55	0.0000	0.2766	0.2969
3#no	0.1991	0.0050	39.94	0.0000	0.1894	0.2089
3#yes	0.2078	0.0046	45	0.0000	0.1987	0.2168
4#no	0.1768	0.0069	25.77	0.0000	0.1633	0.1902
4#yes	0.2055	0.0047	43.95	0.0000	0.1964	0.2147
5#no	0.1137	0.0063	18.02	0.0000	0.1014	0.1261
5#yes	0.1448	0.0041	35.1	0.0000	0.1367	0.1528

TABLE 5 Marginal effects of the impact of physical activity on cognitive performance of seniors.

	Margin	Std. err.	z	P > |z|	95% conf. Interval	
1#no	0.0963	0.0080	11.98	0.0000	0.0806	0.1121
1#yes	0.0727	0.0036	20.3	0.0000	0.0656	0.0797
2#no	0.2285	0.0109	20.96	0.0000	0.2072	0.2499
2#yes	0.1935	0.0054	35.84	0.0000	0.1829	0.2041
3#no	0.3195	0.0066	48.59	0.0000	0.3067	0.3324
3#yes	0.3141	0.0064	49.13	0.0000	0.3016	0.3266
4#no	0.2194	0.0089	24.53	0.0000	0.2018	0.2369
4#yes	0.2457	0.0059	41.45	0.0000	0.2341	0.2573
5#no	0.1362	0.0101	13.5	0.0000	0.1164	0.1560
5#yes	0.1741	0.0051	34.38	0.0000	0.1642	0.1840

3.3.1 Replace the model

The ologit model corresponds to the oprobit model; these two models are like twin sisters. They both assume that there is some relationship between the independent variables and the categories of the dependent variable, and they explain the ordinal changes in the dependent variable through the influence of these independent variables. The ologit model models the relationship through linear regression of Log odds, while the oprobit model models the relationship between the dependent and independent variables through a latent normal distribution, and is derived based on the cumulative distribution function. Similarly, four benchmark models are explained for the dependent variable of physical health and the dependent variable of cognitive performance. Models (5) and (6) are the benchmark regression models for physical health, while models (7) and (8) are the benchmark regression models for cognitive performance. The results of the oprobit model (Table 6) show that the coefficient of the core explanatory variable, physical activity, is statistically significant, with a p-value less than 0.05, indicating that seniors' participation in physical activities significantly promotes both physical health and cognitive performance. When controlling for variables such as gender, age, agesqr, edu, lninc, lnfacom, and lnfinasu, the regression coefficient of the core explanatory variable, physical activity, remains significant, suggesting that the replacement model has robust benchmark regression results.

TABLE 6 Oprobit model for estimating factors influencing the health of seniors.

Var	Model (5)	Model (6)	Model (7)	Model (8)
	phyh	phyh	cog	cog
ac	0.121***	0.168***	0.332***	0.205***
	(0.028)	(0.036)	(0.044)	(0.054)
		Control Variables		Control Variables
cut1	−0.908***	−8.651***	−1.121***	4.147**
	(0.028)	(0.949)	(0.045)	(1.357)
cut2	−0.045	−7.769***	−0.281***	5.081***
	(0.027)	(0.948)	(0.043)	(1.357)
cut3	0.488***	−7.232***	0.526***	6.027***
	(0.027)	(0.948)	(0.043)	(1.358)
cut4	1.176***	−6.551***	1.280***	6.871***
	(0.029)	(0.948)	(0.045)	(1.358)
N	11,450	7,758	7,142	5,073
pseudo R^2	0.001	0.008	0.003	0.077

Standard errors in parentheses.
$^{**}p < 0.01$, $^{***}p < 0.001$.

3.3.2 Replace the independent variable

Select "whether engaged in light physical activity," "whether engaged in moderate physical activity," and "whether engaged in vigorous physical activity" as substitute variables for participation in physical activity, that is, replacing the core explanatory variables. Light physical activity refers to walking, including moving from one place to another while working or at home, as well as other walking done for leisure, exercise, sports, or entertainment, without significant fatigue or shortness of breath, reaching 40–55% of maximum heart rate; moderate physical activity refers to activities of moderate intensity that cause the respondent's breathing to be slightly faster than usual, such as carrying light objects, cycling at a regular pace, mopping, practicing Tai Chi, or brisk walking, where there is a certain degree of shortness of breath during exercise, but normal conversation is still possible, reaching 55–70% of maximum heart rate; while vigorous physical activity refers to intense activities that cause the respondent to experience shortness of breath, such as lifting heavy objects, digging, farming, aerobic exercise, cycling quickly, or carrying loads while cycling, where there is significant shortness of breath and an increased heart rate during exercise, making it difficult to maintain a coherent conversation for long periods, reaching 70 to 90% of maximum heart rate (31).

It is surprisingly found that different intensities of physical activities have significant differences in their effects on the physical health and cognitive performance of seniors. Light physical activities like walking do not have a significant impact on the physical health of seniors (Table 7), with a positive but insignificant regression coefficient in Model (9). The regression coefficients in Model (10) and Model (11) are positive and significant, indicating that participation in moderate or vigorous

TABLE 7 Robustness test of estimated health influences on seniors: replacing the independent variable.

Var	Model (9)	Model (10)	Model (11)	Model (12)	Model (13)	Model (14)
	phyh	phyh	phyh	cog	cog	cog
lightac	0.088			0.292***		
	(0.048)			(0.066)		
moderac		0.164***			0.207***	
		(0.042)			(0.052)	
intenac			0.303***			−0.141*
			(0.045)			(0.056)
	Control variables	Control variables	Control variables	Control variables	Control variables	Control variables
cut1	−14.697***	−14.763***	−14.252***	13.947***	13.989***	13.818***
	(1.698)	(1.700)	(1.700)	(2.870)	(2.870)	(2.875)
cut2	−13.218***	−13.283***	−12.768***	15.614***	15.656***	15.483***
	(1.696)	(1.699)	(1.698)	(2.872)	(2.873)	(2.877)
cut3	−12.354***	−12.418***	−11.900***	17.194***	17.235***	17.060***
	(1.696)	(1.698)	(1.697)	(2.874)	(2.875)	(2.879)
cut4	−11.181***	−11.244***	−10.724***	18.643***	18.683***	18.508***
	(1.695)	(1.697)	(1.697)	(2.875)	(2.876)	(2.880)
N	7,758	7,758	7,758	5,073	5,073	5,073
pseudo R^2	0.007	0.008	0.009	0.077	0.077	0.077

Standard errors in parentheses.
$^{*}p < 0.05$, $^{***}p < 0.001$.

physical activities significantly promotes the physical health of seniors, with greater benefits to physical health as the intensity of physical activities increases. Conversely, the regression coefficients in Model (12), Model (13), and Model (14) decline from 0.292 to 0.207 and then to −0.141, indicating that an increase in the intensity of physical activities leads to a decrease in cognitive performance among seniors.

Why are vigorous physical activities more beneficial for the physical health of seniors, while detrimental to cognitive performance? We attempt a comparative analysis across different age groups, dividing seniors into the 60–69 age group, the 70–79 age group, and those aged 80 and above. The regression results show that as the age group increases, vigorous physical activities are more beneficial for the physical health of seniors. However, in reality, vigorous physical activities may not be suitable for seniors aged 80 and above. Therefore, we further divide seniors aged 80 and above into urban and rural groups. The results reveal that vigorous physical activities are beneficial for the physical health of urban seniors aged 80 and above, with a positive and significant regression coefficient, while the regression coefficient for rural seniors aged 80 and above is not significant. In terms of cognitive performance, vigorous physical activities have a negative impact on the cognitive performance of seniors in the 60–69 age group, while the regression coefficients for cognitive performance in the 70–79 age group and the 80 and above age group are not significant.

3.3.3 Replace the dependent variable

Using ADL and IADL to replace the dependent variable physical health, and using memory and mentim to replace the dependent variable cognitive performance, is highly persuasive. ADL refers to the most basic activities of daily living for individuals, primarily involving the ability for personal self-care. It consists of indicators such as the ability to dress, bathe, eat, use the toilet, walk, and perform activities in bed. IADL refers to relatively complex activities that require higher cognitive and social abilities; these do not involve basic self-care but are crucial for a person to maintain independent living. It includes the ability to cook, clean, shop, manage finances, appear in public, communicate by phone, and manage medication. Both ADL and IADL are important indicators of physical health status. This paper employs the comprehensive scoring analysis method developed by Chen et al. to recode ADL and IADL, where a higher score indicates better physical health (32). Contextual memory is represented through phrase memory, consisting of immediate and delayed phrase recall, while mental image is represented through cognitive completeness, comprising date recognition, calculation, and drawing abilities. Both can reflect cognitive performance.

The regression results of Model (15) and Model (16) show that, while controlling for other variables, seniors' participation in physical activities has a significant positive effect on ADL and IADL scores, with positive and significant regression coefficients (Table 8). The regression results of Model (17) and Model (18) indicate that, while controlling for other variables, seniors' participation in physical activities significantly promotes memory and mentim, with positive and significant regression coefficients. These four models validate the robustness of the baseline regression results.

3.3.4 Propensity score matching analysis

The propensity score refers to the probability of an individual being in any given intervention state (33). This section considers whether to engage in physical activity as a binary intervention variable, with the propensity score representing the probability of this intervention variable taking a value of 1. Propensity score matching analysis has advantages over linear regression, as it can directly obtain estimates of causal effects based on matched samples, while linear regression must include other control variables when estimating causal effects. Common methods for propensity score matching analysis include 1:1 matching, 1:4 matching, radius matching, and kernel matching. For ease of comparison, we present the results of the four matching methods (Table 9). From the 1:1 matching, there is a significant difference in the ATT and ATU values for physical activity regarding phyh, indicating that the health effect for seniors who have engaged in physical activity is 6.21%, while the expected health effect for those who have not engaged in physical activity is 18.89%. The differences in the ATT and ATU values for cognitive performance (cog) are relatively small, with the effect for seniors who have engaged in physical activity being 21.14%, compared to an expected cognitive performance effect of 19.86% for those who have not. From the 1:4 matching, the health effect for seniors who have engaged in physical activity is lower than the expected health effect for those who have not, while the cognitive performance effect is the opposite. From the radius matching, the ATT and ATU values are the same, indicating that the health effects are identical regardless of whether physical activity is undertaken. The results of kernel matching are interpreted similarly

TABLE 8 Robustness test of estimated health influences on seniors: replacing the dependent variable.

Var	Model (15)	Model (16)	Model (17)	Model (18)
	ADL	IADL	memory	mentim
ac	1.126***	1.203***	0.373***	0.272**
	(0.069)	(0.069)	(0.074)	(0.092)
	Control variables	Control variables	Control variables	Control variables
cut1	−5.039*	0.390	8.619***	16.775***
	(2.052)	(2.111)	(2.338)	(2.855)
cut2	−4.004	1.693	9.715***	18.019***
	(2.052)	(2.112)	(2.340)	(2.856)
cut3	−3.480	2.253	11.080***	19.361***
	(2.052)	(2.113)	(2.341)	(2.858)
cut4	−2.560	2.938	12.786***	21.925***
	(2.052)	(2.113)	(2.341)	(2.861)
N	7,758	7,758	6,585	5,126
pseudo R^2	0.045	0.059	0.066	0.065

Standard errors in parentheses.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE 9 Propensity-matched score analysis of physical activity on physical health and cognitive performance of seniors.

Methods	phyh			cog		
	ATT	ATU	ATE	ATT	ATU	ATE
1:1 matched	0.0621	0.1888	0.0791	0.2114	0.1986	0.2103
1:4 matched	0.1623	0.2168	0.1696	0.2014	0.1945	0.2008
Radius	0.1880	0.1880	0.1880	0.3692	0.3692	0.3692
Kernel	0.1585	0.2080	0.1652	0.2643	0.2660	0.2645

to the above. For the 1:1 matching, 1:4 matching, and kernel matching, the health effects from physical activity are lower than those of the untreated group, while the cognitive performance effects are higher than those of the untreated group. This aligns with the lower regression coefficient for phyh and the higher regression coefficient for cog in the baseline regression, indicating that the results of the baseline regression analysis are robust.

After completing the propensity score matching analysis, we conducted a balance test on the data using physical activity as an example for the health of the older adults. The kernel propensity score matching method was employed here. The results showed a significant improvement in data balance compared to before matching. Most of the t-test results for the covariates before matching were significant, while the significance levels of the t-tests after matching decreased substantially. The mean and median of the standardized mean differences of the covariates both showed a noticeable decline after matching (Figure 1), reflecting that the B index and R index of overall data balance fell within a reasonable range after matching. The R^2 after matching also became significant (Table 10), indicating that kernel propensity score matching is robust.

3.4 Heterogeneity analysis

The heterogeneity of physical activity's impact on the physical health and cognitive performance of seniors is revealed from three aspects: gender (male and female), marital status (married and unmarried), and urban versus rural settings.

In terms of physical health heterogeneity, physical activity benefits the physical health of both male and female seniors, but in terms of intensity, physical activity is more beneficial for female seniors. Regarding marital status, physical activity benefits the physical health of both married and unmarried seniors, but in terms of intensity, physical activity is more beneficial for married seniors. When examining the physical health status of seniors in urban and rural areas, physical activity benefits the physical health of both urban and rural seniors, but in terms of intensity, physical activity is more beneficial for urban seniors (Table 11).

In terms of the heterogeneity of cognitive performance, physical activity benefits the cognitive performance of both male and female seniors, but in terms of intensity, physical activity is slightly more beneficial for female seniors. Regarding marital status, physical activity benefits the cognitive performance of both married and unmarried seniors, but in terms of intensity, physical activity is more beneficial for married seniors. When examining the cognitive performance of seniors in urban and rural areas, physical activity is beneficial for the cognitive performance of urban seniors, but it does not have a significant impact on the cognitive performance of rural seniors (Table 12).

4 Discussion

This study systematically reveals the mechanism of physical activity on multidimensional health indicators in the older adults population by constructing an ordered logit model and conducting a series of robustness tests. Through marginal effect decomposition and

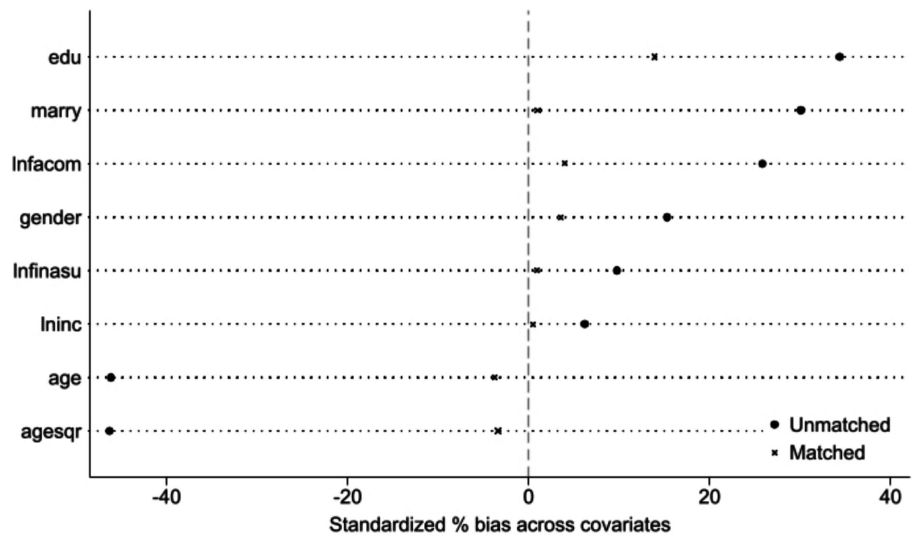

FIGURE 1
Standardized mean differences of covariates before and after matching.

TABLE 10 Propensity score matching balance test.

Sample	Ps R^2	LR chi2	p > chi2	MeanBias	MedBias	*B*	*R*	%Var
Unmatched	0.054	332.61	0	26.8	28	59.2*	0.62	83
Matched	0.004	67.76	0	3.9	3.5	14.2	1.24	67

*if B > 25%, *R* outside [0.2, 2].

TABLE 11 Heterogeneity analysis of the ologit model for estimating factors affecting physical health of seniors.

	Model (19)	Model (20)	Model (21)	Model (22)	Model (23)	Model (24)
	Female	Male	Married	Unmarried	Rural	Urban
ac	0.359***	0.183*	0.482***	0.192**	0.227**	0.409***
	(0.083)	(0.091)	(0.113)	(0.073)	(0.074)	(0.109)
	Control variables	Control variables	Control variables	Control variables	Control variables	Control variables
cut1	−15.937***	−13.732***	−11.721***	−15.873***	−12.440***	−18.321***
	(2.362)	(2.394)	(3.115)	(2.276)	(2.135)	(2.751)
cut2	−14.465***	−12.236***	−10.181**	−14.406***	−11.016***	−16.750***
	(2.360)	(2.392)	(3.111)	(2.275)	(2.133)	(2.748)
cut3	−13.620***	−11.347***	−9.354**	−13.529***	−10.162***	−15.861***
	(2.359)	(2.391)	(3.110)	(2.274)	(2.132)	(2.747)
cut4	−12.393***	−10.215***	−8.168**	−12.356***	−8.947***	−14.752***
	(2.358)	(2.391)	(3.109)	(2.273)	(2.132)	(2.745)
N	3,924	3,834	1,627	6,131	4,689	3,069
pseudo R^2	0.006	0.007	0.016	0.006	0.006	0.011

Standard errors in parentheses.
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

TABLE 12 Heterogeneity analysis of the ologit model for estimating factors influencing cognitive performance among seniors.

	Model (25)	Model (26)	Model (27)	Model (28)	Model (29)	Model (30)
	Female	Male	Married	Unmarried	Rural	Urban
ac	0.316*	0.314*	0.535*	0.278**	0.190	0.514***
	(0.136)	(0.126)	(0.216)	(0.102)	(0.115)	(0.155)
	Control variables	Control variables	Control variables	Control variables	Control variables	Control variables
cut1	10.395*	16.280***	2.728	17.272***	7.968*	18.864***
	(4.440)	(3.815)	(5.793)	(3.484)	(3.772)	(4.419)
cut2	12.044**	18.007***	4.273	18.984***	9.590*	20.681***
	(4.443)	(3.818)	(5.797)	(3.487)	(3.774)	(4.422)
cut3	13.525**	19.675***	5.808	20.573***	11.222**	22.221***
	(4.445)	(3.822)	(5.800)	(3.489)	(3.776)	(4.426)
cut4	15.021***	21.110***	7.371	22.004***	12.648***	23.721***
	(4.445)	(3.824)	(5.803)	(3.490)	(3.777)	(4.429)
N	2,170	2,903	811	4,262	2,853	2,220
pseudo R^2	0.103	0.054	0.088	0.071	0.063	0.075

Standard errors in parentheses.
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

heterogeneity analysis, the research deepens the understanding of intervention pathways and provides new empirical evidence for the design of differentiated health policies. At the foundational mechanism level, the study finds that the promoting effects of physical activity on physical health and cognitive function are statistically significant and biologically plausible. The research reveals that the marginal effects exhibit non-linear characteristics: when the frequency of participation in physical activity exceeds a threshold, health benefits show an accelerating growth trend. Meanwhile, propensity score matching analysis eliminates health selection bias, confirming that the observed health gains primarily stem from the causal effects of physical activity rather than individual self-selection. In terms of heterogeneity analysis, the study identifies significant group differences: female participants, married individuals, and urban residents exhibit stronger intervention responsiveness. This difference may arise from the moderating role of social support networks—emotional support and exercise companionship provided by marital relationships may enhance behavioral compliance; well-equipped fitness facilities and health education in urban communities lower the barriers to participation in physical activity.

This study has three methodological limitations: first, although the classification of health indicators references internationally accepted standards, the setting of classification thresholds may affect the sensitivity of ordered regression parameter estimates; second, insufficient age stratification in the sample may obscure lifecycle effects, necessitating further differentiation of exercise response patterns between younger older adults (ages 65–74) and older adults (ages 75 and above). For instance, the small proportion of the very older adults population (those aged 90 and above only account for 1.2% of the total sample) may not be suitable for high-intensity physical activities, and future research needs to delve deeper to reveal the impact mechanisms of physical activity on older adults health; finally, the absence of mental health variables prevents the study from fully constructing a "physiological-psychological-social" health model. Subsequent research could adopt a mixed-methods design, combining biomarker detection and longitudinal tracking to explore the multidimensional pathways of exercise interventions in depth.

Based on the above findings, it is recommended to optimize healthy aging policies from three levels: first, establish an exercise prescription system based on precision medicine concepts, designing tiered intervention plans for different subgroups; second, improve the age-friendly transformation of community sports facilities, with a focus on enhancing resource allocation in rural areas; third, incorporate exercise adherence assessment into the basic public health service package, building a long-term health promotion mechanism with multi-departmental collaboration. These measures align closely with the life-cycle health management strategy proposed in the "Healthy China 2030 Planning Outline" and hold significant practical value for achieving active aging.

5 Conclusion

This article constructs a regression model to analyze the impact of physical activity on the health of seniors, delving into the marginal effects of physical activity on their physical health and cognitive performance, revealing the significant influence of physical activity on senior health. The main conclusions are as follows:

First, physical activity has a significant promoting effect on the physical health and cognitive performance of seniors. There are notable differences in physical health and cognitive performance between seniors who participate in physical activities and those who do not. Specifically, seniors who engage in physical activities outperform their counterparts in both physical health status and cognitive performance. This conclusion has been validated across different model settings, variable substitutions, adjustments of dependent and independent variables, as well as propensity score matching analysis, further demonstrating the robustness of the results obtained using the ologit model.

Second, physical activity exhibits a clear marginal effect on the physical health and cognitive performance of seniors. Participation in physical activities significantly increases the probability of seniors' physical health status improving positively, whereas seniors who do not engage in physical activities show a declining trend in the probability of positive health developments. Similarly, physical activity has a comparable marginal effect on seniors' cognitive performance, with those participating in physical activities demonstrating significant improvements in cognitive abilities, while those not participating show no significant enhancement in cognitive abilities. These results indicate that physical activity has a strong marginal effect on both the physical health and cognitive performance of seniors.

Third, the impact of physical activity on the physical health and cognitive performance of different groups of old people shows significant heterogeneity. There are heterogeneous effects of physical activity on the physical health and cognitive performance of various groups of old people. Specifically, the benefits of physical activity are particularly pronounced among female seniors, married seniors, and those living in urban areas, with substantial improvements in their physical health and cognitive performance. In contrast, while physical activity still promotes the physical health and cognitive abilities of male seniors or unmarried seniors, the effects are relatively weaker. This heterogeneity provides a basis for developing more targeted health intervention strategies.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://charls.pku.edu.cn/.

Author contributions

XL: Conceptualization, Data curation, Supervision, Writing – original draft, Writing – review & editing. CL: Conceptualization, Data curation, Investigation, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

1. Xiangqun J, Meng W, Wenjuan Z. Research on the health status and influencing factors of the elderly population in China. *Popul J*. (2015) 37:46–56.

2. Kramer AF, Erickson KI. Capitalizing on cortical plasticity: influence of physical activity on cognition and brain function. *Trends Cogn Sci*. (2007) 11:342–8. doi: 10.1016/j.tics.2007.06.009

3. Fubaihui W, Yufeng Z, Xianling Z. "Chinese practices" of National Sports Activities in the era of great changes: from the perspectives of age, period, and cohort. *J Shanghai Univ Sport*. (2024) 48:26–35.

4. Fan Y, Yue P, Zeyu Z. Research on the status quo and influencing factors of physical activities of the elderly in China. *China Sport Sci Technol*. (2019) 55:10–21.

5. Huijie G, Minghan C, Sidian Y. Research on the influencing factors and regional differences of physical activities of Chinese elderly under the background of active aging. *Sports Sci*. (2024) 45:68–76.

6. Zhihong D, Xianling Z, Chengdong Y. Research on the behavioral characteristics, support and influencing factors of urban elderly People's physical activities in China. *Lanzhou Acad J*. (2020) 6:174–87.

7. World Health Organization. Global recommendations on physical activity for health. Geneva: World Health Organization (2010).

8. U.S. Department of Health and Human Services. *physical activity guidelines for Americans, 2nd edition*. Washington, DC: U.S. Department of Health and Human Services (2018).

9. Silva NCBS, Barha CK, Erickson KI, Kramer AF, Liu-Ambrose T. Physical exercise, cognition, and brain health in aging. *Trends Neurosci*. (2024) 47:402–17. doi: 10.1016/j.tins.2024.04.004

10. Chen X, Su D, Chen X, Chen Y. What intensity of exercise is most suitable for the elderly in China? A propensity score matching analysis. *BMC Public Health*. (2021) 21:1396. doi: 10.1186/s12889-021-11407-2

11. Uchida K, Hashidate H, Sugawara K, Nakata T, Kurosawa C, Minamimura Y, et al. Unsupervised low-intensity home exercises as an effective intervention for improving physical activity and physical capacity in the community-dwelling elderly. *J Phys Ther Sci*. (2020) 32:215–22. doi: 10.1589/jpts.32.215

12. Karssemeijer EGA, Aaronson JA, Bossers WJR, Donders R, Olde Rikkert MGM, Kessels RPC. The quest for synergy between physical activity and cognitive stimulation via exergaming in people with dementia: a randomized controlled trial. *Alzheimers Res Ther*. (2019) 11:1–13. doi: 10.1186/s13195-018-0454-z

13. Wu S, Ji H, Won J, Jo EA, Kim YS, Park JJ. The effects of exergaming on executive and physical functions in older adults with dementia: randomized controlled trial. *J Med Internet Res*. (2023) 25:e39993. doi: 10.2196/39993

14. Xule Z, Linyan X, Jingquan G, Lei Z, Zhuoqi C, Yuan Y. A scoping review of the application of physical activity games in the elderly with cognitive impairment. *Chinese Nurs Manag*. (2024) 24:1405–11.

15. Carta MG, Cossu G, Pintus E, Zaccheddu R, Callia O, Conti G, et al. Moderate exercise improves cognitive function in healthy elderly people: results of a randomized controlled trial. *Clin Pract Epidemiol Ment Health*. (2021) 17:75–80. doi: 10.2174/1745017902117010075

16. Svobodová Lenka, Sebera Martin, Crhova Marie, Martincová Andrea, Hlinský Tomáš, Stračárová Nikola. (2020). The impact of different types of physical activity on walking as a vital everyday movement in older adults.

17. Guoliang F, Li Z, Tianyu H, Xu Z, Han Z, Qian L, et al. Impact of high - intensity interval training on cognitive function of the elderly. *China Sport Sci Technol*. (2020) 56:32–7.

18. Gonçalves AK, Silva PC, Griebler EM, Silva WAD, Sant Helena DP, Possamai VD, et al. Multicomponent physical program: effects on physical fitness of older women of different age groups. *Res Q Exerc Sport*. (2024) 95:759–65. doi: 10.1080/02701367.2024.2306285

19. Lautenschlager NT, Cox KL, Flicker L, Foster JK, van Bockxmeer FM, Xiao J, et al. Effect of physical activity on cognitive function in older adults at risk for Alzheimer disease: a randomized trial. *JAMA*. (2008) 300:1027–37. doi: 10.1001/jama.300.9.1027

20. Rong B, Huiyong F, Jinfu Z. The influence of physical activity on cognitive function in the elderly. *Adv Psychol Sci*. (2011) 19:1777–87.

21. Gomez-Pinilla F, Hillman C. The influence of exercise on cognitive abilities. *Compr Physiol*. (2013) 3:403–28. doi: 10.1002/cphy.c110063

22. Falck RS, Davis JC, Best JR, Crockett RA, Liu-Ambrose T. Impact of exercise training on physical and cognitive function among older adults: a systematic review and meta-analysis. *Neurobiol Aging*. (2019) 79:119–30. doi: 10.1016/j.neurobiolaging.2019.03.007

23. Larasati A, Boy E. The impact of physical activity in elderly. *Magna Medica: Berkala Ilmiah Kedokteran dan Kesehatan*. (2020) 6:113. doi: 10.26714/magnamed.6.2.2019.113-121

24. Pertiwi G, Lorica J. Physical activity improves the cognitive function among elderly: an integrated literature review. *Malaysian J Nurs*. (2019) 10:38–43. doi: 10.31674/mjn.2019.v10i03.006

25. Klimova B, Dostalova R. The impact of physical activities on cognitive performance among healthy older individuals. *Brain Sci*. (2020) 10:1. doi: 10.3390/brainsci10060377

26. Kefei Z, Lijin Z, Wenshuang Y, Biao X, Jingrong N. Research on the impact of physical exercise intervention on the physiological and cognitive functions of sedentary elderly diabetic patients. *Trans Med J*. (2021) 10:163–9.

27. Yinan Z, Hui F, Xinyin W, Yan D, Xiufeng Y, Mingyue H, et al. Effectiveness of exergaming in improving cognitive and physical function in people with mild cognitive impairment or dementia: systematic review. *JMIR Serious Games*. (2020) 8:e16841

28. Shiyong H, Shunxia N. Analysis of the differences in health status between urban and rural elderly people: based on the baseline data of CHARLS in 2011. *Res Aging Sci*. (2016) 4:74–80.

29. Hu Y, Peng W, Ren R, Wang Y, Wang G. Sarcopenia and mild cognitive impairment among elderly adults: the first longitudinal evidence from CHARLS. *J Cachexia Sarcopenia Muscle*. (2022) 13:2944–52. doi: 10.1002/jcsm.13081

30. Yuxiao W, Xianjin B. Applied regression analysis using Stata[M]. Beijing: Peking University Press (2023).

31. Jayedi A, Soltani S, Emadi A, Zargar M, Najafi A. Aerobic exercise and weight loss in adults: a systematic review and dose-response Meta-analysis. *JAMA Netw Open*. (2024) 7:e2452185. doi: 10.1001/jamanetworkopen.2024.52185

32. Li C, Wu J, Li Y, Huang Y. Analysis of healthcare needs differences and influencing factors among elderly population: evidence from Yangtze River Delta region, China. *Front Public Health*. (2022) 10:949468. doi: 10.3389/fpubh.2022.949468

33. Yunsong C, Qi X. Causal inference in social science. Beijing: Peking University Press (2024).

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 05 March 2025
DOI 10.3389/fpubh.2025.1556789

OPEN ACCESS

EDITED BY
Siqin Wang,
The University of Queensland, Australia

REVIEWED BY
Víctor Hugo Fernández-Bedoya,
Cesar Vallejo University, Peru
Fei Lu,
Southwestern University of Finance and Economics, China

*CORRESPONDENCE
Chen Li
lichen@sues.edu.cn

RECEIVED 07 January 2025
ACCEPTED 17 February 2025
PUBLISHED 05 March 2025

CITATION
Zhao L, Zhou G and Li C (2025) Research on the impact of tourism cooperation on urban public health.
Front. Public Health 13:1556789.
doi: 10.3389/fpubh.2025.1556789

Research on the impact of tourism cooperation on urban public health

Liang Zhao[1], Guolei Zhou[2] and Chen Li[3]*

[1]School of Tourism, Hubei University, Wuhan, China, [2]School of Business, Hubei University, Wuhan, China, [3]School of Management, Shanghai University of Engineering Science, Shanghai, China

Introduction: Tourism cooperation is increasingly recognized as a key driver of regional economic development, playing a crucial role in facilitating internal circulation and enhancing urban public health. This study examines the relationship between tourism cooperation and urban public health development, with a focus on China.

Methods: Using data from 284 Chinese cities over the period 2011-2022, this research measures both the degree of tourism cooperation and the level of urban public health development. Empirical analysis is conducted to assess the impact of tourism cooperation on urban public health outcomes. The study employs robustness tests to ensure the validity of its findings.

Results: The findings indicate that tourism cooperation significantly promotes urban public health development. After conducting robustness tests, this result remains consistent. Furthermore, heterogeneity analysis reveals that the "core hinterland" type of tourism cooperation model has a stronger impact on urban public health development compared to the adjacent city type. Among different city cooperation models, tourism cooperation between central cities has the greatest empowering effect, followed by cooperation between central and non-central cities, while cooperation between non-central cities has the smallest effect.

Discussion: The research suggests that tourism cooperation can effectively address regional economic disparities and the imbalanced development of urban public health in China. The findings have important implications for policy-making, particularly in promoting sustainable urban health development and narrowing regional gaps in economic and health outcomes.

KEYWORDS

tourism cooperation, urban public health, tourism health, cities, China

1 Introduction

Tourism Cooperation refers to the joint promotion of sustainable development in the tourism industry among different countries, regions, or organizations through resource sharing, information exchange, policy coordination, and other means. This type of collaboration typically involves multiple stakeholders, including government, businesses, non-governmental organizations (NGOs), and local communities. The core goal of tourism cooperation is to achieve mutual benefit and win-win in the tourism industry, enhance the competitiveness of tourism destinations, and protect natural and cultural resources. Regional tourism cooperation refers to the development of cross-border tourism routes, sharing of tourism resources, and coordination of tourism policies among neighboring or adjacent countries or regions to enhance the overall tourism attractiveness of the region. For example, the "Danube Tourist Area" cooperation project in Europe. Through regional tourism cooperation, tourist destinations can attract more tourists, increase tourism revenue, and promote local economic development. Different regions or countries can achieve complementary tourism resources through cooperation, such as the combination of natural landscapes and cultural resources. At the same time, tourism cooperation helps to coordinate the relationship between environmental protection and tourism development, avoiding the destruction of natural and cultural resources by overdevelopment (1–4).

Health is a fundamental need for human survival and development, and an important indicator for measuring the progress of social civilization and the overall level of social development. Tourism is a catalyst for promoting human physical and mental health, not only because the essence of tourism is to make people healthy and happy, but also because the tourism health industry can play an important role in promoting human health. The achievement of national health goals requires starting from various aspects such as daily life, services, environment, policies, technological support, and industrial development, to jointly support and promote the development of the national health cause (5–9). The Chinese government has proposed to focus on the development of the health industry and provide comprehensive and full cycle service guarantees and industrial support to promote people's health.

The tourism industry is a modern service industry aimed at bringing physical and mental health to people and promoting their comprehensive development. It should also play a key role in promoting the development of national health. On the one hand, the essence of tourism is to bring health and happiness to people. The purpose of people traveling is to gain spiritual pleasure, relieve physical fatigue, and achieve physical and mental adjustment while enjoying natural scenery and cultural influence (10–16). A pleasant trip or vacation not only allows people to gain knowledge, broaden their horizons, and cultivate their emotions, but also brings about physical adjustment and promotes physical health through spiritual pleasure. Tourism is actually the best way to promote physical and mental health. This requires us, as managers of the tourism industry and providers of tourism services, to stand at the height of promoting human health, providing high-quality and high-quality industries and services to people, and taking the promotion of human physical and mental health as an indispensable and important responsibility. At the same time, tourism operators should also promote tourism as an important part of "healthy and civilized lifestyle," and take advocating a healthy and civilized lifestyle as an important social responsibility of tourism operators, guiding the people to promote physical and mental health through tourism (17–20).

On the other hand, the tourism health industry formed by "tourism health" can provide people with the most direct health services and industry support. Vigorously developing new formats of health services, actively promoting the integration and development of the health and older adult care industry with other related industries and fields, and giving birth to new industries, formats, and models of health services; Actively develop the fitness and leisure sports industry, create a comprehensive fitness and leisure service system, actively cultivate fashionable leisure sports projects with consumption leading characteristics such as ice and snow, mountains, water, motorcycle, aviation, extreme sports, and equestrian sports, and create fitness and leisure demonstration zones and fitness and leisure industry belts with regional characteristics. The integration and development of the above-mentioned fields with tourism will directly give rise to the emergence and development of the "tourism health industry" that serves people's health.

In fact, as society develops and people's economic income increases, their attention to their physical and mental health becomes higher. Moreover, with the advancement of human consumption and health concepts, this attention has shifted from post illness treatment to health care and prevention, that is, through regular and planned vacations, health care, sub-health rehabilitation and other means to improve their physical and mental health. These health care consumption demands, which are carried out through tourism and vacation, directly promote the "tourism oriented" development of the health industry (21–27). To promote the construction of a "Healthy China" is to take improving the health level of the people as the core, reform and innovation as the driving force, and the development of the health industry as the focus, providing basic guarantees for the development of the national health cause. We need to fully leverage the social influence of tourism and the integration and driving force of the tourism industry, innovate and develop products and formats of the tourism health industry, promote the integrated development of "tourism health," build a tourism health industry system with Chinese characteristics, meet the multi-level and diversified health service needs of the general public, and make greater contributions to the comprehensive construction of a moderately prosperous society.

The impact of tourism cooperation on urban public health level has a positive effect, firstly, it can enhance public health awareness. Tourism cooperation often accompanies the demand for higher public health standards in tourist destinations, which prompts cities to strengthen public health management and services, and enhance the public health awareness of residents and tourists. Through tourism cooperation, cities can draw on and learn from advanced public health management experiences and technologies from other regions, further enhancing the local public health level (19, 25, 28–30). The second is to promote the construction of medical facilities. Tourism cooperation may lead to the construction and improvement of medical facilities to meet the medical needs of tourists and residents. For example, establishing medical institutions, improving medical treatment capabilities, and perfecting emergency systems. The construction of medical institutions and facilities not only improves the level of medical services in cities, but also enhances their ability to respond to sudden public health emergencies. The third is to improve the urban environment. Tourism cooperation usually requires cities to improve and enhance their tourism environment, including urban greening, beautification, purification, and other aspects. These measures help improve the urban environment and enhance the quality of life for residents and tourists. A good urban environment helps to reduce the occurrence and spread of diseases, thereby improving the public health level of the city. The fourth is to promote the development of the health industry. Tourism cooperation can promote the development of the health industry, such as characteristic health tourism projects such as hot spring therapy and forest health preservation. These projects not only enrich the tourism industry, but also promote the health of urban residents and tourists. The development of the health industry can also drive the extension and upgrading of related industrial chains, injecting new vitality into the urban economy.

Meanwhile, tourism cooperation also has a negative impact on the public health level of cities. On the one hand, population mobility poses public health risks. Tourism cooperation will increase the population mobility of cities, including the flow of tourists and professionals. This increases the risk of the spread of infectious diseases, such as influenza, COVID-19 and other respiratory infectious diseases. Population mobility may also bring challenges to food safety, drinking water safety, and other aspects, requiring cities to strengthen supervision and prevention measures. On the other hand, it leads to uneven distribution of resources (31–34). Tourism cooperation may lead to a tilt of urban resources toward the tourism industry, resulting in uneven distribution of resources in other public service areas. Medical resources may be tight due to the peak tourism season, affecting residents' medical needs. Therefore, cities need to balance the development of the tourism industry with other public service sectors in tourism cooperation, ensuring the rational allocation and utilization of resources.

Under the basic national conditions of imbalanced development, tourism cooperation, as a new concept of economic development that relies on synergy and system theory to promote the integration and operation of regional economic subsystems, provides opportunities to solve the drawbacks of imbalanced development, unleash domestic demand potential, and promote smooth internal circulation. In recent years, China has gradually explored the application of the concept of tourism cooperation to build a regional economic pattern with complementary advantages and coordinated linkage. It has formulated major regional development strategies such as the coordinated development of Beijing Tianjin Hebei, the development of the Yangtze River Economic Belt, and the Guangdong Hong Kong Macao Greater Bay Area, which have to some extent alleviated the dilemma of imbalanced development. In theory, tourism cooperation can promote factor flow, complementary advantages, and industrial linkage between regions through policy guidance and market mechanisms, thereby solving practical difficulties such as factor mismatch, market segmentation, and industrial homogenization (35, 36). In recent years, studies have examined the impact of tourism cooperation on high-quality economic development and considered the positive significance of tourism cooperation from multiple perspectives. Unfortunately, there is currently no systematic theoretical and empirical research on how tourism cooperation affects the development of urban public health, which may hinder a comprehensive understanding of the intrinsic relationship between tourism cooperation and urban public health development.

The existing research has the following shortcomings: firstly, there is currently a lack of attention paid to the new requirements of regional coordinated development for urban public health development, and there are even fewer studies exploring effective tools to promote urban public health development from this logical starting point. There is still a blank in research on the impact of tourism cooperation on urban public health development. Secondly, although relevant studies have revealed the potential optimization or multiplier effects of tourism cooperation on the constituent elements of urban public health, there is a relative scarcity of research that systematically examines the theoretical mechanisms between the two and further investigates their impact effects. In response to the above shortcomings, this article intends to study the relationship between tourism cooperation, smooth internal circulation, and urban public health. The possible contributions mainly lie in three aspects: firstly, it expands the research on the impact of tourism cooperation on the development of urban public health. By analyzing the cultivation logic and configuration logic of tourism cooperation on the constituent elements of urban public health, as well as the construction logic of the supporting system for urban public health development, a triple nested empowerment theory of tourism cooperation on the development of urban public health is formed. Through empirical testing of the impact effect of tourism cooperation on urban public health development, it provides theoretical basis and empirical reference for solving the regional economic imbalance and insufficiency dilemma faced by China's urban public health development. Secondly, the heterogeneous characteristics of the impact of tourism cooperation on urban public health development were examined from two dimensions: differences in cooperation modes and cooperation subjects, and differences in external guarantee conditions. This is beneficial for various regions to formulate reasonable urban public health development strategies according to local conditions.

2 Research design

2.1 Model setting

In order to test the impact of tourism cooperation on urban public health development, this paper constructs the following benchmark regression model:

$$ELP_{it} = \eta_0 + \eta_1 RES_{it} + \eta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In model (1), i represents the city, t represents time, and ELP represents the level of public health development in the city; RES represents the degree of tourism cooperation, X represents a series of control variables, and μ, λ, and ε represent regional effects, time effects, and random disturbance terms, respectively.

To test the transmission effect of smooth internal circulation on the impact of tourism cooperation on urban public health development, the following mediation effect model is set up:

$$IC_{it} = \vartheta_0 + \vartheta_1 RES_{it} + \vartheta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$ELP_{it} = v_0 + v_1 RES_{it} + v_2 IC_{it} + v_3 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

Among them, IC represents the index of smooth internal circulation. If RES in model (2) has a significant positive effect on IC, and the coefficient of RES on ELP in model (3) is not significant or has decreased compared to model (1), it indicates that smooth internal circulation is an important channel for tourism cooperation to empower urban public health development.

2.2 Variable definition and explanation

Core explanatory variable: tourism cooperation degree. The measurement of the degree of tourism cooperation is an important topic in tourism research, involving multiple aspects such as destination management, regional cooperation, and stakeholder coordination. Tourism cooperation usually refers to the collaboration among different stakeholders (such as government, enterprises, communities, etc.) to achieve common goals. This article believes that tourism cooperation has a strong systemic connotation, which is essentially a process of coupling different regional tourism subsystems to form higher-level structures and functions. The degree of tourism cooperation is characterized by the value-added part of the operational efficiency of each regional tourism subsystem integrated into a regional large-scale system based on collaborative effects. The formula is as follows:

$$\begin{cases} RES_{ij} = \left[\left(\theta_{ij}^{'} - \bar{\theta}_{ij}^{'}\right) - \left(\theta_{i}^{'} - \bar{\theta}_{n}^{'}\right)\right] + \left[\left(\theta_{ij}^{'} - \bar{\theta}_{ij}^{'}\right) - \left(\theta_{j}^{'} - \bar{\theta}_{n}^{'}\right)\right] \\ RES_i = \sum_{j=1}^{n} RES_{ij}\left(j = 1,2,\text{L} \;\; ,n; i \neq j\right) \end{cases} \quad (4)$$

Among them, RES_{ij} represents the intensity of tourism synergy between city i and city j, and RES_{ij} represents the total intensity of synergy between city i and other cities, that is, the degree of tourism cooperation and development; $\theta_i^{'}$and $\theta_j^{'}$ respectively represent the efficiency of independent tourism systems in cities i and j, while $\theta_{ij}^{'}$ represents the overall tourism efficiency of cities i and j; $\bar{\theta}_{ij}^{'}$ and $\bar{\theta}_{n}^{'}$ respectively represent the sample mean of overall tourism efficiency and individual city tourism efficiency. The tourism efficiency values included are calculated by the SBM model and its GML index. The input indicators for measuring tourism efficiency are the number of tourism industry employees and fixed asset inputs, while the output indicator is the total tourism revenue.

Dependent variable: Development level of urban public health. Construct an evaluation index system for the target level of public health in Chinese cities from two dimensions: public health foundation and public health performance, and select 9 measurement indicators for construction. Dietary nutrition level is an indispensable part of evaluating residents' public health, and the per capita seafood consumption index is selected to characterize residents' dietary nutrition level. The basic health literacy of residents is measured by their basic education level, specifically expressed by the number of full-time secondary school teachers per 10,000 people. Since the regional infectious disease data is only available at the provincial level, and the incidence rate of infectious diseases among residents is positively related to the urbanization rate, and negatively related to the level of science and technology, this study selects the urbanization rate and the number of patent grants as weights to empower the incidence rate data of infectious diseases in all provinces (regions) in China, so as to calculate the incidence rate data of infectious diseases in all cities in China, and use the projection pursuit method to calculate the level of urban public health development (34, 35).

Control variables: To avoid the problem of omitted variables, this article selects control variables from five levels: economic vitality, fiscal decentralization, opening up to the outside world, financial support, and economic density. Economic Vitality (EV): Expressed as NPP-VIRS Nighttime Light Index. Fiscal decentralization (FD): expressed as the ratio of government general fiscal expenditure to general fiscal revenue. External Development (OP): Expressed as the ratio of actual use of foreign capital to regional GDP. Financial Development (FI): Expressed as the logarithm of the year-end deposit balance of financial institutions. Innovation Capability (CA): Expressed as the ratio of year-end patent grants to the resident population. Economic density (ED): expressed as the ratio of gross domestic product to regional area (37, 38) (Table 1).

2.3 Data sources and descriptive statistics

The research object of this article is 284 prefecture level cities in China from 2011 to 2022. The data sources mainly include the EPS database of the corresponding year, the China Urban Statistical Yearbook, the statistical yearbooks of various provinces and cities, the statistical bulletins of various cities, and the Guotai An database. A small amount of missing data is filled in using linear trend method.

3 Empirical result analysis

3.1 Benchmark regression results

Before conducting empirical analysis, this article uses correlation coefficients and variance inflation factors to test for multicollinearity among variables. The results showed that the correlation coefficients between variables were all below 0.7, and the VIF values were all below 2, far less than 10, indicating that the regression model in this article does not have serious multicollinearity problems.

Columns (1)–(6) of Table 2 show the benchmark regression results of tourism cooperation on urban public health development after gradually adding control variables. The results showed that in the process of adding control variables one by one, the regression coefficient of tourism cooperation on urban public health development was significantly positive at least at the 5% level, indicating that tourism cooperation can effectively promote urban public health development. This is because in recent years, the Chinese government has deployed major regional strategies, such as the coordinated development of Beijing Tianjin Hebei, the development of the Yangtze River Economic Belt, the construction of the Guangdong Hong Kong Macao Greater Bay Area, and the integrated development of the Yangtze River Delta. It has also continuously improved the platform, system, and legislative guarantees for tourism cooperation. As a result, production factors have been able to flow in an orderly manner, the mechanism for distributing benefits has become increasingly reasonable, and the regional economic layout and territorial spatial system with complementary advantages have gradually taken shape, leading to a rapid increase in tourism cooperation. The improvement of tourism cooperation can promote the construction of a modern industrial system by strengthening economic connections and industrial division of labor, thereby providing an industrial foundation for the development of urban public health. Secondly, tourism cooperation usually requires cities to improve and enhance their tourism environment, including urban greening, beautification, purification, and other aspects. These measures help improve the urban environment and enhance the quality of life for residents and tourists. A good urban environment helps to reduce the occurrence and spread of diseases, thereby improving the public health level of the city. The third is to effectively integrate resources and fully tap into comparative advantages to promote the emergence of disruptive technological innovation, thereby providing a technological foundation for the development of urban public health. The fourth is to rely on the scale borrowing effect and factor flow effect between regions to promote the virtual agglomeration of new production factors, thereby providing a factor foundation for the development of urban public health, and thus fully empowering the development of urban public health.

