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Spatial linkage and integrated driving pathways of high-quality rural e-commerce development in the context of digital villages in China

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This study investigates the high-quality development of rural e-commerce in China, focusing on its role in bridging the urban-rural divide and supporting rural revitalization in the context of digital village initiatives. Using data from 31 provinces (2018–2022), we assess the development levels, spatial linkages, and key drivers of rural e-commerce. Employing a combination of game-theoretic weighting, a modified gravity model, social network analysis, and fuzzy-set qualitative comparative analysis (fsQCA), the study identifies significant regional disparities in e-commerce development. Key drivers include infrastructure, technology, and policy, with central provinces such as Henan and Shandong playing pivotal roles, while peripheral regions face challenges due to lower digital integration. The study highlights two primary pathways for development: one driven by infrastructure and productivity improvements, and the other by technological innovation. These findings offer policy recommendations for enhancing regional collaboration and reducing the urban-rural divide through targeted investments in infrastructure and digital integration.

KEYWORDS

rural e-commerce, high-quality development, spatial linkage network, digital villages, driving pathways

1 Introduction

E-commerce has profoundly impacted China's economy and society, becoming a key driver of GDP growth, transforming consumer behavior, and promoting social inclusivity. However, the industry also faces challenges such as data privacy, regulatory compliance, and sustainable development. In the future, China's e-commerce sector will continue to focus on global expansion, green logistics, and technological innovation while adapting to stricter regulatory environments to maintain its global leadership and drive long-term sustainable development.

Rural e-commerce has emerged as a transformative force in reshaping the socioeconomic landscapes of developing countries, particularly in China (Jin et al., 2020; Kou et al., 2022). With the advancement of the digital village strategy and rural revitalization initiatives, rural e-commerce is bridging the urban-rural divide, fostering economic inclusivity, and enhancing agricultural supply chains (Lin et al., 2021; Li and Qin, 2022; Liu et al., 2023). By 2023, China's rural e-commerce market had achieved an annual transaction volume of 2.49 trillion-yuan, accounting for 16.2% of the national e-commerce market (Shen et al., 2023). Beyond economic growth, rural e-commerce facilitates information dissemination, cultivates digital literacy, and integrates rural communities into the broader digital economy (Appels et al., 2018). However, despite its rapid growth, the development of rural e-commerce in China remains uneven, with substantial regional disparities that limit its potential for inclusive growth.

Research into rural e-commerce has yielded significant insights into its impacts on economic development, supply chain efficiency, and agricultural modernization (Su et al., 2021). For example, e-commerce platforms have enabled smallholder farmers to access broader markets and leverage digital tools to optimize production and logistics (Sotiriades et al., 2004). Studies have also highlighted the role of policy interventions, such as the digital village initiative, in fostering the growth of rural e-commerce (Song et al., 2022). Nevertheless, the bulk of these studies adopts localized or sector-specific perspectives, focusing primarily on individual success stories or isolated cases (Song, 2022). This fragmented approach overlooks the interconnected nature of rural e-commerce systems and the broader spatial dynamics that underpin them.

The central challenge lies in understanding the systemic spatial patterns and inter-regional dynamics of rural e-commerce development (Su et al., 2021; Sun and Li, 2022). Current research inadequately captures the spatial association networks that reflect flows of goods, information, and capital between regions (Roy, 2014; Reardon et al., 2021). Additionally, there is a lack of comprehensive analysis regarding the interplay of key drivers—such as digital infrastructure, agricultural productivity, and policy support—within complex configurational frameworks (O'Hara and Low, 2020). These gaps hinder the ability of policymakers and stakeholders to design targeted strategies that promote equitable and sustainable growth across regions.

To address these challenges, this study adopts an integrated approach that combines spatial network analysis and configurational analysis to investigate rural e-commerce development in China (Meng, 2021). By focusing on both spatial linkages and multi-factor interactions, the study provides a holistic understanding of the mechanisms driving high-quality rural e-commerce development (Lusso et al., 2006). Specifically, it seeks to identify regional hubs and spillover effects within the spatial association network, while also uncovering diverse pathways through which regions achieve success in rural e-commerce development.

To strengthen the theoretical framework, this study will more explicitly integrate existing theories from rural development, e-commerce, and spatial economics. Specifically, it will explore how the "digital divide" theory and spatial network theory can explain the interaction between digital village initiatives and rural e-commerce development. Digital village initiatives, through infrastructure development, improved digital literacy, and enhanced information flow, contribute to the advancement of rural e-commerce. Additionally, spatial economics and regional development theories help to explain how geographical location and resource flows influence rural e-commerce, particularly how spatial linkages facilitate or constrain collaboration and interaction between regions. By incorporating these theories, this study provides a more systematic understanding of how digital villages, through spatial linkages, promote high-quality rural e-commerce development.

The study employs a three-pronged methodology (Lin et al., 2016; Liu et al., 2020, 2024a). First, a composite index is developed to quantitatively evaluate the development levels of rural e-commerce across 31 provinces. This index integrates metrics related to economic performance, digital infrastructure, and agricultural productivity (Li et al., 2021). Second, spatial network analysis is conducted using a modified gravity model to construct the spatial association network. Key metrics such as centrality, density, and clustering coefficients are used to evaluate network structure (Li and Zhou, 2023). Finally, fuzzy set qualitative comparative analysis (fsQCA) is applied to identify the multi-factor configurations driving rural e-commerce development, emphasizing the interactions among technological, economic, and policy factors (Qun et al., 2023).

Preliminary findings indicate significant spatial disparities, with central provinces such as Henan and Hubei serving as key hubs in the rural e-commerce network, while peripheral regions like Qinghai and Tibet remain marginalized. The spatial analysis reveals strong spillover effects in highly connected regions, while the fsQCA results underscore the importance of tailored, multi-faceted strategies for achieving high-quality development (Qiu et al., 2024). Two primary pathways emerge: one driven by comprehensive improvements in infrastructure, agricultural productivity, and policy support, and another centered-on innovation-led growth (Raven et al., 2007; Rao et al., 2020).

The development of e-commerce in China demonstrates the deep integration of technological innovation and policy support, driving comprehensive economic and social transformation. This evolution can be divided into four stages. The first stage (late 1990s—early 2000s): In 1999, Alibaba was founded, followed by the launch of Taobao in 2003 and Alipay in 2004, which resolved trust issues in online payments and laid the foundation for e-commerce. The second stage (mid-2000s—2010s): In 2008, JD.com transitioned to a B2C platform, and by 2010, the proliferation of mobile internet began. In 2013