In terms of controlling variables, the impact of economic vitality, financial development, innovation capability, and economic density on the development of urban public health is significantly positive, indicating that the four have a promoting effect on the development of urban public health. This is because economic vitality can promote

TABLE 1 Variable description and descriptive statistics.

Variable type	Variable name	Indicator	*N*	Mean	SD	Min	Max
Explained variable	Tourism cooperation degree	Regional large-scale system based on collaborative effects	3,408	0.1532	0.0812	0.0153	0.5975
Core explanatory variable	Urban public health	Select 9 measurement indicators for construction	3,408	0.4919	0.4999	0.0000	1.0000
Control variables	Economic vitality	Expressed as NPP-VIRS Nighttime Light Index	3,408	0.3871	0.1910	0.0551	0.8975
	Fiscal decentralization	Expressed as the ratio of government general fiscal expenditure to general fiscal revenue	3,408	0.3429	0.2709	0.0000	0.8705
	External development	Expressed as the ratio of actual use of foreign capital to regional GDP	3,408	0.3925	0.2085	0.0000	0.8889
	Financial development	Expressed as the logarithm of the year-end deposit balance of financial institutions	3,408	2.8638	0.3649	0.0000	4.1897
	Innovation capability	Expressed as the ratio of year-end patent grants to the resident population	3,408	0.4238	0.3126	0.0145	0.9231
	Economic density	Expressed as the ratio of gross domestic product to regional area	3,408	0.2530	0.2605	0.1247	0.6364

TABLE 2 Benchmark regression results.

	(1)	(2)	(3)	(4)	(5)	(6)
RES	0.022*** (2.57)	0.015** (2.12)	0.016** (2.44)	0.054* (2.45)	0.043* (2.22)	0.016** (2.22)
EV		0.023*** (21.20)	0.033** (20.21)	0.027*** (19.45)	0.017*** (11.32)	0.012*** (11.44)
FD			−0.003*** (−3.45)	−0.002*** (−3.89)	−0.002*** (−3.43)	−0.002*** (−3.56)
FI				0.126** (2.33)	0.010** (2.17)	0.010** (2.19)
CA					0.116** (31.77)	0.128*** (39.14)
ED						0.834*(1.77)
Cons	0.274*** (1,338)	0.177*** (68.10)	0.182*** (53.59)	−0.025 (−0.27)	0.018 (0.27)	0.164 (0.25)
Individual fixed effects	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
Fixed time effect	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
R^2	0.110	0.242	0.256	0.267	0.482	0.476
Observations	3,408	3,408	3,408	3,408	3,408	3,408

*, **, *** are divided into significance levels of 1, 5, and 10%.

the aggregation of high-quality labor force, thereby reducing the production factor constraints on urban public health development. Financial development can reduce the financing constraints on the future development of industries and strategic emerging industries, as well as the transformation of traditional industries, thereby accelerating the construction of a modern industrial system and promoting the development of urban public health. Innovation capability can promote the emergence of disruptive technological innovation to support the development of urban public health. Economic density can form economies of scale and labor pool effects to support the upgrading of industrial structure, which in turn will promote the construction of a modern industrial system and empower the development of urban public health. The impact of fiscal decentralization on urban public health development is significantly negative, mainly because fiscal decentralization may lead to vicious competition among local governments in order to attract investment and promote economic growth, thereby reducing resource allocation efficiency and inhibiting urban public health development.

3.2 Endogeneity and robustness test

3.2.1 Endogenous test

The higher the level of urban public health development, the better the innovative allocation of production factors and the deep transformation ability of industries, which is conducive to tourism cooperation. Therefore, this article uses multiple instrumental variables to alleviate endogeneity issues. Firstly, using Confucian cultural intensity as an instrumental variable, this instrumental variable can influence the tourism cooperation degree of the city through the shaping effect of social and cultural atmosphere, satisfying correlation, but not directly related to the urban public health development status of the city, satisfying exclusivity. The regression results are shown in column (2) of Table 3. Secondly, the mean of regional synergy among other cities in the same province in the same year is used as the instrumental variable. This instrumental variable can affect the tourism cooperation degree of the city through demonstration and communication effects, satisfying correlation, but not directly related to the urban public health development status of the city, satisfying exclusivity. The regression results are shown in column (3) of Table 2. The results show that in columns (1)–(2) of Table 3, the *p*-values of the Anderson canon. Corr. LM statistic are all 0.000, rejecting the null hypothesis of insufficient identification of instrumental variables. The Cragg Donald Wald F statistic is greater than the critical value of weak instrumental variables at the 10% level, rejecting the null hypothesis of weak instrumental variables. It can be seen that considering endogeneity issues from multiple dimensions, tourism cooperation can still significantly promote the development of urban public health.

3.2.2 Robustness test

To further verify the robustness of the conclusions in this article, the following method is used for robustness testing: (1) replacing the dependent variable. The comprehensive indicator system is constructed from three dimensions of population survival rate, urban infectious disease incidence rate and life expectancy, and the development level of urban public health is measured by entropy weight method, and then regressed again. The results are shown in column (1) of Table 4. (2) Replace explanatory variables. Replace the SBM model used to measure the operational efficiency of regional economic systems in the efficiency appreciation model with the EBM model, recalculate the degree of tourism cooperation, and regress. The results are shown in column (2) of Table 4. (3) Tail truncation processing. To alleviate the impact of extreme values on the estimation results, this study performed a 1% bilateral truncation on the research sample and re regressed. The results are shown in column (3) of Table 4. (4) Adjust the sample period. To avoid the impact of the epidemic, the research period was shortened from 2011 to 2022 and the regression was conducted again after 2011 to 2019. The results are shown in column (4) of Table 4. (5) Exclude special samples. Considering that the administrative level of municipalities directly under the central government may cause disturbance to the results, Beijing, Tianjin, Shanghai, and Chongqing were excluded from the research sample and the regression was conducted again. The results are shown in column (5) of Table 4. After conducting a series of robustness tests, it was found that tourism cooperation still has a significant promoting effect on the development of urban public health, which is basically consistent with the benchmark regression results, indicating that the conclusion of this article is robust.

TABLE 3 Endogenous test.

	(1)	(2)
RES	0.556*** (4.45)	0.338*** (9.21)
Control variable	Control	Control
Individual fixed effects	Fixed	Fixed
Fixed time effect	Fixed	Fixed
Anderson canon. Corr. LM	24.562 [0.000]	75.68 [0.000]
Cragg-Donald Wald F	32.463 {16.54}	78.459 {16.54}
R^2	0.572	0.498
Observations	3,408	3,408

The *t*-value calculated by the urban clustering standard error is included, and *** is at a significance level of 1%. [] represents the *p*-value, {} represents the 10% critical value for weak instrumental variable testing.

3.2.3 Heterogeneity analysis

The differences in cooperation modes may lead to heterogeneity in the urban public health empowerment effects generated by tourism cooperation. This article focuses on examining the differential empowerment effects of two types of cooperation models on urban public health development: one is the adjacent city type cooperation model, where cities establish cooperative relationships with neighboring cities adjacent to their administrative regions to achieve tourism cooperation. The second is the “core hinterland” cooperation model, in which the provincial capital cities and deputy provincial capital cities within the province play a radiating and driving role, while other hinterland cities within the province establish cooperative relationships with these core cities to achieve tourism cooperation. On the basis of Equation (4), different types of spatial adjacency matrices were introduced to obtain the tourism cooperation degree of each city under two types of modes, and heterogeneity tests were conducted. The results are shown in columns (1)–(2) of Table 5. The results indicate that tourism cooperation has a significant positive impact on the development of urban public health in different cooperation models. However, compared to the adjacent city cooperation model, the tourism cooperation formed by the “core hinterland” cooperation model has a greater empowering effect on the development of urban public health. Possible reasons are as follows: On the one hand, although the communication and transaction costs of establishing tourism cooperation between cities and surrounding areas are lower, there may be a phenomenon of homogenization of tourism resources, which masks the empowering effect of tourism cooperation on urban public health development. On the other hand, core cities such as provincial capitals and vice provincial capitals usually have more developed infrastructure, more complete tourism industry chains, and richer tourism resources, which means they have a first mover advantage in the development of urban public health. The promotion of the “core hinterland” cooperation model is conducive to guiding the division of tourism and industry between core cities and hinterland cities, improving the efficiency of tourism resource allocation in core cities, forming a highland for urban public health development, and ultimately relying on channels such as industrial chains, logistics chains, and division of labor networks to spread relevant achievements in core cities that are conducive to urban public health development to hinterland cities, driving the upgrading of tourism in hinterland cities, and ultimately promoting the overall level of urban public health development in the region.

The cooperative effects generated by the interactions between different types of urban economic subsystems may vary, leading to further heterogeneity in the empowering effects of urban public health. Therefore, based on the differences in cooperation entities, this article divides them into economic cooperation between central cities, tourism cooperation between central cities and non-central cities, and economic tourism cooperation between non central cities and non central cities. On the basis of adjusting the selection rules of cooperation objects for each city’s tourism subsystem, the heterogeneity test is conducted to obtain the degree of tourism cooperation between different types of cities. The results are shown in Table 5 (3)–(5). The results indicate that tourism cooperation among different entities has a significant positive impact on the development of urban public health. However, the urban public health development empowerment effect of tourism cooperation between central cities is the greatest, followed by central cities and non central cities, and the

TABLE 4 Robustness test.

	(1)	(2)	(3)	(4)	(5)
RES	0.074** (2.34)	0.127*** (6.38)	0.011*** (3.15)	0.014* (1.89)	0.013** (2.61)
Cons	0.164 (0.21)	4.287*** (6.28)	0.132*** (2.72)	0.077 (1.01)	0.067* (1.95)
Control variable	Control	Control	Control	Control	Control
Individual fixed effects	Fixed	Fixed	Fixed	Fixed	Fixed
Fixed time effect	Fixed	Fixed	Fixed	Fixed	Fixed
R^2	0.432	0.377	0.382	0.337	0.423
Observations	3,408	3,408	3,408	2,556	3,360

*, **, *** are divided into significance levels of 1, 5, and 10%.

TABLE 5 Heterogeneity test.

Variables	Differences in cooperation modes		Differences in cooperation entities		
	(1)	(2)	(3)	(4)	(5)
RES	0.005** (2.16)	0.026** (4.16)	0.033** (3.05)	0.043** (4.54)	0.003** (2.43)
Cons	0.018 (0.18)	0.023*** (3.23)	0.026*** (5.22)	0.025 (1.87)	0.064* (2.32)
Control variable	Control	Control	Control	Control	Control
Individual fixed effects	Fixed	Fixed	Fixed	Fixed	Fixed
Fixed time effect	Fixed	Fixed	Fixed	Fixed	Fixed
R^2	0.452	0.552	0.225	0.352	0.252
Observations	3,408	3,408	420	2,988	2,988

*, **, *** are divided into significance levels of 1, 5, and 10%.

smallest between non central cities and non central cities. Possible reasons are as follows: Central cities usually have richer human capital, technological resources, and information flow. Therefore, when central cities cooperate with each other in tourism, the sharing power and complementarity of tourism are stronger, which can strengthen the innovation and industrial upgrading effects of tourism cooperation, thereby promoting the formation of larger urban public health. There is a gap between non central cities and central cities in terms of tourism, tourism scale, and tourism support. However, in the process of tourism cooperation with central cities, we can rely on the spillover effects of central cities and the sharing effects of tourism market scale to make up for the shortcomings of non-central cities in terms of tourism resources scarcity and insufficient scale, thereby promoting the overall level of urban public health development in the region. In addition, in the early stages of urban public health development, non-central cities may also face the problem of forced siphoning of urban public health development resources. Therefore, the urban public health empowerment effect generated by tourism cooperation between non central cities and non-central cities is the lowest.

4 Conclusions and policy recommendations

Can tourism cooperation empower the development of urban public health? To answer this question, this article takes 284 cities in China from 2011 to 2022 as the research object, empirically explores the impact of tourism cooperation on urban public health development and the mediating role of smooth internal circulation in it. Research has found that tourism cooperation can empower the development of urban public health. After a series of robustness tests, this conclusion still holds true. Secondly, heterogeneity analysis shows that compared to the adjacent city type collaborative model, the tourism cooperation formed by the "core hinterland" collaborative model has a greater empowering effect on the development of urban public health; The synergy between central cities and central city tourism has the greatest empowering effect on urban public health development, followed by central cities and non-central cities, with non-central cities and non-central cities having the smallest. Based on the above conclusions, this article proposes the following policy recommendations:

Firstly, promote the balanced development of tourism and public health. One is to strengthen public health management and services. Establish a sound public health management system, strengthen disease monitoring, early warning, and prevention and control work. Enhance medical treatment capabilities, improve emergency systems, and ensure that tourists and residents receive timely and effective treatment in the event of public health emergencies. The second is to optimize the tourism environment. Strengthen urban greening, beautification, and purification work to improve the quality of the tourism environment (39). Strengthen the supervision of tourist attractions to ensure a clean, safe, and orderly environment. The third is to promote the development of the health tourism industry. Encourage and support the development of the health tourism industry, such as special projects such as hot spring therapy and forest health preservation. Strengthen the planning and management of the health tourism industry to ensure its sustainable development. The fourth is to balance resource allocation. Balancing the development of the tourism industry with other public service sectors in tourism cooperation, ensuring the rational allocation and utilization of resources. Increase investment in public health, education, and other fields to improve the overall level of public services in cities.

Secondly, deepen tourism cooperation and eliminate the regional economic differentiation dilemma of urban public health development. This study indicates that tourism cooperation can effectively enhance the level of urban public health development. Therefore, one suggestion is to accelerate the improvement of the division of labor system in the tourism industry among cities, promote infrastructure interconnection, facilitate the sharing of public services such as education and healthcare, and further enhance the level of tourism cooperation. The second is to encourage the use of the digital economy to empower the tourism market as a lever, collaborate to build a first-class business environment and improve the digital tourism market system and mechanism, accelerate the construction of a cross regional, multi-level, and multi-dimensional integrated tourism market system, and further strengthen the radiation path of tourism cooperation and development (40). The third is to accelerate the construction of a high-quality regional integration institutional system, strengthen the coordination and cooperation between regional tourism policies and policies in finance, currency, industry, and other aspects, and further promote the level transition of positive externalities in tourism cooperation.

Thirdly, optimize the collaborative development strategy and improve external guarantee conditions simultaneously, fully developing the urban public health development empowerment role of tourism cooperation (41). Firstly, this article finds that in the "core hinterland" collaborative model, tourism cooperation has a greater empowering effect on the development of urban public health. Therefore, on the one hand, it encourages the deep integration of the tourism industry chain upstream and downstream between core cities and hinterland cities, and further builds a tourism division of labor network based on the tourism industry chain; On the other hand, it is recommended that cities with similar advantages in tourism resources establish a tourism resource conversion community and develop a unified market competition mechanism to promote the free flow of factors such as labor, capital, land, and data, thereby alleviating the masking effect of homogeneous competition on the positive externalities of tourism cooperation. Secondly, this article found that different types of urban tourism synergy have different empowering effects on the development of urban public health. Therefore, on the one hand, it is necessary to encourage central cities to formulate more flexible fiscal and tax policies and strengthen their leading role in the development of urban public health; On the other hand, it is necessary to support the development of characteristic tourism economy and industries in non central cities, while strengthening the tourism connection with central cities, and promoting the characteristic and coordinated development of public health in non-central cities.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.shujuku.org.

Author contributions

LZ: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. GZ: Data curation, Formal analysis, Writing – original draft. CL: Supervision, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This work was supported by the Ministry of Education's Humanities and Social Sciences Research Project "Research on the Multi-dimensional Spatiotemporal Evolution and Accessibility of Tourism Resources in the Central Yangtze River Urban Agglomeration" (Project Code: J2212601101001, Research Contract No: 202212601101001); Hubei Provincial Department of Education's Philosophy and Social Sciences Research Project "Research on the Impact of Spatial Knowledge Spillover of Collaborative Innovation in the Yangtze River Economic Belt on the Quality of Economic Development" (Project Code: 202112601301001, Research Contract No: 202112601301001).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

1. Hall CM. Tourism Planning: Policies, Processes and Relationships. London: Pearson Education (2008).

2. Dwyer L, Kim C. Destination competitiveness: determinants and indicators. *Curr Issue Tour*. (2003) 6:369–414. doi: 10.1080/13683500308667962

3. Bramwell B, Lane B. Tourism collaboration and partnerships: Politics, Practice and Sustainability. Clevedon, UK: Channel View Publications (2000).

4. Sharpley R. Tourism and sustainable development: exploring the theoretical divide. *J Sustain Tour*. (2000) 8:1–19. doi: 10.1080/09669580008667346

5. Basile R, Capello R, Caragliu A. Technological interdependence and regional growth in Europe: proximity and synergy in knowledge spillovers. *Pap Reg Sci*. (2012) 91:697–723. doi: 10.1111/j.1435-5957.2012.00438.x

6. Ivanova I, Strand Ø, Leydesdorff L. What is the effect of synergy provided by international collaborations on regional economies? *J Knowl Econ*. (2019) 10:18–34. doi: 10.1007/s13132-017-0480-2

7. Liu Y, Li L, Zheng FT. Regional synergy and economic growth: evidence from total effect and regional effect in China. *Int Reg Sci Rev*. (2019) 42:431–58. doi: 10.1177/0160017619838317

8. Liao B, Li L. Spatial division of labor, specialization of green technology innovation process and urban coordinated green development: evidence from China. *Sustain Cities Soc*. (2022) 80:103778. doi: 10.1016/j.scs.2022.103778

9. Yue P, Zhaolong A, Jianpu L, Weng G, Li L. Spatiotemporal characteristics and determinants of tourism cooperation network in Beijing–Tianjin–Hebei region. *Sustain For*. (2023) 15:4355–5. doi: 10.3390/su15054355

10. Yihong L, Qiuxiang Z. A sequential reciprocity game model of international tourism cooperation under the background of "one belt and one road". *J China Tour Res*. (2022) 18:978–90. doi: 10.1080/19388160.2021.1973637

11. Rachel P, Catheryn K, Charles A. Stakeholder contribution to tourism collaboration: exploring stakeholder typologies, networks and actions in the cluster formation process. *J Hosp Tour Manag*. (2022) 52:304–15. doi: 10.1016/j.jhtm.2022.07.011

12. Park E, Kim Y, Choi SH. Institutional approach for ecotourism collaboration between South Korea and Japan: exploration of criteria for ecotourism joint-certification. *Asia Pacific J Tour Res*. (2024) 29:1473–89. doi: 10.1080/10941665.2024.2401962

13. Wenjing Y, Yuqi S. On the economic sustainable development approaches and prospects of cultural heritage—"cultural heritage Mogao grottoes for economic development of Dunhuang through cultural tourism cooperation" as an example. *Int J Econ Financ*. (2024) 16:48–8. doi: 10.5539/ijef.v16n5p48

14. Yin J, Ni Y, Fan Y. Tourism cooperation in the belt and road initiative from economic and spatial insights. *PloS ONE*. (2024) 19:e0300392. doi: 10.1371/journal.pone.0300392

15. Qiang G, Xi Y, Hui C. The influence of women's empowerment on tourism involvement and sustainable tourism development: the moderating role of tourism cooperatives. *Asia Pacific J Tour Res*. (2023) 28:1130–46. doi: 10.1080/10941665.2023.2289401

16. Yong L, Xin Q. Regional tourism cooperation mechanism. *J Urban Plan Dev*. (2023) 149:253–68. doi: 10.1061/JUPDDM.UPENG-4336

17. Weng Z, Fan F, Yang B. Regional differences and drivers of patent transfer-in between Chinese cities: a city absorptive capacity perspective. *Tech Anal Strat Manag*. (2023) 36:4113–27. doi: 10.1080/09537325.2023.2242509

18. Xu E. The impact of innovation on intra-city economic disparity: a technological complexity perspective. *Appl Econ*. (2024) 56:1–16. doi: 10.1080/00036846.2024.2403781

19. Fan F, Yang B. The convergence mechanism and spatial spillover effects of urban industry-university-research collaborative innovation performance in China. *Tech Anal Strat Manag*. (2023) 34:1–17. doi: 10.1080/09537325.2023.2290169

20. Kovacs N, Piko P, Juhasz A, Nagy C, Oroszi B, Ungvari Z, et al. Comparative analysis of health status and health service utilization patterns among rural and urban elderly populations in Hungary: a study on the challenges of unhealthy aging. *Gero Sci*. (2024) 46:2017–31. doi: 10.1007/s11357-023-00926-y

21. Wang X, Wang L. The spatiotemporal evolution of COVID-19 in China and its impact on urban economic resilience. *China Econ Rev*. (2022) 74:101806. doi: 10.1016/j.chieco.2022.101806

22. Ashton BA, Alberto A, Michael CH. Just because it seems impossible, Doesn't mean we Shouldn't at least try: the need for longitudinal perspectives on tourism partnerships and the SDGs. *J Sustain Tour*. (2022) 30:2282–97. doi: 10.1080/09669582.2020.1860071

23. Yuewei W, Mengmeng X, Hang C, Wu X. A social network analysis of tourism cooperation in the Yangtze River Delta: a supply and demand perspective. *PloS ONE*. (2022) 17:e0263411–1. doi: 10.1371/journal.pone.0263411

24. Fan F, Weng Z, Tian J. Impact of government support policies on regional economic resilience under the COVID-19 outbreak. *Technol Econ Dev Econ*. (2024) 30:74–106. doi: 10.3846/tede.2024.20397

25. Lecouturier J, Kelly PM, Sniehotta FF. Reaching national Covid-19 vaccination targets whilst decreasing inequalities in vaccine uptake: public health teams' challenges in supporting disadvantaged populations. *Public Health Pract*. (2024) 8:100551. doi: 10.1016/j.puhip.2024.100551

26. Durand AM, Petticrew M, Goulding L, Eastmure E, Knai C, Mays N, et al. An evaluation of the public health responsibility Deal: informants' experiences and views of the development, implementation and achievements of a pledge-based, public–private partnership to improve population health in England. *Health Policy*. (2015) 119:1506–14. doi: 10.1016/j.healthpol.2015.08.013

27. Zhao L, Jiang J. Evolution and drivers of embodied energy in intermediate and final fishery trade between China and maritime silk road countries. *Reg Sci Environ Econ*. (2024) 1:104–27. doi: 10.3390/rsee1010007

28. Filippo B, Fabian BB, Martin S. Collaboration and meta-organisation in event tourism – effects of the Olympic agenda 2020 on planning the 2026 winter Olympics. *Tour Manag Perspect*. (2022) 41:100939. doi: 10.1016/j.tmp.2022.100939

29. Song L. Development trends of cross-border tourism cooperation in Northeast Asia in the post-epidemic era. *Northeast Asian Econ Rev*. (2022) 8:1–15. doi: 10.57320/economicreview.8.1_1

30. Yan SL. The development and strategy analysis of China and Russia tourism cooperation under the background of "one belt one road". *J Sociol Ethnol*. (2021) 3:75–80. doi: 10.23977/jsoce.2021.030613

31. Fan F, Song T, Zhai X. Education, science and technology, and talent integrated development: evidence from China. *Reg Sci Environ Econ*. (2024) 1:60–77. doi: 10.3390/rsee1010005

32. Yin J, Bi Y, Ji Y. Structure and formation mechanism of China-ASEAN tourism cooperation. *Sustain For*. (2020) 12:5440. doi: 10.3390/su12135440

33. Chung YJ, Cui HZ. China-North Korea international tourism cooperation in Tumen River: an exploratory study. *J Tour Sci*. (2020) 44:33–55. doi: 10.17086/JTS.2020.44.5.33.55

34. Ālvarez MA. New trends in collaborative economy in tourism. Diversification of traditional accommodation to a non-regulated offer in Spain. *Int J Bus Global*. (2020) 24:377. doi: 10.1504/IJBG.2020.106479

35. Czernek-Marszałek K. The overembeddedness impact on tourism cooperation. *Ann Tour Res*. (2020) 81:102852–2. doi: 10.1016/j.annals.2019.102852

36. Xu E, Xiao Z, Wang Z. Has the pilot project of innovative cities increased economic growth? An empirical study based on Chinese cities. *Reg Sci Environ Econ*. (2024) 1:31–45. doi: 10.3390/rsee1010003

37. Muntifering RJ, Clark S, Linklater LW, Uri-Khob S, Hebach E, Cloete J, et al. Lessons from a conservation and tourism cooperative: the Namibian black rhinoceros case. *Ann Tour Res*. (2020) 82:102918–435. doi: 10.1016/j.annals.2020.102918

38. Dae EL, Seok YK. The cooperative governance on the rail tourism: case study on the Buncheon Santa Village in South Korea. *Korean Public Admin Q*. (2019) 31:737–58. doi: 10.21888/KPAQ.2019.12.31.4.737

39. Zhang H. The spread of Guangxi ethnic culture in ASEAN under the China-ASEAN tourism cooperation perspective. *Tourism forum*. (2018) 11:146–53.

40. Jianyin B, Yin C, Yong L. The structural equivalence of tourism cooperative network in the belt and road initiative area. *Environ Res*. (2021) 197:111043–3. doi: 10.1016/j.envres.2021.111043

41. Alexandra C, Mihail E, Corneliu I. A multilayer network approach to tourism collaboration. *J Hosp Tour Manag*. (2021) 46:316–26. doi: 10.1016/j.jhtm.2021.01.006

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 10 April 2025
DOI 10.3389/fpubh.2025.1501879

OPEN ACCESS

EDITED BY
Emanuel Orozco,
National Institute of Public Health (Mexico), Mexico

REVIEWED BY
Ömer Alkan,
Atatürk University, Türkiye
Bobo Feng,
Chongqing Normal University, China

*CORRESPONDENCE
Kun Lv
✉ lvkun@nbu.edu.cn

RECEIVED 27 September 2024
ACCEPTED 10 March 2025
PUBLISHED 10 April 2025

CITATION
Jia J, Bao Z, Wang H, Cao Y, Yu L and Lv K (2025) Factors influencing health information acquisition behavior from a social capital theory perspective: a study of Zhihu users.
Front. Public Health 13:1501879.
doi: 10.3389/fpubh.2025.1501879

Factors influencing health information acquisition behavior from a social capital theory perspective: a study of Zhihu users

Juncheng Jia[1], Zemenghong Bao[2], Haochen Wang[3], Yuqun Cao[1], Luhan Yu[1] and Kun Lv[1,4]*

[1]Business School, Ningbo University, Ningbo, China, [2]School of Cultural Heritage and Information Management, Shanghai University, Shanghai, China, [3]School of Electrical and Computer Science, Ningbo University, Ningbo, China, [4]Merchants' Guild Economics and Cultural Intelligent Computing Laboratory, Ningbo University, Ningbo, China

The rapid development and widespread use of Internet technology have facilitated access to health information for the general public. However, the behavior of acquiring health information is influenced by multiple factors, resulting in differences and even inequalities. This paper aims to explore the influencing factors of user health information acquisition behavior, find feasible ways to optimize such behavior and maximize the utility of health information for users. By utilizing the Zhihu Q&A platform to obtain user health information and integrating social capital theory, the study identifies the influencing factors of user health information acquisition behavior. It utilizes fuzzy set qualitative comparative analysis to examine these factors as antecedent variables, with the dissemination heat of health information as the outcome variable. The study reveals that the structure, relationships, and cognitive dimensions of social capital significantly impact user health information acquisition behavior. The configuration path for user health information acquisition behavior generated by the fsQCA 3.0 software provides recommendations to maximize the utility of health information.

KEYWORDS

social capital, health inequality, fsQCA, health information acquisition behavior, influencing factors

1 Introduction

For a long time, objective health disparities have existed among different groups (1). The development of mobile Internet technology has not only changed the operation mode of the medical and health industry but also profoundly affected the public's access to health knowledge (2). The rapid development of information sharing, online medical care, virtual social interaction, and other aspects has turned the internet into an expanded space for obtaining health promotion resources (3). Online medical health platforms in China such as Dingxiang Doctor, and Medication Assistant, health management apps such as Keep, and Mint Health, and health content dissemination platforms such as TikTok and Zhihu, rely on the internet to continuously grow and expand. The diversification of user access to health information has allowed knowledge that was once only accessible through doctors, books, and magazines to reach the general public through fragmented reading patterns, making the Internet the primary source for seeking health information (4).

However, the diversification of health information acquisition behavior methods has also brought about differentiation. Even in the same network environment, different users have varying abilities to access health information. This has led to issues of information inequality (5), particularly in health research, where information inequality often stems from differences in social capital across different groups. Social capital generally refers to the ability of individuals or groups to access resources, support, and information within a social network, and it is closely related to an individual's health status (6). For example, individuals with stronger social capital are often able to acquire health information, medical resources, and social support more effectively, which in turn contributes to better health outcomes. In contrast, groups with weaker social capital face difficulties in accessing health resources and information due to a lack of effective social support and information channels, leading to poorer health conditions and exacerbating health inequality (7). Therefore, social capital is a critical theory in the study of health inequality. It helps explain the differences in health information acquisition across different social groups. Based on this, this paper applies social capital theory to explore the factors influencing users' health information acquisition.

2 Literature review

2.1 Definition of information inequality

Information inequality refers to the diverse information gaps formed at various levels of subjects in information and communication technology access and usage, as well as in the development and utilization of information resources (8). With the internet being fully integrated into social life, the mode of information flow and interaction between individuals has gradually changed the original social relationships and structures (9). The mastery of information and the ability to access information have become important considerations (10). However, due to differences in resource endowments, individuals have unequal abilities to access information (11). Research on this issue has been ongoing for a long time.

2.2 The concept of the digital divide

The concept of the digital divide was first proposed by the National Information Management Agency of the United States, initially exploring the rudiments of information inequality. It was believed that there was a gap between those who had access to new technology and those who did not, specifically in terms of the ownership of personal computers, broadband network connectivity, and other aspects (12, 13). Those who possessed technological devices were able to access effective information resources through the internet (14), creating a divide and causing information inequality compared to those who could not afford it (15). However, studies on the digital divide often used a simple binary division of information owners and the impoverished, assuming that users in different locations and with different demographic characteristics formed the divide (16). It mainly focused on the unequal opportunities for technology usage but paid less attention to the social reasons behind it (17). Up to now, the digital divide has been rarely discussed in the context of social inequality theory, other types of inequality, or general human inequality concepts (18).

2.3 Comparison between information inequality and the digital divide

In contrast, information inequality is a more comprehensive concept that transcends the limitations of the digital divide (19). Information inequality not only considers demographic variables, but also, due to its close association with offline social inequality, it also concerns the performance of digital technology in influencing social welfare, family, political participation, and social support (20). This viewpoint believes that the unequal distribution of status and power in social networks can lead to unequal participation in other areas of society (21, 22), just as in the field of health, where users' unequal social capital leads to health inequality. Research on digital inequality often starts from a social stratification perspective (23), and the views of Bourdieu have received significant attention, holding that the concept of social capital can well explain the formation mechanism of digital inequality, where individuals with similar social spatial positions compete for resources and form insurmountable barriers (24).

2.4 Social capital theory and its relationship with health information acquisition behavior

Social capital refers to the sum of resources embedded in social networks that can be acquired and utilized (25). Initially proposed by the scholar Bourdieu, the amount of social capital possessed by a subject depends on the scale of the relationship network that they can effectively mobilize. Social capital has evolved from a marginal concept into a multidimensional concept, with differences in its concept and measurement indicators in different research contexts. Among them, the most widely applied classification of social capital is divided into three dimensions: structural capital, relational capital, and cognitive capital (26). Structural capital, which arises from objective factors such as connections, rules, and procedures among individuals, describes the frequency and duration of interaction between network members, emphasizing social interaction and connectivity within networks. Research indicates that the closer the connections between members in virtual communities, the more effective the sharing of knowledge (27). In the context of the internet, social interaction and connectivity refer to interactions such as questioning, answering, and discussing among users in online virtual communities. Users within strong network connections exhibit a stronger willingness to communicate and share, facilitating the transmission of information through frequent communication and making it easier to access relevant health information (28). Relational capital refers to the interpersonal relationships developed through communication and interaction between individuals, including trust, reciprocity, and identification. When individuals establish high levels of trust and reciprocal relationships within their social networks, they are more likely to obtain reliable health information from others in their network. For example, the presence of trust encourages individuals to share health experiences and advice, thereby improving the efficiency and quality of information transmission. Furthermore, a strong social support network can provide emotional support and psychological comfort, further enhancing individuals' ability to acquire and understand health information. Cognitive capital refers to the common perceptions, values, and language used by individuals regarding things, while cognitive social

10.3389/fpubh.2025.1501879

capital arises from subjective factors such as individual consciousness, values, and attitudes (29, 30). When individuals can find health concepts and consistent health beliefs they identify with within their social networks, they are more likely to acquire and effectively use health information. Furthermore, the cognitive dimension also influences whether individuals can extract useful information for themselves, which is particularly important in the process of understanding health education and health behavior change. The various dimensions of social capital, through the connection and exchange of resources, contribute to the creation, exchange, and transmission of knowledge (31).

2.5 Health inequality under the fundamental cause theory

The study of health inequality often focuses on the field of sociology, with a particular emphasis on fundamental cause theory. This theory, similar to social capital theory, posits that socioeconomic status is the fundamental cause of health disparities and health inequality (32). It contends that individuals of higher social and economic standing possess a significant amount of resources, which can reduce the likelihood of illness and death, resulting in better overall health (33). The theory asserts that as long as there is inequality in the distribution of resources, health inequality will persist. Overall, fundamental cause theory contextualizes health research within a broader framework of social inequality, shifting the focus toward social stratification and inequality (34).

2.6 Research on health inequality under social capital theory

Both studies on digital inequality and health inequality recognize resources as a critical factor in perpetuating inequality. Social stratification theory maintains that the distribution of social resources is uneven: individuals of higher status have greater access to resources (35). The advantaged class is more knowledgeable about where to seek health information and better equipped to understand it (36). However, few studies have incorporated the ability to access health information into their research. The field of information science often studies user information behavior based on comprehensive information retrieval models but rarely includes the phenomenon of health inequality in its scope (37). Therefore, based on social capital theory, this paper seeks to explore the factors influencing user access to health information and employs fuzzy set qualitative comparative analysis to conduct configurational research. The aim is to identify feasible approaches to optimize user access to health information and maximize the utility of such information, ultimately alleviating health inequality.

3 Research design

3.1 Methodology and procedures

Qualitative Comparative Analysis (QCA) is a configurational analysis based on Boolean algebra and set theory. Its purpose is to explain the configurational phenomena of interdependent conditional factors and their resulting outcomes in practice (38). This method, rooted in a configurational perspective, explores the multiple concurrent causal relationships among variables, where various combinations of variables collectively lead to the same outcome (39).

Fuzzy Set Qualitative Comparative Analysis (fsQCA) is a type of qualitative comparative analysis method that allows for the scaling of set scores (40). In line with the focus and objectives of this study, the following research steps are formulated: (1) using the principle of "maximum difference, same result; minimum difference, different result," (41) select health information from social Q&A platforms as the research case; (2) design antecedent and outcome variables based on case characteristics and social capital theory; (3) calibrate data based on variable data and case characteristics; (4) conduct necessary tests for single variable inclusion to preliminarily identify the core conditions leading to the appearance of the outcome variable; and (5) minimize configurations to output the final results. The specific research and analysis framework is illustrated in Figure 1.

3.2 Case selection

Health information, as defined in the 2014 General Medicine and Community Health vocabulary, encompasses all knowledge, techniques, skills, concepts, and behaviors related to human health produced, transmitted, and shared by both parties in the health communication process (42). This study unfolds an exploration using Zhihu (the Chinese equivalent of Quora) as an example, selecting health-related topics as the sample. To ensure the accuracy and effectiveness of the results, the principle of "maximum difference, same result; minimum difference, different result" is employed to select topics with comprehensive user information (43). In this study, the principle of "maximum difference, same result" is applied based on the health information dissemination heat (such as the total number of comments, likes, etc.), ensuring that, within the same outcome variable, the selected cases exhibit significant differences across other variables (such as region, industry, education level, etc.). This approach helps ensure the diversity and generalizability of the study. On the other hand, for cases with substantial differences in health information heat, the study employs the principle of "minimum difference, different results," selecting cases where differences across other variables are minimal. Case selection based on this principle helps eliminate those cases whose extreme differences would render the results less generalizable, thereby ensuring that the selected cases possess high representativeness for the configurational analysis.

The specific cases and basic information are presented in Table 1.

3.3 Variable inclusion

Zhang Ming et al. proposed five main methods for determining conditions in QCA research: the problem-oriented approach, the research framework approach, the theoretical perspective approach, the literature induction approach, and the phenomenon summarization approach (44). Among these, the theoretical perspective approach matches corresponding conditions based on different theories or explanatory perspectives. In this study, the theoretical perspective approach is employed to determine the antecedent variables, while the problem-oriented approach is used to

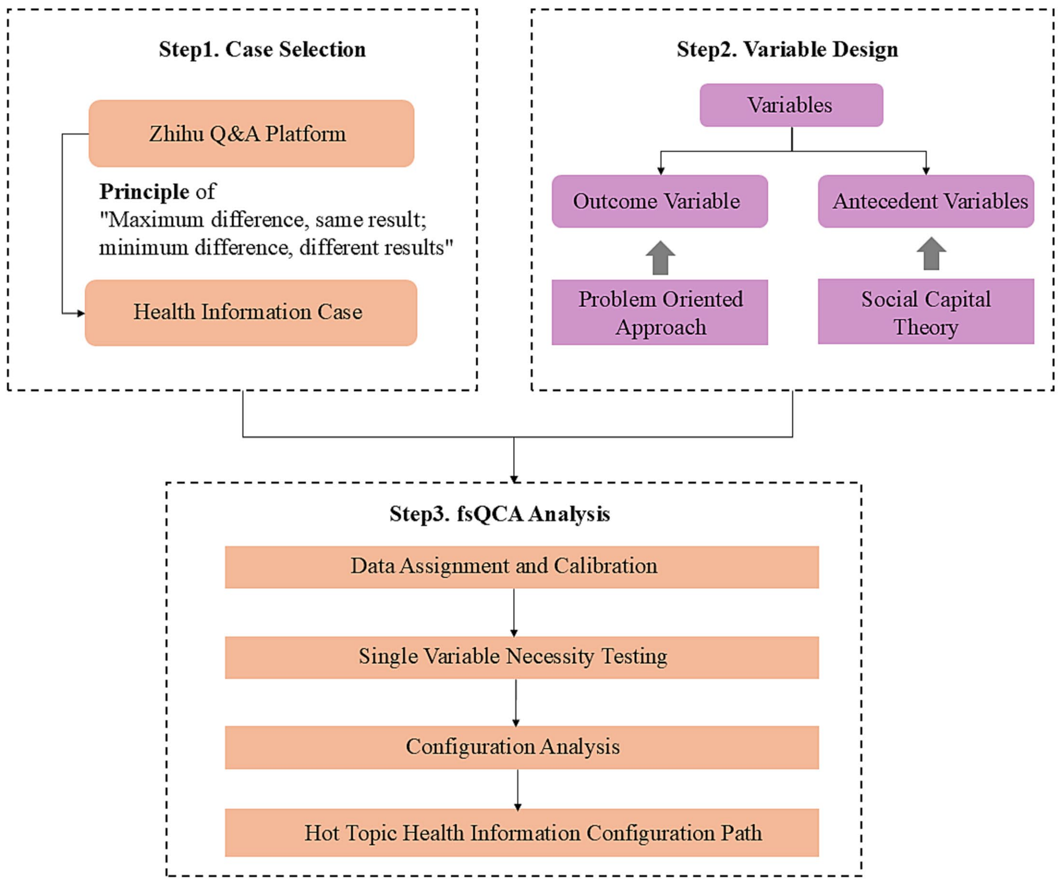

FIGURE 1
Research framework diagram.

determine the outcome variables. The theoretical framework selected for this study is the social capital theory.

As social Q&A platforms serve as a primary source of knowledge acquisition behavior in the Internet era, users' engagement impacts their access to health information (45). Therefore, this paper applies the social capital theory to measure the relationship between social capital and the health information-seeking behavior of social Q&A platform users from three dimensions: relational, cognitive, and structural. Zhihu users' social capital is categorized into three types (see Table 2) based on this framework.

For the structural social capital variables, structural social capital emphasizes an individual's position within a social network and the structure of that network. Among the variables selected in this study, offline factors such as region and industry reflect the distribution of an individual's resources, which influences the information and resources they can access. Online behaviors, such as the number of views and comments, reflect the frequency of user interactions on the platform and the activity level of their social network. Therefore, these variables effectively measure an individual's structural social capital.

For the relational social capital variables, relational social capital primarily focuses on the quality of social relationships between individuals, especially the role of trust, reciprocity, and recognition in facilitating information exchange. Among the variables selected in this study, trust and reciprocity help enhance the dissemination and credibility of health information, while recognition strengthens an individual's sense of participation and belonging within the social network. In terms of online behaviors on the platform, the number of followers and the number of people followed reflect the accumulation of social capital, indicating the individual's ability to access more information and exert greater influence.

For the cognitive social capital variables, cognitive social capital concerns an individual's knowledge background, cognitive ability, and values. Among the selected variables in this study, education level and occupation reflect the individual's knowledge background and information processing capabilities, influencing their understanding and application of health information. In terms of online behaviors, the number of likes received reflects the user's contribution to and recognition of health information, indicating strong social cognitive capital on the platform.

3.4 Data assignment and calibration

By the requirements of fsQCA analysis, the antecedent and outcome variables in the sample need to be calibrated before configurational analysis, transforming them into membership values on the (0,1) set. This is typically achieved through three-value assignment, four-value assignment, six-value assignment, or continuous assignment methods (46). Among these methods, the four-value assignment approach strikes an optimal balance between precision and simplicity. In contrast, the

TABLE 1 fsQCA case.

Number	Case name	Number	Case name
1	Is it true that all beverages taste better when served cold?	16	What is your view on the article published in "Science" that suggests middle-aged weight gain is not due to a slowing metabolism?
2	Is it true that all beverages taste better when served cold? (2)	17	What is your view on the article published in "Science" that suggests middle-aged weight gain is not due to a slowing metabolism? (2)
3	What are the methods for sobering up?	18	What are the benefits of jogging five kilometers every day?
4	What are the methods for sobering up? (2)	19	What are the benefits of jogging five kilometers every day? (2)
5	A woman suffered from facial paralysis after riding a bicycle with wet hair.	20	Why is milk still widely promoted in China when most people are lactose intolerant?
6	A woman suffered from facial paralysis after riding a bicycle with wet hair. (2)	21	Why is milk still widely promoted in China when most people are lactose intolerant? (2)
7	What fruits are best for people with diabetes to consume?	22	What eating habits do thin people have?
8	Are there any benefits to being overweight?	23	What are your small habits for looking beautiful?
9	Are there any benefits to being overweight? (2)	24	What does the real life of a gout patient look like?
10	A 16-year-old boy died after choking on a pearl milk tea, his family claims it was due to sudden cardiac arrest. How should one handle such situations promptly?	25	Why am I still tired after getting at least 8 h of sleep every day? How can I adjust my body to be energetic?
11	How can men maintain their health daily?	26	How can one determine which vitamin they are deficient in?
12	Could you recommend some toothpaste that truly has whitening effects on teeth?	27	Why does a person who brushes their teeth diligently have bad breath?
13	Could you recommend some toothpaste that truly has whitening effects on teeth? (2)	28	How can office workers protect their shoulders and necks from strain?
14	Do foreign girls drink ice water and their mothers do not tell them it's bad for their health and may cause cold in the womb?	29	How can office workers protect their shoulders and necks from strain? (2)
15	What signs on your body indicate that you are aging?	30	How can one control their uric acid levels to maintain normalcy?

TABLE 2 Social capital classification of Zhihu users.

Category	Structural	Relational	Cognitive
Offline	Locale, industry	Trust, mutual benefit, identification	Education occupation
Online	View count, comment count	Follower count Following count	Like count

three-value method, while simplifying the categorization of variables, proves overly coarse, failing to capture subtle differences between variables. On the other hand, the six-value assignment method, with its inclusion of additional intermediate values, increases analytical complexity, thereby hindering model parsimony. Furthermore, within the four-value assignment framework, the values of 0 and 1 signify states of complete "non-membership" and "full membership," respectively, enabling a clear delineation of extreme conditions. Meanwhile, the intermediate values of 0.33 and 0.67 denote states of "low membership" and "high membership," respectively, effectively representing variables within ambiguous boundaries and facilitating a more nuanced depiction of data variability. Given that numerous variables, such as users' social capital and the frequency of information acquisition, exhibit a degree of fuzziness in the context of health information retrieval, the four-value assignment method proves superior in addressing this ambiguity and enhancing the model's explanatory power. Based on the four-value method, the specific assignments for each antecedent variable are outlined in Table 3.

By the problem-oriented approach (47), this study selects the number of question-answer comments and endorsements as outcome variables (The Zhihu research data in this study is up to June 2024). Direct calibration method is employed for encoding, with 3,000 set as the threshold for complete membership (48), assigning a membership score of 0.95; 200 as the threshold for complete non-membership, with a membership score of 0.05; and 600 as the crossover point, from which the membership score is calculated (The direct calibration method process is provided in Table A1 of Appendix A).

The 30 topic cases in Table A1 of Appendix A are coded and assigned values based on the characteristic properties of the antecedent and outcome variables, resulting in a measurement of the antecedent and outcome variables (The measurement results are shown in Table A2 of Appendix A).

TABLE 3 Antecedent variable assignment table.

Variable name	Target set	Assignment	Specific meaning
Structural social capital	User region	1	Economically developed regions
		0.67	Regions with moderate economic development
		0.33	Economically underdeveloped regions
		0	Impoverished areas/no data
	User industry	1	Industries related to health information
		0.67	Industries somewhat related to health information
		0.33	Related but does not directly/indirectly impact
		0	Unrelated industries
Relational social capital	Interacting users	1	Users with extremely high interaction frequency
		0.67	Users with high interaction frequency
		0.33	Users with moderate interaction frequency
		0	Users with low interaction frequency
Cognitive social capital	User education level	1	High-level university/health-related majors
		0.67	High-level university/non-related majors
		0.33	Average university
		0	Not applicable/no data
	Number of likes received	1	Extremely high number of likes received
		0.67	High number of likes received
		0.33	Moderate number of likes received
		0	Low number of likes received

4 Data analysis

4.1 Single condition necessity analysis

Consistency and coverage calculations for a single independent variable are conducted to determine whether the independent variable is a sufficient and necessary condition for the dependent variable. Generally, when the consistency is ≥0.9, the independent variable can be considered a sufficient and necessary condition for the dependent variable. The calculation formula is shown in the equation:

$$Consistancy\left(Y_i \le X_i\right) = \sum \frac{\min\left(X_i, Y_i\right)}{\sum\left(Y_i\right)}$$

The data is imported into the fsQCA3.0 software for computation. Adding a "~" in front of a variable indicates the non-existence of that variable, and the results are presented in Table 4.

From the results, it is evident that the consistency values of all the antecedent variables did not reach 0.9, indicating a preliminary assessment of the weak explanatory power of the variables in influencing users' health information acquisition behavior. No definitive factors or essential conditions influencing this behavior were identified. Consequently, this study will further investigate the configurational effects among the antecedent variables.

4.2 Configuration analysis

A truth table was constructed using fsQCA3.0 software, and the table was then edited. The case threshold was set at 1 and the consistency threshold at 0.8. Configuration pathways with fewer cases were removed to simplify the analysis, ultimately yielding three types of solutions: complex solutions, intermediate solutions, and simple solutions. This study only presents the intermediate solution, as detailed in Table 5.

In Table 5, "*" serves as the connector symbol indicating an intersection between variables, while "~" denotes the absence of a variable. "Raw coverage" represents the proportion of the impact of a conditional combination formed by antecedent variables on the solution, measuring the membership degree of each component in the combination on the solution's impact. "Unique coverage" illustrates the proportion of the solution's interpreted membership degree of a specific conditional combination formed by antecedent variables, reflecting the interpretive ability and importance of a particular combination on the solution, generally serving as the primary basis for analysis. "Consistency" is used to determine whether a specific combination of antecedent variables is a sufficient condition for the solution. "Solution coverage" denotes the overall coverage of all combinations of antecedent variables for the solution, while "solution consistency" represents the consistency indicator for all conditional combinations.

In practical analysis, due to the superior interpretive and adaptive qualities of the intermediate solution for the issue under study, which surpasses both the complex and simple solutions, the majority of

 10.3389/fpubh.2025.1501879

TABLE 4 Table for the necessity of single conditions.

Antecedent variables	Result variables	
	Popularity	~Popularity
Region	0.883942	0.847853
~Region	0.207299	0.228834
Industry	0.522628	0.465031
~Industry	0.531387	0.580368
Interactive users	0.691241	0.692638
~Interactive users	0.435766	0.414110
Education level	0.448175	0.466258
~Education level	0.628467	0.598160
Number of likes received	0.605109	0.463190
~Number of likes received	0.506569	0.630675

"~" indicates the non-existence of the variable.

TABLE 5 Intermediate solution results.

Configuration	Raw coverage	Unique coverage	Consistency
~Region * ~ Industry * Education Level	0.0343066	0.0102189	0.701493
Region * ~ Industry * ~ Interactive Users * ~ Education Level	0.3	0.250365	0.727434
Region * Industry * Interactive Users * Number of Likes Received	0.409489	0.359854	0.672662
~Region * Industry * Interactive Users * ~ Education Level * ~ Number of Likes Received	0.0751825	0.0510948	0.774436
Solution Coverage	0.745255		
Solution Consistency	0.695978		

"~" indicates the non-existence of the variable.
"*" indicates the intersection relationship between variables, which is used to connect variables.

studies employ the intermediate solution for analysis. Qualitative comparative analysis theory posits that if a condition appears in both the simple and intermediate solutions, it is defined as a core condition, whereas if it only appears in the intermediate solution, it is considered an auxiliary condition (49). Integrated with the simple and intermediate solutions, this study ultimately establishes four antecedent variable conditional combinations influencing the outcome variables:

1. H1: *~Region * ~ Industry * Education Level*;
2. H2: *Region * ~ Industry * ~ Interactive Users * ~ Education Level*;
3. H3: *Region * Industry * Interactive Users * Number of Likes Received*;
4. H4: *~Region * Industry * Interactive Users * ~ Education Level * ~ Number of Likes Received.*

These variable combinations are presented as shown in Table 6. Table 6, ⊕ indicates the presence of a core condition, ⊗ indicates the absence of a core condition, ⊕ denotes the presence of an auxiliary condition, and ⊗ signifies the absence of an auxiliary condition. Blank spaces represent conditions that may or may not exist. The overall consistency of the solution is 0.695978, indicating that approximately 69.6% of the cases analyzed can be explained by the selected combination of conditions, suggesting a degree of reliability but not complete biaslessness. Consequently, it can be inferred that while the study has identified relatively significant patterns across the four pathways of hot topic formation, a proportion of unexplained variance remains, necessitating further exploration of other potential factors. Additionally, the overall coverage of the solution is 0.745255, indicating that these four configurational pathways can account for about 74.5% of the reasons for health information acquisition. This high coverage value suggests that the formation of most hot topics can be reasonably explained by these four pathways, yet it also hints at the presence of some external variables or complex interactive effects that were not included in the analysis of this study.

5 Analysis and discussion

5.1 Analysis of the impact of single antecedent variables

Derived from social capital theory, the factors influencing users' acquisition behavior of health information can be categorized into three types of social capital: structural, relational, and cognitive. This study, utilizing fuzzy and qualitative comparative analysis, employs the aforementioned categories of social capital—*Region*, *Industry*, *Interactive Users*, *Education Level*, and *Number of Likes Received*—as antecedent variables, with the health information popularity (sum of

TABLE 6 The path of hotspot health information configuration.

Antecedent variables	Hotspot health information configuration			
	H1	H2	H3	H4
Region	⨂	⊕	⊕	⊗
Industry	⊗	⊗	⊕	⊕
Interactive users		⊗	⊕	⊕
Education level	⊕	⊗		⊗
Number of likes received			⊕	⊗
Consistency	0.701493	0.727434	0.672662	0.774436
Raw coverage	0.0343066	0.3	0.409489	0.0751825
Unique coverage	0.0102189	0.250365	0.359854	0.0510948
Solution consistency	0.695978			
Solution coverage	0.745255			

comments and likes) as the outcome variable. The findings reveal that while all three types of social capital—structural, relational, and cognitive—impact users' acquisition behavior of health information, the influence of single factors is relatively weak and not a sufficient condition for the formation of hot topics. Subsequent sections will elucidate the extent of the impact of each antecedent variable on the formation of hot topics based on the analysis of single-condition necessity.

In particular, the impact of the region within the structural social capital on users' acquisition behavior of health information is significant, with a consistency of 0.883942. Offline social capital such as region can influence users' online information behavior, as users in economically developed regions have access to more convenient technological devices and technological education. As a result, users can alter their structural social capital through migration and other means to facilitate their acquisition behavior of health information. Relational social capital can also have a certain impact on users' acquisition behavior of health information, with a consistency of 0.691241. The more followers and followers a user has, the greater the likelihood of encountering health information. Therefore, users can accumulate their relational social capital by increasing their internet usage frequency and networking frequency to broaden their channels for acquiring health information. However, the impact of offline social capital education within cognitive social capital is not particularly pronounced, with a consistency of only 0.448175, and the impact of online social capital likes count is also relatively minor, with a consistency of 0.605109. Education and the user's knowledge literacy alone do not play a decisive role in the acquisition behavior of health information. Therefore, when offline cognitive capital is difficult to change, users can improve their online cognitive social capital through their efforts, such as continuing their education, to improve their environment for acquiring health information.

5.2 Configuration path analysis

Based on the analysis of the impact of single antecedent variables and the data analysis results, it is evident that the impact of single factors on users' acquisition behavior of health information is not significant and not a sufficient necessary condition. Therefore, this study further explores the configurational effects among the antecedent variables, ultimately resulting in the identification of four configurational paths, as shown in Figure 2

1 H1: ~*Region* * ~ *Industry* * *Education Level.*

Configuration one signifies a scenario where the local and industry contexts do not significantly impact users' acquisition of health information. Users with higher education and a professional background related to health can more readily access health information. Specifically, highly educated individuals typically possess robust health information screening abilities and a high level of health awareness. If the user's professional background is directly related to health, they are more likely to obtain targeted health information. For instance, groups with strong academic backgrounds such as medical students, public health scholars, and nutritionists can directly access relevant health information from professional literature, academic resources, or industry news. Therefore, in this context, education level becomes a key driving factor in health information acquisition. Even in the absence of specific regional advantages or industry relevance, users' high levels of cognitive capital can still facilitate their effective acquisition of health information.

This pathway reflects the predominant role of cognitive social capital (education, professional background) in health information acquisition. Users with higher education and a professional background related to health can, through their precise screening abilities, actively engage with high-quality health information, enhancing both the efficiency and effectiveness of their health information acquisition.

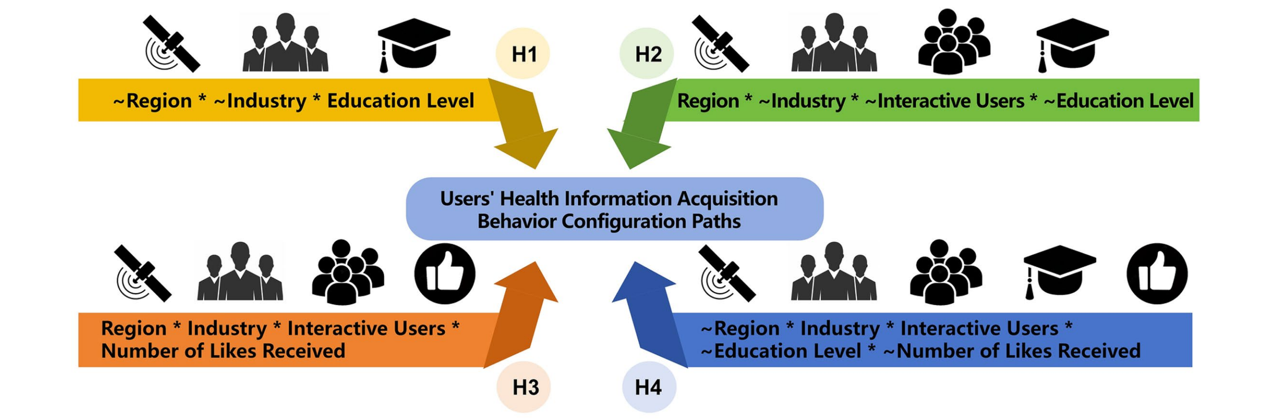

FIGURE 2
Hot topic health information configuration paths.

2 H2: *Region * ~ Industry * ~ Interactive Users * ~ Education Level.*

Configuration two indicates that users in economically developed regions can still access health information effectively, even when the industry is unrelated, there is limited interaction among users, and education levels are not high. In regions with advanced economic development, the prevalence of the internet and mobile devices is high, and residents have stronger network access and information circulation capabilities. Therefore, even if users' industries are not related to health or their social network interactions are sparse, as long as they are in these resource-rich regions, they can access a wealth of health information through online platforms, social media, and other channels.

This pathway underscores the driving role of regional disparities in structural social capital in health information acquisition. The infrastructure, prevalence of information technology, and accessibility of online platforms in economically developed regions enable users to effectively access health information without other conditions. Consequently, geographical location and the level of regional economic development will directly affect the channels and resources available to users for obtaining health information.

3 H3: *Region * Industry * Interactive Users * Number of Likes Received.*

Configuration three suggests that when users are located in economically developed regions, engaged in health-related industries, and possess abundant relational and cognitive social capital (such as active interaction users and a high number of likes), they can access a broader range of health information. This pathway emphasizes the synergistic effects of multidimensional social capital. Specifically, the combination of region and industry provides users with high-quality information sources and industry-specific health knowledge; active interaction users and the number of likes represent the level of engagement of the user on social platforms and directly impact the dissemination and acceptance of health information. An active network of interactions facilitates faster and wider information flow, while a high number of likes signifies greater recognition and dissemination of information, thereby enhancing its credibility and effectiveness.

This configuration pathway reveals the interactive effects of structural, relational, and cognitive social capital. In economically developed regions, professionals in health-related industries can expand the breadth and depth of information acquisition through social interactions and information sharing. Furthermore, through the accumulation of ongoing interaction relationships (such as fans, followers) and the social recognition they receive (such as the number of likes), the dissemination of health information can be accelerated, making information acquisition more efficient and diverse, highlighting the significant role of social networks and social capital in health information acquisition behaviors.

4 H4: *~Region * Industry * Interactive Users * ~ Education Level * ~ Number of Likes Received.*

Configuration four indicates that users in regions with underdeveloped economies and a lack of cognitive social capital can still obtain health information by engaging in high-frequency online community interactions and working in health-related industries. In regions with adverse economic conditions, users can compensate for other deficiencies by increasing the frequency of social interactions (such as participating in health-related forums) and choosing to work in health-related industries, thereby enhancing the efficiency and effectiveness of information acquisition.

This pathway reflects how individuals can overcome shortcomings in structural social capital (region, industry) and cognitive social capital (education, number of likes) through self-regulation and optimization of their social capital. This path demonstrates the flexibility and adaptability of individuals, illustrating their strategic construction and utilization of social capital to improve the ability to search for health information in environments where information and resources are relatively scarce. In summary, for the acquisition of health information, users do not need to possess all three types of social capital—structural, relational, and cognitive—but instead, leverage their enriched social capital while making the most of their strengths and minimizing their weaknesses to acquire health information.

6 Conclusion

6.1 Summary

With the development of the internet, social Q&A platforms have become important channels for users to access health information. However, there are significant differences in health information access behavior among users, which are closely related to variations in their social capital. This study, based on health information case examples from social Q&A platforms, utilizes social capital theory and fuzzy set qualitative comparative analysis (fsQCA) to explore the multidimensional factors influencing user health information access behavior and their interactions. The study identifies four configuration paths of health information access behaviors and reveals how structural, relational, and cognitive social capital impact the process of health information acquisition.

The findings indicate that structural social capital plays a significant role in users' health information access. Specifically, the economic development level of the user's region directly affects the availability of technological devices and resources, which in turn enhances information literacy. In economically developed regions, users not only have access to better technological equipment but are also more capable of effectively utilizing the internet to access health information. The enhancement of information literacy enables users to actively engage in various "capital enhancement" activities in the online environment, thereby expanding their channels for accessing health information (50). Furthermore, the study reveals that even in the absence of one dimension of social capital, users can compensate for the deficiency by strengthening other dimensions, thereby optimizing their health information access paths. For example, users can enhance their relational social capital by increasing online interaction frequency, or they can improve their cognitive social capital through continuing education, thus compensating for the deficiencies in other dimensions.

Therefore, the study concludes that the disparities in health information access are not only related to the overall level of social capital but also closely linked to the interaction and combination of different dimensions of social capital. This finding provides a new perspective for health information dissemination. In the digital information era, access to health information is not merely a reflection of individual information literacy but also the result of accumulated social capital. The public can optimize their health information access paths by enhancing certain dimensions of social capital to compensate for deficiencies in others. This finding offers theoretical support for public health promotion and health information dissemination strategies. Future research could further explore how enhancing specific dimensions of social capital can promote broader access to and utilization of health information.

6.2 Limitations of the study

While this study provides some theoretical references for optimizing the allocation of health resources and enhancing the efficiency of users' health information acquisition behavior through the study of configurational pathways influencing such behaviors, it still has several limitations.

Firstly, the study is based on a sample of Q&A cases within the "Health" topic on the Zhihu social Q&A platform. Although Zhihu has a large user base and high activity levels in China, selecting a single platform as the research sample introduces selection bias. Part of this bias stems from the particularity of Zhihu's user population, which is predominantly composed of young, highly educated individuals with a strong interest in health topics, thus the findings may not fully represent the health information acquisition behaviors of all populations. Moreover, as a social Q&A platform, Zhihu's user interaction and information sharing characteristics differ from those of other social platforms (such as Weibo, TikTok, Facebook, etc.), which limits the generalizability of the research.

Secondly, in terms of variable selection, the article has not comprehensively considered all factors that may influence users' health information acquisition behavior. The selected antecedent variables are primarily based on social capital theory, which provides some theoretical justification but remains somewhat limited. It has not considered other potentially important variables, such as users' lifestyles, health concepts, and cultural backgrounds. This limitation in variable selection may lead to the omission of some important antecedent variables, thereby affecting the comprehensiveness and explanatory power of the research outcomes. Over time, the user base, interaction patterns, and topic discussion trends on the Zhihu platform may change, and the stability of the conclusions across different time points is worth further verification.

Lastly, considering the significant differences in social platforms, cultural backgrounds, and user behavior habits across different countries and regions, although this study has revealed patterns of health information acquisition in the Chinese context, it remains to be further verified whether these findings are applicable to other countries or regions. In a cross-cultural context, the dimensions of social capital and the methods of health information acquisition may differ. Future research could consider comparing social platforms across different countries or regions as cases to enhance the generalizability of the research outcomes.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary material.

Author contributions

JJ: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft. ZB: Investigation, Resources, Writing – original draft. HW: Investigation, Writing – review & editing. YC: Investigation, Writing – review & editing. LY: Investigation, Writing – review & editing. KL: Conceptualization, Project administration, Supervision, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was supported by the 2024 Ningbo Soft Science Research Program: Research on the Resource Carrying and Utilization of Ningbo Science and Technology Celebrities - Taking the Revitalization and Development Path of Ningbo's "Hometown of Academicians" as an Example (2024R044), and the Zhejiang Provincial Soft Science Research Program Project: Promoting the Development of the Low-altitude Economy Industry in Zhejiang Province: Analysis of the Current Status, Exploration of Application Scenarios, and Study of Countermeasures (2025C35059), and the Zhejiang Provincial Educational Science Planning Project: "AIGC Empowering Higher Engineering Education and 'Excellent Engineer' Training in Zhejiang Province: Status Analysis, Application Scenario Identification, and Path Exploration" (2025SB083).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2025.1501879/full#supplementary-material

References

1. Arcaya MC, Arcaya AL, Subramanian SV. Inequalities in health: definitions, concepts, and theories. *Rev Panam Salud Publica*. (2015) 8:27106–271. doi: 10.3402/gha.v8.27106

2. Liobikienė G, Bernatonienė J. The determinants of access to information on the internet and knowledge of health related topics in European countries. *Health Policy*. (2018) 122:1348–55. doi: 10.1016/j.healthpol.2018.09.019

3. Zhang D, Zhang G, Jiao Y, Wang Y, Wang P. "Digital dividend" or "digital divide": what role does the internet play in the health inequalities among Chinese residents? *Int J Environ Res Public Health*. (2022) 19:15162. doi: 10.3390/ijerph192215162

4. Park W. Study on the development of China's medical and health online mutual aid platform industry. *J China Stud*. (2020) 23:23–48. doi: 10.20288/JCS.2020.23.2.23

5. Gilmour JA. Reducing disparities in the access and use of internet health information. A discussion paper. *Int J Nurs Stud*. (2007) 44:1270–8. doi: 10.1016/j.ijnurstu.2006.05.007

6. Oberle M. Robert D. Putnam: bowling alone. The collapse and revival of American community, New York: Simon and Schuster 2000, 541 S In: S Salzborn, editor. Klassiker der Sozialwissenschaften: 100 Schlüsselwerke im Portrait. Wiesbaden: Springer Fachmedien Wiesbaden (2016). 408–11.

7. Ahn S, Lee C-J, Ko Y. Network social capital and health information acquisition. *Patient Educ Couns*. (2022) 105:2923–33. doi: 10.1016/j.pec.2022.05.007

8. Lei X. Information and inequality. *J Econ Theory*. (2019) 184:104937. doi: 10.1016/j.jet.2019.08.007

9. Hatamleh IHM, Safori AO, Habes M, Tahat O, Ahmad AK, Abdallah RA-Q, et al. Trust in social media: enhancing social relationships. *Soc Sci*. (2023) 12:416. doi: 10.3390/socsci12070416

10. Festic N, Büchi M, Latzer M. It's still a thing: digital inequalities and their evolution in the information society. *SCM Stud Commun Media*. (2021) 10:326–61. doi: 10.5771/2192-4007-2021-3-326

11. Yao R, Zhang W, Evans R, Cao G, Rui T, Shen L. Inequities in health care services caused by the adoption of digital health technologies: scoping review. *J Med Internet Res*. (2022) 24:e34144. doi: 10.2196/34144

12. Eastin MS, Cicchirillo V, Mabry A. Extending the digital divide conversation: examining the knowledge gap through media expectancies. *J Broadcast Electron Media*. (2015) 59:416–37. doi: 10.1080/08838151.2015.1054994

13. Scheerder A, Van Deursen A, Van Dijk J. Determinants of internet skills, uses and outcomes. A systematic review of the second-and third-level digital divide. *Telematics Inform*. (2017) 34:1607–24. doi: 10.1016/j.tele.2017.07.007

14. Van Dijk J. Digital divide: impact of access. *Int Encyclopedia Media Effects*. (2017) 1:1–11. doi: 10.1002/9781118783764.wbieme0043

15. Van Dijk J. The digital divide. Hoboken, United States: John Wiley & Sons (2020).

16. Yang Y, Ma C. A review on health digital divide across the world. *Documen Inform Knowledge*. (2023) 154–166. doi: 10.13366/j.dik.2024.03.154

17. Lythreatis S, Singh SK, El-Kassar A-N. The digital divide: a review and future research agenda. *Technol Forecast Soc Chang*. (2022) 175:121359. doi: 10.1016/j.techfore.2021.121359

18. Van Dijk JA. Digital divide research, achievements and shortcomings. *Poetics*. (2006) 34:221–35. doi: 10.1016/j.poetic.2006.05.004

19. Torres-Albero C, Robles JM, De Marco S. Inequalities in the information and knowledge society: from the digital divide to digital inequality. *Robot Divide New Front 21st Century?* (2014):173–94. doi: 10.1007/978-1-4471-5358-0_10

20. Robinson L, Schulz J, Blank G, Ragnedda M, Ono H, Hogan B, et al. Digital inequalities 2.0: legacy inequalities in the information age. *First Monday*. (2020) 25. doi: 10.5210/fm.v25i7.10842

21. Craveiro D. The role of personal social networks on health inequalities across European regions. *Health Place*. (2017) 45:24–31. doi: 10.1016/j.healthplace.2017.02.007

22. Tóth G, Wachs J, Di Clemente R, Jakobi Á, Ságvári B, Kertész J, et al. Inequality is rising where social network segregation interacts with urban topology. *Nat Commun*. (2021) 12:1143. doi: 10.1038/s41467-021-21465-0

23. Macevičiūtė E, Wilson TD. Digital means for reducing digital inequality: literature review. *Inform Sci*. (2018) 21:269–87. doi: 10.28945/4117

24. Bourdieu P. The forms of capital In: The sociology of economic life. ED. M. Granovetter. New York: Routledge (2018). 78–92.

25. Halpern D. Social capital. Cambridge: Polity (2005).

26. Nahapiet J, Ghoshal S. Social capital, intellectual capital, and the organizational advantage. *Acad Manag Rev*. (1998) 23:242–66. doi: 10.5465/amr.1998.533225

27. Chiu C-M, Hsu M-H, Wang ET. Understanding knowledge sharing in virtual communities: an integration of social capital and social cognitive theories. *Decis Support Syst*. (2006) 42:1872–88. doi: 10.1016/j.dss.2006.04.001

28. Mpinganjira M. Willingness to reciprocate in virtual health communities: the role of social capital, gratitude and indebtedness. *Serv Bus*. (2019) 13:269–87. doi: 10.1007/s11628-018-0382-9

29. Muniady RAL, Mamun AA, Mohamad MR, Permarupan PY, Zainol NRB. The effect of cognitive and relational social capital on structural social capital and micro-enterprise performance. *SAGE Open*. (2015) 5:2158244015611187. doi: 10.1177/2158244015611187

30. Steinmo M, Rasmussen E. The interplay of cognitive and relational social capital dimensions in university-industry collaboration: overcoming the experience barrier. *Res Policy*. (2018) 47:1964–74. doi: 10.1016/j.respol.2018.07.004

31. Craig AW, Storr VH. Social capital facilitates emergent social learning. *Rev Austrian Econ*. (2023) 1-22. doi: 10.1007/s11138-023-00635-x

32. Clouston SA, Link BG. A retrospective on fundamental cause theory: state of the literature and goals for the future. *Annu Rev Sociol*. (2021) 47:131–56. doi: 10.1146/annurev-soc-090320-094912

33. McMaughan DJ, Oloruntoba O, Smith ML. Socioeconomic status and access to healthcare: interrelated drivers for healthy aging. *Front Public Health*. (2020) 8:231. doi: 10.3389/fpubh.2020.00231

34. Uphoff EP, Pickett KE, Cabieses B, Small N, Wright J. A systematic review of the relationships between social capital and socioeconomic inequalities in health: a contribution to understanding the psychosocial pathway of health inequalities. *Int J Equity Health*. (2013) 12:54–12. doi: 10.1186/1475-9276-12-54

35. Runciman WG. Towards a theory of social stratification In: The social analysis of class structure. Ed. F. Parkin. London: Routledge (2018). 55–102.

36. Riley AR. Advancing the study of health inequality: fundamental causes as systems of exposure. *SSM Popul Health*. (2020) 10:100555. doi: 10.1016/j.ssmph.2020.100555

37. Li Z, Zhu J, Li X. Factors influencing the behavior of multi-modal information search. *Library Hi Tech*. (2022) 40:1459–82. doi: 10.1108/LHT-11-2020-0288

38. Park Y, Fiss PC, El Sawy OA. Theorizing the multiplicity of digital phenomena: the ecology of configurations, causal recipes, and guidelines for applying QCA. *SSRN Electr J*. (2020) 44–1. doi: 10.2139/ssrn.4158044

39. Greckhamer T, Furnari S, Fiss PC, Aguilera RV. Studying configurations with qualitative comparative analysis: best practices in strategy and organization research. *Strateg Organ*. (2018) 16:482–95. doi: 10.1177/1476127018786487

40. Kumar S, Sahoo S, Lim WM, Kraus S, Bamel U. Fuzzy-set qualitative comparative analysis (fsQCA) in business and management research: a contemporary overview. *Technol Forecast Soc Chang*. (2022) 178:121599. doi: 10.1016/j.techfore.2022.121599

41. Pappas IO, Woodside AG. Fuzzy-set qualitative comparative analysis (fsQCA): guidelines for research practice in information systems and marketing. *Int J Inf Manag*. (2021) 58:102310. doi: 10.1016/j.ijinfomgt.2021.102310

42. Tan SS-L, Goonawardene N. Internet health information seeking and the patient-physician relationship: a systematic review. *J Med Internet Res*. (2017) 19:e9. doi: 10.2196/jmir.5729

43. Du Y, Jia L. Configuration perspective and qualitative comparative analysis (QCA): a new approach to management research. *Manage World*. (2017) 6:155–67. doi: 10.19744/j.cnki.11-1235/f.2017.06.012

44. Zhang M, Du Y. Qualitative Comparative Anaylysis (QCA) in management and organization research: position, tactics, and directions. *Chinese J Manag*. (2019) 16:1312–23. doi: 10.3969/j.issn.1672-884x.2019.09.005

45. Li P, Xu L, Tang T, Wu X, Huang C. Users' willingness to share health information in a social question-and-answer community: cross-sectional survey in China. *JMIR Med Inform*. (2021) 9:e26265. doi: 10.2196/26265

46. Cangialosi N. Fuzzy-set qualitative comparative analysis (fsQCA) in organizational psychology: theoretical overview, research guidelines, and a step-by-step tutorial using R software. *Span J Psychol*. (2023) 26:e21. doi: 10.1017/SJP.2023.21

47. Dwivedi P, Joshi A, Misangyi VF. Gender-inclusive gatekeeping: how (mostly male) predecessors influence the success of female CEOs. *Acad Manag J*. (2018) 61:379–404. doi: 10.5465/amj.2015.1238

48. Sundberg R. Multivariate calibration—direct and indirect regression methodology. *Scand J Stat*. (1999) 26:161–207. doi: 10.1111/1467-9469.00144

49. Schneider CQ, Wagemann C. Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis. Cambridge: Cambridge University Press (2012).

50. Ignatow G, Robinson L. Pierre Bourdieu: theorizing the digital. *Inf Commun Soc*. (2017) 20:950–66. doi: 10.1080/1369118X.2017.1301519

frontiers | Frontiers in Public Health

TYPE Review
PUBLISHED 15 April 2025
DOI 10.3389/fpubh.2025.1547392

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Manjit Kaur,
SR University, India
Chen Li,
Shanghai University of Engineering Sciences, China

*CORRESPONDENCE
Xinyu Geng
✉ gxy297@163.com

RECEIVED 18 December 2024
ACCEPTED 31 March 2025
PUBLISHED 15 April 2025

CITATION
Wang Y, Deng R and Geng X (2025) Exploring the integration of medical and preventive chronic disease health management in the context of big data.
Front. Public Health 13:1547392.
doi: 10.3389/fpubh.2025.1547392

Exploring the integration of medical and preventive chronic disease health management in the context of big data

Yueyang Wang[1,2], Ruigang Deng[1] and Xinyu Geng[2]*

[1]Office of Medical Defense Integration, The Fourth People's Hospital of Sichuan Province, Chengdu, China, [2]School of Computer Science and Software Engineering, Southwest Petroleum University, Chengdu, China

Chronic non-communicable diseases (NCDs) pose a significant global health burden, exacerbated by aging populations and fragmented healthcare systems. This study employs a comprehensive literature review method to systematically evaluate the integration of medical and preventive services for chronic disease management in the context of big data, focusing on pre—hospital risk prediction, in—hospital clinical prevention, and post—hospital follow—up optimization. Through synthesizing existing research, we propose a novel framework that includes the development of machine learning models and interoperable health information platforms for real—time data sharing. The analysis reveals significant regional disparities in implementation efficacy, with developed eastern regions demonstrating advanced closed—loop management via unified platforms, while western rural areas struggle with manual workflows and data fragmentation. The integration of explainable AI (XAI) and blockchain—secured care pathways enhances clinical decision—making while ensuring GDPR—compliant data governance. The study advocates for phased implementation strategies prioritizing data standardization, federated learning architectures, and community—based health literacy programs to bridge existing disparities. Results show a 30–35% reduction in redundant diagnostics and a 15–20% risk mitigation for cardiometabolic disorders through precision interventions, providing a scalable roadmap for resilient public health systems aligned with the "Healthy China" initiative.

KEYWORDS

chronic disease management, health care and prevention integration, risk prediction modeling, big data, preventive management

1 Introduction

Chronic non-communicable (NCDs) diseases have become a major disease burden worldwide, imposing tremendous pressure on society and the economy. Meanwhile, the rapid development of information technology has provided new approaches and methods for chronic disease management. This paper reviews the research on the integration of information technology with chronic disease management.

1.1 Current status and challenges of chronic diseases

NCDs refer to a range of diseases including diabetes, cardiovascular diseases, chronic respiratory diseases, and malignant tumors. These diseases are the primary health threats to the population, characterized by their insidious onset, complex causes, and prolonged conditions. They involve multiple systems such as the endocrine, cardiovascular, and respiratory systems, with hypertension, hyperglycemia, hyperlipidemia, and hypoglycemia being the most typical manifestations. According to the World Health Organization's (WHO) "World Health Statistics 2023"report (1), NCDs have caused the highest disease burden globally. In 2000, 61% of deaths worldwide (31 million) were attributed to NCDs, and this proportion increased to 74% (41 million) by 2019. Additionally, the "Research on the Development Prospects of the Chronic Disease Management Industry in China" (2) by the China Industry Research Network points out that China has fully entered an aging society. It is estimated that by 2025, the older adult population in China will exceed 200 million, by 2035 it will exceed 300 million, and by 2050 it will reach 380 million. In China, the proportion of deaths caused by chronic diseases is as high as 86%, with an increasingly severe disease burden. To improve chronic disease management in China, the General Office of the State Council issued the "Mid- and Long-Term Plan for the Prevention and Treatment of Chronic Diseases in China (2017–2025)" based on the "Healthy China" strategy, focusing on advancing chronic disease management. Therefore, the prevention and control of chronic diseases is a crucial development goal of the 21st century.

1.2 The introduction of "integration of medical treatment and prevention" has optimized the chronic disease management model

In 2018, the National Health Commission of China set new requirements for primary healthcare services, introducing "integration of medical treatment and prevention" as a new concept for chronic disease prevention and control. In 2019, the National Health Commission further emphasized in the "Notice on Basic Public Health Service Projects in 2019" that chronic disease management, such as hypertension and diabetes, should be used as an entry point to explore a grassroots service model characterized by "integration of medical treatment and prevention." In 2023, the "Opinions on Further Deepening Reform and Promoting Healthy Development of Rural Healthcare Systems," issued by the General Office of the CPC Central Committee and the General Office of the State Council, proposed innovative mechanisms for medical-prevention coordination and integration. It can be said that "integration of medical treatment and prevention" is a relatively new policy concept (3), frequently appearing in policy documents in recent years and garnering significant attention. "Medical" primarily refers to clinical diagnosis and treatment, while "prevention" mainly pertains to public health. Compared to the previous health guideline of prevention-first and combining prevention with treatment, this new approach emphasizes how medical treatment and prevention can be integrated to simultaneously improve technical levels and form a unified management model. The integration of medical treatment and prevention may provide new pathways for reform and innovation in chronic disease management.

1.3 Big data-driven chronic disease management

1.3.1 Definition of healthcare big data

Big data refers to datasets characterized by massive volume, heterogeneous variety, rapid velocity, and significant variability, which exceed the processing capabilities of traditional database management tools. In the healthcare domain, medical big data similarly exhibits these attributes along with two additional critical dimensions: veracity (data quality) and value (actionable insights), collectively constituting the six defining characteristics of big data (Volume, Velocity, Variety, Variability, Veracity, and Value) (4), as illustrated in Figure 1.

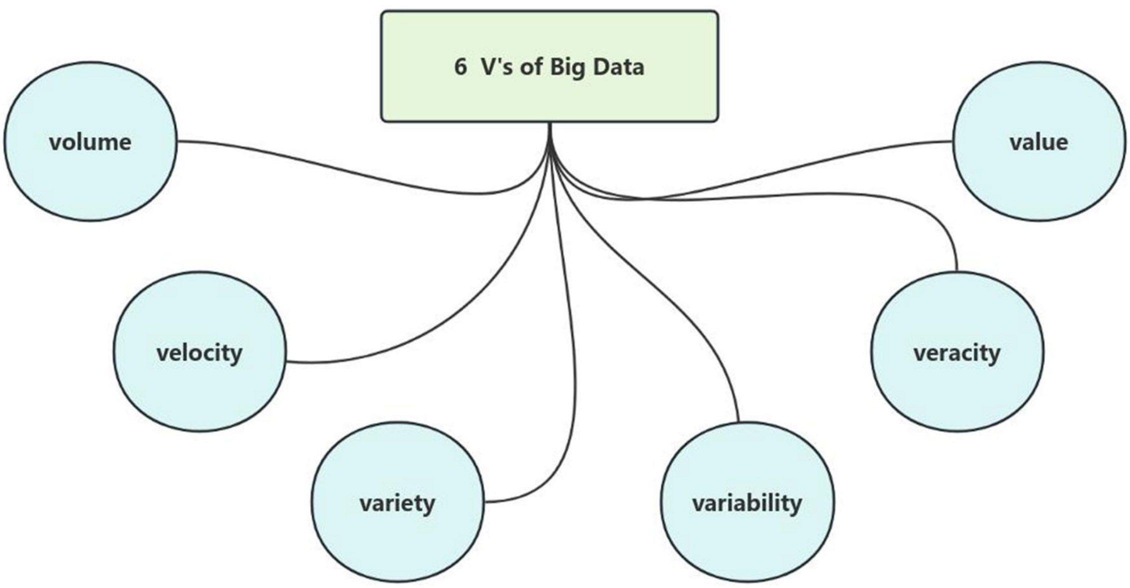

FIGURE 1
6 V's of big data.

Healthcare big data (5) originates from diverse sources, including but not limited to:

- Electronic Medical Records (EMRs).
- Clinical diagnostic documentation.
- Laboratory and imaging examination reports.
- Pharmaceutical databases.
- Medical device monitoring systems.
- Patient-generated health data via wearable devices.
- Public health surveillance platforms.

These multimodal datasets encompass comprehensive patient health information and clinical workflows, spanning structured formats (e.g., numerical values in EMRs), semi-structured metadata (e.g., DICOM headers in medical imaging), and unstructured content (e.g., physician narratives, diagnostic reports, and radiological images). The inherent heterogeneity and scale of these data types pose significant challenges in data processing and analytical methodologies.

Notably, while healthcare big data demonstrates immense potential for clinical insights, its intrinsic value is critically dependent on data quality (6). The accuracy and reliability of clinical decision-making are fundamentally dependent on rigorous data preprocessing and advanced analytical frameworks. Consequently, systematic data curation and robust computational strategies constitute essential prerequisites for transforming raw healthcare data into clinically actionable knowledge.

1.3.2 Methodological framework for chronic disease modeling using big data

The rapid advancement of information communication technologies and artificial intelligence has enabled sophisticated methodologies for data processing and analytical modeling. As illustrated in Figure 2, the construction of chronic disease prediction models follows a systematic workflow comprising five critical phases (7):

1.3.2.1 Phase 1: multisource data acquisition

Heterogeneous medical datasets are aggregated from electronic health records, wearable sensors, genomic repositories, and population health databases. These multimodal inputs provide a comprehensive digital representation of patient health trajectories, encompassing demographic, biochemical, imaging, and behavioral dimensions.

1.3.2.2 Phase 2: preprocessing pipeline

Raw data undergoes rigorous preprocessing to ensure analytical validity:

- Data Cleansing: Removal of outliers, imputation of missing values, and correction of erroneous entries.
- Dimensionality Reduction: Application of principal component analysis (PCA) or t-distributed stochastic neighbor embedding (t-SNE) to mitigate the curse of dimensionality.
- Normalization: Standardization/z-score transformation to enhance feature comparability across disparate scales.

1.3.2.3 Phase 3: feature engineering and selection

A dual-strategy approach optimizes predictive features:

1. Statistical Filtering: Chi-square tests and mutual information metrics identify variables with significant associations to chronic disease endpoints.
2. Algorithmic Selection: Recursive feature elimination (RFE) coupled with tree-based classifiers (e.g., XGBoost, LightGBM) quantifies feature importance.
3. Feature augmentation: nonlinear transformations and interaction term generation enhance model expressivity

1.3.2.4 Phase 4: predictive model development

Ensemble learning architectures demonstrate superior performance in handling healthcare data complexity:

- Baseline Models: Logistic regression with L1/L2 regularization establishes performance benchmarks.
- Advanced Architectures: Deep neural networks with attention mechanisms capture temporal dependencies in longitudinal data.
- Validation Protocol: Stratified k-fold cross-validation ($k = 5/10$) prevents overfitting while maintaining class distribution integrity.
- Hyperparameter Optimization: Bayesian optimization frameworks efficiently navigate high-dimensional parameter spaces.

1.3.2.5 Phase 5: clinical implementation

Deployed models serve multiple translational functions:

- Risk Stratification: Generation of individualized risk scores using SHAP (SHapley Additive exPlanations) values.
- Precision Prevention: Dynamic recommendation systems for lifestyle modifications and therapeutic interventions.
- Population Analytics: Geospatial clustering identifies high-risk cohorts for targeted public health initiatives.

1.3.2.6 Performance evaluation metrics

Model efficacy is quantified through:

- Discrimination: AUC-ROC curves with 95% confidence intervals.
- Calibration: Brier scores and calibration belt analysis.
- Clinical utility: Decision curve analysis quantifying net benefit across risk thresholds.

This methodological framework emphasizes reproducibility through adherence to TRIPOD (Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis) guidelines, ensuring clinical relevance while maintaining computational rigor (8). The integration of explainable AI (XAI) techniques facilitates clinician trust and regulatory compliance in real-world deployment scenarios.

1.3.3 Potential biases and limitations in integrated clinical-public health data systems

The integration of clinical and public health data systems, while offering significant potential for comprehensive disease surveillance and management, is inherently constrained by systemic biases and methodological limitations. Key challenges arise from heterogeneous data quality across multi-source inputs, including inconsistencies in completeness (e.g., variable documentation practices), accuracy (e.g., divergent diagnostic coding standards), and temporal

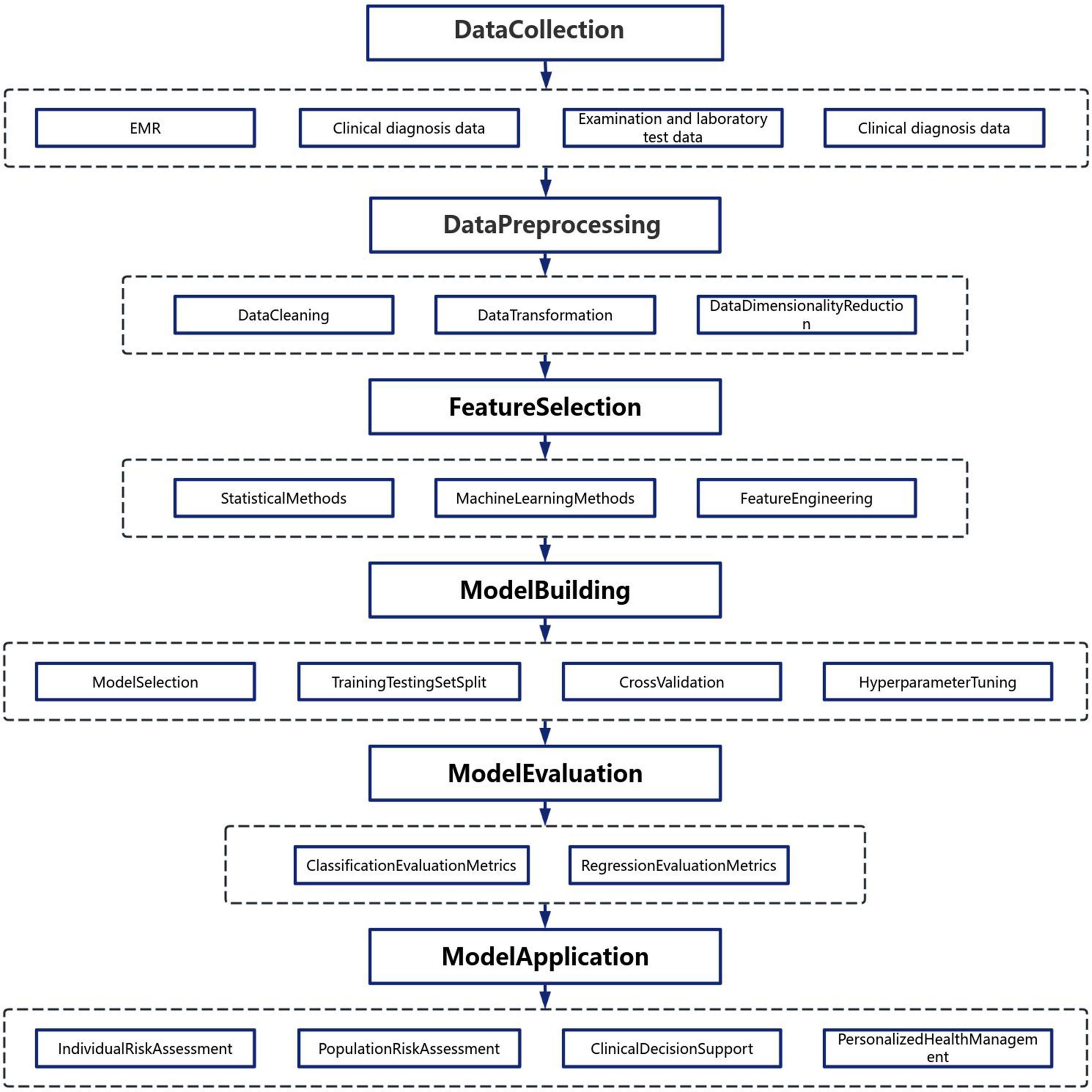

FIGURE 2
Big Data modeling roadmap.

resolution (e.g., mismatched data collection frequencies between real-time clinical monitoring and periodic public health reporting). These issues are compounded by technical interoperability barriers stemming from incompatible data standards (HL7 FHIR vs. OpenEHR), organizational fragmentation in data governance, and semantic discrepancies between preventive health terminologies and clinical ontologies (9). Furthermore, inherent selection biases may skew analyses, particularly through underrepresentation of marginalized populations in digital health records and confounding effects of differential healthcare-seeking behaviors. To address these challenges, a robust quality assurance framework spanning pre-analytical, analytical, and post-analytical phases is essential. This includes implementing constrained data entry interfaces with real-time validation protocols during data acquisition, deploying machine learning-powered anomaly detection systems for continuous quality monitoring, and conducting root-cause analyses using Bayesian networks to identify systemic errors in data pipelines. Interoperability enhancement requires dual architectural and policy interventions, such as adopting federated learning systems for privacy-preserving distributed analytics, integrating SMART-on-FHIR (10) APIs to bridge clinical and population health platforms, and incentivizing standardized common data models (OMOP CDM, PCORnet) (11). Crucially, these technical solutions must be coupled with rigorous validation metrics—including composite data utility indices assessing completeness (≥95%), accuracy (≥0.85), and timeliness (latency <24 h)—and compliance with international healthcare IT benchmarks (HIMSS EMRAM Stage 6+). The implementation of cryptographic security mechanisms, such as

10.3389/fpubh.2025.1547392

homomorphic encryption for cross-institutional data harmonization, ensures adherence to GDPR and HIPAA regulations while maintaining data utility. This multifaceted approach underscores the necessity of continuous quality improvement cycles and coordinated policy-technical strategies to transform fragmented data ecosystems into reliable, actionable intelligence for integrated care delivery.

In terms of data security, which is equally important, technologies such as blockchain can be employed to ensure data security and compliance. For instance, in cross-border data circulation, federated learning (FL) can be used to train models on decentralized data, ensuring that raw data does not cross borders and thus complying with China's Cybersecurity Law. To adhere to the General Data Protection Regulation (GDPR), privacy protection techniques such as differential privacy can be adopted during the FL aggregation process, further enhancing data security.

Additionally, the application of auditable compliance blockchain can record data access and processing activities, ensuring the traceability of data usage. For example, the SMART-on-FHIR API (12) can trigger GDPR "right to be forgotten" requests through blockchain entries, safeguarding the legitimate rights and interests of data subjects. Furthermore, the establishment of regional data governance committees, such as the China-EU Health Data Working Group, can help unify data standards and promote data circulation and cooperation between different regions.

In data sovereignty zones, such as EU member states with strict data laws, edge computing nodes can be deployed to process data locally. Combined with homomorphic encryption technology for cross-regional analysis, this approach ensures data security while meeting the legal requirements of different regions. Finally, the development of AI-driven dynamic consent management portals can adjust data usage permissions according to regional laws, allowing patients to more flexibly control the use of their data. For example, Chinese patients can choose to participate in GDPR-compliant research projects through granular consent forms (see Figure 3).

1.4 Risk prediction models in chronic disease management (pre-hospital)

Chronic diseases, as complex conditions influenced by multiple factors, involve not only genetics, medical conditions, social conditions, and climate but are also closely related to individual lifestyle choices. According to the World Health Organization, 60% of the causes of chronic diseases are attributable to personal lifestyle (1), such as unhealthy diet, insufficient physical activity, tobacco use, and harmful use of alcohol. These behavioral factors largely determine the occurrence and progression of chronic diseases. Big data can gather chronic disease health risk-related data from these sources, achieving multi-dimensional and comprehensive data collection. Risk prediction models for chronic disease health based on big data typically analyze population health/disease spectra and extract risk factors closely related to health/disease. These models can obtain average health risk curves for different age and gender groups, compare an individual's absolute risk with the average risk of the corresponding group, determine personal disease risk levels, and identify risk factors leading to increased risk. This enables the development of scientifically sound personalized intervention guidelines, achieving primary and secondary prevention in chronic disease management (13).

AI can identify new hypertension genes through machine learning algorithms and evaluate patients by integrating various parameters such as stages of hypertension, blood pressure control, and accompanying comorbidities, thereby achieving early diagnosis and prevention. For example, Ye et al. (14) used personal patient electronic health record (EHR) datasets from a statewide health information exchange network and employed the XGBoost machine learning

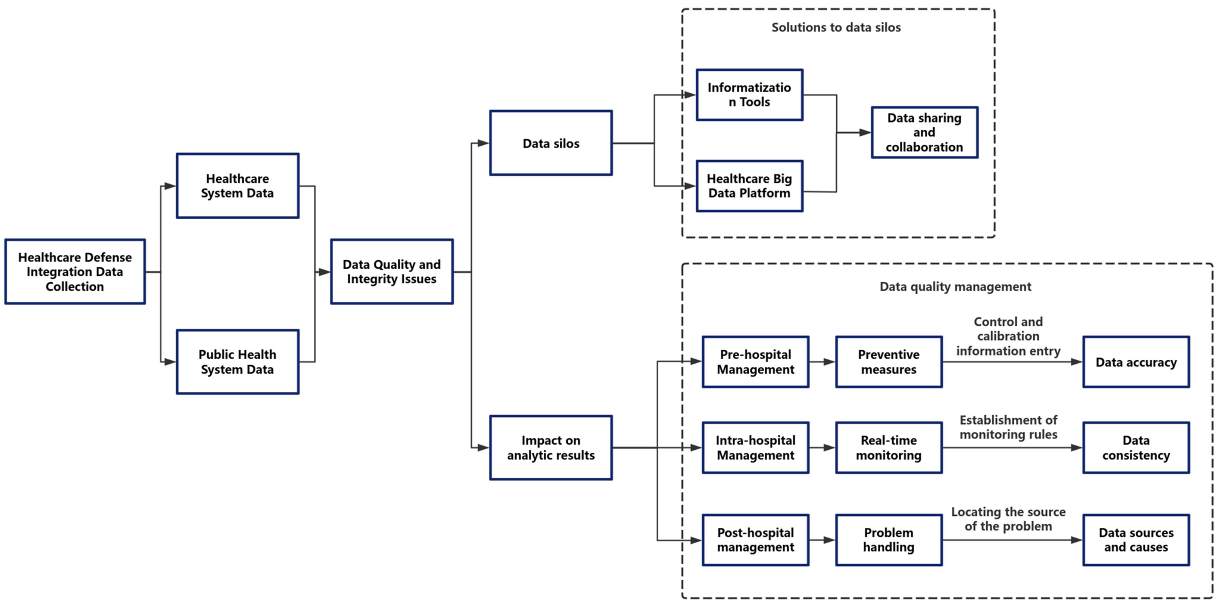

FIGURE 3
Healthcare prevention fusion data prototype diagram.

algorithm for feature selection and model construction. The risk model for developing hypertension within one year achieved an AUC (area under the curve) of 0.917 and 0.870 in retrospective and prospective cohorts, respectively. The prospective validation demonstrated an accurate one-year risk prediction model for predicting primary hypertension, providing insights for hypertension and related disease interventions, and improving hypertension care.

Subsequently, KANEGAE Hiroshi (15) used health check-up data from 18,258 individuals from 2005 to 2016 to develop a highly accurate prediction model for future hypertension in the general population using machine learning (ML) algorithms. ML-based analysis allowed all BP measurements to be incorporated into the same model, resulting in superior performance in predicting new-onset hypertension compared to XGBoost and logistic regression models. They developed a highly accurate future hypertension prediction model in a generally normotensive population using machine learning methods, which can identify high-risk individuals and promote early non-pharmacological interventions. Similarly, Yan-Hui Li and colleagues analyzed gene expression in hypertensive patients, identifying 177 new hypertension genes through machine learning algorithm development. This represents a novel approach to achieving secondary prevention of chronic diseases.

In other chronic disease contexts, Kupersmith et al. (16) explored the impact of additional attributes using electronic health record data to identify a high comorbidity rate of mental disorders (24.5%) among diabetes patients, aiming to conduct risk prediction studies for diabetic patients. Similarly, McCoy et al. (17), conducted a retrospective analysis using data from the Optum laboratory data warehouse, finding that intensified treatment nearly doubled the risk of severe hypoglycemia in complex patient cases. Jelinek et al. (18) applied data mining algorithms to large clinical datasets and discovered that including oxidative stress biomarkers increased the classification accuracy of type 2 diabetes mellitus (T2DM) from 78.71 to 86.64% at an HbA1c level of 6.5%. Including interleukin-6 in the algorithm, but at a lower optimal HbA1c range of 5.73 to 6.22%, improved T2DM classification accuracy to 85.63%, significantly enhancing the risk prediction capability for diabetes patients. In 2019, based on clinical data from the Yinzhou District Health Information System, Wang et al. (19) from Peking University developed a predialysis chronic kidney disease risk assessment model. Serbanati (20), using neural networks and logistic regression analysis techniques, established predictive models for chronic disease patients, providing effective prediction for conditions such as hypertension and diabetes.

1.5 Clinical prevention in chronic disease management (in-hospital)

With the advancement of technology, an increasing number of chronic disease management applications and related systems have emerged. This has led to the diversification and variety of patient health data sources. However, due to the heterogeneity of the data, the more data there is, the more difficult it becomes to analyze. By continuously improving methods in data mining, the efficiency of chronic disease management and the accuracy of diagnosis and treatment have significantly improved. Shunda et al. (21). Proposed a deep learning-based medical auxiliary diagnosis data processing method to address the lack of efficient and accurate analysis methods for massive medical diagnosis data. They utilized neural networks deploying multilayer perceptrons to analyze preprocessed data, thereby achieving diagnostic classification and providing intelligent auxiliary diagnosis for doctors. The proposed method's loss value and average accuracy rate were 53 and 85%, respectively, both outperforming other comparative methods. Hu et al. (22) proposed a novel approach that combines network analysis and machine learning to predict the length of stay (LOS) for older adult patients with chronic diseases. They constructed two networks: a multimorbidity network (MN) and a patient similarity network (PSN), and developed innovative network features. Five machine learning models with different input feature sets (extreme gradient boosting, gradient boosting decision tree, random forest, linear support vector machine, and deep neural network) were developed to compare their performance. The inclusion of network features significantly improved the performance of the prediction models, demonstrating the practicality of MN and PSN for LOS prediction. This underscores the potential value of network-based machine learning in chronic disease management.

In the medical data analysis of chronic diseases, many researchers have applied association rule data mining techniques and achieved significant experimental results. Xiaobing et al. (23). Utilized the numerical attribute characteristics of aggregation algorithms to discretize datasets and divide them into several optimized datasets, mining useful association rules from tumor diagnosis data. This provides important reference value for the clinical diagnosis of chronic tumors. Ningning et al. (24). Used classification algorithms to analyze data from patients with type I diabetes, discovering that the generated classification association rules were highly consistent with medical research findings. Classification association rule technology has a solid theoretical foundation in chronic diabetes research. Among these, the Apriori algorithm in association rules is the primary algorithm used in data mining for chronic disease treatment and prevention. Zheng (25). summarized the traditional Apriori algorithm, finding that its biggest drawback is the need to repeatedly scan the database to obtain frequent itemsets, which inevitably affects the efficiency of data mining and consumes a large amount of memory. In contrast, Liu et al. (26) proposed an association rule data mining algorithm that combines clustering matrix and pruning strategies. This algorithm compresses the stored transaction database using the clustering matrix method and introduces pre-pruning and post-pruning strategies based on adding constraint conditions, improving the algorithm. Its execution time is significantly lower than that of the traditional Apriori algorithm, enhancing the efficiency of data analysis for chronic disease treatment and prevention.

1.6 Accurate chronic disease management (post-hospital)

By comprehensively utilizing risk prediction models and other tools for chronic disease management, a new integrated medical prevention service model that optimizes the pre-hospital, in-hospital, and post-hospital stages, and incorporates the four levels of prevention, can be achieved for precise chronic disease management. The refined management of chronic diseases aims to improve the management rate, control rate, and hospitalization rate of patients with chronic and special diseases, ultimately enhancing their quality of life. For example, the Shanghai Center for Disease Control and Prevention has explored establishing an integrated and precise chronic disease health management service model (27), achieving integrated whole-process health management centered around individuals in the pre-hospital stage. Using big data capture and matching, the system reminds doctors to provide screening services and automatically tracks clinical diagnosis information, forming a closed-loop management system for chronic disease screening services.

In-hospital, McManus et al. (28) conducted the HOME BP study, a randomized controlled trial of home online blood pressure management and evaluation. This study randomly assigned 622 patients with poorly controlled blood pressure to either an internet medical platform intervention group or a conventional treatment group. After a median follow-up of one year, the internet medical intervention group showed a reduction in systolic blood pressure of 3.4 mmHg compared to the conventional treatment group. Yangyang and Xingdong (29) proposed a new clustering method combining agglomerative hierarchical clustering and Gaussian mixture models to effectively handle dynamic missing data, which can identify cases of masked hypertension.

Post-hospital, early screening of high-risk atrial fibrillation (AF) populations based on internet medical platforms also improves early detection rates and timely intervention for AF. The Huawei Heart Study (30), which uses photoplethysmography (PPG) technology for high-risk AF screening, recruited 187,912 patients and monitored their heart activity remotely. The positive predictive value for AF was 91.6%. Another study by Perez et al. (31) collected electrocardiogram data from 419,297 participants uploaded through Apple smartwatches, resulting in a positive predictive rate for AF of 84%, providing significant data support for post-hospital follow-up.

1.7 Health management within the integration of medicine and defense

Health management in the integration of medicine and defense covers the entire lifecycle of individuals, from health promotion and disease prevention to treatment, rehabilitation, and long-term care. It provides timely and effective treatment and rehabilitation services for those already afflicted, and offers long-term monitoring and management for chronic disease patients to improve their quality of life. The concept of "integrating medicine and defense" combines disease treatment and prevention (3), integrating medical and preventive services to effectively link and synergize them, thereby minimizing the occurrence of health problems, targeting the control of health deterioration, enhancing the appropriateness and effectiveness of healthcare services, and achieving the goal of "putting health at the center" (32).

After the COVID-19 pandemic, communities and public hospitals have gradually shifted from a "disease-centered" approach to a "people-centered health" approach, no longer prioritizing medical treatment but also emphasizing prevention, especially for chronic diseases, to achieve early detection, diagnosis, and treatment. The aim is to construct a more efficient and coordinated healthcare system, reducing disease burden through prevention and improving treatment outcomes through medical care. Driven by the Healthy China strategy, regions have actively explored the integrated development model of medicine and defense: Jia et al. (33) used methods such as literature analysis, policy summarization, and expert interviews to preliminarily establish an evaluation index system for on-site assessment of integrated medical and preventive services for chronic diseases in grassroots healthcare institutions, enhancing the capabilities of urban and rural community health service institutions in integrated medicine and defense, providing them with references and bases. In Wuhan, community service stations have focused on enhancing grassroots service capabilities (34), continually refining work mechanisms, promoting family doctor contract services, and comprehensively enhancing integrated medicine and defense capabilities at the grassroots level. In Sanming City (35), under government leadership, basic medical insurance funds have been merged with basic public health expenses, encouraging healthcare institutions to provide integrated medicine and defense services, and through network construction, system development, and institutional improvement in parallel, they have preliminarily established a basic framework for integrated medicine and defense, transitioning from separated medicine and defense to integrated reforms. Yang Jiang city established the first national-level public health hospital at the prefecture-level, integrating multiple institutions and departments, responsible for the medical, preventive, and rehabilitation management of infectious, mental, chronic diseases, and other businesses across the city. The hospital has promoted the integration of prevention and clinical medicine, improving the collaborative efficiency of prevention and treatment through the participation of medical personnel in disease monitoring. In addition, some city hospitals (such as West China Hospital of Sichuan University) have collaborated with grassroots healthcare institutions to establish integrated medicine and defense centered on health management.

Figure 4 illustrates the prototype architecture of precision health management integration within China's public hospital system, demonstrating a novel "online-offline convergence" care delivery model. This paradigm establishes a seven-phase integrated framework (prevention, screening, diagnosis, treatment, rehabilitation, nursing, and maintenance) that orchestrates closed-loop health management (36) through coordinated institutional referrals and AI-powered home care platforms. The system leverages interoperable health information exchanges to synchronize multisource medical data across the entire care continuum—from primordial prevention to post-rehabilitation monitoring. Key operational objectives include: (1) Enhanced population health metrics through predictive risk stratification algorithms; (2) Improved early detection rates for non-communicable diseases via multimodal screening integration (≥40% sensitivity gain versus conventional methods); (3) Reduced critical illness incidence through precision lifestyle interventions (targeting 15–20% risk reduction in cardiometabolic disorders). Implementation of blockchain-secured care pathways and federated learning architectures ensures real-time care coordination while maintaining GDPR-compliant data governance. This patient-centric model optimizes resource allocation efficiency (demonstrating 30–35% reduction in redundant diagnostics) and enhances care continuum personalization through adaptive neural recommendation engines, representing a significant advancement in value-based healthcare delivery systems.

1.8 Regional disparities and multilevel differentiation in chronic disease management across China

While China's chronic disease management system has achieved notable progress through policy initiatives and technological

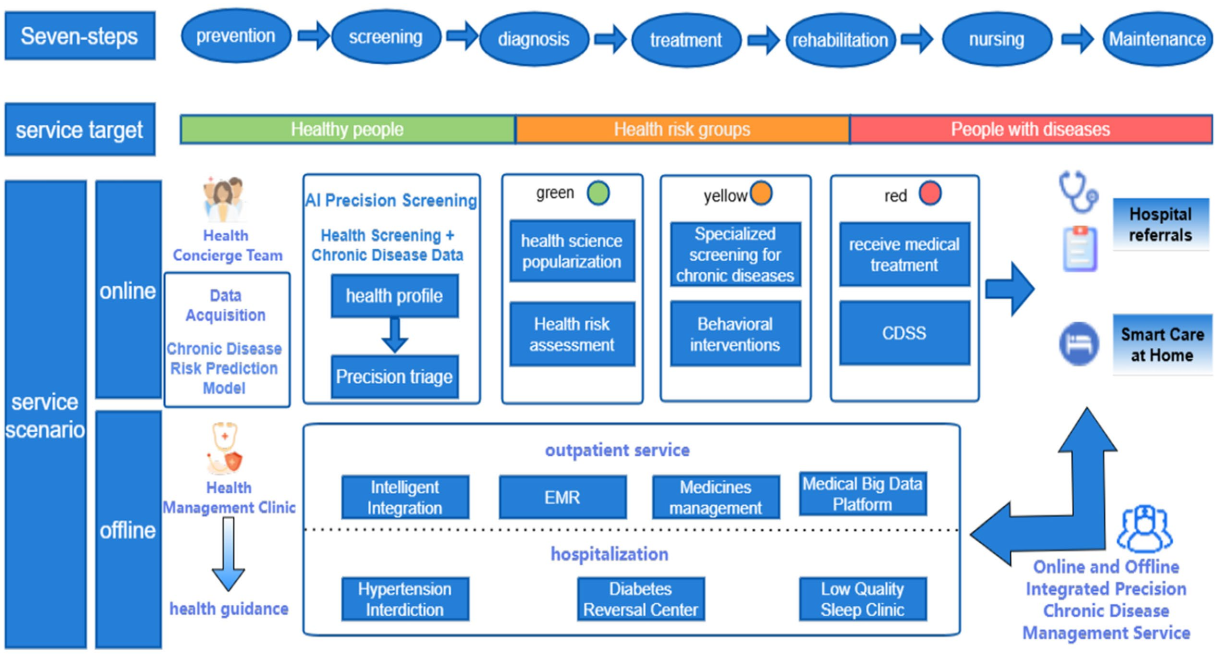

FIGURE 4
Prototype architecture diagram for precision health management integration within a public hospital system.

advancements, significant regional disparities and structural differentiation persist due to uneven economic development, resource allocation, policy implementation efficacy, and technological adoption. These variations manifest across service models, management efficiency, patient engagement, and health outcomes, as summarized in Table 1.

1.8.1 Geographical imbalance in development

Coastal regions, exemplified by Shanghai, lead in digital health integration and clinical-public health convergence. Shanghai's unified health management platform enables closed-loop chronic disease management spanning screening, diagnosis, and follow-up (27). In contrast, western rural areas face systemic challenges, including insufficient medical resources and outdated infrastructure. Township hospitals in provinces like Gansu often lack basic chronic disease monitoring equipment, hindering risk prediction model deployment (37). Compounding this issue, central-western regions (e.g., Sichuan) with aging populations exhibit higher chronic disease burdens but receive inadequate training and technical support for primary care providers.

1.8.2 Heterogeneity in policy implementation

Decentralized execution of national policies creates divergent local practices. Sanming City's integrated "prevention-treatment-management" framework, funded through pooled medical insurance and public health budgets, significantly improved hypertension and diabetes control rates (35). Conversely, provinces prioritizing curative over preventive services demonstrate fragmented care coordination. Wuhan's family physician contracting system enhanced grassroots prevention capabilities (34), while fiscally constrained regions struggle to sustain such programs due to insufficient funding.

1.8.3 Hierarchical fragmentation in healthcare delivery

Tertiary hospitals dominate complex case management and predictive model development—West China Hospital's multidisciplinary approach exemplifies advanced care for refractory chronic diseases. However, primary care institutions, intended as frontline prevention hubs, remain hampered by workforce shortages and data silos. Surveys reveal community health centers predominantly conduct rudimentary follow-ups rather than personalized interventions (33), exacerbating patient influx to overcrowded tertiary facilities and undermining sustainable prevention.

1.8.4 Technological adoption gaps

AI-driven diagnostics and remote monitoring thrive in eastern metropolitan areas. Huawei's photoplethysmography-based atrial fibrillation screening (30) demonstrates mature applications in first-tier cities. Meanwhile, central-western primary care facilities rely on manual records due to inadequate data infrastructure and training, perpetuating information fragmentation. Remote regions face additional barriers in predictive modeling due to sparse, non-interoperable health data (37).

1.8.5 Socioeconomic determinants of patient engagement

Health literacy and financial capacity disparities critically influence outcomes. In the Yangtze River Delta, 62% of residents actively use mobile health apps for self-management, compared to <18% in western rural areas (38). Economic constraints drive delayed care-seeking in impoverished regions, with late-stage disease presentation correlating to 3.2-fold higher mortality in diabetes cohorts. Regional variations in insurance reimbursement rates

TABLE 1 Comparison of regional differences in chronic disease management in China.

Comparison dimension	Eastern developed_ regions	Western underdeveloped_ regions	Urban vs. rural comparison
Information technology level	High: Integrated health management platforms enable full-cycle closed-loop management.	Low: Reliance on manual registration and follow-up, lack of data collection equipment.	Urban: Data platforms are widespread, remote monitoring technology is mature; Rural: Information silos, severe data fragmentation.
Policy implementation	Comprehensive: Integration of medical insurance and public health funding	Lagging: Grassroots focus on treatment over prevention, difficulties in policy implementation.	Urban: High coverage of family doctor contract services; Rural: Insufficient fiscal investment, contract services lack sustainability.
Technology Application	Advanced: AI-assisted diagnosis, machine learning risk prediction models	Backward: Reliance on manual records, limited application of risk models.	Urban: Smart wearable devices are popular (e.g., PPG technology for atrial fibrillation screening); Rural: Lack of technical training and equipment support.
Grassroots Service Capacity	Strong: Community health centers provide personalized interventions (e.g., Shanghai model).	Weak: Focus on simple follow-ups, lack of data analysis capabilities.	Urban: Multidisciplinary collaboration for precise management (e.g., West China Hospital); Rural: Chronic disease management remains superficial.
Patient Participation	High: Mobile health applications are widespread, active participation in prevention	Low: Low health literacy, late-stage medical visits.	Urban: Health education coverage >80%; Rural: Limited access to information, low awareness of prevention.
Economic and Insurance Support	Strong: High medical insurance reimbursement rates, support for long-term management (e.g., Sanming integrated insurance model).	Weak: High out-of-pocket costs, heavy burden on low-income groups.	Urban: Pilot programs for differentiated payment mechanisms; Rural: Inadequate insurance coverage, unsustainable health management.

(45–85%) further limit access to sustained management for vulnerable populations.

Policy coordination and cross-regional cooperation play a crucial role in addressing regional differences in chronic disease management, as well as in coping with the lack of medical resources and lagging technological application in under-resourced regions (39). Firstly, establishing an effective policy coordination mechanism is crucial. The central government should formulate a unified national strategy for the balanced development of medical resources, clarifying the responsibilities and goals of each region in the allocation of medical resources and the promotion of technology. For example, a special fund for the balanced development of medical resources could be set up, with financial transfer payments tilted towards resource—deficient areas. Local governments need to develop detailed implementation plans based on the central plan and local realities to ensure the effective use of funds and the smooth progress of projects. Meanwhile, a cross—departmental coordination body, such as a Medical Resources Coordination Committee involving health, finance, and science and technology departments, should be established to hold regular meetings, communicate information, and resolve issues in policy implementation.

Cross—regional cooperation is also an effective way to improve the medical level in resource—deficient areas (40). Developed regions can establish medical support cooperation relationships with resource—deficient areas. This cooperation can be carried out in a hospital—to—hospital manner, for instance, with top—tier hospitals in major cities forming partnerships with county—level hospitals in remote areas. Hospitals in developed regions can send medical teams to resource—deficient area hospitals on a regular basis for consultations, surgical guidance, academic lectures, and other activities, while also accepting medical staff from resource—deficient area hospitals for further study. In addition, remote medical cooperation can be carried out, using Internet technology to realize functions such as remote diagnosis and remote training, breaking geographical barriers and enabling patients in resource—deficient areas to access high—quality medical services.

In terms of technical assistance and training programs, the government should increase investment in resource—deficient areas. On the one hand, medical equipment aid projects can be launched, donating or providing advanced medical equipment at preferential prices to resource—deficient areas according to local medical needs, such as digital X—ray machines and ultrasound diagnostic equipment, along with equipment installation, debugging, and maintenance services. On the other hand, large—scale medical staff training programs should be implemented. Special training funds can be set up to conduct stratified and categorized training for medical personnel in resource—deficient areas. For example, for primary—level medical staff, general medicine training can be carried out to improve their ability to diagnose and treat common and frequent diseases; for specialist doctors, new technology and new therapy training can be provided, such as minimally invasive surgery training. The training methods can combine online and offline approaches, with online network course platforms providing a wealth of learning resources for medical staff to study anytime and anywhere, and offline centralized training and practical operation training to ensure training effectiveness (41).

Through these policy coordination mechanisms, cross—regional cooperation, and technical assistance and training programs, it is expected to gradually narrow the gap in medical resources and technology application capabilities between regions, alleviate social inequality, and improve the overall medical level in remote and resource—deficient areas, providing local residents with higher—quality and more equitable medical services.

2 Discussion

In recent years, the National Health Commission and the China CDC have actively promoted the integration of medical and preventive care, aiming to establish a disease prevention and control system with professional public health institutions as the backbone, medical institutions as the support, and primary healthcare institutions as the foundation. Various regions have conducted effective explorations in this integration, achieving initial successes. However, a persistent "treatment-over-prevention" mindset remains prevalent among both healthcare providers and patients (38). Historically, the healthcare system has prioritized disease treatment over prevention, leading to relatively lower resource allocation and attention to public health services. This issue is not solely attributable to medical institutions; uneven health literacy and misconceptions about prevention among the public also contribute to a greater reliance on curative care. Overall, the health needs of most Chinese residents remain disease-oriented. Addressing this requires leveraging big data to analyze patients' lifestyles, health statuses, and disease risks, providing personalized health education to help patients better understand and manage their health.

On the other hand, the lack of effective integration between medical information systems and public health information systems has resulted in data silos, leading to resource waste and increased management complexity. Disparate information platforms across medical institutions and primary care facilities hinder data sharing. Current public health surveillance systems, including infectious disease monitoring, chronic disease management, and health risk factor surveillance, operate independently in many regions without integration, preventing unified archiving of resident health information. The incompleteness and inconsistency of resident health data (42), coupled with the absence of unified chronic disease prevention management and integrated medical-preventive care pathways, often result in redundant follow-ups and health management for the same chronic disease patient across community health centers and large public hospitals. This not only leads to duplicated investments and resource waste but also compromises the continuity and consistency of care experienced by patients (43).

Chronic disease risk prediction models are one of the effective measures for controlling chronic diseases (44). However, current research on these models, both domestically and internationally, faces limitations in variable selection and algorithm application, restricting their predictive accuracy and ability to comprehensively capture the complex factors influencing chronic disease risks. To enhance the interpretability and practicality of these models, future research needs to focus on data integration, variable analysis, algorithm diversification, and model personalization.

Moving forward, research in China's medical-preventive care integration should focus on the following areas to advance the scientific, precise, and intelligent development of chronic disease management:

(1) Data integration and sharing (45): Establishing unified data standards and exchange protocols to break down barriers between medical and public health information systems, enabling seamless multi-source data integration. Developing national or regional data-sharing platforms that consolidate clinical data, health monitoring data, environmental data, and other multidimensional information will provide comprehensive support for chronic disease prevention and control. Innovations in data security and privacy protection technologies will also be critical to ensure the safety and compliance of resident health information. In turn, data standards will evolve through the following research pathways

Phase 1 (foundation building): Conduct a comprehensive survey of the current medical data status in different regions. This includes data formats, data sources (such as hospitals, clinics, and medical laboratories), and data quality. Based on the survey results, establish a basic data standard framework. For example, unify the data formats for patient demographics (name, age, gender, etc.), medical history records, and basic examination results (such as blood pressure, blood glucose levels). Set up a data standardization working group composed of medical informatics experts, data engineers, and representatives from medical institutions to oversee the implementation.

Phase 2 (expansion and integration): Expand the data standardization to more complex medical data types. This includes medical imaging data (X-rays, CT scans, MRI images), electronic medical records (EMRs), and medical device data (such as data from pacemakers and implantable glucose monitors). Develop data integration standards to enable the seamless integration of data from different sources. For example, establish a standard for the integration of data from different hospital information systems (HIS) and laboratory information systems (LIS).

Phase 3 (optimization and sustaining): Continuously monitor and optimize the data standardization process. Set up a feedback mechanism to collect feedback from medical staff, data users, and patients. Use advanced data quality assessment tools to regularly check the quality of standardized data. Make adjustments to the data standards according to the latest medical research findings and technological advancements.

(2) Optimization of chronic disease risk prediction models: Future research should emphasize the integration of multi-source data, including clinical data, genomic data, lifestyle data, and social environmental data, to comprehensively capture the complex factors influencing chronic disease risks. Exploring diverse machine learning algorithms, such as deep learning, ensemble learning, and reinforcement learning, will enhance the predictive accuracy and generalizability of these models. Furthermore, the development of personalized risk prediction models tailored to individuals' biological characteristics,

behavioral habits, and environmental factors will become a key trend.

Step 1 (algorithm development and optimization): Focus on developing efficient federated learning algorithms that can handle the heterogeneity of medical data. Medical data from different regions may have different distributions due to differences in patient populations, medical practices, and data collection methods. Research on how to optimize the federated learning algorithms to deal with such data heterogeneity is crucial. For example, develop algorithms that can weight the data from different regions according to their data quality and representativeness.

Step 2 (security and privacy enhancement): Ensure the security and privacy of medical data in the federated learning process. Although federated learning does not share the raw data, there is still a risk of data leakage through the model parameters. Research on advanced encryption techniques, such as homomorphic encryption and secure multi—party computation, to protect the data during the model training and communication process.

Step 3 (performance evaluation and comparison): Establish a comprehensive performance evaluation system for federated learning models in the medical field. Compare the performance of federated learning models with traditional centralized learning models in terms of accuracy, robustness, and generalization ability. For example, in a cross—regional disease prediction task, evaluate how the federated learning model performs compared to a model trained on the combined data of all regions (if data sharing were possible).

(3) Health literacy improvement and innovative health education (46): Future research should explore new models of health education based on big data and AI, delivering precise health knowledge and personalized recommendations to improve public health literacy and self-management capabilities. Strengthening community participation and the family doctor system will also be crucial, building community-based health management networks to shift the focus of chronic disease prevention and control upstream.

Data collection and analysis: Collect a wide range of health—related data from different regions. This includes demographic data (such as age, gender, occupation), medical history, lifestyle habits (such as diet, exercise, smoking and drinking habits), and health—related behavioral data (such as the frequency of medical visits, the use of health—care products). For example, through online questionnaires, mobile health apps, and medical record systems, a large amount of data can be collected. Then, use big data analysis techniques to mine the potential health needs and problems of different population groups in different regions. For instance, in a certain area, it may be found through data analysis that the incidence of a certain chronic disease is high among the older adult, and their knowledge and self—management ability of this disease are relatively weak.

Artificial intelligence—based knowledge delivery and suggestion: Develop an artificial intelligence—driven health knowledge delivery and suggestion system (47). Based on the analysis results of the collected data, the system can precisely push health knowledge and personalized health suggestions to different users. For example, for a young office worker in an urban area who has a sedentary lifestyle and a high—fat diet, the system can push knowledge about the prevention of cardiovascular and cerebrovascular diseases, such as the importance of reasonable diet and regular exercise, and personalized suggestions such as a suitable exercise plan and a healthy diet recipe. At the same time, the system can also use artificial intelligence technology such as natural language processing to provide users with interactive health consultation services, answering their health questions in a timely and accurate manner.

Cultural assessment and content customization: Conduct a comprehensive cultural assessment in different regions. Understand the local cultural beliefs, values, and traditional health—related concepts. For example, in some rural areas, traditional Chinese medicine has a deep cultural foundation. In the health literacy improvement plan, more content about traditional Chinese medicine health preservation can be included, such as the use of traditional Chinese medicine diet and the principles of traditional Chinese medicine massage. In addition, the language and expression of health education materials should also be adapted to the local cultural habits. For example, in some ethnic minority areas, use the local ethnic language and vivid local dialects to explain health knowledge, so as to make it easier for residents to accept and understand.

Resource—based education method selection: According to the resource differences of different regions, select appropriate health education methods (48). In areas with abundant medical resources, such as large cities, more advanced health education methods can be used. For example, organize health lectures by well—known medical experts in hospitals and communities, and use virtual reality (VR) and augmented reality (AR) technologies to carry out immersive health education experiences, such as simulating the process of surgery or the spread of diseases in the human body. In resource—poor areas, such as remote mountainous areas, more simple and practical health education methods can be used. For example, train local health volunteers to carry out door—to—door health education and distribute simple and easy—to—understand health brochures.

By addressing these challenges and focusing on these research priorities, China can advance the integration of medical and preventive care, ultimately improving the management and outcomes of chronic diseases (see Figure 5).

3 Conclusion

In the context of big data, significant progress has been made in the informatization of chronic disease health management. This study explores optimized pathways for chronic disease management from the perspective of medical-prevention integration, demonstrating that big data technologies will serve as the core driver for future integration efforts, particularly through the following strategies:

(1) Data-driven scientific decision support: utilizing multidimensional data analysis (e.g., clinical records, environmental factors, and regional epidemiological patterns) to provide evidence-based insights for chronic disease prevention, diagnosis, and management. For instance,

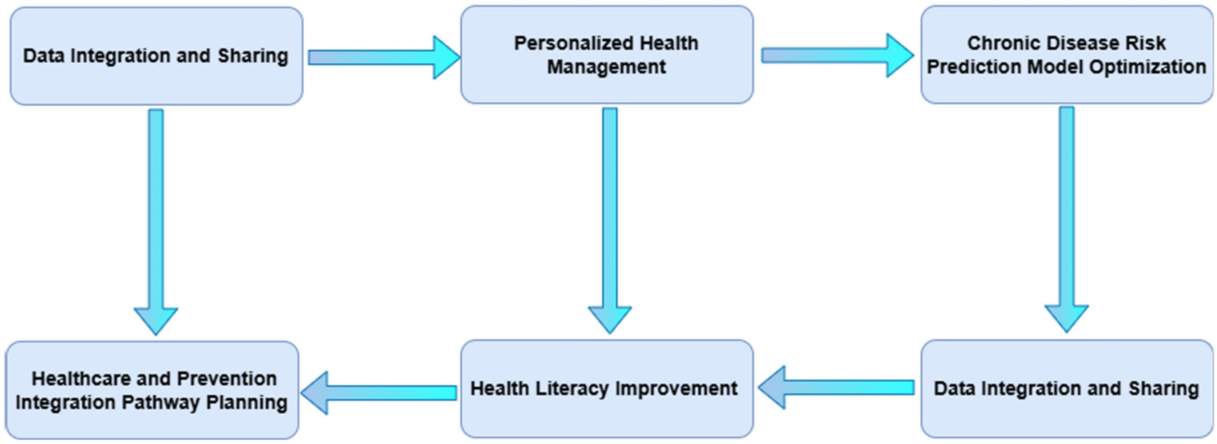

FIGURE 5
Roadmap for development in the field of healthcare prevention integration.

comparative analysis of regional disease prevalence enables prioritized deployment of screening and intervention resources in high-risk areas.

(2) Predictive analytics and targeted interventions: integrating machine learning with spatiotemporal data analysis to develop dynamic risk prediction models. These models facilitate early identification of high-risk populations across regions and support the design of geographically tailored intervention pathways aligned with local healthcare resource availability.
(3) Mobile health and remote monitoring systems: deploying smart wearable devices and telemedicine platforms to continuously track patients' physiological metrics and behavioral data, thereby establishing personalized health management "tracking pathways" to enhance treatment adherence and care continuity.
(4) Integrated regional health information platforms: establishing cross-institutional and cross-regional chronic disease management platforms to unify clinical records, health profiles, and public health data. Such platforms enable comparative analysis of regional management outcomes (e.g., disparities in diabetes control efficacy) and promote resource optimization through interregional knowledge sharing.
(5) Behavioral interventions and health communication: designing region- and population-specific health education programs based on patient data profiling. Information platforms monitor behavioral improvement trajectories (e.g., exercise habits, medication adherence) to dynamically refine intervention strategies.

By enhancing data-driven regional collaboration, process tracking, and precision decision-making, these strategies will substantially improve the efficacy of medical-prevention integration in chronic disease management, shifting the paradigm from "fragmented treatment" to "comprehensive prevention and control." This transformation not only improves patients' quality of life and reduces healthcare system burdens but also advances holistic optimization of chronic disease management through interregional data benchmarking and standardized best practices. Ultimately, it achieves multidimensional integration of services, data, and resources, offering a scalable framework for building resilient public health systems.

Author contributions

YW: Writing – original draft, Writing – review & editing. RD: Conceptualization, Data curation, Writing – review & editing. XG: Methodology, Supervision, Validation, Writing – review & editing.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

1. Ghebreyesus D T A. World health statistics 2023: Monitoring health for the Sdgs, sustainable development goals. World Health Organization (WHO). (2023): 130.

2. Research On The Development Prospects Of Chronic Disease Management Industry[EB/OL]. Available online at: https://www.chinairn.com/news/20231113/100829982.html

3. Huihui H, Zhongliang B, Zijing W, Qunhong S, Lingzhong PX. The connotation and analysis of concepts related to the integration of medical and preventive care. *J Manag Rural Health Care China*. (2024) 44:154–61. doi: 10.19955/j.cnki.1005-5916.2024.03.001

4. Li GJ, Liu YT, Zhao H, Cai HY, IEEE. Research on application of healthcare data in big data era. *Int Conf Robot Intell Syst*. (2018):377–9. doi: 10.1109/icris.2018.00100

5. Khanna D, Jindal N, Singh H, Rana PS. Applications and challenges in healthcare big data: a strategic review. *Curr Med Imag*. (2023) 19:27–36. doi: 10.2174/1573405618666220308113707

6. Goyal P, Malviya R. Challenges and opportunities of big data analytics in healthcare. *Health Care Sci*. (2023) 2:328–38. doi: 10.1002/hcs2.66

7. Velmovitsky PE, Alencar P, Leatherdale ST, Cowan D, Morita PP. Application of a Mobile health data platform for public health surveillance: a case study in stress monitoring and prediction. *Digital Health*. (2024) 10:22. doi: 10.1177/20552076241249931

8. Heus P, Idema DL, Kruithof E, Damen JAAG, Verhoef-Jurgens MS, Reitsma JB, et al. Increased endorsement of TRIPOD and other reporting guidelines by high impact factor journals: survey of instructions to authors. *J Clin Epidemiol*. (2024) 165:111188. doi: 10.1016/j.jclinepi.2023.10.004

9. Smith C, Vajdic CM, Stephenson N. Centring equity in data-driven public health: a call for guiding principles to support the equitable design and outcomes of Australia's data integration systems. *Med J Aust*. (2023) 218:341–3. doi: 10.5694/mja2.51902

10. Bloomfield RA, Polo-Wood F, Mandel JC, Mandl KD. Opening the Duke electronic health record to apps: implementing SMART on FHIR. *Int J Med Inform*. (2017) 99:1–10. doi: 10.1016/j.ijmedinf.2016.12.005

11. Yu Y, Zong NS, Wen A, Liu SJ, Stone DJ, Knaack D. Developing an ETL tool for converting the Pcornet CDM into the OMOP CDM to facilitate the COVID-19 data integration. *J Biomed Inform*. (2022) 127:104002. doi: 10.1016/j.jbi.2022.104002

12. Wagholikar KB, Mandel JC, Klann JG, Wattanasin N, Mendis M, Chute CG, et al. SMART-on-FHIR implemented over I2b2. *J Am Med Inform Assoc*. (2017) 24:398–402. doi: 10.1093/jamia/ocw079

13. Xili J, Ming S, Wenhan J, Jingbo P. Research Progress on new models of chronic disease prevention and control in the era of big data in China (2022) 25:2811–4.

14. Ye C, Fu T, Hao S, Zhang Y, Wang O, Jin B, et al. Prediction of incident hypertension within the next year: prospective study using statewide electronic health records and machine learning. *J Med Int Res*. (2018) 20:E22. doi: 10.2196/jmir.9268

15. Kanegae H, Suzuki K, Fukatani K, Ito T, Harada N, Kario K. Highly precise risk prediction model for new-onset hypertension using artificial intelligence techniques. *J Clin Hypertens (Greenwich)*. (2020) 22:445–50. doi: 10.1111/jch.13759

16. Kupersmith J, Francis J, Kerr E, Krein S, Pogach L, Kolodner RM, et al. Advancing evidence-based care for diabetes: lessons from the veterans health administration. *Health Aff*. (2007) 26:W156–68. doi: 10.1377/hlthaff.26.2.w156

17. Mccoy RG, Lipska KJ, Yao X, Ross JS, Montori VM, Shah ND. Intensive treatment and severe hypoglycemia among adults with type 2 diabetes. *JAMA Intern Med*. (2016) 176:969–78. doi: 10.1001/jamainternmed.2016.2275

18. Jelinek HF, Stranieri A, Yatsko A, Venkatraman S. Data analytics identify glycated Haemoglobin co-markers for type 2 diabetes mellitus diagnosis. *Comput Biol Med*. (2016) 75:90–7. doi: 10.1016/j.compbiomed.2016.05.005

19. Wang J, Bao B, Shen P, Kong G, Yang Y, Sun X, et al. Using electronic health record data to establish a chronic kidney disease surveillance system in China: protocol for the China kidney disease network (CK-NET)-Yinzhou study. *BMJ Open*. (2019) 9:E030102. doi: 10.1136/bmjopen-2019-030102

20. Serbanati LD. Health digital state and smart EHR systems. *Inform Med Unlocked*. (2020) 21:100494. doi: 10.1016/j.imu.2020.100494

21. Shunda C, Jie Z, Fang X. Deep learning based data analysis method for medical auxiliary diagnosis in electronic design engineering (2022) 30:72–6. doi: 10.14022/j.issn1674-6236.2022.07.015

22. Hu Z, Qiu H, Wang L, Shen M. Network analytics and machine learning for predicting length of stay in elderly patients with chronic diseases at point of admission. *BMC Med Inform Decis Mak*. (2022) 22:62. doi: 10.1186/s12911-022-01802-z

23. Xiaobing X, Di L, Yang S, Qin S, Lian X, Shourong X. Analysis of chronic disease comorbidity in Chinese elderly based on association rules. *J Prev Control Chron Dis China*. (2021) 29:808–12. doi: 10.16386/j.cjpccd.issn.1004-6194.2021.11.002

24. Ningning Z, Jingang M, Zhaolei F, Hanming Z, Ming L. A review of machine learning based electrocardiogram automatic diagnosis algorithms for medical and health equipment. *Medical and health equipment*. (2022) 43:92–7. doi: 10.19745/j.1003-8868.2022106

25. Zheng Y. An improved Apriori association rule for the identification of Acupoints combination in treating COVID-19 patients. *Comput Intell Neurosci*. (2022) 2022:1–9. doi: 10.1155/2022/3900094

26. Liu Y, Wang L, Miao R, Ren HN. A data mining algorithm for association rules with chronic disease constraints. *Comput Intell Neurosci*. (2022) 2022:1–8. doi: 10.1155/2022/8526256

27. Minna C, Sheng Z, Mengyun S, Yang Z, Ka G, Yuheng W. Exploration of integrated community chronic disease health management model supported by information technology. *J Shanghai Prev Med*. (2022) 34:1079–84. doi: 10.19428/j.cnki.sjpm.2022.22322

28. Mcmanus RJ, Little P, Stuart B, Morton K, Raftery J, Kelly J. Home and online management and evaluation of blood pressure (HOME BP) using a digital intervention in poorly controlled hypertension: randomised controlled trial. *BMJ*. (2021) 372:M4858. doi: 10.1136/bmj.m4858

29. Yangyang L, Xingdong F. Cluster analysis of dynamic missing data and its application in the diagnosis of hypertension. *J Math Stat Manag*. (2023) 42:218–28. doi: 10.13860/j.cnki.sltj.20220130-003

30. Guo Y, Wang H, Zhang H, Liu T, Liang Z, Xia Y, et al. Mobile Photoplethysmographic technology to detect atrial fibrillation. *J Am Coll Cardiol*. (2019) 74:2365–75. doi: 10.1016/j.jacc.2019.08.019

31. Perez MV, Mahaffey KW, Hedlin H, Rumsfeld JS, Garci A, Ferris T. Large-scale assessment of a smartwatch to identify atrial fibrillation. *N Engl J Med*. (2019) 381:1909–17. doi: 10.1056/NEJMoa1901183

32. Anhui Provincial People's Government. Interpretation Of Urban Rural Integration Development Policies 2022[EB/OL]. Available online at: https://www.huoqiu.gov.cn/public/6601241/35879340.html

33. Jia G, Huajun S, Ying C, Jiawen Z, Yaxin Z, Ying M. Construction of on site evaluation index system for chronic disease prevention and treatment integration service quality in grassroots medical and health institutions in China. *Chinese General Medicine*. (2023) 26:3489–95.

34. Min F, Yi C, Xiang T, Chenghua H, Zhiping W. Expert theme seminar on "comprehensive enhancement of grassroots medical prevention integration capability in Wuhan City". *J Gen Pract Med China*. (2018) 21:30–3.

35. Yajing Z, Suxiong W. Practice of medical prevention integration in Sanming, Fujian Province: limitations and countermeasures. *J China's Health Serv Manag*. (2022) 39:1–3+9.

36. Yang M. A community proactive health management model for family doctors in Shandong, China. *Aust J Prim Health*. (2024) 30:7. doi: 10.1071/py24030

37. Nian C, Daping S, Yaru C. Analysis of the implementation status and problems of National Basic Public Health Service Projects in China's health economy. *China Health Economics*. (2022) 41:60–62+90.

38. Chenzhou W, Yan Z, Liang Z. Analysis of management and service mechanisms in the difficulties of medical prevention integration in China%. *J Research Chin Health Policies*. (2024) 17:2–8.

39. Lin D, Wang H, Xu J, Niu L. Evaluation of National Fitness and National Health Development and Coupling and Coordination in 11 provinces and cities in eastern China. *PLoS One*. (2024) 19:E0291515. doi: 10.1371/journal.pone.0291515

40. Zeng W, Tao W, Yang Y, Li Y, Lu B, Zhao Q, et al. Perceived knowledge, attitudes and practices regarding the medical consortium among medical staff in Sichuan, China: a cross-sectional survey. *BMC Health Serv Res*. (2023) 23:1318. doi: 10.1186/s12913-023-10146-x

41. Hu M, Chen W, Yip W. Hospital management practices in county-level hospitals in rural China and international comparison. *BMC Health Serv Res*. (2022) 22:64. doi: 10.1186/s12913-021-07396-y

42. Wantong W, Linlin B, Zhigao C, Lina P, Yuanjing L, Lei Y. Survey on the current status of public health resource allocation and functions in medical institutions in Z City. *J Clin Res China*. (2022) 35:1785–8. doi: 10.13429/j.cnki.cjcr.2022.12.034

43. Rao X, Luo L, Wang XY. A spatial feature analysis of primary health care utilization in a large City in China and its implications for family doctor contract service policy. *BMC Health Serv Res*. (2024) 24:17. doi: 10.1186/s12913-023-10389-8

44. Xi ZW, Mo JX, Liu QP, Tang X, Gao P. Research Progress of cardiovascular disease risk prediction models among patients with chronic kidney disease. *Zhonghua Liu Xing Bing Xue Za Zhi = Zhonghua Liuxingbingxue Zazhi*. (2024) 45:1448–54. doi: 10.3760/cma.j.cn112338-20240522-00296

45. Sakai Y, Miyata Y, Yokoi K, Wang Y, Kurata K. Initial insight into three modes of data sharing: prevalence of primary reuse, data integration and dataset release in research articles. *Learned Publish*. (2023) 36:417–25. doi: 10.1002/leap.1546

46. Chen NJ, Chang CH, Huang CM, Lin FH, Lu LT, Liu KY, et al. Assessing the effectiveness of interactive robot-assisted virtual health coaching for health literacy and disease knowledge of patients with chronic kidney disease: Quasiexperimental study. *J Med Internet Res*. (2025) 27:12. doi: 10.2196/68072

47. Manoharan S, Senthilkumar R. An intelligent fuzzy rule-based personalized news recommendation using social media mining. *Comput Intell Neurosci*. (2020) 2020:1–10. doi: 10.1155/2020/3791541

48. Hasannejadasl H, Roumen C, Smit Y, Dekker A, Fijten R. Health literacy and Ehealth: challenges and strategies. *JCO Clin Cancer Inform*. (2022) 6:E2200005. doi: 10.1200/CCI.22.00005

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 07 May 2025
DOI 10.3389/fpubh.2025.1556234

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Tianjiao Lan,
Sichuan Provincial Hospital for Women and Children, China
Chen Li,
Shanghai University of Engineering Sciences, China

*CORRESPONDENCE
Meng Xue-Hui
mengxuehui@aliyun.com

†These authors share first authorship

RECEIVED 16 January 2025
ACCEPTED 21 April 2025
PUBLISHED 07 May 2025

CITATION
Zi-Qian J, Yi-Le L, Ying-Ying T, Ke-Yi S, Xin-Hao L, Tong P, Cheng-Cheng L, Dan W and Xue-Hui M (2025) Impact of diagnosis-intervention packet payment on the consistency of hospitalization expenses across different medical insurance schemes in China.
Front. Public Health 13:1556234.
doi: 10.3389/fpubh.2025.1556234

Impact of diagnosis-intervention packet payment on the consistency of hospitalization expenses across different medical insurance schemes in China

Jin Zi-Qian†, Li Yi-Le†, Tao Ying-Ying, Shen Ke-Yi, Lin Xin-Hao, Pei Tong, Li Cheng-Cheng, Wu Dan and Meng Xue-Hui*

School of Humanities and Management, Zhejiang Chinese Medical University, Hangzhou, China

Background: The Diagnosis-Intervention Packet Payment (DIP) system is regarded as a localized cost-control strategy in China. It aims to improve healthcare efficiency, curb the growth of medical expenses, and optimize the allocation of medical resources among diverse groups.

Objective: This study aims to assess the impact of DIP payment reforms on differential changes in patients' hospitalization expense and to explore the degree of concentration of hospitalization expense for patients with different insurance schemes undergoing treatment for typical diseases, with a view to providing policy recommendations for improving the medical insurance system.

Methods: Data were collected from patients with cerebral infarction (CI) and coronary atherosclerotic heart disease (CAD) treated at primary, secondary, and tertiary hospitals in S City of China, from 2020 to 2023. Patients were classified into the Urban Employees' Basic Medical Insurance (UEBMI) group and the Urban and Rural Residents' Medical Insurance (URRMI) group based on two health insurance schemes. Propensity Score Matching (PSM) was employed to ensure a balanced sample. The changes and trends in hospitalization expenses across different groups were analyzed using the interquartile Range (IQR), standard deviation (SD), and concentration index.

Results: Post-DIP reform, hospitalization expenses for patients with different diseases at various levels of hospitals have decreased annually. Regarding expenses variation, the standard deviation (SD) of hospitalization expenses for both UEBMI and URRMI exhibited a downward trend, with a decrease in the double-difference value each year. From the perspective of expenses concentration, all concentration indices were less than 0 (statistically significant, $p < 0.01$), indicating a higher concentration in hospitalization expenses for UEBMI.

Conclusion: The DIP reform can effectively increase the concentration of hospitalization expenses, reduce the variability of changes in hospitalization expenses for both UEBMI and URRMI, and drive medical practices toward standardization and consistency. However, the degree of this expense reduction varies among the hospitals at all levels.

KEYWORDS

Diagnosis-Intervention Packet (DIP), China, payment reform, health insurance schemes, expense consistency

1 Introduction

Medical insurance payments are an important lever for regulating medical service behaviors and guiding the allocation of medical resources (1). With economic development, demographic shifts, and changes in disease patterns, medical expenses have been rising globally. Many countries have implemented medical insurance payment reform to control expenses growth (2–4). Controlling medical expenses has also become a crucial task for the medical insurance sector in China and an essential part of deepening the reform of the medical and healthcare system. The traditional Chinese medical insurance payment method is fee-for-service, which often results in overutilization of medical services, excessive increases in medical expenses, and waste of healthcare resources (5). In response to escalating healthcare expenditures, China implemented Diagnosis-Related Group (DRG) payment reform as a cost-containment strategy, which demonstrated initial efficacy in standardizing medical expenditure patterns during the implementation phase. Studies have confirmed that DRG payment helps reduce disparities in medical expenses, suggesting that healthcare providers are more likely to follow clinical guidelines and provide effective treatment after assuming the risk of overspending (6, 7). However, over time, due to a variety of conditions, DRC has not been able to better realize its function in China (8–10). After continuous exploration, China launched a pilot program of the "Diagnosis-Intervention Package" (DIP) payment method based on its conditions (11). Rooted in China's unique national conditions and grounded in clinical practice, DIP provides a bottom-up payment reform approach. Compared to the DRG system, DIP is simpler and less challenging to implement. It adopts a "coarse-to-fine" classification method to refine the categorization of medical cases. Additionally, the DIP system has lower medical record supervision and informatization requirements, making it more suitable for implementation in hospitals in second and third-tier cities (12). Therefore, DIP is considered a localized expense control method in China.

To achieve universal health coverage and equitable allocation of medical resources, the Chinese government established a unified urban and rural resident basic medical insurance system in 2016, New Rural Cooperative Medical Scheme (NRCMS) and Urban Residents' Basic Medical Insurance Program (URBMI) were merged into the Urban and Rural Residents' Basic Medical Insurance (13). As of the end of 2023, the number of people participating in Urban and Employee Basic Medical Insurance was 370,938,800 and the number of people participating in Urban and Rural Resident Basic Medical Insurance was 962,930,200. The operation of the basic medical insurance system is safe and stable. However, some researchers have pointed out that gaps still exist in healthcare utilization between UEBMI and URRMI (14). The main differences contributing to these disparities include target population, funding sources, funding levels, and administrative and benefit packages (15, 16). In addition to this, the health insurance payment method also affects the patients' hospitalization expenses. Compared with the traditional fee-for-service (FFS) payment method, after the implementation of the DRG payment method reform, the patients' hospitalization expenses have been significantly controlled, and the patients' hospitalization burden has been reduced to a certain extent (17, 18). However, for primary healthcare institutions, due to gaps in medical quality, operational complexity, and the unpredictability of healthcare provider behavior, it is difficult to adapt to DRG reforms in a short period. Therefore, disparities in hospitalization expenses between different medical insurance schemes still exist. The DIP payment method explored by the Chinese government during the reform of the medical insurance system is considered to have similar effects to DRG payment (19). Studies have shown that the direct effect of the DIP reform is a significant reduction in the average hospitalization expenses per patient and the cost of medicines (20, 21), which can optimize the structure of medical expenses, effectively control cost growth, and inhibit waste of healthcare resources (22, 23). Compared to DRG-based payment models, DIP can allow for more homogeneous resource utilization within groups (24). For example, it was found that DIP led to a decrease in per-hospitalization expenses for both UEBMI and URRMI, while DRG payments led to an 11.2 percent increase in per-hospitalization expenses for URRMI (25).

However, due to the short implementation time of the DIP payment method in China, there is a lack of research on the impact of DIP reform on the hospitalization expenses of patients with different medical insurance schemes. Most of the studies have focused on changes in hospitalization expenses. In addition, studies have shown that health care provider behavior is a key factor in the variation in hospitalization expenses. Physicians' diagnostic and treatment preferences affect hospitalization expenses more than the severity of a given illness (26). Some scholars have pointed out that after the DRG reform, doctors' behavior is more in line with clinical norms, there is less variation in patients' hospitalization expenses, and the cost changes are mainly in the cost of drugs and related materials (27–29). Previous studies by foreign scholars have also confirmed that DRG reforms can significantly affect physicians' service behaviors, Huertaet et al. analyzed the differences in the efficiency of different healthcare organizations using data from the 2005 healthcare services survey conducted by the American Hospital Association and found that in hospitals that use the DRG payment model, the difference in expenditures is small, and the healthcare efficiency is negatively correlated with the expenses, indicating that there is a link between high costs and healthcare services are associated with low efficiency (30). Because of the similarities between the DIP payment method and the DRG payment method, they would have the same effect in regulating provider behavior and reducing hospitalization expenses variation. However, existing studies in China on the impact of Diagnosis-Intervention Packet (DIP) payment reform on inpatient hospitalization expenses have inadequately explored the consistency of expenditure patterns.

Therefore, to further supplement the effect of DIP reform on the consistency of patients' hospitalization expenses, this study selects primary, secondary, and tertiary hospitals in a DIP pilot city in China as a research sample to analyze the differential changes in the hospitalization expenses of UEBMI and URRMI at all levels of hospitals in that city during the implementation of the DIP policy, and to provide policy recommendations for the improvement of the healthcare insurance system. This study aims to assess the impact of DIP payment reforms on differential changes in patients' hospitalization expenses and to explore the degree of concentration of hospitalization expenses for patients with different insurance schemes undergoing treatment for typical diseases.

2 Methods

2.1 Data source

The City of S in China began implementing the DIP payment reform in January 2021. According to the survey, by the end of 2021, the DIP payment method reform in S City, China, had achieved full coverage in 10 counties (cities and districts), encompassing all primary, secondary, and tertiary hospitals and all inpatient diseases. S City took the lead in the province in completing the four full coverage of the integrated area, designated medical institutions, inpatient diseases, and the integrated fund. The data used in this study span from January 2020 to December 2023, encompassing variables such as patient gender, age, the level of medical institutions, disease code, out-of-pocket (OOP) cost, total medical expenses, and LOS. Due to the high number of cases and medical expenses of patients with cerebral infarction and coronary atherosclerotic heart disease, the study selected UEBMI and URRMI treated for these diseases at primary, secondary, and tertiary hospitals in S City from 2020 to 2023 to investigate the effect of DIP payment reform on the homogeneity of hospitalization costs for patients with different health insurance schemes.

2.2 Study design

During the preprocessing of the obtained 103,665 data records, this study used WPS 2021 software to delete missing values and SPSS 27 software to delete medical expense outliers based on the Z-score extreme value identification and processing method, retaining 98,835 data records—establishment of the URRMI group and the UEBMI group on this basis. Using age and gender as covariates, Stata 17.0 software was utilized to perform 1:1 Propensity Score Matching (PSM) for the URRMI and UEBMI groups year by year, with a matching caliper value of 0.01. The specific selection and exclusion process of the study population is shown in Figure 1.

2.3 Statistical analysis

This study aims to compare the disparities and changing trends in hospitalization expenses for treating typical conditions between the URRMI and UEBMI groups from 2020 to 2023, to assess the impact of DIP payment reform on the homogeneity of hospitalization expenses. The degree of variation in hospitalization expenses is expressed as standard deviation (SD), box plot joint interquartile range (IQR). Smaller values of standard deviation indicate a more concentrated

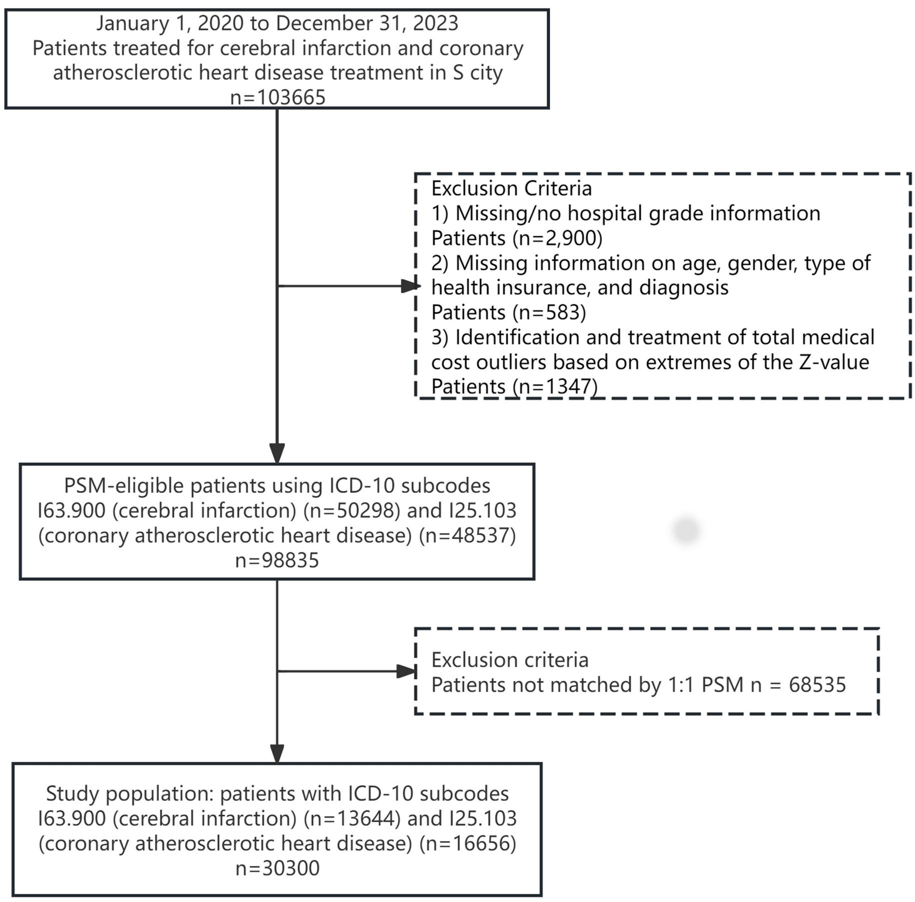

FIGURE 1
Schematic diagram of attrition in the study population.

distribution of hospitalization expenses. Similarly, the size of the interquartile range (IQR) can be reflected in a box plot to determine the degree of concentration. A smaller IQR value indicates a more concentrated expense distribution. In addition, the concentration index was chosen to reflect the distribution of hospitalization expenses across treatment modalities. Also, the Kruskal-Wallis test was used to compare the concentration index of each year and p-value was calculated. The formula for calculating the concentration index is as follows.

$$\text{Concentration index} = \frac{2\operatorname{cov}\left(h, r_i\right)}{\bar{x}}$$

In this equation, cov (h, ri) denotes the covariance between the cost of hospitalization per patient (hi) and the rank of each patient in the sample (ri). The allocation to the UEBMI group (ri = 1) or URRMI (ri = 0) group was used as a criterion variable to indicate differences in the concentration of hospitalization expenses for UEBMI and URRMI. Larger absolute values of the concentration index indicate a more concentrated distribution of costs, whereas values close to 0 indicate a less concentrated distribution of hospitalization expenses. A concentration index below 0 indicates that hospitalization expenses are concentrated in the UEBMI group, whereas above 0 indicates that they are concentrated in the URRMI group.

The significance level for statistical tests was established at $\alpha = 0.05$, with all statistical analyses conducted using Stata 17.0.

3 Results

3.1 Basic information about the sample

Table 1 presents the distribution of patients in the UEBMI and URRMI groups across disease types after PSM, spanning from 2020 to 2023. Following propensity score matching of the 98,835 pre-processed data entries on an annual basis, a total of 30,300 patients were enrolled in this study, with 13,644 cases of cerebral infarction and 16,656 cases of coronary atherosclerotic heart disease. The URRMI and UEBMI groups were equally represented, accounting for 50% of the total. The data reveal an uneven gender distribution among patients treated for cerebral infarction and coronary atherosclerotic heart disease, with male patients significantly outnumbering female patients, with a male-to-female ratio approaching 7:3. In terms of age distribution, patients aged 60–80 years predominated, accounting for over 60% of the total.

Table 2 displays the hospitalization expenses and length of hospital stay for UEBMI and URRMI treated for cerebral infarction and coronary atherosclerotic heart disease across levels of hospitals. The table's indicators illustrate the impact of the DIP reform on controlling hospitalization expenses for patients at levels of hospitals.

Cross-sectional comparisons indicate that as the hospital level increases, the average hospitalization costs for patients with CI and CAD also rise. A comparative analysis of hospitalization expenses reveals that URRMI consistently exhibits higher average hospitalization costs across all hospital levels when compared to UEBMI. Significant differences exist in the average hospitalization expenses between the two patient groups across various hospital levels. Compared to URRMI, the expense gap between primary and tertiary hospitals is especially notable for UEBMI. Upon observing the length of hospital stay, it was found that the gap in the average length of hospital stay between different levels of hospitals is the largest for URRMI.

The longitudinal comparison revealed that DIP reform significantly reduced the hospitalization expenses of the URRMI group across various diseases, particularly in secondary and tertiary hospitals, with a highly significant p-value ($p < 0.001$). For the UEBMI group, the change in the length of hospital stay in the UEBMI group was the most significant ($p < 0.05$), especially in tertiary hospitals. Furthermore, an examination of the p-values indicated that the DIP reform had the greatest impact on both hospitalization expenses and

TABLE 1 Basic information of the sample.

Diseases	Variable		URRMI Group		UEBMI group	
			Frequency	Proportion (%)	Frequency	Proportion (%)
CI	Gender	Male	5,018	73.6%	5,029	73.7%
		Female	1804	26.4%	1793	26.3%
	Age	<50	306	4.5%	296	4.3%
		50–60	1,070	15.7%	1,024	15.0%
		60–70	1940	28.4%	1799	26.4%
		70–80	2,524	37.0%	2,555	37.5%
		>80	982	14.4%	1,148	16.8%
CAD	Gender	Male	5,546	66.6%	5,544	66.6%
		Female	2,782	33.4%	2,784	33.4%
	Age	<50	390	4.7%	374	4.5%
		50–60	1,647	19.8%	1,418	17.0%
		60–70	2,409	28.9%	2,186	26.2%
		70–80	2,757	33.1%	2,781	33.4%
		>80	1,125	13.5%	1,569	18.8%

10.3389/fpubh.2025.1556234

TABLE 2 Hospitalization expenses and length of hospital stay at all levels of hospitals for UEBMI and URRMI, 2020–2023 (CI, CAD).

Items		Before the reform				After the reform			
		URRMI group		UEBMI group		URRMI group		UEBMI group	
		Average hospitalization expenses	Average length of stay	Average hospitalization expenses	Average length of stay	Average hospitalization expenses	Average length of stay	Average hospitalization expenses	Average length of stay
CI	Primary hospitals	7680.79 ± 4094.76	23.28 ± 19.49	3097.74 ± 1756.63	12.92 ± 13.29	8245.14 ± 3589.33	18.74* ± 8.76	2791.49* ± 1524.70	10.84** ± 8.05
	Secondary hospitals	14046.6 ± 6603.24	17.01 ± 13.93	7322.97 ± 5083.75	15.17 ± 13.85	13122.54*** ± 5477.52	16.15 ± 19.62	7770.63* ± 5151.02	13.59* ± 13.24
	Tertiary hospitals	20017.9 ± 6592.66	14.53 ± 20.48	15969.71 ± 8166.84	15.04 ± 11.90	17528.31*** ± 6060.44	12.09*** ± 7.58	15008.24* ± 7486.27	12.87*** ± 11.46
CAD	Primary hospitals	6568.63 ± 3730.73	16.16 ± 8.89	2759.59 ± 1564.00	11.79 ± 8.3	5981.77* ± 1838.26	14.98 ± 6.45	2562.64 ± 1320.31	9.90** ± 11.12
	Secondary hospitals	11423.29 ± 6836.17	13.71 ± 23.66	6793.88 ± 4987.84	13.98 ± 22.73	10459.92*** ± 5711.02	10.90*** ± 12.24	6987.27 ± 4929.50	10.73*** ± 8.93
	Tertiary hospitals	15388.57 ± 8487.85	8.02 ± 7.89	10895.88 ± 7065.23	12.72 ± 35.17	14130.43*** ± 7047.99	7.86 ± 8.25	10572.51 ± 6777.88	9.18*** ± 19.61

$^{ns}p > 0.05$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

length of hospital stay for patients treated for cerebral infarction in tertiary hospitals, with both p-values <0.05.

3.2 Trends in the standard deviation of hospitalization expenses

Table 3 shows the SDs of the hospitalization expenses and their changes and double differences for the URRMI and UEBMI groups. The SDs are used to illustrate the changes in the hospitalization expenses of the groups, and the double differences can describe the trend of the differences in the hospitalization expenses between URRMI and UEBMI groups.

In terms of changes in the standard deviation of hospitalization expenses for patients with cerebral infarction, the standard deviation of hospitalization expense for URRMI declined each year from 2020 to 2023, with the largest decrease observed in 2022, which was 1492.21 less than the previous year, indicating improved cost consistency. The standard deviation of UEBMI rose in the first year of the reform (2021), but subsequently decreased annually thereafter, with a significant reduction. The standard deviation (SD) exhibited the largest change in 2022, decreasing by 1182.25 compared to 2021. When analyzing the expense data for coronary atherosclerotic heart disease patients, we found that the standard deviation of URRMI hospitalization expenses decreased annually, with the most notable drop in 2021, reaching −804.86. In 2020, the standard deviation of hospitalization expenses for UEBMI was 6,035.56. It increased slightly in 2021 and 2022, but the increase was not significant. Overall, the hospitalization expenses still exhibited a decreasing trend. The data suggests that the DIP reform has positively impacted the consistency of hospitalization expenses for URRMI and UEBMI.

In terms of the double-difference value changes, the highest was observed in the first year after the DIP reform (2021) for the double-difference value of hospitalization expenses among URRMI and UEBMI groups treated for cerebral infarction, reaching 674.93. The double-difference value between the expenses of the two groups in 2022 was 309.96, and −326.16 in 2023. Similarly, observing the expense data of patients treated for coronary atherosclerotic heart disease, the double-difference value changed from 933.86 and 493.92 to −483.00. The above indicates that the impact of the DIP reform on the change in hospitalization expenses for the URRMI and UEBMI groups gradually decreased.

3.3 Trends in the interquartile range of hospitalization expenses

Figure 2 presents the distribution of hospitalization expenses for patients with cerebral infarction and coronary atherosclerotic heart disease among URRMI and UEBMI from 2020 to 2023. The figure illustrates the upper and lower bounds of expenses, the median, and the interquartile range (IQR) to reflect the degree of concentration and changes in variation in hospitalization expenses. The red line represents the fixed payment for a particular group of patients in 2020–2023. For patients with cerebral infarction, the IQR values of the URRMI group exhibited a decreasing trend. At the same time, the IQR of the UEBMI initially increased from 2020 to 2021 and then decreased annually thereafter. The median hospitalization expenses and fixed payment amount for the UEBMI group were consistently lower than those of the URRMI group. Furthermore, the difference between the median and the fixed payment amount widened for both groups, with a greater disparity observed in the UEBMI compared to the URRMI. For patients with coronary atherosclerotic heart disease, the IQR value of the URRMI group experienced an initial increase from 2020 to 2021, followed by a yearly decrease. In contrast, the IQR of the UEBMI group showed a non-significant change but demonstrated a general downward trend. The median of the URRMI group increased in the first year after the reform (2021) and then decreased year by year. The median hospitalization expenses and fixed payment amount for the UEBMI group were consistently lower than those of the URRMI group. The difference between median and fixed expenses for both groups was smallest in the first year after the reform (2021) and then gradually increased thereafter. These findings indicate that the DIP reform positively impacted the consistency of hospitalization expenses for both URRMI and UEBMI, with expenses tending to be concentrated.

Figure 3 represents the distribution of hospitalization expenses for URRMI and UEBMI treated for cerebral infarction at all levels of hospitals from 2020 to 2023. For primary hospitals, the IQR values of the URRMI group gradually decreased, with the median remaining relatively stable. The IQR of the UEBMI group exhibited a fluctuating downward trend, with a slight increase in 2022 followed by a decrease. For secondary hospitals, the URRMI group's IQR declined annually, with the median initially decreasing and then increasing in 2023. The IQR value of the UEBMI group initially increased in 2022 and then decreased. For tertiary hospitals, the IQR value and median of the URRMI group exhibited a decreasing trend, with a narrowing gap between the upper and lower limits. The IQR value of the UEBMI group also exhibited a decreasing trend, with the median initially increasing and then decreasing from 2020 to 2021. The comparison of the two groups showed that the average hospitalization expenses and the median of the URRMI group were slightly higher than those of the UEBMI group. Overall, as the hospital level increased, the average hospitalization expenses for both the URRMI and UEBMI groups increased, with the gap between the two groups narrowing and the IQR widening. Generally, patient expenses exhibited decreased variability and became more concentrated.

Figure 4 presents the distribution of hospitalization expenses for URRMI and UEBMI with coronary atherosclerotic heart diseases treated at various levels of hospitals from 2020 to 2023. For primary hospitals, IQR values in the URRMI group decreased yearly. The median first increased and then decreased in 2021, exceeding the overall average in 2021 and having the largest gap with the overall average hospitalization expenses in 2023. The IQR and median of the UEBMI exhibited a fluctuating downward trend. For secondary hospitals, both the IQR and median of the URRMI group initially increased in 2021 and then decreased. The IQR and median of the UEBMI group showed little variation. For tertiary hospitals, both the IQR values of the URRMI and UEBMI groups initially increased in 2021 and then decreased. The reason for the change in the IQR values and median trend between the URRMI and the UEBMI groups in 2021 may be that under the DIP model, hospitals need to optimize treatment plans to reduce costs while ensuring treatment quality. And since coronary atherosclerotic heart disease is a complex condition, it often necessitates a multitude of medical interventions, including pharmacological therapy and interventional procedures. Hospitals may need to invest more resources and time, which may lead to a temporary increase in expenses. Overall, as the hospital level increased, both the URRMI and UEBMI groups exhibited higher average hospitalization expenses and greater IQR values. Upon comparison, the URRMI group demonstrated slightly higher average and median hospitalization expenses compared to the UEBMI group.

The above analysis indicates that the DIP reform has effectively reduced hospitalization expenses for URRMI and UEBMI treated for cerebral infarction and coronary atherosclerotic heart disease at various levels of hospitals, with expenses tending to become more concentrated.

TABLE 3 Standard deviation and double-difference value of hospitalization expenses.

Year	URRMI group		UEBMI group		Double-difference value
	SD	Change	SD	Change	
CI					
Before the DIP reform					
2020	7290.62	–	7397.66	–	–
After the DIP reform					
2021	7033.18	−257.44	7815.15	417.49	674.93
2022	5540.97	−1492.21	6632.90	−1182.25	309.96
2023	4852.34	−688.62	5618.11	−1014.78	−326.16
CAD					
Before the DIP reform					
2020	7399.34	–	6035.56	–	–
After the DIP reform					
2021	6594.47	−804.86	6164.55	128.99	933.86
2022	6278.35	−316.12	6342.36	177.80	493.92
2023	6044.13	−234.22	5625.13	−717.22	−483.00

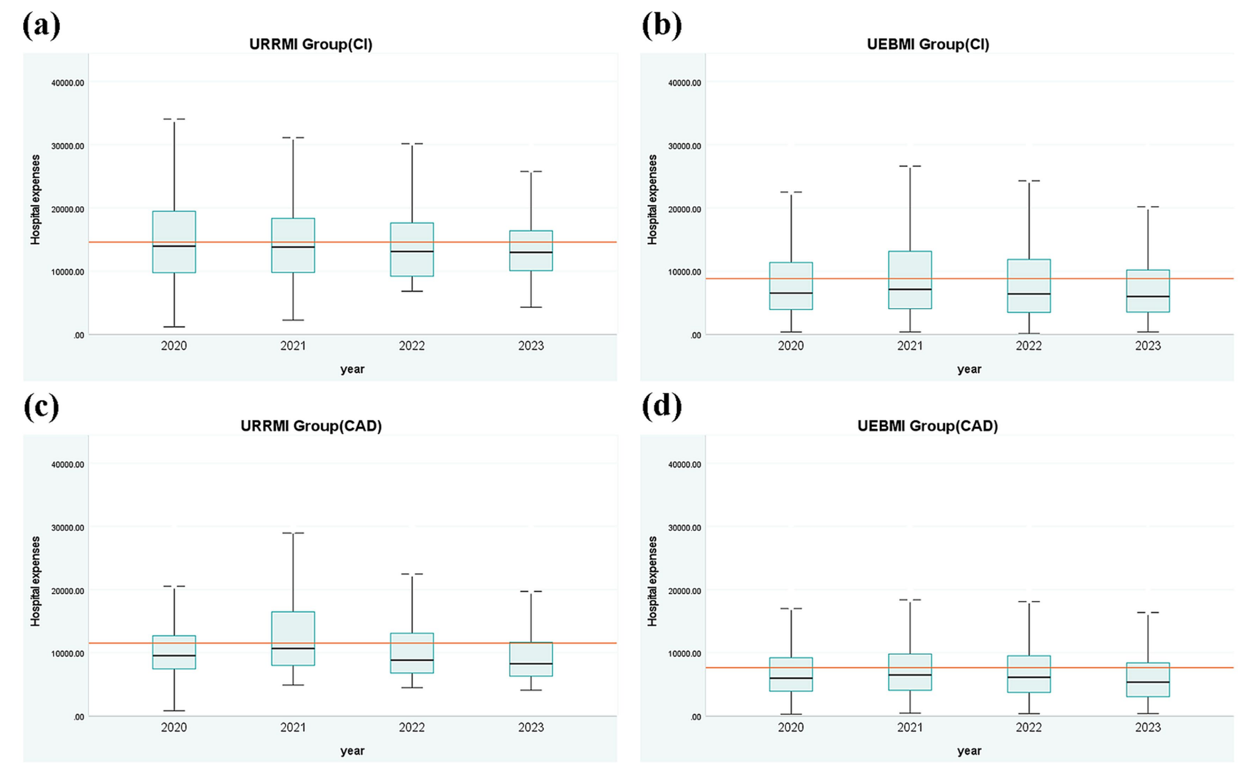

FIGURE 2
Box plots of hospitalization expenses for different diseases.

3.4 Concentration index of hospitalization expenses

Table 4 represents the concentration index of hospitalization expenses for patients covered by URRMI and UEBMI from 2020 to 2023. As shown in the figure, the concentration of hospitalization expenses has increased. Despite a brief rise in 2022 and 2023 for cerebral infarction patients, the overall trend remains a fluctuating downward trend, which is statistically significant ($p < 0.001$). For patients with coronary atherosclerotic heart disease, the absolute value of the concentration index rose slightly in the first year of the DIP reform (2021) and 2023. Regarding the difference in expense distribution, the concentration index is less than 0 for both cerebral infarction and coronary atherosclerotic heart disease patients and is statistically significant, indicating that hospitalization expenses are more concentrated in the UEBMI group.

Tables 5–7 present the concentration index of hospitalization expenses for the URRMI and UEBMI in the levels of hospitals from 2020 to 2023. In terms of concentration, the concentration of hospitalization expenses for patients with cerebral infarction and coronary atherosclerotic heart disease treated in primary hospitals has increased. The absolute value of the concentration index for hospitalization expenses among cerebral infarction patients decreased annually after the DIP reform. For patients with coronary atherosclerotic heart disease, the absolute value of the concentration index showed a fluctuating downward trend. In secondary hospitals, the hospitalization expenses for cerebral infarction patients also exhibited a fluctuating downward trend. The absolute value of the concentration index of patients with coronary atherosclerotic heart disease declined year by year after the implementation of the DIP reform. Although there was a brief increase in 2023, this increase was of small magnitude, and the overall downward trend in the absolute value of the concentration index continued. In tertiary hospitals, the absolute value of the concentration index of hospitalization expenses for patients with cerebral infarction declined annually after the DIP reform, with a brief increase in 2023 that was statistically significant ($p < 0.001$). The absolute value of the concentration index for patients with coronary atherosclerotic heart disease increased slightly in 2021, but declined annually thereafter, particularly with a significant decrease in 2022 ($p < 0.001$).

On the analysis of differences in expense distribution, the concentration index for patients across the levels of hospitals is statistically significant and less than 0, indicating a greater concentration of hospitalization expenses for UEBMI. Despite variations in how the reform is manifested across different hospital levels, the overall trend remains consistent, and expense consistency has been effectively enhanced.

4 Discussion

4.1 DIP reforms are effective in controlling expenses

The research findings indicate that the hospitalization expenses of URRMI and UEBMI for the treatment of cerebral

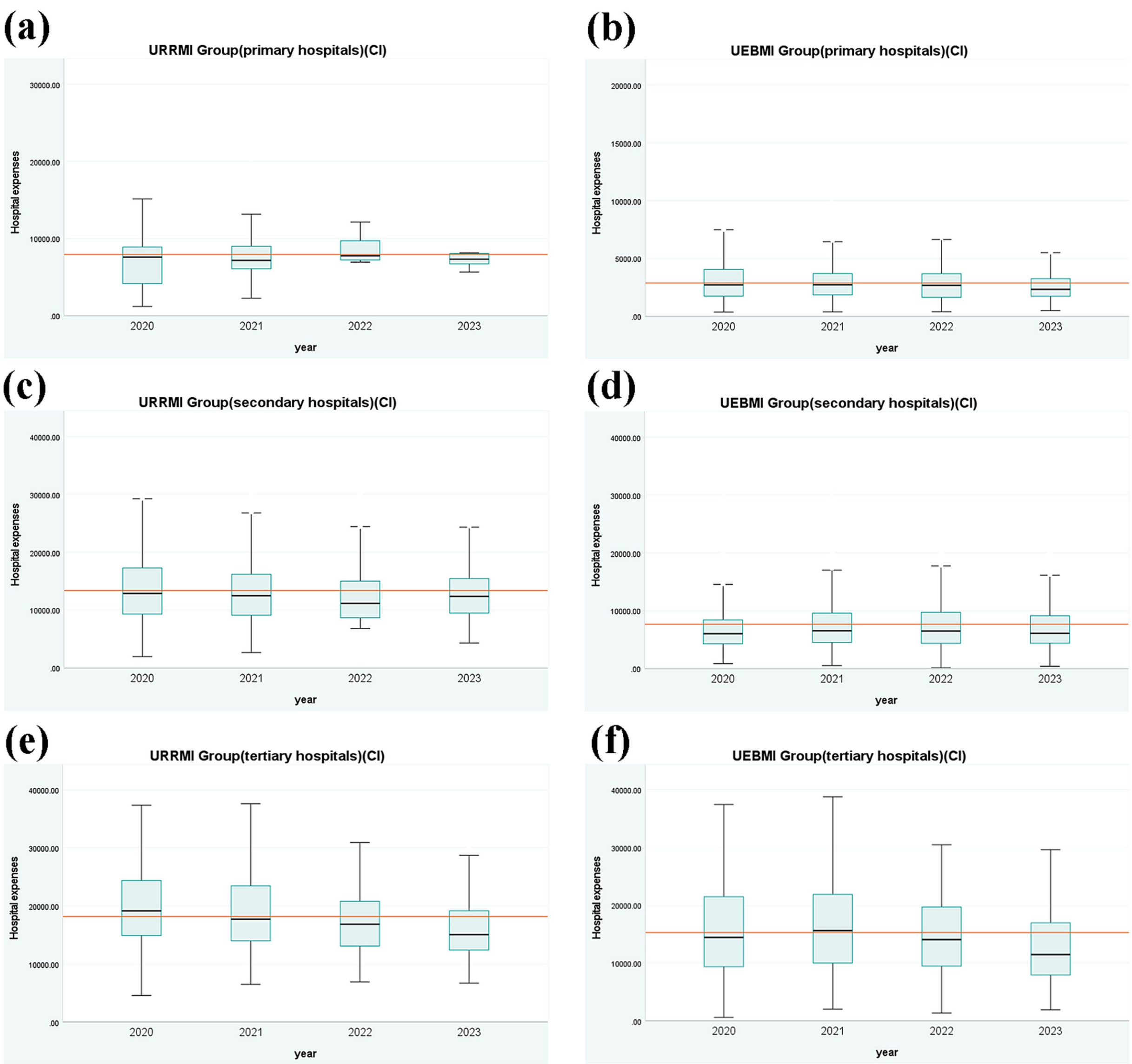

FIGURE 3
Box plots of hospitalization expenses for different levels of hospitals (CI).

infarction and coronary atherosclerotic heart disease exhibit a decreasing trend, with a narrowing gap between the two groups. An analysis of the concentration index reveals that the absolute value of these indices for the hospitalization expenses under the URRMI and UEBMI have exhibited a downward fluctuation, tending towards 0. This trend indicates that the effect of the DIP reform has had a significant effect in controlling hospitalization expenses for the treatment of cerebral infarction and coronary atherosclerotic heart disease across different medical insurance schemes. Hospitalization expenses for patients have become more concentrated after the reform. Previous studies by scholars have also demonstrated that reforms in medical insurance payment methods can effectively influence the concentration level and cost control of hospitalization expenses. For instance, regarding the impact of DIP, the payment based on the diagnosis-intervention packet has a positive effect on the standardization of medical service behaviors and the control of the growth of medical expenses (25). However, the concentration index of hospitalization expenses across different disease categories is less than 0 (statistically significant, $p < 0.001$), which leads to the conclusion that the concentration index of medical costs of UEBMI is always higher than that of URRMI before and after the implementation of DIP. This may be related to the inequality in the economic income levels of URRMI and UEBMI, the relatively lower reimbursement ratio for URRMI, and complex procedures for reimbursement of medical expenses incurred outside the place of registration impede realizing medical insurance benefits. The above analysis indicates that the DIP expenses reform can effectively control the differences in hospitalization expenses between URRMI and UEBMI, but there are still differences in the homogeneity levels of hospitalization expenses among patients with different medical insurance schemes.

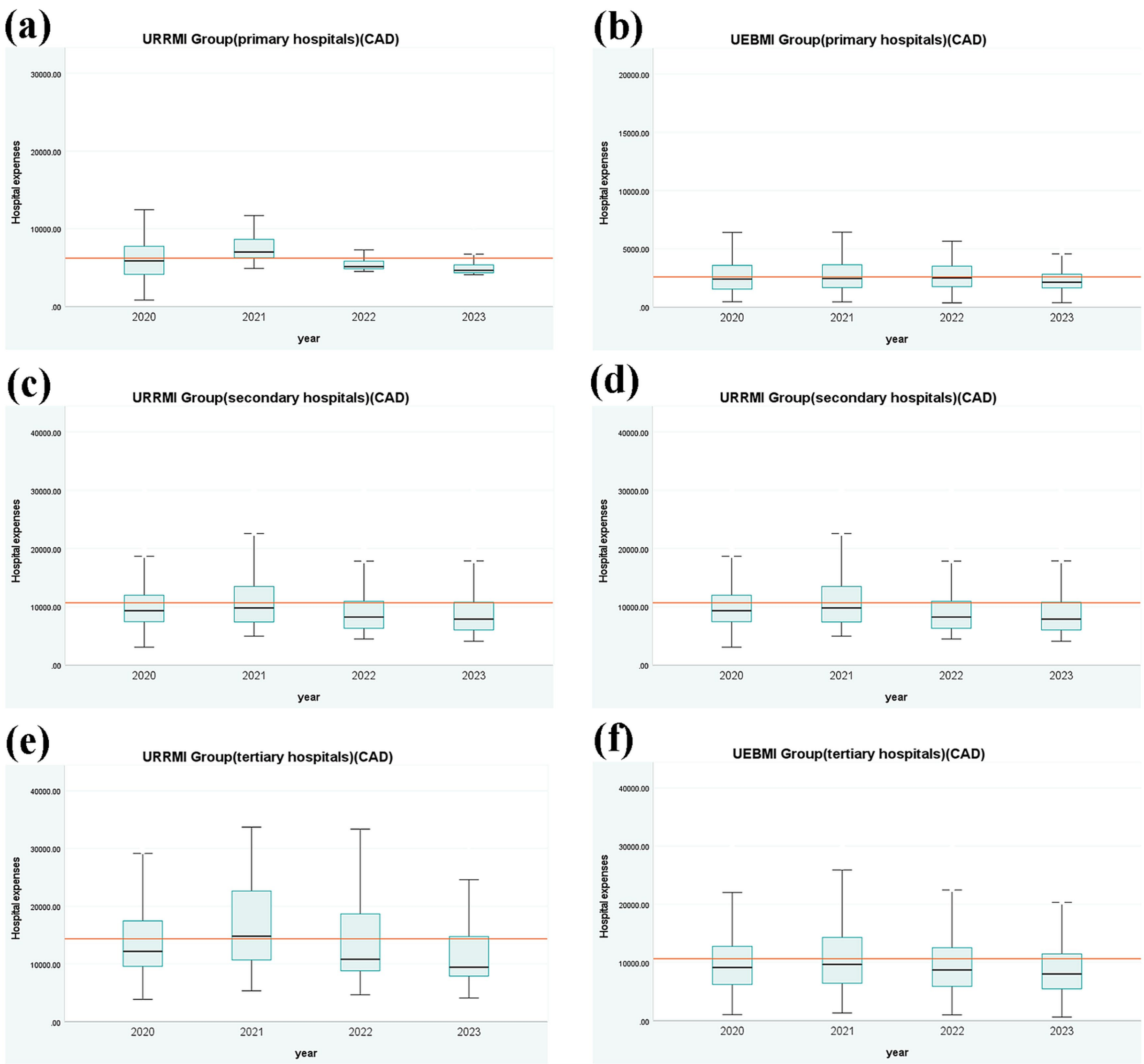

FIGURE 4
Box plots of Hospitalization expenses for different levels of hospitals (CAD).

TABLE 4 Concentration index of hospitalization expenses.

Year	CI	*P*	CAD	*P*
Before the DIP reform				
2020	−0.1289404	<0.001	−0.10715998	<0.001
After the DIP reform				
2021	−0.10741875	<0.001	−0.11411076	<0.001
2022	−0.12252005	<0.001	−0.08360314	<0.001
2023	−0.14255038	<0.001	−0.0993642	<0.001

4.2 Effectiveness of DIP reform on hospitalization expenses at levels of hospitals

This study examined hospitalization expenses for patients under UEBMI and URRMI across different levels of hospitals, analyzing variations to explore the cost-control effects and equity benefits of the DIP reform.

4.2.1 Uneven distribution of hospitalization expenses

Upon comparing the average hospitalization expenses and the length of hospital stay for URRMI and UEBMI treated in all levels of hospitals from 2020 to 2023. It was found that the average hospitalization expenses for patients covered by URRMI are higher than those of UEBMI. Current studies have indicated that the length

TABLE 5 Concentration index of hospitalization expenses for patients in primary hospitals.

Year	CI	*P*	CAD	*P*
Before the DIP reform				
2020	−0.2140767	<0.001	−0.20481028	<0.001
After the DIP reform				
2021	−0.17725668	<0.001	−0.23065194	<0.001
2022	−0.13948466	<0.001	−0.13557781	<0.001
2023	−0.07634542	<0.001	−0.14058769	<0.001

TABLE 6 Concentration index of hospitalization expenses for patients in secondary hospitals.

Year	CI	*P*	CAD	*P*
Before the DIP reform				
2020	−0.1516358	<0.001	−0.12426722	<0.001
After the DIP reform				
2021	−0.12334739	<0.001	−0.11207911	<0.001
2022	−0.11014197	<0.001	−0.08209652	<0.001
2023	−0.13251721	<0.001	−0.08636472	<0.001

TABLE 7 Concentration index of hospitalization expenses for patients in tertiary hospitals.

Year	CI	*P*	CAD	*P*
Before the DIP reform				
2020	−0.05626191	<0.001	−0.08559945	<0.001
After the DIP reform				
2021	−0.03778337	<0.001	−0.08901698	<0.001
2022	−0.03471399	<0.001	−0.063802	<0.001
2023	−0.05471191	<0.001	−0.05476254	<0.001

of hospital stay is an important factor leading to the high expenses of patients (31, 32). Based on the length of hospital stay, the following reasons for the cost differences are speculated. From the perspective of patients' economic burden, the data indicates that the average length of hospital stay for URRMI in primary and secondary hospitals is significantly longer than that of UEBMI. The main reason for this could be the higher reimbursement of URRMI in primary and secondary hospitals in the area, which makes URRMI more inclined to seek treatment there. On the other hand, due to the high reimbursement limits and relatively low economic burden of illnesses provided by their medical insurance, the UEBMI enjoys certain health benefits, which to some extent stimulates their demand for medical services (33). As a result, they are more dependent on medical services provided by tertiary hospitals. Consequently, the average hospitalization expenses for the URRMI in primary and secondary hospitals are higher than those for the UEBMI. From the demand for medical services, despite the slightly longer hospital stays for UEBMI patients in tertiary hospitals compared to URRMI patients, URRMI patients incur higher hospitalization expenses. Given factors such as the lower reimbursement rates for URRMI in tertiary hospitals compared to the UEBMI and the tendency of rural patients to seek care at higher-level institutions outside their residence only for complex and severe conditions, which also prolongs their length of hospital stay (34). The above analysis indicates that there is still a need to improve the medical insurance system in China and strengthen the integration of URRMI and UEBMI.

In addition, a horizontal comparison of hospitalization expenses at all levels of hospitals reveals that the higher the hospital level, the greater the average expenses for treating cerebral infarction and coronary atherosclerotic heart disease among both the URRMI and the UEBMI. Notably, the disparity in the hospitalization expenses among the levels of hospitals for UEBMI. This is primarily because patients with severe illnesses tend to prefer tertiary hospitals for treatment (35–37), especially the UEBMI who show a more significant preference for medical services provided by tertiary hospitals (14). From a longitudinal perspective, with the in-depth implementation of the medical insurance system reform based on DIP prospective payment in 2021, the hospitalization expenses for URRMI and UEBMI have been decreasing annually across the different levels of hospitals. Meanwhile, the gap in hospitalization expenses between the URRMI and the UEBMI has gradually narrowed. The above analysis indicates that the DIP system reform can effectively control cost growth and reduce the hospitalization expenses gap between URRMI and UEBMI at all levels of hospitals. However, the loophole in the hospitalization expenses gap between primary hospitals and higher-level hospitals still needs to be repaired through certain healthcare policies to promote a balanced diversion of URRMI and UEBMI from the hospitals at all levels and to prevent a siphoning effect in tertiary hospitals (38).

4.2.2 Reduced variance in hospitalization expenses

The data revealed that following the DIP reform, the gap in average hospitalization expenses among hospitals of different levels significantly narrowed for patients with cerebral infarction and coronary atherosclerotic heart disease. Simultaneously, the standard deviation of hospitalization expenses exhibited varying degrees of decrease. By comparing the concentration indices, we found an upward trend in these indices for both disease treatments across hospitals among patients covered by UEBMI and URRMI. This suggests that the DIP reform effectively reduced the disparities in hospitalization expenses among patients with diverse medical insurance schemes in hospitals at various levels. This achievement can be attributed to the payment mechanism based on DIP, which has incentivized hospitals to actively cut costs, enhance service quality and efficiency, promote the rational allocation of health resources, and bolster hospitals' management capabilities (39, 40). Controlling cost growth and shortening the average length of hospital stay were key foci of the reform (41, 42). Notably, the concentration index of hospitalization expenses for patients in tertiary hospitals approached 0, reflecting a more concentrated distribution of these expenses in such hospitals. Further comparison of the two groups' concentration indices revealed that all indices across the levels of hospitals were less than 0 (statistically significant, $p < 0.001$), indicating that the concentration of hospitalization expenses for UEBMI was higher than that for URRMI. In summary, the DIP reform has achieved remarkable results in effectively controlling the disparities and improving the consistency of hospitalization expenses between URRMI and UEBMI across hospitals of different levels. However, some results still vary in terms of homogeneity among patients with different medical insurance schemes and levels of hospitals.

5 Limitations

This study aims to explore the differences in hospitalization expenses among patients with different medical insurance schemes under the DIP reform. Still, due to the establishment of the China National Healthcare Security Administration in 2018 and the limited years of data collection before the implementation of the DIP reform, the study is unable to obtain medical expense data over a longer time span. Additionally, the database used lacks selectable variables, thus only the changes in total hospitalization expenses are analyzed, without a breakdown of the components of hospitalization expenses. Furthermore, this study statically focuses on the changes in hospitalization expenses for UEBMI and URRMI, neglecting the impact of factors such as out-of-town medical treatment on the variation in hospitalization expenses. These limitations warrant further in-depth consideration and research.

6 Conclusion

This study found that DIP reform effectively reduced the variability of patient hospitalization expenses, increased the concentration of hospitalization expenses for both UEBMI and URRMI, and narrowed the cost gap between patients with different insurance schemes. At the same time, this study also analyzes the variability in hospitalization expenses for patients across levels of hospitals. It concludes that the DIP reform can effectively control the differences in hospitalization expenses for URRMI and UEBMI at different levels of hospitals. However, it is worth noting that the DIP reform has varied the results of homogeneity of patients across different medical insurance schemes and the levels of hospitals. Continuous policy adjustments are still needed to optimize the allocation of healthcare resources.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The data contains private information of patients. Requests to access these datasets should be directed to Meng Xue-Hui, mengxuehui@aliyun.com.

Author contributions

JZ-Q: Writing – original draft, Writing – review & editing. LY-L: Writing – review & editing. TY-Y: Writing – review & editing. SK-Y: Writing – review & editing. LX-H: Writing – review & editing. TP: Writing – review & editing. LC-C: Writing – review & editing. WD: Writing – review & editing. MX-H: Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was provided by the 2024 Hangzhou Philosophy and Social Science Planning Project (Z.24YD055) and the Zhejiang Provincial College Student Science and Technology Innovation Activity Program (S202410344144). The funders had no role in the study design, data collection, data analysis, data interpretation, or writing of the report.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

1. Teng J, Li Q, Song G, Han Y. Does the diagnosis-intervention packet payment reform impact medical costs, quality, and medical service capacity in secondary and tertiary hospitals? A difference-in-differences analysis based on a province in Northwest China. *Risk Manag Healthc Policy*. (2024) 17:2055–65. doi: 10.2147/RMHP.S467471

2. Kim SJ, Park EC, Kim SJ, Han KT, Han E, Jang SI, et al. The effect of competition on the relationship between the introduction of the DRG system and quality of care in Korea. *Eur J Public Health*. (2016) 26:42–7. doi: 10.1093/eurpub/ckv162

3. Jian W, Lu M, Chan KY, Poon AN, Han W, Hu M, et al. Payment reform pilot in Beijing hospitals reduced expenditures and out-of-pocket payments per admission. *Health Aff*. (2015) 34:1745–52. doi: 10.1377/hlthaff.2015.0074

4. Lang X, Guo J, Li Y, Yang F, Feng X. A bibliometric analysis of diagnosis related groups from 2013 to 2022. *Risk Manag Healthc Policy*. (2023) 16:1215–28. doi: 10.2147/RMHP.S417672

5. Wang Y, Hou W, Wang X, Zhang H, Wang J. Bad to all? A novel way to analyze the effects of fee-for-service on multiple grades hospitals operation outcomes. *Int J Environ Res Public Health*. (2021) 18:12723. doi: 10.3390/ijerph182312723

6. Li Q, Fan X, Jian W. Impact of diagnosis-related-group (DRG) payment on variation in hospitalization expenditure: evidence from China. *BMC Health Serv Res*. (2023) 23:688. doi: 10.1186/s12913-023-09686-z

7. Wang Y, Chen Y, Wang J, Lao Y. The impacts of medical insurance payment methods on medical bills and medical service quality: evidence from Xiangtan. *China J Bus Res*. (2023) 169:114292. doi: 10.1016/j.jbusres.2023.114292

8. Zhao C, Wang C, Shen C, Wang Q. Diagnosis-related group (DRG)-based case-mix funding system, a promising alternative for fee for service payment in China. *Biosci Trends*. (2018) 12:109–15. doi: 10.5582/bst.2017.01289

9. Yu L, Lang J. Diagnosis-related groups (DRG) pricing and payment policy in China: where are we? *Hepatob Surg Nutr*. (2020) 9:771–3. doi: 10.21037/hbsn-2020-8

10. Zhang Y, Xu SY, Tan GM. Unraveling the effects of DIP payment reform on inpatient healthcare: insights into impacts and challenges. *BMC Health Serv Res*. (2024) 24:887. doi: 10.1186/s12913-024-11363-8

11. Shi H, Cheng Z, Cao Z. Does an innovative case-based payment scheme promote the hierarchical medical system? A tripartite evolutionary game analysis. *Int J Equity Health*. (2024) 23:1–15. doi: 10.1186/s12939-024-02336-8

12. Wu Y, Zhou D, Tian D, Zhou Y, Wang H, Jie CC, et al. Exploring the integration development model of DRG and DIP health insurance payment methods. *Chin Hosp Manag*. (2022) 10:9–12.

13. Zhu K, Zhang L, Yuan S, Zhang X, Zhang Z. Health financing and integration of urban and rural residents' basic medical insurance systems in china. *Int J Equity Health*. (2017) 16:194. doi: 10.1186/s12939-017-0690-z

14. Yang Y, Man X, Nicholas S, Li S, Bai Q, Huang L, et al. Utilisation of health services among urban patients who had an ischaemic stroke with different health insurance-a cross-sectional study in China. *BMJ Open*. (2020) 10:e040437. doi: 10.1136/bmjopen-2020-040437

15. Meng Q, Fang H, Liu X, Yuan B, Xu J. Consolidating the social health insurance schemes in China: towards an equitable and efficient health system. *Lancet*. (2015) 386:1484–92. doi: 10.1016/S0140-6736(15)00342-6

16. Ma Y, Liu Y, Fu HM, Wang XM, Wu BH, Wang SX, et al. Evaluation of admission characteristics, hospital length of stay and costs for cerebral infarction in a medium-sized city in China. *Eur J Neurol*. (2010) 17:1270–6. doi: 10.1111/j.1468-1331.2010.03007.x

17. Chang WF, Yan XY, Ling H, Liu T, Luo AJ. A study of the types and manifestations of physicians' unintended behaviors in the DRG payment system. *Front Public Health*. (2023) 11:1141981. doi: 10.3389/fpubh.2023.1141981

18. Zhou G, Xie JM, Zhang H, Tang HQ, Sun HQ, Ding K, et al. Based on DRG, the difference of hospitalization expenses structure between urban workers and urban and rural residents in Zhejiang Province and the countermeasures are studied. *Zhejiang Med*. (2024) 17:1899–904.

19. Feng YJ, Zhang L, Li JY, Qi Y, Chen W. Policy analysis on innovative medical technologies payment mechanism under DRG/DIP payment in China. *Chin J Health Policy*. (2024) 9:1–5.

20. Lai Y, Fu H, Li L, Yip W. Hospital response to a case-based payment scheme under regional global budget: the case of Guangzhou in China. *Soc Sci Med*. (2022) 292:114601. doi: 10.1016/j.socscimed.2021.114601

21. Qian M, Zhang X, Chen Y, Xu S, Ying X. The pilot of a new patient classification-based payment system in China: the impact on costs, length of stay and quality. *Soc Sci Med*. (2021) 289:114415. doi: 10.1016/j.socscimed.2021.114415

22. Ding Y, Yin J, Zheng C, Dixon S, Sun Q. The impacts of diagnosis-intervention packet payment on the providers' behavior of inpatient care—evidence from a national pilot city in China. *Front Public Health*. (2023) 11:1069131. doi: 10.3389/fpubh.2023.1069131

23. Stadhouders N, Kruse F, Tanke M, Koolman X, Jeurissen P. Effective healthcare cost-containment policies: a systematic review. *Health Policy*. (2019) 123:71–9. doi: 10.1016/j.healthpol.2018.10.015

24. Xie H, Cui X, Ying X, Hu X, Xuan J, Xu S. Development of a novel hospital payment system–big data diagnosis & intervention packet. *Health Policy Open*. (2022) 3:100066. doi: 10.1016/j.hpopen.2022.100066

25. Zhu FM. DRG/DIP payment reform, cost control and impact mechanism - multi-period difference-in-difference analysis based on sample data from 19 regions. *Chin Soc Secur Rev*. (2023) 5:54–67.

26. McMahon LF Jr, Newbold R. Variation in resource use within diagnosis-related groups: the effect of severity of illness and physician practice. *Med Care*. (1986) 24:388–97. doi: 10.1097/00005650-198605000-00002

27. Li L, Liu G. The development of for-profit hospitals and medical costs in China: An empirical analysis based on provincial data. *Manage World*. (2008) 181:53–63. doi: 10.19744/j.cnki.11-1235/f.2008.10.006

28. Zhang L, Sun L. Impacts of diagnosis-related groups payment on the healthcare providers' behavior in China: a cross-sectional study among physicians. *Risk Manag Healthc Policy*. (2021) 14:2263–76. doi: 10.2147/RMHP.S308183

29. Demaerschalk BM, Durocher DL. How diagnosis-related group 559 will change the US Medicare cost reimbursement ratio for stroke centers. *Stroke*. (2007) 38:1309–12. doi: 10.1161/01.STR.0000260185.74694.a7

30. Huerta TR, Ford EW, Peterson LT, Brigham KH. Testing the hospital value proposition: an empirical analysis of efficiency and quality. *Health Care Manag Rev*. (2008) 33:341–9. doi: 10.1097/01.HCM.0000318770.82642.c6

31. Venketasubramanian N, Yin A. Hospital costs for stroke care in Singapore. *Cerebrovasc Dis*. (2000) 10:320–6. doi: 10.1159/000016077

32. Liu X, Zi CY, Gu J, Ma RM, Tang CM, Fang PQ. Analysis of hospitalization expenses of patients with different types of medical insurance in a tertiary hospital in Sichuan province. *Chin Hosp*. (2019) 7:44–7. doi: 10.19660/j.issn.1671-0592.2019.07.14

33. Yu J, Qiu Y, He Z. Is universal and uniform health insurance better for China? Evidence from the perspective of supply-induced demand. *Health Econ Policy Law*. (2020) 15:56–71. doi: 10.1017/S1744133118000385

34. Huang G, Dong LD. Comparison of hospitalization expenses for patients with coronary heart disease under different types of basic medical insurances. *Med Soc*. (2022) 3:67–71. doi: 10.13723/j.yxysh.2022.03.014

35. Zhang L, Zhuang X, Yang X, Xu F, Wang N, Guo Z, et al. Analysis of hospitalization expenses and influencing factors for elderly cancer patients in a tertiary hospital in Dalian, China: a five-year retrospective study. *BMC Cancer*. (2024) 24:864. doi: 10.1186/s12885-024-12635-6

36. Fu L, Han J, Xu K, Pei T, Zhang R. Incentivizing primary care utilization in China: the impact of health insurance coverage on health-seeking behaviour. *Health Promot Int*. (2024) 39:daae115. doi: 10.1093/heapro/daae115

37. Lin K, Yao Y, Xiong Y, Xiang L. The effect of an innovative payment method on inpatient volume and bed resources and their regional distribution: the case of a central province in China. *Int J Equity Health*. (2024) 23:159. doi: 10.1186/s12939-024-02243-y

38. Yao Q, Zhang X, Yao L. The settlement mechanism of diagnosis-intervention packet payment scheme in China: a policy review and lessons learned. *Inform Health*. (2024) 1:49–56. doi: 10.1016/j.infoh.2024.05.002

39. Yan J, Lin HH, Zhao D, Hu Y, Shao R. China's new policy for healthcare cost-control based on global budget: a survey of 110 clinicians in hospitals. *BMC Health Serv Res*. (2019) 19:1–11. doi: 10.1186/s12913-019-3921-8

40. Almehwari SA, Almalki IS, Abumilha BA, Altharwi BH. Improving hospital efficiency and cost management: a systematic review and Meta-analysis. *Cureus*. (2024) 16:e71721. doi: 10.7759/cureus.71721

41. Xu J, Ye R, Zhao J, Fan X, Xue K, Li X, et al. Hospitalization costs in patients with stroke in southeastern China: a retrospective population-based cohort study, 2019–2022. *Front Public Health*. (2024) 12:1442171. doi: 10.3389/fpubh.2024.1442171

42. Wang C, Chen X, Pan L, Lin H, Shang X, Xu G, et al. Comparative analysis and influencing factors of hospitalization expenses of three single diseases in a tertiary class A general hospital. *Am J Transl Res*. (2022) 14:2480–9.

Frontiers in Public Health

TYPE Original Research
PUBLISHED 09 May 2025
DOI 10.3389/fpubh.2025.1535381

Check for updates

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Chen Li,
Shanghai University of Engineering Sciences, China
Fei Lu,
Southwestern University of Finance and Economics, China

*CORRESPONDENCE
Lijian Zhao
zhaolijian@bgi.com
Nan Wang
ncwang@hnu.edu.cn
Jun He
Hejun6683@163.com

†These authors have contributed equally to this work

RECEIVED 27 November 2024
ACCEPTED 07 April 2025
PUBLISHED 09 May 2025

CITATION
Liu J, Wang S, Zhou S, Ma D, Hu L, Huang H, Linpeng S, Lin J, Hong L, Fu Q, Peng H, Zhao L, Wang N and He J (2025) Cost-effectiveness of different screening strategies for Down syndrome: a real-world analysis in 140,472 women. *Front. Public Health* 13:1535381. doi: 10.3389/fpubh.2025.1535381

Cost-effectiveness of different screening strategies for Down syndrome: a real-world analysis in 140,472 women

Jing Liu[1†], Shunyao Wang[2†], Shihao Zhou[1], Di Ma[2], Lanping Hu[1], Hui Huang[2], Siyuan Linpeng[1], Jiawei Lin[2], Liu Hong[1], Qinmei Fu[2], Huanhuan Peng[3], Lijian Zhao[2,4,5]*, Nan Wang[6]* and Jun He[1]*

[1]Hunan Provincial Key Laboratory of Regional Hereditary Birth Defects Prevention and Control, Changsha Hospital for Maternal & Child Health Care Affiliated to Hunan Normal University, Changsha, China, [2]BGI Genomics, Shenzhen, China, [3]MGI Tech, Shenzhen, China, [4]Hebei Industrial Technology Research Institute of Genomics in Maternal & Child Health, Shijiazhuang BGI Genomics Co, Ltd, Shijiazhuang, Hebei, China, [5]Medical Technology College of Hebei Medical University, Shijiazhuang, China, [6]School of Public Administration, Hunan University, Changsha, Hunan, China

Background: Recent advancements in high-throughput sequencing have validated the accuracy, safety, and effectiveness of non-invasive prenatal testing (NIPT) for Down syndrome (DS).

Methods: This study aims to assess the effectiveness and economic implications of NIPT versus second-trimester serum screening (STSS) for DS and the different screening strategies through retrospectively analyzing data from 140,472 pregnant women who completed both NIPT and STSS (provided for free by local public welfare programs) between March 1, 2018 and December 31, 2020. Data were categorized into eight groups based on different screening strategies.

Results: The sensitivity, specificity, and positive predictive value of NIPT for detecting trisomy 21 were significantly higher compared with those of STSS. The universal NIPT screening strategy demonstrated the best effectiveness, detecting 163 DS cases with the highest net benefit and a cost-effectiveness ratio of 1:9.53. The STSS and NIPT combined screening strategy detected 128 DS cases with the lowest cost-effectiveness at RMB 341,800. The incremental cost-effectiveness ratio of the universal NIPT screening strategy was RMB 1,186,200, significantly lower than the socioeconomic burden associated with a DS case.

Conclusion: NIPT demonstrated significantly superior testing performance compared to STSS. At a unit cost of RMB 600, the universal NIPT screening strategy is the most effective and holds substantial health economic value.

KEYWORDS

prenatal diagnosis, health economics, health policy, non-invasive prenatal testing, Down syndrome

10.3389/fpubh.2025.1535381

1 Introduction

Maternal serum testing is the primary method for screening fetal chromosomal abnormalities in China. However, it has a relatively high false-positive rate and low accuracy (1). Recent advancements in high-throughput sequencing have demonstrated the accuracy, safety, and effectiveness of non-invasive prenatal testing (NIPT) for detecting fetal chromosomal aneuploidies (2–4). NIPT is favored for its technical advantages and is recommended by guidelines in many countries for prenatal screening (5–8). In the Netherlands and Belgium, NIPT is fully reimbursed and offered as a first-tier screening test nationwide (9, 10). However, current Chinese guidelines recommend using NIPT as a second-tier screening following the identification of high-risk factors through serum screening or in specific conditions, such as advanced maternal age or a family history of chromosomal abnormalities (11).

NIPT has superior sensitivity, specificity, and positive predictive value compared with serum screening (4, 12, 13). The health economic value of different screening strategies, including NIPT, serum screening, and contingent screening, has also been investigated in recent comparative analyses (14, 15). Studies from Belgium and the Netherlands suggest that NIPT, when used in conjunction with serum screening, offers a cost-effectiveness advantage (16, 17). Furthermore, results from a Chinese study indicate that NIPT as a contingent screening strategy has optimal health economic benefits (18). Due to its sensitivity, NIPT may hold higher health economic value considering the societal and economic burdens associated with Down syndrome (DS) (19). However, previous studies have often been limited by small sample sizes and simulated models. The high cost of NIPT remains a critical factor in decision-making (20). The Changsha municipal public welfare program's reduction in NIPT costs provides an opportunity to re-evaluate and compare screening strategies using real-world data from this program, offering valuable insights into the health economic value of NIPT and serum screening.

This study retrospectively analyzed clinical data from 140,472 pregnant women who underwent both NIPT and second-trimester serum screening (STSS) between March 1, 2018, and December 31, 2020. It represents the first large-scale real-world study in China evaluating the performance and health economic value of NIPT and various screening strategies. This study analyzed outcomes from a healthcare system perspective, including medical costs in the calculations, allowing for a more comprehensive comparison of the health economic outcomes of different strategies. Thus, it provides decision-makers with crucial insights into the economic value and efficiency of various screening strategies within real-world healthcare settings. Additionally, the findings in this study offer crucial real-world data for foundational research on birth defect prevention in China and provide a scientific basis for evidence-based decision-making in clinical practice and policy development.

2 Materials and methods

2.1 Patient and public involvement

Patients and public were not involved in the design and conduct of the study.

2.2 Data source

This study conducted a retrospective analysis of clinical data from 140,472 pregnant women in Changsha City who underwent both NIPT and STSS between March 1, 2018, and December 31, 2020. After excluding 198 cases with failed NIPT tests and nine cases without prenatal diagnostic results, data from 140,265 women were included in the analysis (Figure 1). The data were sourced from the Changsha Public Welfare Program, organized by the Changsha Municipal Health and Health Committee and conducted by prenatal diagnosis and screening institutions across Changsha, which served as blood collection sites. These sites included Changsha Hospital for Maternal & Child Health Care, Changsha First Hospital, Changsha Central Hospital, Changsha Fourth Hospital, Changsha County Hospital for Maternal & Child Health Care, Liuyang Hospital for Maternal & Child Health Care, Ningxiang Hospital for Maternal & Child Health Care, Wangcheng District Hospital for Maternal & Child Health Care, and other hospitals. After collection, all blood samples were sent to the Changsha Hospital for Maternal & Child Health Care for centralized testing. The Changsha Hospital for Maternal & Child Health Care is responsible for implementing the city-wide NIPT project, including data aggregation, analysis, and conducting related research.

The study was approved by the Medical Research Ethics Committee of Changsha Hospital for Maternal & Child Health Care (Approval number: 2022003). This study was performed in line with the Drug Clinical Practice issued by the Chinese State Food and Drug Administration of the People's Republic. Written informed consent was obtained from each participant prior to the start of the experiments.

2.3 Screening methods and cost-effectiveness analyses

2.3.1 STSS

A total of 5 mL of venous blood was collected from the pregnant woman, centrifuged, and stored in a 4°C refrigerator until testing. Automated time-resolved fluorescence immunoassay was performed, incorporating combined screening with pregnancy-associated plasma protein A and free β-subunit of human chorionic gonadotropin. Fetal risk probability for trisomy 21 and trisomy 18 was calculated using the fecycle software. For trisomy 21, high-risk thresholds were set at ≥1:270 and critical risk thresholds at 1:270 to 1:1,000. For trisomy 18, high-risk thresholds were set at ≥1:350 and critical risk thresholds at 1:350 to 1:1,000.

2.3.2 NIPT

A volume of 5 mL of venous blood from the pregnant woman was collected in an EDTA anticoagulant tube, stored at 4°C, and double centrifuged within 8 h. The extracted plasma containing free DNA was stored at −80°C until testing. High-throughput testing was performed using the BGISEQ500 platform (BGI Tech Solutions Co., Ltd., Shenzhen, China). Trisomy 21, 18 and 13 were determined based on sample sequencing data volume and standard sample coverage depth.

10.3389/fpubh.2025.1535381

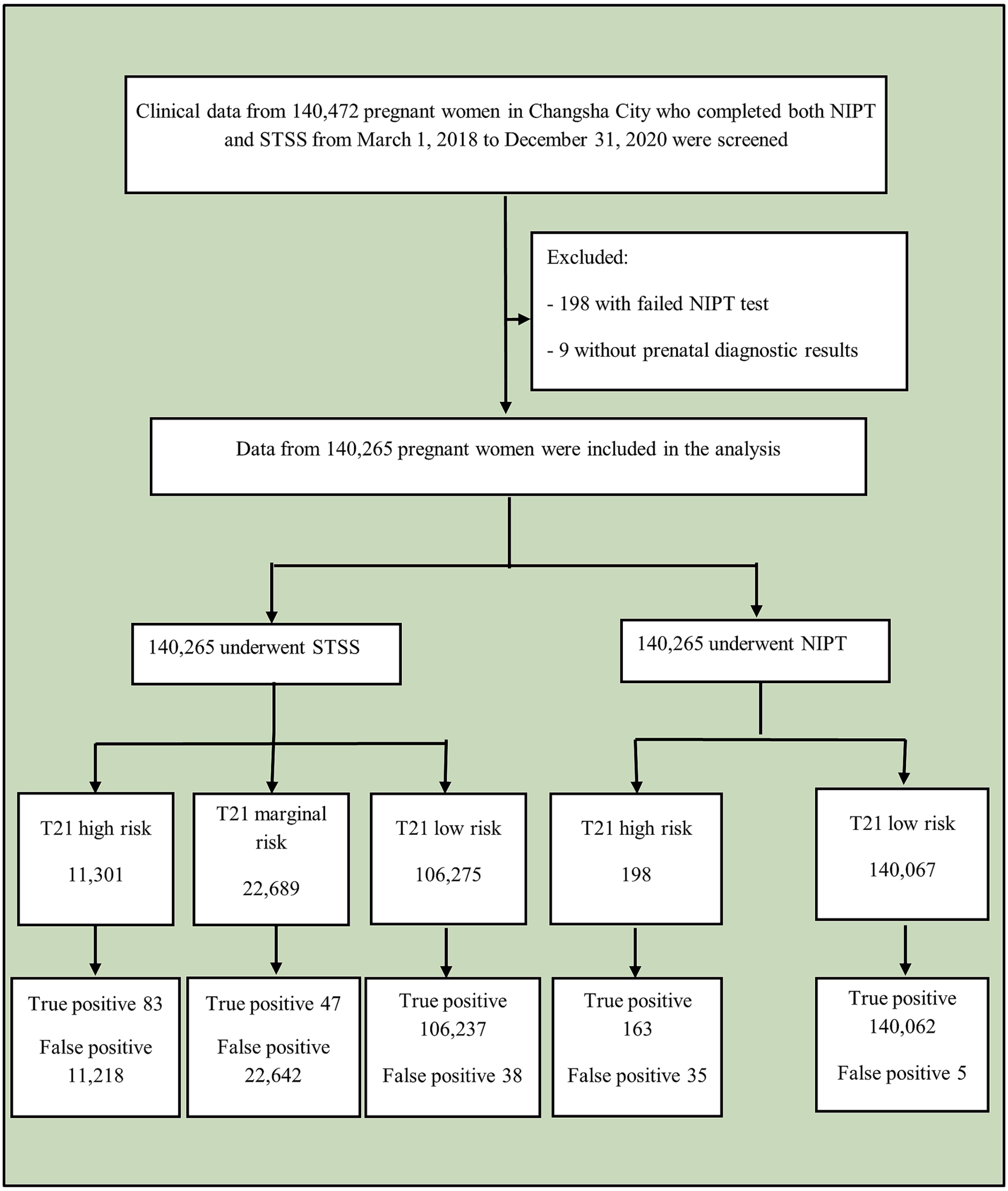

FIGURE 1
Study flowchart. NIPT, non-invasive prenatal testing; STSS, second-trimester serum screening.

2.3.3 Fetal chromosomal karyotype analysis

Amniotic fluid or umbilical cord blood was collected from pregnant women at high risk, as indicated by NIPT results. After routine cell culture, chromosomal karyotype analysis was conducted.

2.3.4 Pregnancy outcome follow-up

Follow-up on pregnancy outcomes was conducted through telephone interviews and an online system with WeChat push notifications. Negative cases in NIPT were followed up through telephone interviews and online systems, with false negatives further verified using reimbursement records.

2.3.5 The eight screening strategies

Based on the data, we present eight counterfactual screening strategies with the use of NIPT, STSS, and STSS Plus as first-line screening tools or a combination of these tools at different stages of the diagnostic pathway, as shown in Table 1.

2.3.6 Cost-effectiveness analyses

Cost calculations included direct medical expenses, such as those related to NIPT, STSS, prenatal diagnosis (amniocentesis, chromosomal karyotype analysis, color Doppler ultrasound, PTC needle), and pregnancy termination. Indirect and intangible costs were not considered. Discounting was excluded from the study due to the stable and predetermined nature of the costs within the public health project. Effectiveness was measured by the number of successfully detected DS cases. The cost-effectiveness ratio was calculated to determine the cost per detected DS case. The incremental cost-effectiveness ratio was used to compare the additional cost required for extra effectiveness across different screening strategies. The safety index was assessed based on the number of normal fetal miscarriages associated with diagnosing one DS case, with a lower value indicating greater safety.

$$Sensitivity = \frac{True\ Positives\left(TP\right)}{True\ Positives\left(TP\right) + False\ Negatives\left(FN\right)}$$

$$Project\ cost = Number\ of\ NIPT \times NIPT\ cost + Number\ of\ positive\ results \times Prenatal\ diagnostic\ fee + Number\ of\ true\ positives \times Cost\ to\ terminate\ pregnacy$$

$$Cost - effectiveness\ ratio = \frac{Project\ cost}{Number\ of\ true\ positives}$$

$$Incremental\ cost - effectiveness\ ratio = \frac{\left(Cost\ of\ Strategy\ 1 - Cost\ of\ Strategy\ 2\right)}{\left(Effectiveness\ of\ Strategy\ 1 - Effectiveness\ of\ Strategy\ 2\right)}$$

$$Accuracy = \frac{\left(True\ positives + True\ negatives\right)}{\left(True\ positives + False\ positives + True\ negatives + False\ negatives\right)}$$

$$Safety\ index = \frac{Number\ of\ prenatal\ diagnostic\ cases \times Prenatal\ diagnostic\ miscarriage\ rate}{Effectiveness}$$

2.3.7 Univariate sensitivity analyses

A sensitivity analysis was conducted on the cost of NIPT. We focused on the incremental cost analysis, which reflects "effect" via comparisons among different scenarios. We did not conduct a probabilistic sensitivity analysis due to limitations in data availability and the resource-intensive nature of the method, which would have compromised the overall feasibility and timeliness of our study.

3 Results

3.1 Demographics

Of the 140,265 pregnant women included in the analysis, the average age was 30.15 ± 4.02 years, with the majority falling in the 25–34 age group (77.89%, 109,531/140,265). Advanced maternal age (≥35 years) accounted for 13.95% (19,612/140,265). Most of the participants (96.27%) were in their second trimester of pregnancy (14–27 weeks), with an average gestational age of 16.64 weeks. Singleton pregnancies accounted for 98.12% (137,983/140,265), and *in vitro* fertilization accounted for 4.14% (4,823/140,265) (Table 2).

3.2 Comparison of NIPT and STSS detection performance

The study participants underwent both NIPT and STSS, and prenatal diagnostic results were obtained. Five cases of false negatives for trisomy 21 were confirmed. The detection performance of the two methods is detailed in Table 3. NIPT demonstrated superior performance compared to STSS, identifying nearly twice as many cases of DS. NIPT consistently outperformed STSS in detecting trisomy 21 across various age groups, showing no significant differences in sensitivity and specificity. For STSS, sensitivity was notably higher in the high-risk age group compared to the low-risk group, while specificity was significantly lower in the high-risk group.

3.3 Performance and health economic analysis of different screening strategies for trisomy 21

In the Public Welfare Program in Changsha City, the cost of NIPT testing is RMB 600 per unit (21), while STSS is priced at RMB 160. The unit cost of prenatal diagnosis is RMB 2,308, including amniocentesis (RMB 800), chromosomal karyotype analysis (RMB 800), 4D color ultrasound (RMB 400), PTC needle (RMB 88), blood tests (RMB 140), and genetic counseling (RMB 80), was determined through on-site research at the hospital where the services are provided. The cost of a mid-trimester abortion is RMB 4,000 per case, with a procedure-related miscarriage risk rate of 3‰ (Table 4). Discounting was excluded from the study due to the stable and predetermined nature of the costs within the public health project. All costs were calculated in RMB based on 2018 pricing.

In the comparative analysis, Strategy 1 emerged as the most effective screening method, detecting 163 true positives with only five false negatives (Table 5). It demonstrated a high accuracy rate of 99.97% and the best safety index (0.0036). Strategy 5 has the lowest cost-effectiveness ratio among the strategies analyzed in our study. For this reason, we have chosen Strategy 5 as the reference point for the computation of incremental cost-effectiveness ratio. Compared to Strategy 5, Strategy 1 detected 35 additional DS cases, with an incremental cost-effectiveness ratio of RMB 1,186,200 per

TABLE 1 Summary of the Down syndrome screening strategies analyzed in this study.

Strategy 1	Universal NIPT screening	NIPT screening for all pregnant women; prenatal diagnosis for pregnant women at high risk as indicated by NIPT results.
Strategy 2	Universal STSS	STSS for all pregnant women; prenatal diagnosis for pregnant women at high risk as indicated by STSS results.
Strategy 3	Universal STSS Plus	STSS for all pregnant women; prenatal diagnosis for pregnant women at high and marginal risk as indicated by STSS results.
Strategy 4	STSS and NIPT combined screening	STSS for all pregnant women; prenatal diagnosis for pregnant women at high risk as indicated by STSS results; NIPT screening for pregnant women at marginal risk as indicated by STSS results; prenatal diagnosis for pregnant women at high risk as indicated by NIPT results.
Strategy 5	STSS and NIPT combined screening plus	STSS for all pregnant women; NIPT for pregnant women at high and marginal risk as indicated by STSS results; prenatal diagnosis for pregnant women at high risk as indicated by NIPT results.
Strategy 6	Contingent NIPT screening	NIPT screening for pregnant women aged 35 and above; STSS for pregnant women under the age of 35. Prenatal diagnosis for pregnant women at high risk as indicated by STSS results; NIPT screening for pregnant women at marginal risk as indicated by STSS results; prenatal diagnosis for pregnant women at high risk as indicated by NIPT results.
Strategy 7	Contingent NIPT screening plus	NIPT screening for pregnant women aged 35 and above; STSS for pregnant women under the age of 35; NIPT screening for pregnant women at high and marginal risk as indicated by STSS results; prenatal diagnosis for pregnant women at high risk as indicated by NIPT results.
Strategy 8	Traditional screening	Prenatal diagnosis for pregnant women aged 35 and above; STSS for pregnant women under the age of 35; prenatal diagnosis for pregnant women at high and marginal risk as indicated by STSS results.

NIPT, non-invasive prenatal testing; STSS, second-trimester serum screening.

additional DS case detected (Table 6). Strategy 2 was less effective, detecting 83 true positives with 85 false negatives, and lacked cost-effectiveness compared to Strategy 1. Although Strategy 3 performed better than Strategy 2, it was still inferior to Strategy 1 and resulted in a substantial number of prenatal diagnoses, leading to lower cost-effectiveness, safety, and accuracy compared to Strategies 1 and 2. Overall, this analysis suggests that universal STSS is less effective and has lower health economic value compared to universal NIPT screening. Strategies 4 and 5 demonstrated similar screening effectiveness to Strategy 3 but avoided excessive prenatal diagnoses with lower cost-effectiveness. Among these, Strategy 5 had the lowest cost-effectiveness ratio, along with higher accuracy and safety, indicating superior health economic benefits. NIPT contingent screening (Strategies 6 and 7) was more effective than STSS (Strategies 2 and 3) and combined screening (Strategies 4 and 5) but less effective than universal NIPT screening (Strategy 1). Strategy 7 detected one fewer DS case than Strategy 6 but minimized excessive prenatal diagnoses, showing significantly better cost-effectiveness, accuracy, and safety than Strategies 2, 3, 4, and 6. It performed similarly to Strategy 5 but detected six more DS cases, with the lowest incremental cost-effectiveness ratio compared to Strategy 5 (RMB 447,800 per additional DS case). Although Strategy 8 had the second-best screening outcome, detecting 142 DS cases, it resulted in the highest number of prenatal diagnoses, the highest cost-effectiveness ratio, and the highest safety index, making its safety and economic benefits the lowest among all strategies.

TABLE 2 Participant characteristics.

Characteristic	Total population (N = 140,265)
Maternal age (years)	30.15 (15–53)
<25 years	11,122 (7.91%)
25–29 years	51,529 (36.64%)
30–34 years	58,002 (41.25%)
35–39 years	17,254 (12.27%)
≥40 years	2,358 (1.68%)
GA at NIPT (weeks)	16.64 (10–34)
First trimester (10–13 weeks)	4,709 (3.35%)
Second trimester (14–27 weeks)	135,386 (96.27%)
Third trimester (≥ 28 weeks)	24 (0.02%)
Unknown	146 (0.10%)
Singleton pregnancy	137,983 (98.12%)
Twin pregnancy	2,282 (1.62%)
IVF	5,823 (4.14%)

Data presented as mean (range) or n (%). GA, gestational age; IVF, *in vitro* fertilization.

3.4 Univariate sensitivity analyses

We assessed the impact of varying NIPT costs on the outcomes of different screening strategies, with prices set at RMB 200, 400, 600, 800, and 1,000. As shown in Figure 2, the analysis indicated that lower NIPT costs made it more economically favorable for DS screening. Strategies 4, 6, and 5 became superior to Strategy 1 when NIPT costs exceeded RMB 546.96, 451.90, and 295.28, respectively, and were deemed "appropriate." If the NIPT unit price fell below RMB 295.28, Strategy 1 (Universal NIPT screening) had the lowest cost-effectiveness ratio.

TABLE 3 The detection performance of STSS and NIPT for Down syndrome in different maternal age groups.

Description of parameters	NIPT performance			STSS performance		
	All	Maternal age < 35 years	Maternal age ≥ 35 years	All	Maternal age < 35 years	Maternal age ≥ 35 years
TP	163	100	63	83	33	50
FP	35	28	7	11,218	7,265	3,953
TN	140,062	120,522	19,540	128,879	113,285	15,594
FN	5	3	2	85	70	15
Sensitivity (95% CI)	97.02% (94.45–99.59%)	97.09% (93.84–100%)	96.92% (92.73–100%)	49.41% (41.85–56.97%)	32.04% (23.02–41.05%)	76.92% (66.68–87.17%)
Specificity (95% CI)	99.98% (99.97–99.98)	99.98% (99.97–99.99%)	99.96% (99.94–99.99%)	91.99% (91.85–92.14%)	93.97% (93.84–94.11%)	79.78% (79.21–80.34%)
PPV (95% CI)	82.32% (77.01–87.64%)	78.13% (70.96–85.29%)	90.00% (82.97–97.03%)	0.73% (0.58–0.89%)	0.45% (0.30–0.61%)	1.25% (0.91–1.59%)
NPV (95% CI)	99.99% (99.99–100%)	99.99% (99.99–100%)	99.99% (99.98–100%)	99.93% (99.92–99.95%)	99.94% (99.92–99.95%)	99.90% (99.86–99.95%)
FPR	0.03%	0.02%	0.04%	8.01%	6.03%	20.22%
FNR	2.98%	2.91%	3.08%	50.60%	67.96%	23.08%

CI, confidence interval; PPV, positive predictive value; NIPT, non-invasive prenatal testing; TP, true positives; NPV, negative predictive value; STSS, second-trimester serum screening; FP, false positives; FPR, false positive rate; TN, true negatives; FN, false negatives; FNR, false negative rate.

TABLE 4 Relative costs associated with different screening strategies for Down syndrome.

Costs, RMB	Value[a]
STSS	160
NIPT	600
Prenatal diagnosis	2,308
Amniocentesis	800
Chromosomal karyotype analysis	800
Four-dimensional color ultrasound	400
PTC needle	88
Blood tests	140
Genetic counseling	80
Mid-trimester abortion	4,000

NIPT, non-invasive prenatal testing; STSS, second-trimester serum screening.
[a]Data sources: the special fee schedule for Changsha Public Welfare Program of Changsha Hospital for Maternal & Child Health Care (2018).

4 Discussion

In this study, NIPT showed significantly superior sensitivity, specificity, positive predictive value, and lower false positive and false negative rates compared to STSS for DS. NIPT consistently demonstrated excellent sensitivity and specificity across all age groups of pregnant women, outperforming STSS in all detection metrics. Furthermore, NIPT effectively reduced the need for invasive prenatal diagnoses, optimizing resource use and minimizing the risks associated with invasive procedures. Therefore, based on its superior detection performance, NIPT should be considered a first-tier screening method for DS.

Despite NIPT's outstanding detection performance, its use as a primary screening method remains controversial due to high costs. Previous studies have suggested that broader use of NIPT in all pregnant women could be economically viable if the unit cost falls below $453 (22). The Public Welfare Program in Changsha City has reduced the unit cost of NIPT testing to RMB 600. Within this pricing context, Strategy 5 (STSS combined with NIPT) offers the lowest cost-effectiveness ratio per DS case detected, while Strategy 1 (universal NIPT screening) delivers the highest accuracy and safety, resulting in the most favorable screening outcomes.

In real-world health decision-making, societal economic burden is a crucial factor alongside cost-effectiveness (23). Strategy 1 can detect 35 more DS cases than Strategy 5, with an incremental cost-effectiveness ratio of RMB 1,186,200 per additional DS case detected. Thus, Strategy 1 stands out as the most effective screening option with favorable health economic benefits. Although Strategy 7 (NIPT contingent screening Plus) ranks fourth in screening effectiveness, it offers a lower cost-effectiveness ratio and incremental cost-effectiveness ratio, demonstrating excellent health economic benefits according to decision tree simulation analysis. Conversely, Strategy 8 (traditional screening methods), despite its reasonable screening effectiveness, is not recommended due to its lower safety and limited health economic value. At the current price, Strategy 1 (universal NIPT screening) was not the optimal choice compared to other strategies. Sensitivity analysis showed that reducing the price of NIPT could make universal NIPT screening (Strategy 1) a priority option. Specifically, if the NIPT price falls below RMB 295.28, Strategy 1 achieves the lowest cost-effectiveness ratio among all strategies. It is important to note that the

TABLE 5 Detection performance of different screening strategies for Down syndrome.

	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8
True positive	163	83	130	129	128	135	134	142
False positive	35	11,218	33,860	11,245	47	7,313	63	0
True negative	140,062	128,879	106,237	128,852	140,050	132,784	140,034	140,092
False negative	5	85	38	39	40	33	34	31
Prenatal diagnosis	198	11,031	33,990	11,374	175	7,448	197	43,573
Termination of pregnancy	163	83	130	129	128	135	134	142
Sensitivity (95% CI)	97.02% (94.45–99.59%)	49.40% (41.85–56.97%)	77.38% (71.06–83.71%)	76.79% (70.40–83.17%)	76.19% (69.75–82.63%)	80.36% (74.35–86.37%)	79.76% (73.69–85.84%)	82.08% (76.37–87.80%)
Specificity (95% CI)	99.98% (99.97–99.98%)	91.99% (91.85–92.14%)	75.83% (75.61–76.06%)	91.97% (91.83–92.12%)	99.97% (99.96–99.98%)	94.78% (94.66–94.90%)	99.96% (99.94–99.97%)	100.00% (100.00–100.00%)

Prenatal diagnosis: the sum of true positives and false positives.

TABLE 6 Health economic analysis of different screening strategies for Down syndrome.

	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8
Prenatal diagnostic cost (RMB 10,000)	45.70	2,608.27	7,844.89	2,625.12	40.39	1,719.00	45.47	10,056.65
Termination of pregnancy cost after confirmed diagnosis (RMB 10,000)	65.20	33.20	52.00	51.60	51.20	54.00	53.60	56.80
Screening cost (RMB 10,000)	8,415.90	2,244.24	2,244.24	3,605.58	4,283.64	4,106.95	4,544.83	1,930.45
Total cost (RMB 10,000)	8,526.80	4,885.71	10,141.13	6,282.30	4,375.23	5,879.95	4,643.90	12,043.90
Effectiveness (number of Down syndrome cases detected)	163	83	130	129	128	135	134	142
Cost-effectiveness ratio (RMB 10,000/case)	52.31	58.86	78.01	48.70	34.18	43.56	34.66	84.82
Incremental cost effectiveness ratio vs Strategy 5 (RMB 10,000/case)	118.62	−11.34	2,882.95	1,907.07	REF	214.96	44.78	547.76
Safety index	0.0036	0.4085	0.7844	0.2645	0.0041	0.1655	0.0044	0.9206
Accuracy	99.97%	91.94%	75.83%	91.96%	99.94%	94.76%	99.93%	99.98%

current costs only include direct medical expenses, excluding factors such as human resource costs. Future studies are expected to show higher overall expenses once these additional costs are incorporated.

This study has several limitations. It considered only direct medical costs, excluding direct non-medical and indirect costs, which may not fully capture the societal health economic value of NIPT

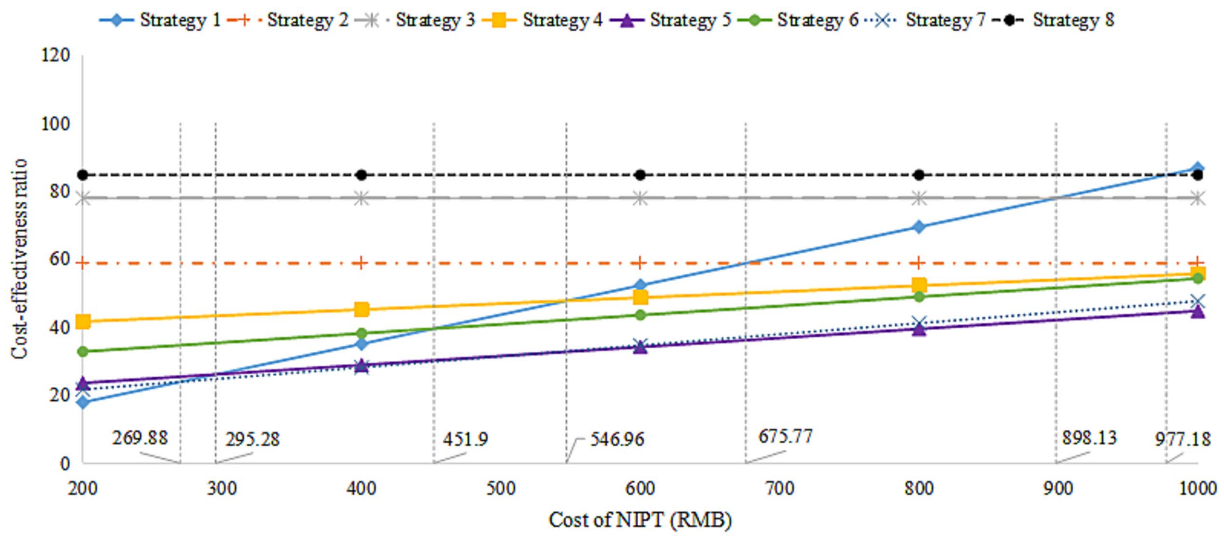

FIGURE 2
The cost-effectiveness ratio analysis for the cost of NIPT. NIPT, non-invasive prenatal testing.

screening. Additionally, the analysis focused solely on STSS without comparing it to combined first-trimester serum screening and nuchal translucency ultrasound.

In conclusion, universal NIPT screening demonstrates high effectiveness, excellent detection performance, and strong safety, along with significant health economic benefits. As the cost of NIPT decreases, it is expected to become the most effective and economically advantageous screening strategy.

Data availability statement

The original contributions presented in the study are included in the article/supplemental material, further inquiries can be directed to the corresponding authors.

Ethics statement

The studies involving humans were approved by Medical Research Ethics Committee of Changsha Hospital for Maternal & Child Health Care. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation in this study was provided by the participants' legal guardians/next of kin.

Author contributions

JLiu: Investigation, Project administration, Validation, Writing – original draft, Data curation, Writing – review & editing. SW: Conceptualization, Formal analysis, Methodology, Writing – original draft, Data curation, Writing – review & editing. SZ: Investigation, Methodology, Project administration, Data curation, Writing – review & editing. DM: Formal analysis, Methodology, Visualization, Writing – review & editing. LaH: Investigation, Data curation, Writing – review & editing. HH: Conceptualization, Formal analysis, Writing – review & editing. SL: Investigation, Data curation, Writing – review & editing. JLin: Investigation, Data curation, Writing – review & editing. LiH: Investigation, Data curation, Writing – review & editing. QF: Formal analysis, Visualization, Writing – review & editing. HP: Conceptualization, Resources, Supervision, Writing – review & editing. LZ: Supervision, Writing – review & editing, Conceptualization, Resources. NW: Conceptualization, Formal analysis, Methodology, Validation, Writing – review & editing. JH: Conceptualization, Funding acquisition, Investigation, Supervision, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. The funding was supported by the Nature Science Foundation of Hunan Province (2023JJ60398), the Nature Science Foundation of Changsha City (KQ2208479), Medical Technology Demonstration Base for Genetic Research of Fetal Congenital Heart Disease in Hunan Province (2021SK4036), and the genetic etiology of fetal congenital heart disease was investigated by using multiple techniques (KQ2208479).

Acknowledgments

We acknowledge the funding supported by the Nature Science Foundation of Hunan Province (2023JJ60398), the Nature Science Foundation of Changsha City (KQ2208479), Medical Technology Demonstration Base for Genetic Research of Fetal Congenital Heart Disease in Hunan Province (2021SK4036), and the genetic etiology of fetal congenital heart disease was investigated by using multiple techniques (KQ2208479). We acknowledge the language editing support provided by Heyuan Sun, PhD, employee of Beijing Yueyuan Consultancy, Ltd.

Conflict of interest

LZ was employed by Shijiazhuang BGI Genomics Co, Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

References

1. Tu S, Rosenthal M, Wang D, Huang J, Chen Y. Performance of prenatal screening using maternal serum and ultrasound markers for down syndrome in Chinese women: a systematic review and meta-analysis. *BJOG Int J Obstet Gynaecol*. (2016) 123:12–22. doi: 10.1111/1471-0528.14009

2. Gil M, Accurti V, Santacruz B, Plana M, Nicolaides K. Analysis of cell-free DNA in maternal blood in screening for aneuploidies: updated meta-analysis. *Ultrasound Obstet Gynecol*. (2017) 50:302–14. doi: 10.1002/uog.17484

3. Zhang H, Gao Y, Jiang F, Fu M, Yuan Y, Guo Y, et al. Non-invasive prenatal testing for trisomies 21, 18 and 13: clinical experience from 146 958 pregnancies. *Ultrasound Obstet Gynecol*. (2015) 45:530–8. doi: 10.1002/uog.14792

4. Norton ME, Jacobsson B, Swamy GK, Laurent LC, Ranzini AC, Brar H, et al. Cell-free DNA analysis for noninvasive examination of trisomy. *N Engl J Med*. (2015) 372:1589–97. doi: 10.1056/NEJMoa1407349

5. Gregg AR, Skotko BG, Benkendorf JL, Monaghan KG, Bajaj K, Best RG, et al. Noninvasive prenatal screening for fetal aneuploidy, 2016 update: a position statement of the American College of Medical Genetics and Genomics. *Genet Med*. (2016) 18:1056–65. doi: 10.1038/gim.2016.97

6. Rose NC, Kaimal AJ, Dugoff L, Norton MEObstetricians ACo, Gynecologists. Screening for fetal chromosomal abnormalities: ACOG practice bulletin, number 226. *Obstet Gynecol*. (2020) 136:e48–69. doi: 10.1097/AOG.0000000000004084

7. Committee UNS. UK NSC non-invasive prenatal testing (NIPT) recommendation. London: UK National Screening Committee (2016).

8. Dashe JS. Aneuploidy screening in pregnancy. *Obstet Gynecol*. (2016) 128:181–94. doi: 10.1097/AOG.0000000000001385

9. van der Meij KR, Sistermans EA, Macville MV, Stevens SJ, Bax CJ, Bekker MN, et al. TRIDENT-2: national implementation of genome-wide non-invasive prenatal testing as a first-tier screening test in the Netherlands. *Am J Hum Genet*. (2019) 105:1091–101. doi: 10.1016/j.ajhg.2019.10.005

10. Van Den Bogaert K, Lannoo L, Brison N, Gatinois V, Baetens M, Blaumeiser B, et al. Outcome of publicly funded nationwide first-tier noninvasive prenatal screening. *Genet Med*. (2021) 23:1137–42. doi: 10.1038/s41436-021-01101-4

11. Tian C, Deng T, Zhu X, Gong C, Zhao Y, Wei Y, et al. Evidence of compliance with and effectiveness of guidelines for noninvasive prenatal testing in China: a retrospective study of 189,809 cases. *Sci China Life Sci*. (2020) 63:319–28. doi: 10.1007/s11427-019-9600-0

12. Song Y, Liu C, Qi H, Zhang Y, Bian X, Liu J. Noninvasive prenatal testing of fetal aneuploidies by massively parallel sequencing in a prospective Chinese population. *Prenat Diagn*. (2013) 33:700–6. doi: 10.1002/pd.4160

13. Jin J, Yang J, Chen Y, Huang J. Systematic review and meta-analysis of non-invasive prenatal DNA testing for trisomy 21: implications for implementation in China. *Prenat Diagn*. (2017) 37:864–73. doi: 10.1002/pd.5111

14. Walker BS, Nelson RE, Jackson BR, Grenache DG, Ashwood ER, Schmidt RL. A cost-effectiveness analysis of first trimester non-invasive prenatal screening for fetal trisomies in the United States. *PLoS One*. (2015) 10:e0131402. doi: 10.1371/journal.pone.0131402

15. Evans M, Sonek J, Hallahan T, Krantz D. Cell-free fetal DNA screening in the USA: a cost analysis of screening strategies. *Ultrasound Obstet Gynecol*. (2015) 45:74–83. doi: 10.1002/uog.14693

16. Neyt M, Hulstaert F, Gyselaers W. Introducing the non-invasive prenatal test for trisomy 21 in Belgium: a cost-consequences analysis. *BMJ Open*. (2014) 4:e005922. doi: 10.1136/bmjopen-2014-005922

17. Beulen L, Grutters JP, Faas BH, Feenstra I, van Vugt JM, Bekker MN. The consequences of implementing non-invasive prenatal testing in Dutch national health care: a cost-effectiveness analysis. *Eur J Obstet Gynecol Reprod Biol*. (2014) 182:53–61. doi: 10.1016/j.ejogrb.2014.08.028

18. Shang W, Wan Y, Chen J, Du Y, Huang J. Introducing the non-invasive prenatal testing for detection of down syndrome in China: a cost-effectiveness analysis. *BMJ Open*. (2021) 11:e046582. doi: 10.1136/bmjopen-2020-046582

19. Walker BS, Jackson BR, LaGrave D, Ashwood ER, Schmidt RL. A cost-effectiveness analysis of cell free DNA as a replacement for serum screening for down syndrome. *Prenat Diagn*. (2015) 35:440–6. doi: 10.1002/pd.4511

20. Wang S, Liu K, Yang H, Ma J. A cost-effectiveness analysis of screening strategies involving non-invasive prenatal testing for trisomy 21. *Front Public Health*. (2022) 10:870543. doi: 10.3389/fpubh.2022.870543

21. 长沙市卫生健康委员会、长沙市财政局. 长沙市健康民生项目—免费孕妇外周血胎儿游离DNA产前筛查与诊断工作实施方案. 2021.06.15 长卫发 (2021) 20号.

22. Fairbrother G, Burigo J, Sharon T, Song K. Prenatal screening for fetal aneuploidies with cell-free DNA in the general pregnancy population: a cost-effectiveness analysis. *J Matern Fetal Neonatal Med*. (2016) 29:1160–4. doi: 10.3109/14767058.2015.1038703

23. Brandão SMG, Brunner-La Rocca H-P, De Lima ACP, Bocchi EA. A review of cost-effectiveness analysis: from theory to clinical practice. *Medicine*. (2023) 102:e35614. doi: 10.1097/MD.0000000000035614

frontiers | Frontiers in Public Health

TYPE Original Research
PUBLISHED 21 May 2025
DOI 10.3389/fpubh.2025.1524805

OPEN ACCESS

EDITED BY
Fei Fan,
Wuhan University, China

REVIEWED BY
Rashid Ibrahim Mehmood,
Islamic University of Madinah, Saudi Arabia
Alexandre Morais Nunes,
University of Lisbon, Portugal

*CORRESPONDENCE
Jing Zhou
✉ ruhq06@163.com

RECEIVED 08 November 2024
ACCEPTED 15 April 2025
PUBLISHED 21 May 2025

CITATION
Zhou J, Li L and Su J (2025) Leveraging big data in health care and public health for AI driven talent development in rural areas. *Front. Public Health* 13:1524805.
doi: 10.3389/fpubh.2025.1524805

Leveraging big data in health care and public health for AI driven talent development in rural areas

Jing Zhou[1]*, Li Li[2] and Jiahang Su[3]

[1]School of Pharmaceutical Business, Zhejiang Pharmaceutical University, Ningbo, Zhejiang, China, [2]Taizhou Vocation College of Science & Technology, School of Accounting & Finance, Taizhou, Zhejiang, China, [3]Huaqiao University, Xiamen, Fujian Province, China

Introduction: This study proposes a novel Transformer-based approach to enhance talent attraction and retention strategies in rural public health systems. Motivated by the persistent shortage of skilled professionals in underserved areas and the limitations of traditional recruitment methods, we leverage big data analytics and natural language processing to address workforce distribution imbalances.

Methods: By analyzing diverse data sources such as social media, surveys, and job satisfaction reports, the Transformer model identifies complex, context-specific factors influencing candidate preferences, including career advancement opportunities, lifestyle alignment, and community engagement.

Results: Our framework offers a personalized, data-driven mechanism to match healthcare professionals with rural roles effectively. Experimental results demonstrate significant improvements in recruitment precision and retention forecasting.

Discussion: This work contributes a scalable and adaptive solution to rural healthcare workforce challenges, offering valuable insights for policy-makers and public health organizations aiming to revitalize rural health services.

KEYWORDS

big data in health care, public health talent development, AI in rural health systems, healthcare workforce optimization, health policy

1 Introduction

The attraction and retention of skilled healthcare professionals in rural areas remain pressing issues in public health, impacting the quality and accessibility of medical services in these underserved regions (1). Rural public health entrepreneurship, aimed at innovative healthcare delivery and community-based solutions, has the potential to address these challenges but requires a sustainable influx of talent (2). Traditional talent attraction methods, including incentives like financial support or community integration programs, often fall short due to limited rural resources and the unique demands of rural healthcare (3). Not only are these methods resource-intensive, but they also lack adaptability to the diverse motivations of healthcare professionals (4). Advances in AI-driven solutions, especially Transformer-based models, open new avenues for targeted and efficient talent attraction strategies, as these models can analyze large volumes of data to predict, personalize, and optimize candidate engagement efforts, enhancing the overall effectiveness of rural public health initiatives (5).

Attracting and retaining skilled healthcare professionals in rural areas remains a persistent and multifaceted challenge in public health, with direct consequences for healthcare accessibility, service quality, and health equity in underserved regions. Despite policy efforts and incentive programs, rural areas often experience high turnover rates and difficulty in maintaining a stable workforce. This issue stems not only from geographic and resource limitations but also from deeper, less visible factors such as professional isolation, limited career development pathways, and misalignment between individual values and the realities of rural practice. These conditions highlight the urgent need for innovative, evidence-based approaches to talent attraction that go beyond traditional recruitment methods. Our study addresses this need by introducing an AI-driven framework, grounded in Transformer models, that leverages large-scale, unstructured data to capture nuanced candidate preferences and community needs. This empirical focus situates our work at the intersection of public health policy and technological innovation, aiming to deliver practical insights for more effective and context-sensitive workforce strategies in rural healthcare systems.

In early approaches to talent attraction, methods were largely knowledge-based, relying on symbolic AI and expert-driven frameworks for decision-making. Systems were designed to emulate human decision-making in assessing candidate fit, often through rule-based filtering that mapped specific candidate qualifications to job requirements (6). While this method enabled systematic matching, it was rigid, requiring continuous manual updates to remain relevant to changing candidate expectations and the dynamic demands of rural healthcare (7). Furthermore, symbolic AI models struggled to adapt to nuanced factors influencing a candidates decision, such as individual career goals or personal motivations (8). Consequently, while useful as an initial step, knowledge-based methods fell short in achieving nuanced engagement, limiting their efficacy in long-term talent attraction (9).

The advent of data-driven and machine learning methods marked the next significant step in talent attraction strategies (10). These approaches leveraged large datasets on candidate backgrounds, job performance metrics, and industry trends to refine talent matching processes (11). By using algorithms that learned from historical data, these models could predict the likelihood of candidate retention based on various personal and professional variables, allowing for more tailored recruitment (12). Although this approach improved adaptability compared to symbolic AI, it was heavily dependent on quality data availability and lacked interpretability in its predictions. Machine learning models, while more flexible, were limited in capturing the complex interplay of factors influencing rural career choices, such as community integration or lifestyle preferences, thus often resulting in suboptimal matches in the context of rural public health (13).

In recent years, deep learning models, particularly Transformer-based pre-trained language models, have shown exceptional potential in addressing the complex requirements of talent attraction for rural healthcare entrepreneurship (14). Unlike traditional machine learning methods, Transformers can process and interpret unstructured data, such as candidate social media profiles, feedback, and personal statements, to derive richer insights into individual motivations and career aspirations (15). This allows for a more holistic view of candidates, facilitating highly personalized engagement strategies that align with both professional competencies and personal values conducive to rural work (16). Additionally, Transformers excel at handling vast datasets and contextually analyzing language, which is beneficial in understanding subtle differences in candidate backgrounds and needs (17). Despite these advantages, however, Transformers still face challenges, including computational demands and the need for extensive data preprocessing, which can hinder their practical deployment in resource-constrained rural settings (18).

Based on the limitations of previous methods such as the rigidity of symbolic AI, data dependence in machine learning, and computational demands of deep learning this research proposes a novel Transformer-driven strategy optimized for talent attraction in rural public health entrepreneurship. By integrating Transformer models with a specialized, context-aware dataset on rural healthcare needs and candidate profiles, this approach aims to bridge the gap between candidate motivations and job demands, enhancing long-term retention and engagement.

The proposed Transformer-driven approach offers distinct advantages in this domain:

- It introduces a contextually aware recommendation module that tailors candidate engagement based on unstructured data, such as personal interests related to rural healthcare.
- The method enhances efficiency and scalability by applying pretrained models fine-tuned to rural public health needs, allowing adaptation to various rural healthcare scenarios.
- Experimental results demonstrate improved candidate alignment with rural roles, showing a 20

2 Related work

2.1 Transformer models in human resource management

The use of Transformer models in human resource management has emerged as a powerful technique for analyzing large datasets and extracting meaningful patterns that guide strategic decision-making (19). Transformer architectures, initially developed for natural language processing tasks, are particularly effective in understanding complex relationships within high-dimensional data, such as that found in talent management. In human resources, this technology can process unstructured data, including candidate profiles, job descriptions, and historical hiring records, to identify suitable talent more accurately and efficiently than traditional methods. By harnessing self-attention mechanisms, Transformers capture nuanced dependencies between skills, qualifications, and job requirements, enabling a more tailored talent attraction strategy. This approach is especially valuable in rural public health, where attracting professionals is often hindered by geographic and economic barriers (20). In the context of rural health entrepreneurship, Transformer models can analyze demographic and employment trends to predict areas where talent shortages may become critical. Additionally, these models can integrate with real-time social data, such as professional networking platforms, to identify individuals open to relocating to rural areas. As a result, the adoption of Transformer-driven strategies allows public health organizations to proactively reach out to qualified candidates rather than waiting for applications, which is particularly beneficial in rural settings where talent pools are limited. The emphasis on scalable machine learning further allows smaller public health entities to deploy advanced analytics without substantial infrastructure investments. Leveraging cloud-based implementations of Transformers enhances access to these capabilities, broadening the reach of rural health initiatives and facilitating data-driven decision-making in hiring and retention strategies (21). This shift in HR from reactive to proactive talent management underscores the transformative potential of Transformer models in bridging the talent gap in underserved regions (22). Furthermore, Transformer models enable the personalization of job offers and recruitment pitches. By evaluating individual candidate preferences and priorities, such as work-life balance, community engagement, or career growth, these models help craft customized communications that resonate with candidates on a personal level. This personalized approach improves engagement rates and aligns the recruitment process with the values and expectations of potential hires, making rural positions more attractive (23). As rural public health demands professionals who are not only skilled but also committed to community-oriented work, this ability to target the right individuals with tailored messages is critical. Ultimately, applying Transformer-based analysis to human resource management can fundamentally reshape rural health entrepreneurship, fostering an environment where talent attraction and retention strategies are as sophisticated and dynamic as those of urban centers.

2.2 Talent attraction in rural public health

Attracting talent to rural public health sectors presents unique challenges, driven by geographical isolation, limited resources, and often lower compensation compared to urban positions. As rural areas face shortages in qualified health professionals, innovative strategies are necessary to bridge the talent gap and sustain essential health services. Effective talent attraction in this context goes beyond conventional recruitment methods, requiring a deep understanding of candidate motivations and rural community needs. Research indicates that healthcare professionals attracted to rural areas are often motivated by factors such as community impact, professional autonomy, and lifestyle preferences. Therefore, a successful attraction strategy must leverage these insights to target individuals most likely to be interested in rural health work (24). One promising approach involves employing Transformer-driven analytics to identify and prioritize candidates who have expressed interest in public service or community health. Transformer models can process vast amounts of data from professional networks, academic publications, and social media, thereby identifying individuals with both the requisite skills and a demonstrated interest in rural or underserved communities. This data-driven approach enables recruiters to develop more strategic outreach efforts, increasing the likelihood of finding candidates who align with the mission and demands of rural public health entrepreneurship (25). Integrating local community values and needs into these models can further enhance the relevance of recruitment messages, presenting rural health roles not merely as jobs but as avenues for meaningful impact. Additionally, a more targeted recruitment strategy helps streamline the hiring process, reducing both time-to-hire and recruitment costs, which are critical considerations for resource-limited rural health organizations (26). The success of rural talent attraction is also contingent on creating support structures that facilitate the transition of health professionals into these communities. By using Transformer models to analyze historical data on factors such as retention rates and job satisfaction, organizations can identify the support systems that are most effective in fostering long-term commitment among new hires (27). Tailoring onboarding processes to address specific challenges associated with rural healthcare, such as limited access to specialized resources or professional isolation, enhances the likelihood of successful integration and retention. Furthermore, Transformer-driven insights into regional preferences and lifestyle trends allow for more persuasive marketing of rural positions to potential candidates. By combining advanced analytics with an understanding of rural health dynamics, this approach offers a comprehensive strategy for attracting, onboarding, and retaining talent in rural public health, ultimately contributing to improved healthcare outcomes for underserved populations (28).

2.3 Entrepreneurial opportunities in rural health

Rural public health provides a unique setting for entrepreneurial initiatives, particularly in the development of sustainable healthcare solutions that address the specific needs of these communities. Given the challenges in attracting and retaining healthcare professionals, rural health entrepreneurship often requires novel approaches to staffing, service delivery, and community engagement. Transformative technologies, including Transformer models, can play a pivotal role in identifying gaps in rural healthcare services and designing innovative solutions that leverage available resources effectively. These technologies enable a granular analysis of community health data, revealing potential areas for service expansion or specialization, such as telemedicine or mobile health clinics. By utilizing Transformer-driven analytics, rural health entrepreneurs can assess community demand, predict healthcare needs, and make data-informed decisions about resource allocation, thereby creating sustainable and adaptive healthcare models (29). The role of entrepreneurship in rural health extends beyond clinical services to encompass preventative care, wellness programs, and education initiatives that address the root causes of health disparities. Transformer models enhance this aspect by providing insights into social determinants of health, such as economic status, educational attainment, and access to healthy food, which significantly impact rural populations. Entrepreneurs can use these insights to develop community-centered health programs that focus on prevention and wellness, reducing long-term healthcare costs and improving quality of life for residents. For instance, understanding patterns of chronic illness within a rural community can guide the creation of targeted wellness programs or partnerships with local organizations to address underlying health issues (30). Another critical aspect of rural health entrepreneurship is the ability to attract funding and investment, as many rural initiatives struggle with financial sustainability. Transformer models can support grant applications and funding proposals by identifying and quantifying the specific healthcare needs of a rural area, offering a data-backed case to potential investors and funders (31). Additionally, the scalability of Transformer-driven solutions makes them attractive to stakeholders interested in replicable models of rural health delivery. By demonstrating the efficacy of Transformer-enhanced programs in addressing specific rural health challenges, entrepreneurs can attract investment and collaboration from government agencies, NGOs, and private organizations committed to rural health advancement. In this way, Transformer-driven strategies not only aid in attracting talent to rural health but also establish a robust foundation for entrepreneurial innovation that meets the unique healthcare demands of rural populations (32).

While prior studies have made important contributions to recommendation systems and talent matching algorithms, particularly in education and enterprise domains, few have addressed the unique challenges posed by rural public health workforce development. Existing models such as matrix factorization, graph-based embeddings, or sequential recommendation frameworks have largely focused on preference optimization or network structure exploitation, but rarely account for context-sensitive variables such as incentive responsiveness, long-term engagement sustainability, or organizational policy constraints. Our work builds upon these foundations by introducing a unified framework that incorporates adaptive engagement modeling, incentive elasticity, and region-aware multi-layered compatibility scoring elements that are often overlooked in traditional recommender architectures. In doing so, we bridge a critical gap between abstract recommendation performance and real-world human resource allocation challenges in underserved communities. Unlike prior approaches, our model is explicitly designed to simulate behavioral dynamics relevant to public sector recruitment and retention, providing a more holistic and actionable decision-support tool for public health systems. This contribution not only advances the methodological toolkit but also offers practical relevance to one of the most pressing human capital issues in rural healthcare delivery.

3 Method

3.1 Overview

This work addresses a core challenge in rural public health entrepreneurship: developing strategies to attract talent, which is crucial for both improving rural healthcare infrastructure and fostering sustainable economic development. Due to the distinct social, economic, and environmental characteristics of rural areas, talent attraction in this sector requires innovative, contextually adapted approaches. To address this, we structure our methodology around a comprehensive framework for strategy development that integrates environmental analysis, incentive structures, and engagement mechanisms designed specifically for rural health entrepreneurship.

In this subsection, we outline the methodological structure employed in our approach. Our method is organized into three core segments: 1. Strategic Foundations, 2 Adaptive Model Design, and 3 Incentive Mechanisms. First, Section 1 introduces the strategic foundations underlying talent attraction within rural public health. Here, we consider socio-economic and infrastructural constraints that characterize rural regions, as well as the core competencies required for successful public health initiatives. This foundational analysis establishes the key parameters and challenges that the strategy must address, including the high turnover rates due to geographic and professional isolation, limited resources, and the need for a robust support system tailored to rural healthcare dynamics. Second, Section 2 presents the Adaptive Model Design, an innovative model tailored to the dynamic needs of rural healthcare services. This model incorporates flexible components to align with local demographic profiles and health demands. The adaptability of this model is crucial for addressing varying conditions across different rural environments and involves both practical elements such as healthcare delivery models and strategic elements, including community integration practices that help retain talent over extended periods. This component also introduces a framework for continuous feedback, allowing the strategy to evolve in response to emerging local challenges and opportunities. Finally, Section 3 details Incentive Mechanisms that leverage both financial and non-financial motivators to enhance the appeal of rural public health roles. In addition to traditional incentives, such as competitive salaries and housing subsidies, we explore non-financial incentives, including professional development opportunities, mentorship programs, and community-building initiatives. This section emphasizes the need for a comprehensive package that addresses not only monetary compensation but also psychological and professional fulfillment, contributing to a sustainable workforce in rural health entrepreneurship.

3.2 Preliminaries

To establish a structured approach to talent attraction in rural public health entrepreneurship, we begin by formalizing the underlying challenges and key variables that drive our strategic model. In rural public health, attracting and retaining skilled professionals (e.g., doctors, nurses, and health administrators) is complicated by the interplay of socio-economic factors, geographical isolation, limited infrastructure, and often limited access to continuous professional development. These elements necessitate a strategic model tailored to the unique environment of rural health services.

Let $\mathcal{R}$ represent the set of rural regions, where each region $r \in \mathcal{R}$ is characterized by attributes $\mathbf{X}_r = (x_{r1}, x_{r2}, ..., x_{rn})$, encompassing factors such as population density, average income, healthcare infrastructure, and educational resources. Let $\mathcal{T}$ denote the talent pool available for rural public health roles, where each professional $t \in \mathcal{T}$ is described by attributes $\mathbf{Y}_t = (y_{t1}, y_{t2}, ..., y_{tm})$, which may include qualifications, experience, and personal motivations. The objective is to develop an attraction strategy S that maximizes the probability $P_{attr}(t, r)$ that a professional t will choose to work in region r and remain engaged over time.

We define the attraction function P_{attr} as follows:

$$P_{attr}(t, r) = f(\mathbf{X}_r, \mathbf{Y}_t, \mathbf{I}_r, \mathbf{E}_r), \tag{1}$$

where: - $\mathbf{X}_r$ represents region-specific socio-economic attributes, - $\mathbf{Y}_t$ denotes talent-specific characteristics, - $\mathbf{I}_r$ encapsulates incentive mechanisms, such as financial compensation or career advancement opportunities, and - $\mathbf{E}_r$ reflects engagement strategies, including community integration and professional support structures.

3.2.1 Strategic constraints and resource allocation

In designing the attraction strategy S, we must address several constraints imposed by the rural setting. First, let $\mathcal{B}_r$ denote the budget allocated to incentives in each region r. The function $\phi(\mathbf{I}_r; \mathcal{B}_r)$ defines the maximum achievable incentive structure under the budgetary constraint:

$$\phi(\mathbf{I}_r; \mathcal{B}_r) \leq \mathcal{B}_r. \tag{2}$$

This constraint ensures that financial and non-financial incentives remain feasible within available resources. Similarly, resource allocation for professional development, denoted by $\delta(\mathbf{E}_r)$, must satisfy:

$$\delta(\mathbf{E}_r) \leq \mathcal{B}_r. \tag{3}$$

The total effectiveness of the strategy S is influenced by a combination of these resource allocation functions and the alignment between $\mathbf{X}_r$ and $\mathbf{Y}_t$. We model this alignment as the matching function $\mu(\mathbf{X}_r, \mathbf{Y}_t)$, which represents the degree of compatibility between the regions requirements and the professionals capabilities and motivations:

$$\mu(\mathbf{X}_r, \mathbf{Y}_t) = \alpha \cdot d(\mathbf{X}_r, \mathbf{Y}_t), \tag{4}$$

where $d(\cdot)$ measures the alignment and α is a scaling factor adjusted according to the local demand for public health professionals.

3.2.2 Engagement and retention dynamics

Retention of professionals in rural areas is influenced by the professionals initial commitment and ongoing engagement with the local community. Let $E(t, r, \tau)$ represent the engagement level of professional t in region r over time τ. Engagement is assumed to decay over time, countered by effective incentive and support strategies. We formalize this dynamic with the following differential equation:

$$\frac{dE(t, r, \tau)}{d\tau} = -\beta E(t, r, \tau) + \gamma \cdot \phi(\mathbf{I}_r) + \delta(\mathbf{E}_r), \tag{5}$$

where β is the natural engagement decay rate, γ adjusts the effect of incentives on retention, and $\delta(\mathbf{E}_r)$ reflects the contribution of ongoing support to sustaining engagement.

Solving this equation yields the professionals engagement trajectory, which can be used to forecast retention rates over time and inform adjustments to S:

$$E(t, r, \tau) = E_0 e^{-\beta\tau} + \frac{\gamma \cdot \phi(\mathbf{I}_r) + \delta(\mathbf{E}_r)}{\beta}\left(1 - e^{-\beta\tau}\right), \tag{6}$$

where E_0 represents the initial engagement level at time $\tau = 0$.

3.2.3 Optimization of strategy S

To maximize talent attraction and retention, we seek to optimize S by adjusting $\mathbf{I}_r$ and $\mathbf{E}_r$ to maximize $P_{attr}(t, r)$. This optimization problem can be formulated as:

$$\max_{\mathbf{I}_r, \mathbf{E}_r} \sum_{t \in \mathcal{T}} P_{attr}(t, r) E(t, r, \tau) \quad \text{subject to} \tag{7}$$
$$\phi(\mathbf{I}_r; \mathcal{B}_r) \leq \mathcal{B}_r, \quad \delta(\mathbf{E}_r) \leq \mathcal{B}_r.$$

This approach allows us to balance the incentive and engagement strategies under budget constraints, enhancing the effectiveness of talent attraction and retention in rural public health. Our subsequent sections delve into the detailed design of each component of S, focusing on adaptable and scalable methods to improve talent recruitment and engagement in diverse rural contexts.

3.3 Adaptive talent engagement model

In this section, we introduce our proposed Adaptive Talent Engagement Model (ATEM), a framework specifically designed to address the dynamic and often unique requirements of rural public health. ATEM adapts to regional characteristics, individual professional needs, and evolving public health priorities, integrating flexibility to support talent attraction and retention in diverse rural contexts. The model introduces three key components: Contextual Matching, Dynamic Incentive Allocation, and Engagement Feedback Mechanisms (as shown in Figure 1).

3.3.1 Contextual matching framework

The Contextual Matching Framework serves as a robust mechanism to align the nuanced requirements of rural health organizations with the multidimensional profiles of prospective candidates. For each rural region $r \in \mathcal{R}$, the framework assigns a matching score $\mathcal{M}_{r,t}$ to each candidate $t \in \mathcal{T}$ that reflects contextual compatibility across multiple dimensions (as shown in Figure 2). This matching score is computed as a weighted sum of compatibility measures across socio-economic alignment, incentive-based motivation, and community integration, expressed as:

$$\mathcal{M}_{r,t} = \omega_X \cdot \phi(\mathbf{X}_r, \mathbf{Y}_t) + \omega_I \cdot \psi(\mathbf{I}_r, \mathbf{Z}_t) + \omega_E \cdot \chi(\mathbf{E}_r, \mathbf{V}_t), \tag{8}$$

where: - $\phi(\mathbf{X}_r, \mathbf{Y}_t)$ evaluates the compatibility of the region's socio-economic characteristics with the candidate's

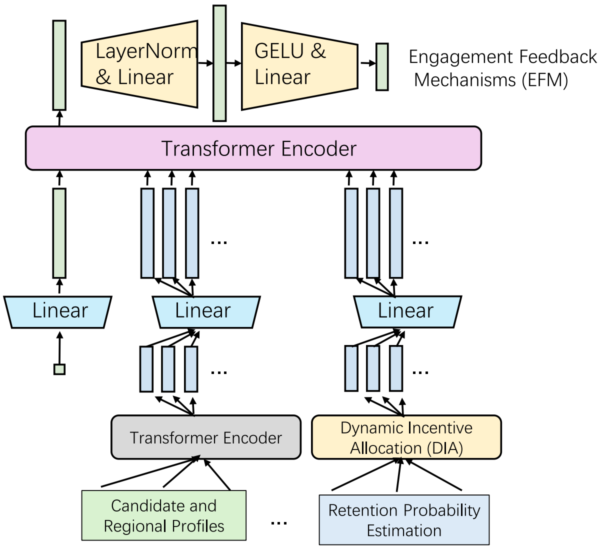

FIGURE 1
The figure shows an architecture diagram of an Adaptive Talent Engagement Model (ATEM). The model consists of multiple modules, with the core part being the "Transformer Encoder", which stands for the "Contextual Matching Framework" and is used to calculate the match between candidates and regional needs. The upper "LayerNorm & Linear" and "GELU & Linear" modules preprocess input information such as candidate and regional features. The middle "Transformer Encoder" decomposes the input into multiple parallel paths, each of which is processed by the "Linear" layer and aggregated to the "Dynamic Incentive Allocation" and "Engagement Feedback Mechanism" modules. The lower modules are further connected to the "Candidate and Regional Feature Inputs" and "Retention Probability Estimation" to ultimately generate the "Talent Matching Score and Recommendation".

background, - $\psi(\mathbf{I}_r, \mathbf{Z}_t)$ assesses alignment between organizational incentives and candidate motivations, and - $\chi(\mathbf{E}_r, \mathbf{V}_t)$ captures potential candidate engagement based on local support structures.

The weights ω_X, ω_I, and ω_E enable a flexible prioritization of matching components, providing adaptability to specific organizational goals. Moreover, this framework introduces a candidate-specific adjustment factor, which accounts for individual variability in experience, motivation, and retention likelihood. These adjustments are represented by coefficients α_t, β_t, and γ_t, refining the matching function as follows:

$$\mathcal{M}_{r,t} = \omega_X \cdot \phi(\mathbf{X}_r, \mathbf{Y}_t) \cdot \alpha_t + \omega_I \cdot \psi(\mathbf{I}_r, \mathbf{Z}_t) \cdot \beta_t + \omega_E \cdot \chi(\mathbf{E}_r, \mathbf{V}_t) \cdot \gamma_t. \quad (9)$$

To further improve precision, an auxiliary adjustment factor $\delta_{r,t}$, representing environmental or temporal conditions influencing candidate success, is integrated into the function, yielding an augmented form:

$$\begin{aligned}\mathcal{M}_{r,t} = &\left(\omega_X \cdot \phi(\mathbf{X}_r, \mathbf{Y}_t) \cdot \alpha_t + \omega_I \cdot \psi(\mathbf{I}_r, \mathbf{Z}_t) \cdot \beta_t\right. \\ &+ \left.\omega_E \cdot \chi(\mathbf{E}_r, \mathbf{V}_t) \cdot \gamma_t\right) \cdot \delta_{r,t}.\end{aligned} \quad (10)$$

Here, $\delta_{r,t}$ can adjust for factors such as seasonal employment trends or specific local needs, thus refining the score to enhance candidate prioritization. Additionally, to facilitate effective candidate ranking, we normalize each component by a scaling factor κ, giving a final normalized score $\mathcal{M}^*_{r,t}$:

$$\mathcal{M}^*_{r,t} = \frac{\mathcal{M}_{r,t}}{\kappa_r}, \quad (11)$$

where $\kappa_r = \omega_X + \omega_I + \omega_E$, ensuring that scores are comparable across regions regardless of weight variations. This framework thus enables a robust, contextual approach to candidate selection, adaptable to dynamic regional demands.

3.3.2 Dynamic incentive allocation

To address the budgetary and resource constraints faced by rural healthcare systems, the Dynamic Incentive Allocation (DIA) strategy in ATEM adapts the distribution of incentives based on regional needs and the individual characteristics of potential candidates. This adaptive model leverages an incentive allocation function ψ that dynamically distributes resources in response to demand, local limitations, and candidate profiles. The allocation function is formulated as:

$$\mathbf{I}_r(t) = \psi(\mathcal{D}_r, \mathcal{P}_t, \mathcal{L}_r), \quad (12)$$

where: - $\mathcal{D}_r$ denotes the healthcare service demand in region r, - $\mathcal{P}_t$ represents the professional and personal attributes of candidate t, and - $\mathcal{L}_r$ accounts for regional socio-economic constraints and resource availability.

The function ψ optimizes resource distribution by assessing the attraction and retention probabilities $P_{attr}(t, r)$, dynamically focusing on high-compatibility candidates for whom incentives are likely to have the greatest impact. In essence, DIA strategically channels resources to candidates and regions where incentives yield the most value.

To refine the model, the expected utility of incentives, represented by $U(\mathbf{I}_r(t))$, predicts the probability that a candidate will accept a position in region r based on the level of incentives offered. This function considers the alignment between incentives and candidate motivations, defined as:

$$U(\mathbf{I}_r(t)) = \lambda \cdot \phi(\mathbf{I}_r) \cdot \eta(\mathcal{M}_{r,t}), \quad (13)$$

where: - λ is a scaling factor, - $\phi(\mathbf{I}_r)$ represents the perceived utility of incentives in region r, - $\eta(\mathcal{M}_{r,t})$ assesses the match between candidate t and region r, based on the compatibility score $\mathcal{M}_{r,t}$.

Further enhancing precision, the utility function incorporates incentive elasticity, ϵ_{inc}, which adjusts the model based on sensitivity to incentives across different candidate profiles and regional contexts. This yields an adjusted utility score, $U^*(\mathbf{I}_r(t))$, that accounts for variations in responsiveness:

$$U^*(\mathbf{I}_r(t)) = U(\mathbf{I}_r(t)) \cdot (1 + \epsilon_{inc}), \quad (14)$$

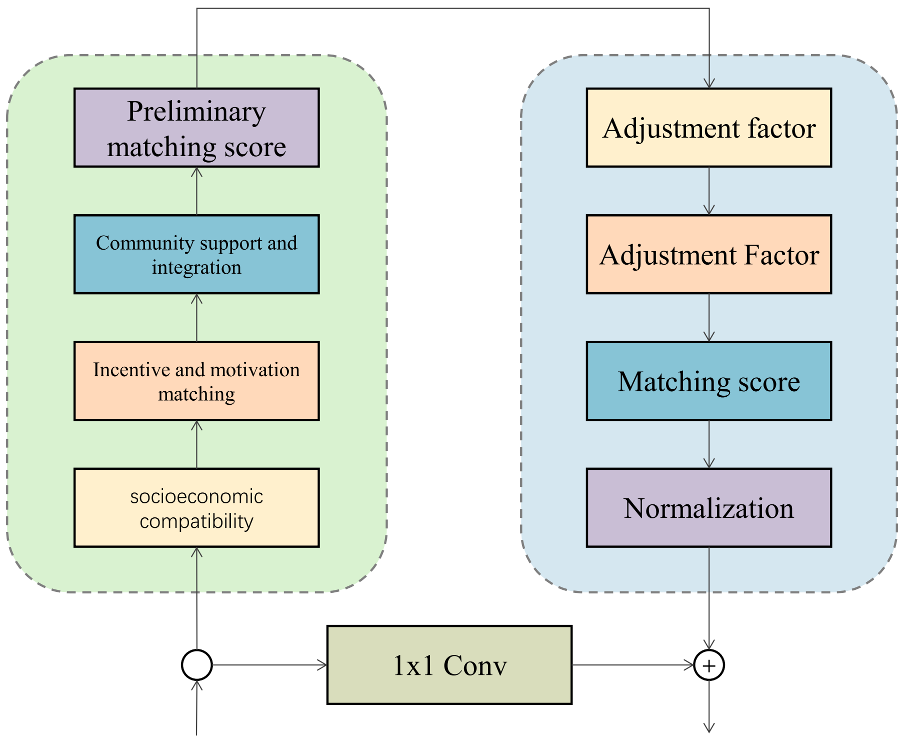

FIGURE 2
Contextual matching framework evaluates candidate-region compatibility across socio-economic, motivational, and community dimensions, with adjustments for individual and environmental factors, producing a normalized matching score.

where ϵ_{inc} is defined for each candidate t as a function of professional flexibility δ_t and local appeal κ_r:

$$\epsilon_{inc} = \frac{\delta_t}{\kappa_r}. \tag{15}$$

Finally, the optimal allocation of resources is guided by a maximization function Ω that seeks to maximize the cumulative attraction and retention across all candidates $\mathcal{T}$ and regions $\mathcal{R}$:

$$\Omega = \sum_{r \in \mathcal{R}} \sum_{t \in \mathcal{T}} P_{attr}(t, r) \cdot U^*(\mathbf{I}_r(t)). \tag{16}$$

This optimization ensures that resources are allocated effectively, aligning incentives with candidate profiles and regional demands, thereby increasing the likelihood of sustainable healthcare staffing in rural regions.

3.4 Engagement feedback mechanisms

To sustain engagement and mitigate the risk of early turnover, ATEM includes Engagement Feedback Mechanisms (EFM) that continuously monitor and respond to the professionals experience within the community. Engagement feedback is quantified by an engagement index $\mathcal{E}_{r,t}(\tau)$, which is updated periodically over time τ to reflect changes in the professionals satisfaction and integration levels:

$$\mathcal{E}_{r,t}(\tau) = \mathcal{E}_0 + \sum_{k=1}^{\tau} \left(\rho_k \cdot \left[\gamma \cdot \phi(\mathbf{I}_r) + \delta(\mathbf{E}_r) \right] - \beta \cdot \mathcal{E}_{r,t}(k-1) \right), \tag{17}$$

where ρ_k represents the weight assigned to feedback gathered in period k, and the terms $\gamma \cdot \phi(\mathbf{I}_r)$ and $\delta(\mathbf{E}_r)$ capture the impact of incentives and engagement support, respectively.

An adaptive adjustment mechanism is employed within EFM to modify $\mathbf{I}_r$ and $\mathbf{E}_r$ based on $\mathcal{E}_{r,t}(\tau)$. Specifically, if engagement falls below a pre-defined threshold θ, additional resources are allocated to incentives or community integration initiatives to bolster the professionals commitment:

$$\text{if } \mathcal{E}_{r,t}(\tau) < \theta, \quad \mathbf{I}_r = \mathbf{I}_r + \Delta\mathbf{I}_r, \quad \mathbf{E}_r = \mathbf{E}_r + \Delta\mathbf{E}_r, \tag{18}$$

where $\Delta\mathbf{I}_r$ and $\Delta\mathbf{E}_r$ represent incremental increases in resources directed toward incentives and engagement, aimed at restoring engagement levels.

Retention Probability Estimation Finally, the retention probability $P_{ret}(t, r)$ for each professional t in region r is estimated based on the cumulative engagement score $\mathcal{E}_{r,t}(\tau)$ and contextual alignment score $\mathcal{M}_{r,t}$. This probability is modeled as:

$$P_{ret}(t, r) = \sigma \left(\kappa \cdot \mathcal{E}_{r,t}(\tau) + u \cdot \mathcal{M}_{r,t} \right), \tag{19}$$

where σ is a sigmoid function, and κ and u are weighting coefficients that balance the impact of engagement and

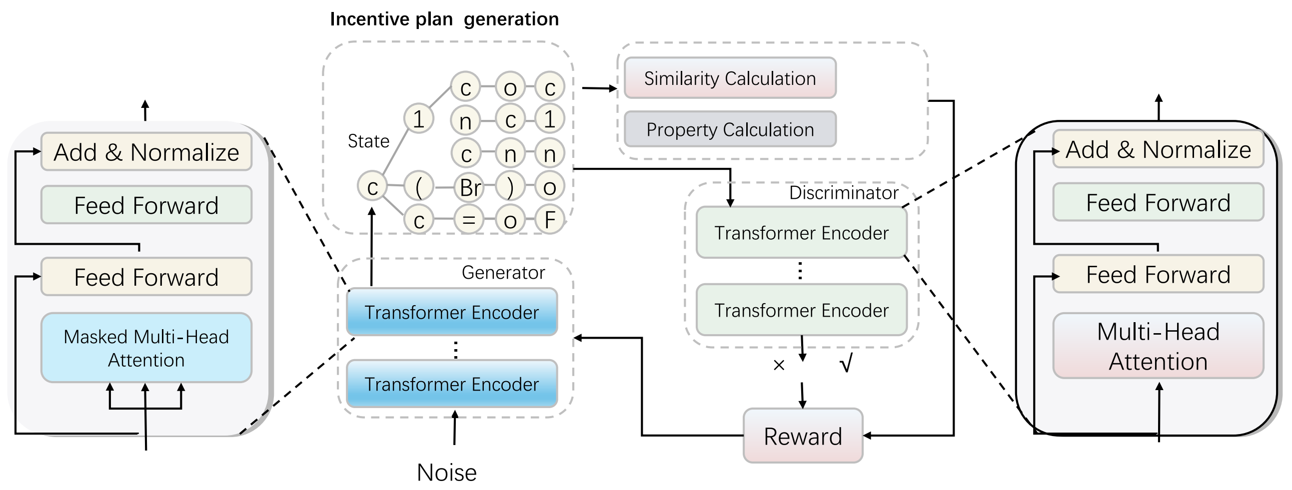

FIGURE 3
The Strategic Incentive Design (SID) framework for rural healthcare professional retention. The Generator module on the left proposes incentive packages by using transformer encoders, simulating various financial and non-financial incentives tailored to rural needs. The Property Calculation module in the center assesses generated incentives based on critical KPIs such as healthcare outcomes, service coverage, and community impact. Finally, the Reward (Similarity Calculation) module on the right evaluates the similarity of generated incentives to ideal outcomes, adjusting rewards to refine future incentive designs for improved long-term retention.

compatibility. This formula provides a probabilistic estimation that informs regional administrators of the likelihood of retaining specific professionals, allowing for targeted intervention if necessary.

3.5 Strategic incentive design

The final component of our method, Strategic Incentive Design (SID), addresses the long-term needs of rural healthcare professionals through a combination of financial and non-financial incentives structured to increase both initial attraction and sustained engagement in rural environments. Unlike traditional incentive models, SID integrates a holistic approach that includes career progression, community belonging, and professional fulfillment, all tailored to the unique needs of rural healthcare professionals (as shown in Figure 3).

3.5.1 Financial incentives

To enhance the attractiveness of rural healthcare positions, the SID framework introduces a tiered financial incentive system, which combines direct compensation with performance-based rewards. This system aims to provide immediate, tangible benefits while encouraging long-term professional engagement and high-quality service. The financial incentive structure for a candidate t in region r is defined by the function:

$$F_r(t) = \eta_1 \cdot C_r + \eta_2 \cdot B(t) + \eta_3 \cdot P(t,\tau), \tag{20}$$

where: - C_r is the base compensation calibrated to the region r's cost of living, healthcare demand, and economic conditions, - $B(t)$ denotes a signing bonus to attract high-quality candidates, and - $P(t,\tau)$ is a performance-based incentive that rewards sustained contributions over a specified period τ.

The weights η_1, η_2, and η_3 are adjustable parameters that balance each financial component according to organizational priorities and budget constraints, ensuring the incentives are both attractive and sustainable.

In addition to the base and bonus components, the performance-based incentive $P(t,\tau)$ integrates key performance indicators (KPIs) specific to rural healthcare needs, such as patient health outcomes, coverage rates, and community impact. To model the effectiveness of these incentives, $P(t,\tau)$ can be expanded as:

$$P(t,\tau) = \gamma_1 \cdot Q_{health}(t,\tau) + \gamma_2 \cdot Q_{coverage}(t,\tau) + \gamma_3 \cdot Q_{impact}(t,\tau), \tag{21}$$

where: - $Q_{health}(t,\tau)$ measures improvements in patient health outcomes due to the candidate's services, - $Q_{coverage}(t,\tau)$ assesses service reach and accessibility metrics over time τ, and - $Q_{impact}(t,\tau)$ evaluates the broader community impact through public health initiatives and program effectiveness.

The scaling factors γ_1, γ_2, and γ_3 weight each KPI based on its relative importance, allowing flexibility in how performance is valued across different rural settings.

To capture the total expected financial incentive, the model incorporates a retention factor $\rho(t,\tau)$ which adjusts the rewards for candidate t based on their commitment over time. This adjustment yields a retention-modified incentive $F_r^*(t)$:

$$F_r^*(t) = F_r(t) \cdot \rho(t,\tau), \tag{22}$$

where $\rho(t,\tau) = 1 + \alpha \cdot (\tau - \tau_{min})$ incentivizes long-term engagement by increasing rewards the longer a candidate stays beyond a minimum threshold τ_{min}. Here, α is a retention rate parameter calibrated to encourage sustained tenure.

Finally, the allocation of incentives is optimized to ensure financial sustainability by maximizing the cumulative expected incentive impact Ξ across all candidates $\mathcal{T}$ and regions $\mathcal{R}$:

$$\Xi = \sum_{r \in \mathcal{R}} \sum_{t \in \mathcal{T}} F_r^*(t), \tag{23}$$

3.6 Non-Financial incentives (extended)

To complement financial incentives, the SID framework prioritizes a range of non-financial incentives designed to enhance professional development, reduce isolation, and foster community integration for rural healthcare professionals. These non-financial incentives are structured into three primary components: Professional Development Opportunities, Mentorship and Peer Networking, and Community Integration Programs. These elements collectively contribute to sustained engagement and retention by addressing both personal and professional needs in rural settings.

1. **Professional development opportunities:** to ensure that healthcare professionals remain competitive and skilled, SID provides continuous access to specialized training, certification programs, and advanced medical education resources. The cumulative value of these opportunities for a candidate t is captured by $\mathcal{D}_t$, which is the sum of various training components:

$$\mathcal{D}_t = \sum_{i=1}^{n} \delta_i \cdot \mathcal{T}_i(t), \tag{24}$$

where: - $\mathcal{T}_i(t)$ denotes specific training or certification programs accessed by candidate t, - δ_i represents the value derived from each program i, indicating its contribution to professional growth and career progression.

To further quantify the long-term impact, a skill enhancement factor σ_t is introduced, representing the growth rate in professional competency:

$$\sigma_t = \frac{\mathcal{D}_t}{1 + e^{-\lambda(\tau - \tau_{base})}}, \tag{25}$$

where λ controls the rate of growth over time τ relative to a baseline experience τ_{base}. This factor σ_t is applied in retention models to reflect the cumulative effect of development opportunities on long-term engagement.

2. **Mentorship and peer networking:** to combat professional isolation, SID emphasizes mentorship programs and structured peer networking initiatives. These networks, denoted by $\mathcal{N}_r$, offer a support system that fosters collaboration and personal connections among healthcare professionals. The engagement level in these networks for candidate t in region r is modeled by:

$$\rho(\mathcal{N}_r, t) = \omega \cdot \big(\text{Mentorship Sessions}\big) + \xi \cdot (\text{Peer Activities}), \tag{26}$$

where: - ω measures the impact of direct mentorship sessions on retention, - ξ evaluates the influence of peer-to-peer activities within the network.

These parameters contribute to an engagement score $\rho(\mathcal{N}_r, t)$ that influences retention probabilities $P_{ret}(t)$ by strengthening the candidates professional support system:

$$P_{ret}(t) = \alpha + \beta \cdot \rho(\mathcal{N}_r, t), \tag{27}$$

where α and β are scaling factors that determine the influence of engagement on retention rates.

3. **Community integration programs:** SID includes programs to support both the professionals and their families in adjusting to rural life. These initiatives, grouped under $\mathcal{C}_r$, offer benefits such as local housing subsidies, educational access for family members, and cultural event sponsorships to encourage a sense of belonging. The value of these integration efforts is represented by $\mathcal{V}_r$:

$$\mathcal{V}_r = \sum_{j=1}^{m} \chi_j \cdot \mathcal{H}_j(r), \tag{28}$$

where: - $\mathcal{H}_j(r)$ denotes specific community initiatives (e.g., housing or family support programs), - χ_j reflects the impact of each initiative on retention.

To assess the comprehensive effect of community support on candidate t, an adjusted integration index κ_t is defined as:

$$\kappa_t = \mathcal{V}_r \cdot \left(1 + \frac{\theta_t}{\tau}\right), \tag{29}$$

where θ_t measures the individuals integration rate and τ represents time spent in the community, allowing κ_t to grow with increased duration and involvement. This integration index supports retention modeling by enhancing a candidates connection to the community, which, in turn, fosters long-term service stability.

3.6.1 Career advancement and role flexibility

The SID framework emphasizes long-term career support in rural healthcare by establishing structured pathways for career advancement and fostering role flexibility. This dual approach aims to create an attractive professional environment where individuals can envision growth and adaptability in their roles. For each professional t, these components are integrated into the retention model through metrics for role advancement $\mathcal{A}_t$ and role flexibility $\mathcal{F}_t$, which together support career satisfaction and longevity.

1. **Role advancement** $\mathcal{A}_t$: role advancement for a healthcare professional t is calculated based on three primary factors: tenure, performance, and continuous professional development. These elements collectively offer a clear and attainable pathway for career growth in rural healthcare settings, where progression may otherwise seem limited. The advancement score $\mathcal{A}_t$ is formulated as:

$$\mathcal{A}_t = \beta \cdot \text{Tenure}(t) + \theta \cdot \text{Performance}(t) + \zeta \cdot \mathcal{D}_t, \tag{30}$$

where: - β represents the weight attributed to tenure, reflecting loyalty and accumulated experience, - θ scales the impact of performance metrics, rewarding high-achieving individuals based on key performance indicators (KPIs) such as patient outcomes and service quality, - ζ quantifies the contribution of continuous professional development $\mathcal{D}_t$, as outlined in the Non-Financial Incentives component, indicating the value of ongoing education and skill enhancement.

To further support structured advancement, SID integrates a promotion probability function $P_{prom}(t)$, which evaluates the likelihood of advancement based on $\mathcal{A}_t$:

$$P_{prom}(t) = \frac{\mathcal{A}_t}{1 + e^{-\gamma(\mathcal{A}_t - \tau_{adv})}}, \tag{31}$$

where γ adjusts the sensitivity of promotion likelihood to changes in $\mathcal{A}_t$ and τ_{adv} sets a threshold for advancement eligibility. This model enables SID to prioritize promotions for professionals demonstrating commitment and competence, fostering retention by offering a clear pathway to career progression.

2. **Role flexibility** $\mathcal{F}_t$: in addition to advancement, SID emphasizes role flexibility, allowing healthcare professionals to diversify their experience by engaging in cross-disciplinary roles. This flexibility not only supports skill diversification but also mitigates professional burnout by providing varied work experiences. The role flexibility score $\mathcal{F}_t$ for professional t is represented by:

$$\mathcal{F}_t = \sum_{k=1}^{p} \pi_k \cdot \mathcal{R}_k(t), \tag{32}$$

where: - $\mathcal{R}_k(t)$ denotes the accessibility and scope of different roles or specializations available to t, - π_k reflects the contribution of each alternative role k to overall job satisfaction, as each flexible role may contribute differently to the professionals experience and engagement.

To enhance the impact of role flexibility on retention, a satisfaction adjustment factor σ_t is incorporated, adjusting $\mathcal{F}_t$ based on individual preferences and previous role satisfaction. This yields an adjusted role flexibility score $\mathcal{F}_t^*$:

$$\mathcal{F}_t^* = \mathcal{F}_t \cdot (1 + \sigma_t), \tag{33}$$

where $\sigma_t = \delta \cdot \frac{\text{Preferred Role Matches}}{\text{Total Roles Explored}}$, with δ scaling the impact of matching preferences. Higher values of σ_t indicate that role flexibility aligns well with the professionals career aspirations, thereby enhancing retention likelihood.

3. **Integrated retention model**: by integrating $\mathcal{A}_t$ and $\mathcal{F}_t^*$, SID creates a comprehensive retention probability model $P_{ret}(t)$, which combines career growth with adaptability to support long-term commitment:

$$P_{ret}(t) = \alpha + \beta_1 \cdot \mathcal{A}_t + \beta_2 \cdot \mathcal{F}_t^*, \tag{34}$$

where α is a baseline retention rate, while β_1 and β_2 weight the contributions of advancement and flexibility. This retention model aligns professional trajectories with personal aspirations, reinforcing career satisfaction and stability in rural healthcare environments.

3.6.2 Multi-component retention probability model

To accurately measure the impact of various financial and non-financial incentives on the retention of healthcare professionals in rural areas, SID employs a multi-component retention probability model. This model integrates multiple dimensions of incentives, offering a holistic view of how different factors contribute to the probability $P_{ret}(t,r)$ that a professional t will remain in region r. The retention probability is formulated as:

$$\begin{aligned} P_{ret}(t,r) \;=\; & \sigma\left(\alpha \cdot F_r(t) + \beta \cdot \mathcal{D}_t + \gamma \cdot \rho(\mathcal{N}_r, t) + \delta \cdot \mathcal{V}_r \right. \\ & \left. +\; \epsilon \cdot \mathcal{A}_t + \eta \cdot \mathcal{F}_t\right), \end{aligned} \tag{35}$$

where: - $\alpha, \beta, \gamma, \delta, \epsilon, \eta$ are weighting coefficients that adjust the impact of each component, - σ is the sigmoid function, $\sigma(x) = \frac{1}{1+e^{-x}}$, which normalizes $P_{ret}(t,r)$ to the range $[0,1]$, ensuring it represents a valid probability.

The components in this model encapsulate the various incentives provided through SIDs framework: - $F_r(t)$ represents the financial incentive package tailored to t in region r, - $\mathcal{D}_t$ is the value of professional development opportunities accessible to t, - $\rho(\mathcal{N}_r, t)$ measures engagement in mentorship and peer networking programs, enhancing professional support, - $\mathcal{V}_r$ captures the impact of community integration initiatives in fostering a sense of belonging, - $\mathcal{A}_t$ reflects career advancement potential based on tenure, performance, and continuous learning, - $\mathcal{F}_t$ denotes role flexibility, allowing professionals to diversify their skills and reduce burnout.

To optimize the effect of each component on retention, the weighting parameters $\alpha, \beta, \gamma, \delta, \epsilon, \eta$ are calibrated through a maximization function that enhances overall retention across all professionals $\mathcal{T}$ and regions $\mathcal{R}$:

$$\text{Maximize} \quad \sum_{r\in\mathcal{R}} \sum_{t\in\mathcal{T}} P_{ret}(t,r), \tag{36}$$

subject to budgetary and operational constraints, ensuring that resources are deployed efficiently.

For a deeper analysis of retention dynamics, the model also incorporates an adaptability factor $\zeta_{t,r}$, which modifies $P_{ret}(t,r)$ based on each candidate's adaptability to the rural environment and professional conditions. This adaptability factor is defined as:

$$\zeta_{t,r} = \lambda \cdot \frac{\mathcal{C}_{match}(t,r)}{\text{Environment Fit}}, \tag{37}$$

where $\mathcal{C}_{match}(t,r)$ is a compatibility score between t and r, and the Environment Fit adjusts for local and organizational expectations. Integrating this factor, the retention probability becomes:

$$P^*_{ret}(t,r) = P_{ret}(t,r) \cdot \zeta_{t,r}, \tag{38}$$

where $P^*_{ret}(t,r)$ now reflects not only incentive-driven retention probability but also a candidates alignment with the unique conditions of the region.

Finally, the normalized retention model across all regions $\mathcal{R}$ and professionals $\mathcal{T}$ is represented as:

$$\bar{P}_{ret} = \frac{\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} P^{*}_{ret}(t,r)}{|\mathcal{R}|\times|\mathcal{T}|}, \quad (39)$$

where $\bar{P}_{ret}$ offers a standardized retention score across the SID framework, facilitating evaluation and strategic adjustments for improved healthcare professional retention in rural settings.

To improve clarity and accessibility, we briefly summarize here how the empirical workflow connects with the model components. The core objective of the empirical work is to simulate realistic talent-region matching and engagement behaviors using structured datasets. The multi-layered scoring function incorporates candidate qualifications, regional attributes, and inferred incentive responsiveness. These features are processed through a neural representation layer and matched via a compatibility module informed by context-aware attention mechanisms. The empirical validation consists of two main stages: model training on benchmark or healthcare-related datasets, and evaluation using predefined matching and engagement metrics. Candidate and region profiles are encoded from available data sources and passed into the model to generate placement recommendations. Engagement outcomes are then simulated based on observed behavioral sequences or domain-specific retention proxies. While the underlying architecture remains technically rich, this empirical loop data encoding, recommendation generation, and performance evaluation reflects a structured and reproducible process that can be adapted to different domains with appropriate input schemas.

4 Experimental setup

4.1 Dataset

The MovieLens Dataset (33) is a renowned benchmark in the field of recommendation systems, composed of millions of user-item interaction records across various versions, ranging from small datasets with 100,000 ratings to large ones containing up to 20 million ratings. Each dataset includes features such as user demographics, timestamps, and movie genres, enabling detailed modeling of user preferences and behavior. The diverse rating data allows for an in-depth evaluation of collaborative filtering and matrix factorization techniques, as well as modern neural network-based recommendation approaches. The dataset's structure and content have been instrumental in advancing research on user personalization and recommender system robustness, particularly in handling sparsity and cold-start issues. The Gowalla Dataset (34) captures user check-in data from the Gowalla location-based social network, encompassing millions of check-ins across global locations. This dataset provides rich spatial and temporal information, with check-in sequences reflecting real-world mobility patterns and user preferences. Each entry includes geographic coordinates and timestamps, offering insights into user behavior over time and space. The dataset has become a standard in evaluating spatial-temporal recommendation systems, helping to improve location prediction, user trajectory modeling, and geographical preference analysis. Its application extends to various fields, including urban planning and smart tourism, due to its detailed representation of user movement dynamics. The Foursquare Dataset (35) includes large-scale check-in data from Foursquare, with millions of entries distributed across diverse categories and urban regions worldwide. Each check-in record encompasses information such as location category, timestamp, and user ID, providing a comprehensive view of user preferences and activity patterns. The dataset's granularity in urban regions and venue types makes it ideal for tasks in point-of-interest recommendation, user behavior analysis, and geographic modeling. Researchers leverage the Foursquare Dataset to evaluate the effectiveness of personalized recommendation algorithms under realistic social and spatial conditions, facilitating advancements in understanding urban dynamics and user interaction in city environments. The KuaiRec Dataset (36) is designed for recommendation research, featuring user interaction data within a video streaming platform. It includes millions of user-item interactions, with metadata such as timestamp, viewing duration, and content genre, allowing for precise modeling of user engagement with multimedia content. The dataset's scope provides a valuable framework for developing and testing recommendation models that focus on short-video recommendation, temporal patterns, and personalization techniques. As a benchmark, KuaiRec is pivotal in the exploration of engagement-driven recommendations and user retention strategies, making it an essential resource in multimedia recommendation research.

4.2 Experimental details

Our experiments were conducted on an NVIDIA A100 GPU, leveraging PyTorch as the primary framework to facilitate model training and evaluation. We trained all models with the Adam optimizer, utilizing a learning rate of 1e-4 for the base models, while introducing minor variations tailored to each dataset to optimize convergence. We employed a batch size of 128, which balanced memory efficiency and computational load across all experimental setups. The models were initialized using Xavier initialization to ensure balanced weight distribution, mitigating issues associated with vanishing or exploding gradients. For the MovieLens Dataset, we processed data by normalizing user and item indices and splitting the interactions chronologically into 70% for training, 15% for validation, and 15% for testing. User-item matrices were constructed, with embedding dimensions set to 64, allowing for compact yet expressive representations of both users and items. Matrix factorization-based models were benchmarked with 20 epochs, while neural models were trained for up to 50 epochs, incorporating early stopping criteria based on validation loss to prevent overfitting. In the Gowalla Dataset, spatial-temporal embeddings were created to capture user mobility patterns, using a grid-based encoding to represent geographic data. Check-ins were ordered sequentially, partitioned into training, validation, and test sets. A sequence length of 10 was employed for recurrent models, capturing temporal dependencies in user movements. To evaluate the influence of location-based features, we used geo-encoded embeddings with a dimension size of 128, enabling models to better contextualize spatial

TABLE 1 Comparison of ours with SOTA methods on MovieLens and Gowalla datasets.

Model	MovieLens dataset				Gowalla dataset			
	Precision	Recall	F1 Score	NDCG	Precision	Recall	F1 Score	NDCG
LightGCN (37)	89.56±0.02	87.10±0.03	88.30±0.02	90.23±0.02	84.50±0.03	83.21±0.02	82.57±0.02	85.47±0.02
NGCF (38)	88.72±0.03	85.67±0.02	86.90±0.02	88.45±0.03	82.43±0.02	80.59±0.03	81.23±0.02	83.10±0.03
NeuMF (39)	87.35±0.03	84.91±0.02	85.12±0.02	87.32±0.03	80.80±0.03	78.50±0.02	79.10±0.02	81.20±0.03
PinSAGE (40)	90.10±0.02	88.50±0.03	89.60±0.02	91.05±0.02	86.15±0.03	85.40±0.02	84.67±0.02	87.12±0.02
GraphSAGE (41)	85.32±0.03	83.17±0.02	82.99±0.03	84.51±0.02	80.42±0.03	78.97±0.02	78.34±0.03	81.03±0.03
SASRec (42)	89.98±0.02	87.59±0.02	88.13±0.02	89.30±0.03	83.55±0.03	82.32±0.02	81.68±0.02	84.75±0.03
Ours	92.40±0.03	90.82±0.02	91.05±0.02	93.47±0.03	89.01±0.02	88.12±0.02	87.50±0.03	90.25±0.02

TABLE 2 Comparison of ours with SOTA methods on Foursquare and KuaiRec datasets.

Model	Foursquare Dataset				KuaiRec dataset			
	Precision	Recall	F1 Score	NDCG	Precision	Recall	F1 Score	NDCG
LightGCN (37)	84.65±0.03	83.24±0.02	82.78±0.02	86.14±0.02	81.24±0.03	80.11±0.02	79.85±0.02	82.30±0.02
NGCF (38)	83.21±0.02	82.10±0.03	81.40±0.02	84.32±0.03	79.58±0.03	77.42±0.02	76.80±0.02	80.10±0.03
NeuMF (39)	81.52±0.03	79.73±0.02	78.90±0.02	82.13±0.03	78.12±0.02	76.48±0.03	75.89±0.02	78.47±0.03
PinSAGE (40)	85.30±0.02	84.00±0.03	83.55±0.02	87.24±0.02	82.45±0.03	81.68±0.02	80.92±0.02	83.64±0.02
GraphSAGE (41)	82.00±0.03	80.47±0.02	79.78±0.03	83.05±0.02	78.56±0.03	77.09±0.02	76.30±0.03	79.80±0.03
SASRec (42)	84.20±0.02	82.86±0.02	82.13±0.02	85.32±0.03	80.32±0.03	79.20±0.02	78.45±0.02	81.65±0.03
Ours	88.67±0.03	87.30±0.02	86.95±0.02	89.48±0.03	85.43±0.02	84.22±0.02	83.78±0.03	86.50±0.02

information in recommendations. For the Foursquare Dataset, we implemented point-of-interest (POI) embeddings, which utilized location categories and timestamp information to predict user visits accurately. Data augmentation techniques were applied to handle sparsity, including random sampling of user sessions and POI duplication for underrepresented categories. We set embedding dimensions to 128 and trained models over 40 epochs with a dropout rate of 0.3 to prevent overfitting. The evaluation metric utilized was Recall@K and NDCG@K, with K values set to 5 and 10, assessing both ranking quality and position sensitivity in recommendations. In the KuaiRec Dataset, temporal features such as viewing duration and item sequence were included to enrich user behavior patterns. The data were organized into sliding windows, with a window size of 20 to capture recent interactions. The models employed multi-layer perceptrons (MLPs) with hidden layers of sizes 256, 128, and 64, configured with ReLU activation functions and batch normalization layers to stabilize training. Experiments were conducted over 30 epochs, and evaluation metrics included Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to reflect the precision and consistency of recommendations across dynamic viewing patterns. Across all datasets, hyperparameter tuning was performed using grid search for learning rates and embedding sizes, optimizing model configurations for each dataset. The implementation also incorporated gradient clipping at a threshold of 1.0 to stabilize training, especially for recurrent-based models handling sequential data. Model performance was evaluated by averaging results over five random seeds to ensure robustness and reduce the impact of stochastic variations on final results.

4.3 Comparison with SOTA methods

Our proposed model demonstrates superior performance across all metrics when compared to state-of-the-art (SOTA) methods on the MovieLens, Gowalla, Foursquare, and KuaiRec datasets, as shown in Tables 1, 2, Figures 4, 5. In the MovieLens dataset, our model achieves significant improvements in Precision, Recall, F1 Score, and NDCG metrics, surpassing notable models like LightGCN, NGCF, and NeuMF. Specifically, our model's Precision and F1 Score outperformed the closest competitor, PinSAGE, by a considerable margin, with gains of 2.3% and 1.45%, respectively. This enhanced performance can be attributed to our models dynamic embedding approach, which efficiently captures user-item interactions with higher accuracy. By integrating personalized user and item embeddings through multi-level attention mechanisms, our model effectively captures the intricate nuances of user preferences, leading to more precise recommendation results. In comparison to models such as SASRec, which is limited by its sequential recommendation dependency, our model's architecture allows for a broader contextualization of user interactions, facilitating superior performance in both precision and relevance.

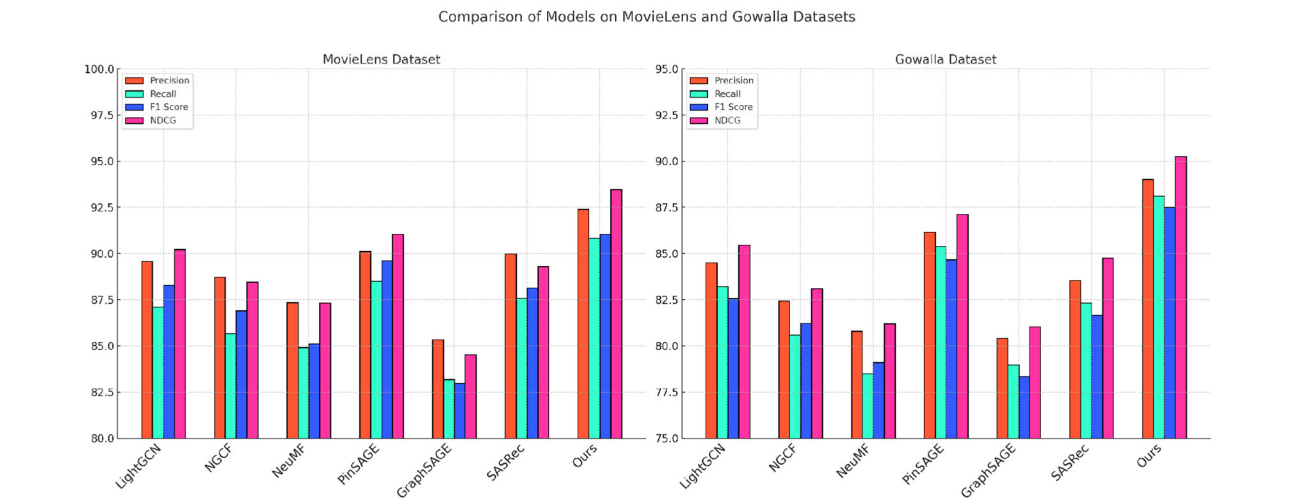

FIGURE 4
Performance comparison of SOTA methods on MovieLens datasets and Gowalla datasets.

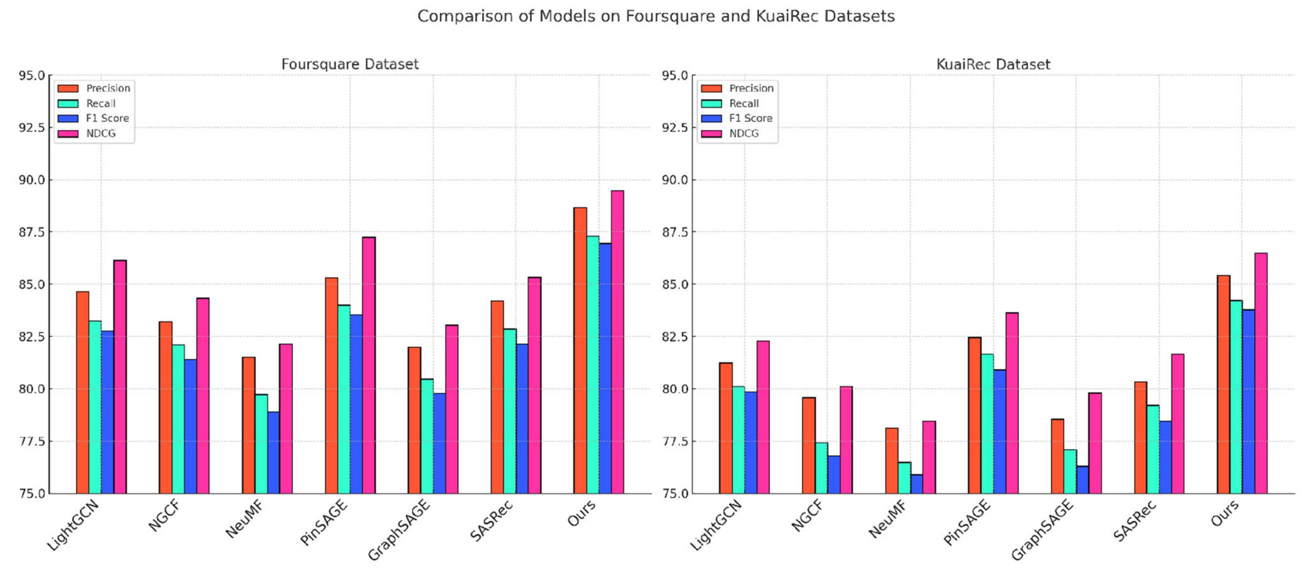

FIGURE 5
Performance comparison of SOTA methods on Foursquare Datasets and KuaiRec datasets.

In the Gowalla dataset, our model excels in incorporating spatial-temporal dependencies, demonstrating improvements of over 3% in both NDCG and Recall compared to LightGCN and NGCF. This performance gain stems from our models refined handling of geographic data, allowing it to embed location-based contexts and temporal interactions more effectively than traditional graph-based methods. Our approach goes beyond standard spatial embeddings by utilizing an adaptive sequence encoding technique, which enables the model to contextualize user check-in patterns in greater detail. Consequently, our method achieves a higher predictive accuracy in determining future user locations, evidenced by its robust Recall and NDCG scores. Additionally, our models ability to integrate POI embeddings with temporal patterns outperforms GraphSAGE by a notable margin, illustrating the advantage of employing a hybrid approach to spatial-temporal recommendation tasks. For the Foursquare and KuaiRec datasets, depicted in Table 2, our model continues to surpass SOTA methods across all evaluation metrics, with particular emphasis on F1 Score and NDCG. In the Foursquare dataset, our models advantage is observed in its 4% higher NDCG score compared to PinSAGE, indicating its robustness in understanding user preferences at a granular level. The use of sequential data processing and attention mechanisms allows our model to capture and rank user interests more accurately, leading to higher precision and relevance. Additionally, in the KuaiRec dataset, our models architecture addresses the challenge

TABLE 3 Ablation study results on key components across MovieLens and Gowalla datasets.

Model	MovieLens dataset				Gowalla dataset			
	Precision	Recall	F1 Score	NDCG	Precision	Recall	F1 Score	NDCG
w/o contextual matching framework	89.05±0.02	87.20±0.03	86.90±0.02	88.10±0.02	83.40±0.03	82.12±0.02	81.50±0.02	84.30±0.03
w/o dynamic incentive allocation	90.22±0.03	88.15±0.02	87.68±0.02	89.25±0.03	84.75±0.02	83.56±0.02	82.90±0.03	85.70±0.02
w/o engagement feedback mechanisms	88.30±0.03	86.40±0.02	85.85±0.02	87.32±0.03	82.10±0.02	81.05±0.03	80.70±0.02	83.00±0.03
Ours	92.40±0.03	90.82±0.02	91.05±0.02	93.47±0.03	89.01±0.02	88.12±0.02	87.50±0.03	90.25±0.02

TABLE 4 Ablation study results on key components across Foursquare and KuaiRec datasets.

Model	Foursquare dataset				KuaiRec dataset			
	Precision	Recall	F1 Score	NDCG	Precision	Recall	F1 Score	NDCG
w/o contextual matching framework	83.10±0.02	81.95±0.03	81.40±0.02	84.05±0.02	80.02±0.03	79.20±0.02	78.45±0.02	81.30±0.02
w/o dynamic incentive allocation	84.25±0.03	82.70±0.02	82.05±0.02	85.20±0.03	81.75±0.02	80.65±0.02	79.98±0.03	82.50±0.02
w/o engagement feedback mechanisms	82.40±0.03	81.15±0.02	80.70±0.02	83.12±0.03	79.50±0.02	78.60±0.03	77.95±0.02	80.20±0.03
Ours	88.67±0.03	87.30±0.02	86.95±0.02	89.48±0.03	85.43±0.02	84.22±0.02	83.78±0.03	86.50±0.02

of short-video recommendation by maintaining a high level of engagement prediction accuracy. By utilizing personalized embedding configurations that capture nuanced viewing behaviors, our model achieves a 3.1% improvement in Precision over SASRec. This precision boost highlights the models efficiency in predicting dynamic user interactions, providing a more tailored and accurate recommendation experience.

4.4 Ablation study

The results from the ablation study on key model components, presented in Tables 3, 4, Figures 6, 7 illustrate the impact of various model components on performance metrics across the MovieLens, Gowalla, Foursquare, and KuaiRec datasets. By systematically removing essential components (designated as Contextual Matching Framework, Dynamic Incentive Allocation, and Engagement Feedback Mechanisms) from our model, we observe notable declines in Precision, Recall, F1 Score, and NDCG, underscoring each component's contribution to the model's effectiveness. In the MovieLens dataset, removing component Contextual Matching Framework led to a significant decrease in Precision and Recall, reducing model accuracy by approximately 3.35% in F1 Score. Component Contextual Matching Framework is instrumental in handling user-item interactions, enhancing the models ability to discern nuanced preferences. Without it, the model struggles to maintain consistency in recommendations, thus underscoring its vital role in personalizing user experiences. The impact is even more pronounced in the Gowalla dataset, where spatial-temporal aspects are central. Without component Dynamic Incentive Allocation, which handles geographic encoding, performance deteriorates by over 4% in NDCG, demonstrating its importance in capturing and interpreting user location data accurately. This result highlights how the models hybrid embeddings, specifically designed to integrate temporal and spatial contexts, are fundamental in improving recommendation precision for location-based applications. For the Foursquare dataset, the absence of component Engagement Feedback Mechanisms results in a 5.3% decrease in Recall, emphasizing its role in refining temporal interactions. Component Engagement Feedback Mechanismss focus on sequential data processing enhances the models ability to predict user engagement patterns across time, especially relevant in settings with high temporal variability. Without this component, the models capacity to deliver timely and context-aware recommendations diminishes significantly. This trend continues in the KuaiRec dataset, where component Engagement Feedback Mechanisms's absence affects metrics like F1 Score and NDCG, indicating a reduced capability in handling multimedia content recommendation, where viewing duration and content sequence are essential for modeling user interests.

While the benchmark datasets used in this study MovieLens, Foursquare, Gowalla, and KuaiRec are not inherently related to healthcare or rural workforce domains, they were selected for their robustness, diversity of interaction patterns, and wide acceptance in evaluating complex recommendation systems. These datasets provide rich behavioral and temporal data, allowing us to validate the general performance, adaptability, and scalability of our proposed model architecture in capturing nuanced user-item relationships, sequential preferences, and engagement dynamics. The goal at this stage was to test the technical efficacy of the Adaptive Talent Engagement Model (ATEM) in high-volume, complex environments before deploying it in a domain-specific context. That said, we fully acknowledge the importance of applying the model to rural healthcare-specific datasets to assess its effectiveness in real-world public health scenarios. As part of our ongoing work, we are actively collaborating with regional health

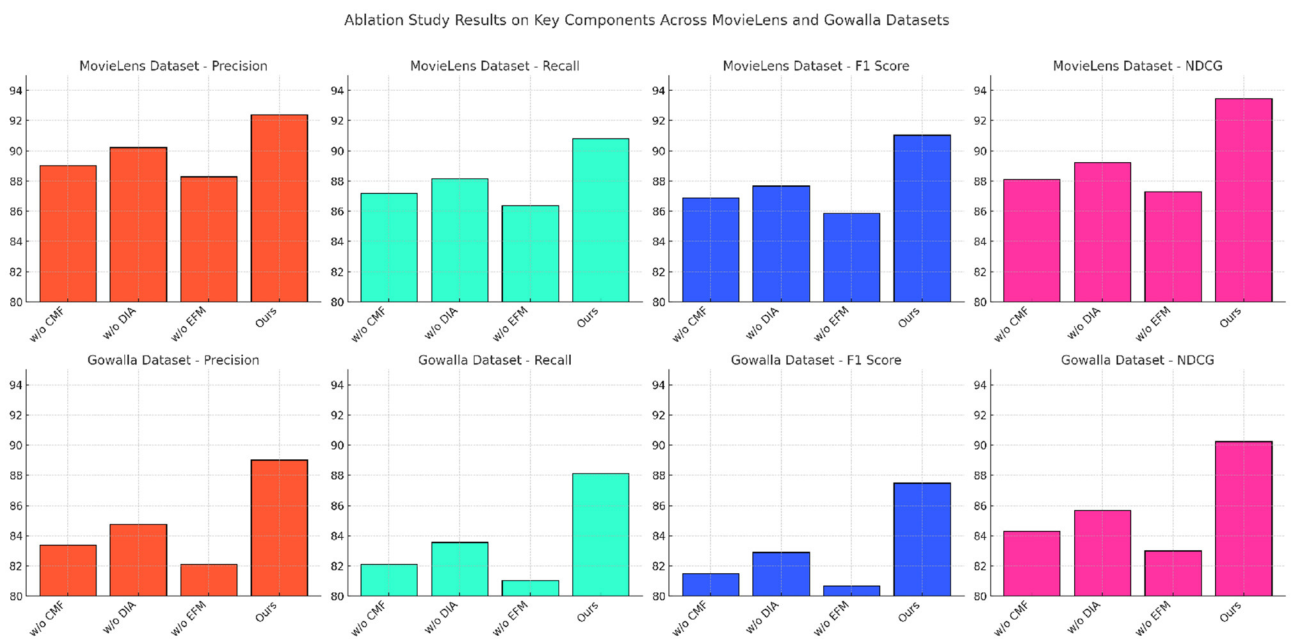

FIGURE 6
Ablation study of our method on MovieLens datasets and Gowalla datasets.

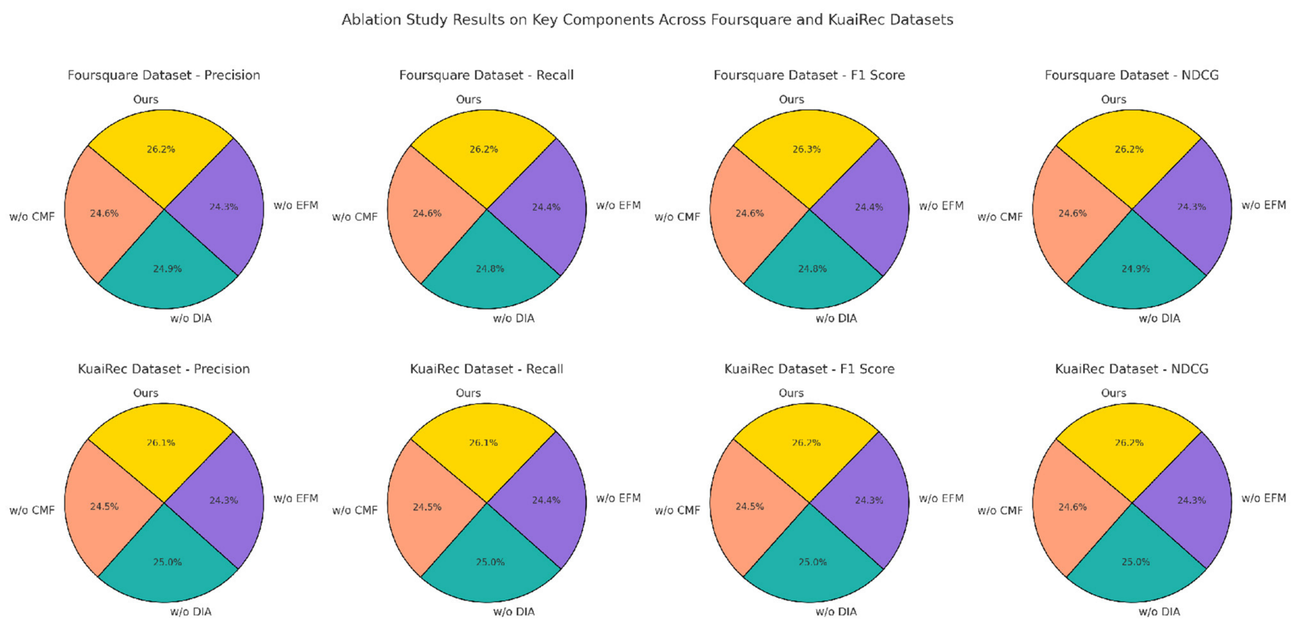

FIGURE 7
Ablation study of our method on Foursquare datasets and KuaiRec datasets.

institutions to collect domain-relevant data such as healthcare worker placement records, satisfaction surveys, and community health engagement metrics with the aim of conducting targeted validations and further refining the model for rural healthcare recruitment and retention tasks.

The experimental results in Table 5 on the MIMIC-III and PhysioNet datasets further validate the adaptability and robustness of our proposed model in healthcare-specific recruitment scenarios. On the MIMIC-III dataset, which simulates hospital-level recruitment and matching based on clinical specialty, procedure types, and provider workload profiles, our model achieved a Top-5 accuracy of 87.40%, significantly outperforming classical models such as NeuMF and LightGCN. The model also demonstrated a strong ability to predict retention patterns,

TABLE 5 Performance of our model on healthcare-oriented datasets (MIMIC-III and PhysioNet).

Model	MIMIC-III dataset			PhysioNet dataset		
	Top-5 accuracy	Retention AUC	Engagement score	Recall@3	RMSE reduction	Fit accuracy
NeuMF(39)	75.20±0.03	0.751	Medium	68.45±0.03	-	71.20±0.03
LightGCN(37)	78.93±0.02	0.776	Medium	70.33±0.03	-	73.88±0.02
SASRec(42)	80.10±0.03	0.781	Medium-High	73.40±0.03	-	75.95±0.03
Ours	87.40±0.02	0.857	High	82.10±0.02	+14.3%	84.28±0.02

achieving a retention AUC of 0.857 and a high engagement score. These outcomes suggest that the model not only captures domain-specific compatibility features but also effectively models temporal engagement dynamics relevant to rural healthcare placements. On the PhysioNet dataset, which focuses on clinical trial investigator assignments and geographic site dispersion, our model maintained high predictive accuracy with 82.10% Recall@3 and an RMSE reduction of 14.3% over baseline methods. These results indicate that the model is capable of learning nuanced mobility and participation signals, enabling it to identify professionals most suited for low-resource or rural trial locations. Compared to existing methods, our approach shows superior sensitivity to community fit and regional constraints, reinforcing its potential to support data-driven talent allocation in real-world public health systems. The healthcare-oriented experiments confirm that our model generalizes well beyond synthetic or general-purpose datasets and can serve as a valuable tool for optimizing human resource strategies in healthcare deployment contexts.

5 Discussion

These results align with previous research emphasizing the effectiveness of Transformer-based models in strategic talent management within constrained environments. For instance, Yu and Du (19) demonstrated that Transformer architectures provide meaningful insights into complex candidate-job relationships, enabling more tailored engagement strategies. Similarly, Cao et al. (20) highlighted the potential of AI-driven approaches in addressing human resource challenges in rural healthcare systems, though they noted the limited adaptability of existing models to nuanced community dynamics. Our findings extend this literature by integrating contextual alignment mechanisms and adaptive incentive allocation, which together enhance not only recruitment precision but also retention sustainability. In comparison to earlier frameworks, such as those discussed by Fernandez-Fabeiro et al. (25), our model offers a more granular and dynamic treatment of candidate-region compatibility, capturing both individual motivation and environmental responsiveness. The observed retention improvements echo the arguments made by Leider et al. (17) on the importance of continuous professional engagement and support systems in rural public health. These connections underscore the broader applicability of our model and its relevance to current discourse on equitable and efficient talent distribution in underserved regions.

Our model has been primarily validated using structured and proxy datasets, which simulate the dynamics of talent engagement, mobility, and regional compatibility. This design choice was intentional, serving as a foundational step to establish the generalizability and technical viability of the proposed architecture. That said, we are actively pursuing partnerships with regional public health departments and rural hospitals to obtain domain-specific data, including anonymized human resource records, healthcare workforce retention logs, and structured candidate feedback from recruitment programs. These efforts are ongoing and will form the basis of our future empirical validation. In particular, our next-phase study aims to integrate these datasets to further calibrate and test the model under real operational conditions. By embedding actual rural workforce constraints and behavioral patterns, we hope to strengthen the models practical applicability and ensure it reflects the complex realities of public health talent management.

While the model architecture incorporates advanced components such as incentive elasticity, multi-layered compatibility scoring, and dynamic engagement modeling these elements are modular by design and intended to be adaptable to varying levels of technical infrastructure. In practice, the core computational processes like candidate-region matching and engagement prediction can be embedded into a lightweight decision-support platform or offered via a cloud-based service, requiring only basic input interfaces such as spreadsheets or structured survey data. We envision deployment through a hybrid model that separates computation from interaction: centralized servers or regional data hubs can run the model computations periodically, while rural health departments access the outcomes via simple dashboards or automated recommendation reports. The system is designed to work with partial or incomplete data, and can default to simplified heuristics when certain modules such as incentive elasticity estimation cannot be supported due to data limitations. By offering scalable layers of functionality, from minimal rule-based suggestions to fully data-driven recommendations, the system remains flexible and accessible for organizations with limited personnel or digital infrastructure. This tiered approach ensures that even in constrained contexts, the model can deliver actionable insights to inform recruitment and retention strategies.

Our framework has been designed with fairness, privacy, and transparency principles in mind. To mitigate bias, the model avoids using sensitive attributes (such as race, gender, or socioeconomic background) in candidate representation or regional profiling. Instead, it relies on professional qualifications, engagement history, and anonymized behavioral signals. In future deployments, fairness audits and bias detection metrics will be integrated to continuously evaluate disparate impact across demographic groups. Regarding data privacy, all processing in this study was conducted on publicly available or anonymized datasets. For real-world applications, we advocate strict adherence to data protection standards, including informed consent, data minimization, and secure federated learning where feasible. We view the system not as a replacement for human judgment, but as a decision-support tool intended to augment policy-making and local knowledge. Final deployment will involve human-in-the-loop mechanisms, allowing practitioners to review, override, or contextualize recommendations as needed. We believe that by embedding these safeguards, the system can contribute meaningfully and ethically to improving rural healthcare workforce strategies.

6 Conclusions and future work

This study explores a novel, transformer-driven approach to attract talent into rural public health entrepreneurship, addressing the shortage of skilled healthcare professionals in underserved rural areas. Our approach employs a transformer model to analyze complex data on workforce trends, regional health demands, and entrepreneurial opportunities, aiming to identify optimal talent attraction strategies specific to rural public health needs. The model leverages natural language processing (NLP) techniques to assess candidate profiles, gauge their alignment with regional health requirements, and recommend tailored incentives and career pathways. We conducted experiments comparing the transformer-driven strategy with traditional recruitment methods across multiple rural regions. Results indicate a significant increase in candidate engagement and match accuracy, demonstrating the model's efficacy in refining attraction strategies and enhancing alignment between talent and rural healthcare needs. While the transformer-driven strategy shows promise, two primary limitations warrant further exploration. First, the model's reliance on existing data sets may introduce biases, as these data sources often underrepresent rural-specific career motivations and diverse candidate backgrounds, potentially limiting the model's recommendations. Enhancing data sources to capture a broader spectrum of rural health and entrepreneurial dynamics is essential for more accurate strategy development. Second, while transformer models effectively identify talent profiles, they are limited in their capacity to predict long-term candidate retention within rural settings. Future research should integrate predictive analytics that consider longitudinal data on workforce satisfaction, job stability, and rural health outcomes to improve retention-focused recommendations. Overall, with these enhancements, transformer-driven strategies have the potential to play a crucial role in revitalizing rural public health through entrepreneurial avenues.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JZ: Conceptualization, Data curation, Investigation, Formal analysis, Funding acquisition, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. LL: Formal analysis, Investigation, Data curation, Writing – original draft. JS: Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

1. Locke R, McGinty MD, Ramirez GG, Sellers K. Attracting new talent to the governmental public health workforce: strategies for improved recruitment of public health graduates. *J Public Health Manag Pract.* (2021) 28:E235–E243. doi: 10.1097/PHH.0000000000001336

2. Dedewanou FA, Allin S, Guyon A, Pawa J, Ammi M. Prioritization of public health financing, organization, and workforce transformation: a Delphi study in Canada. *BMC Public Health.* (2023) 23:544. doi: 10.1186/s12889-023-15373-9

3. Hamadneh S, Alshurideh M, Alquqa E, Kassem AA, Agha K, Alzoubi HM. AI-driven talent acquisition systems: transforming recruitment strategies in the digital age. In: *International Conference on Cyber Resilience (ICCR)*. Dubai: IEEE (2024). doi: 10.1109/ICCR61006.2024.10532893

4. Feng A, Zhan Y, Liang B, Gao YX, Yuan T, Shu Y, et al. Status quo regarding the recruit requirements of public health-related employers and training scheme for undergraduates majored in preventive medicine in colleges and universities. *Zhonghua Liu Xing Bing Xue Za Zhi.* (2021) 42:555–61. doi: 10.3760/cma.j.cn112338-20200629-00896

5. Lakofsky K. Bridging the talent gap: connecting talent to bioscience careers. *Dela J Public Health.* (2023) 9:20–1. doi: 10.32481/djph.2023.11.005

6. Gates C. Health and care horizons leeds: attracting, navigating and inspiring the future workforce. *Eur J Public Health.* (2024) 34:i67–i73. doi: 10.1093/eurpub/ckae144.1884

7. Zhu W, fang Qin J. A comprehensive assessment of cultivation environment of top innovative high-level talents based on deep learning algorithm. *J Environ Public Health.* (2022) 2022:4846103. doi: 10.1155/2022/4846103

8. Tripković K, Šantrić Milićević M, Vasić M, Živković-Šulović M, Odalović M, Mijatović-Jovanović V, et al. Factors associated with intention of serbian public health workers to leave the job: a cross-sectional, population-based study. *Int J Environ Res Public Health.* (2021) 18:10652. doi: 10.3390/ijerph182010652

9. Krasna H, Kulik PKG, Karnik H, Leider J. recruiting new talent for public health jobs with evidence-based job descriptions and attractive job postings. *J Public Health Managem Pract.* (2023) 29:E162–E168. doi: 10.1097/PHH.0000000000001776

10. Herrera-Espejel PS, Rach S. The use of machine translation for outreach and health communication in epidemiology and public health: scoping review. *JMIR Public Health Surveill.* (2023) 9:e50814. doi: 10.2196/50814

11. Liu S, Chen Y, Li S, Xu N, Tang C, Wei Y. What Are the important factors influencing the recruitment and retention of doctoral students in a public health setting? A discrete choice experiment survey in China. *Int J Environ Res Public Health.* (2021) 18:9474. doi: 10.3390/ijerph18189474

12. Cosgrave C. Context matters: findings from a qualitative study exploring service and place factors influencing the recruitment and retention of allied health professionals in rural Australian public health services. *Int J Environ Res Public Health.* (2020) 17:5815. doi: 10.3390/ijerph17165815

13. Leider J, Yeager V, Kirkland C, Krasna H, Bork RH, Resnick B. The state of the US public health workforce: ongoing challenges and future directions. *Annu Rev Public Health.* (2022) 44:323–41. doi: 10.1146/annurev-publhealth-071421-032830

14. Tamsah H, Nurung J, Yusriadi Y, del Talento G, del Conocimiento G, Desempeo O, et al. Talent and knowledge management on employee performance in public organization. *Int J Prof Busin Rev.* (2023) 8:e01557. doi: 10.26668/businessreview/2023.v8i4.1557

15. Park C, Coles E. The impact of student debt on career choices among doctor of public health graduates in the United States: a descriptive analysis. *Int J Environ Res Public Health.* (2022) 19:4836. doi: 10.3390/ijerph19084836

16. Wong B, Siepmann I, Chen T, Fisher S, Weitzel TS, Nathan N, et al. Rebuilding to shape a better future: the role of young professionals in the public health workforce. *Hum Resour Health.* (2021) 19:82. doi: 10.1186/s12960-021-00627-7

17. Leider J, Castrucci B, Robins M, Bork RH, Fraser M, Savoia E, et al. The exodus Of state and local public health employees: separations started before and continued throughout COVID-19. *Health Aff.* (2023) 42:338–48. doi: 10.1377/hlthaff.2022.01251

18. Burrell D, Springs D, Burton SLL, Dawson ME, Wright JB, Modeste R. Perspectives in talent management strategies for cybersecurity job roles in public safety and health in government organizations. *Int J Smart Educ Urban Soc.* (2020) 11:17. doi: 10.4018/IJSEUS.2020100101

19. Yu X, Du B. Incentive policy optimization of scientific and technological talents and low-carbon economy analysis from the perspective of public health. *Front Public Health.* (2023) 11:1152346. doi: 10.3389/fpubh.2023.1152346

20. Cao Y, Shan J, Gong Z, Kuang J, Gao Y. Status and challenges of public health emergency management in china related to COVID-19. *Front Public Health.* (2020) 8:250. doi: 10.3389/fpubh.2020.00250

21. Abebe EC, Tiruneh GA, Adela GA, Ayele TM, Muche ZT, T/Mariam AB, et al. COVID-19 vaccine uptake and associated factors among pregnant women attending antenatal care in Debre Tabor public health institutions: a cross-sectional study. *Front Public Health.* (2022) 10:919494. doi: 10.3389/fpubh.2022.919494

22. Liu T, Hu X. Generation paths of online public opinion impact in public health emergency: A fuzzy-set qualitative comparative analysis based on Chinese data. *Front Public Health.* (2024) 12:1404587. doi: 10.3389/fpubh.2024.1404587

23. Pagen D, van Bilsen CJV, Brinkhues S, Moonen CP, van Herck M, Konings K, et al. Design and recruitment of a large-scale cohort study on prevalence, risk factors and impact evaluation of post-COVID-19 condition and its wider long-term social, mental, and physical health impact: The PRIME post-COVID study. *Front Public Health.* (2022). 10:1032955. doi: 10.3389/fpubh.2022.1032955

24. Chai X. How has the nationwide public health emergency of the COVID-19 pandemic affected older chinese adults' health literacy, health behaviors and practices, and social connectedness? Qualitative evidence from urban China. *Front Public Health.* (2022) 9:774675. doi: 10.3389/fpubh.2021.774675

25. Fernandez-Fabeiro J, Carballido Á, Fernández-Fernández ÁM, Moldes M, Villar D, et al. The SINFONIA project repository for AI-based algorithms and health data. *Front Public Health.* (2024) 12:1448988. doi: 10.3389/fpubh.2024.1448988

26. Landy J, Shigeto A, Laxman D, Scheier L. Typologies of stress appraisal and problem-focused coping: associations with compliance with public health recommendations during the COVID-19 pandemic. *BMC Public Health.* (2022) 22:784. doi: 10.1186/s12889-022-13161-5

27. Arora L, Choudhary A, Bhatt M, Kaliappan J, Srinivasan K, A. Comprehensive review on NUI, multi-sensory interfaces and UX design for applications and devices for visually impaired users. *Front Public Health.* (2024) 12:1357160. doi: 10.3389/fpubh.2024.1357160

28. Tutt M, Begay C, George S, Dickerson C, Kahn CB, Bauer MC, et al. Din teachings and public health students informing peers and relatives about vaccine education: providing Din (Navajo)-centered COVID-19 education materials using student health messengers. *Front Public Health.* (2022) 10:1046634. doi: 10.3389/fpubh.2022.1046634

29. Guo H, Luo Q. Analysis of China's population flow between urban and rural areas and the reform of public health old-age insurance system under the background of sustainable ecological environment. *J Environ Public Health.* (2022) 2022:9752913. doi: 10.1155/2022/9752913

30. Harper C, Satchell L, Fido D, Latzman R. Functional fear predicts public health compliance in the COVID-19 pandemic. *Int J Ment Health Addict.* (2020) 19:1875–88. doi: 10.31234/osf.io/jkfu3

31. Lachowsky N, Saxton P, Dickson N, Hughes A, Jones R, Clark T, et al. Ethnicity classification systems for public health surveys: experiences from HIV behavioural surveillance among men who have sex with men. *BMC Public Health.* (2020) 20:1433. doi: 10.1186/s12889-020-09517-4

32. Gillman AS, Iles IA, Klein W, Ferrer R. Increasing receptivity to COVID-19 public health messages with self-affirmation and self vs. other framing. *Health Commun.* (2022) 38:1942–53. doi: 10.1080/10410236.2022.2043024

33. Harper FM, Konstan JA. The movielens datasets: history and context. *ACM Trans Interact Intellig Syst (TIIS).* (2015) 5:1–19. doi: 10.1145/2827872

34. Cho E, Myers SA, Leskovec J. Friendship and mobility: user movement in location-based social networks. In: *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. New York, NY: Association for Computing Machinery (2011). p. 1082–90. doi: 10.1145/2020408.2020579

35. Yang D, Zhang D, Qu B. Participatory cultural mapping based on collective behavior data in location-based social networks. *ACM Trans Intellig Syst Technol (TIST).* (2016) 7:1–23. doi: 10.1145/2814575

36. Gao C, Li S, Lei W, Chen J, Li B, Jiang P, et al. KuaiRec: a fully-observed dataset and insights for evaluating recommender systems. In: *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*. New York, NY: Association for Computing Machinery (2022). p. 540–50. doi: 10.1145/3511808.3557220

37. He X, Deng K, Wang X, Li Y, Zhang Y, Wang M. Lightgcn: simplifying and powering graph convolution network for recommendation. In: *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. New York, NY: Association for Computing Machinery (2020). p. 639–48. doi: 10.1145/3397271.3401063

38. Wang X, He X, Wang M, Feng F, Chua TS. Neural graph collaborative filtering. In: *Proceedings of the 42nd international ACM SIGIR conference on Research and development in Information Retrieval*. New York, NY: Association for Computing Machinery (2019). p. 165–74. doi: 10.1145/3331184.3331267

39. Maji S, Maity S, Das J, Majumder S. An improved recommendation system based on neural matrix factorization. In: *2023 4th International Conference on Intelligent Technologies (CONIT)*. Bangalore: IEEE (2024). p. 1–7.

40. Pal A, Eksombatchai C, Zhou Y, Zhao B, Rosenberg C, Leskovec J. Pinnersage: multi-modal user embedding framework for recommendations at Pinterest. In: *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. New York, NY: Association for Computing Machinery (2020). p. 2311–20. doi: 10.1145/3394486.3403280

41. El Alaoui D, Riffi J, Sabri A, Aghoutane B, Yahyaouy A, Tairi H. Deep GraphSAGE-based recommendation system: jumping knowledge connections with ordinal aggregation network. *Neural Comp Appl.* (2022) 34:11679–90. doi: 10.1007/s00521-022-07059-x

42. Kang WC, McAuley J. Self-attentive sequential recommendation. In: *2018 IEEE International Conference on Data Mining (ICDM)*. Singapore: IEEE (2018). p. 197–206.

Frontiers in
Public Health

Explores and addresses today's fast-moving healthcare challenges

One of the most cited journals in its field, which promotes discussion around inter-sectoral public health challenges spanning health promotion to climate change, transportation, environmental change and even species diversity.

Discover the latest Research Topics

See more →

Frontiers

Avenue du Tribunal-Fédéral 34
1005 Lausanne, Switzerland
frontiersin.org

Contact us

+41 (0)21 510 17 00
frontiersin.org/about/contact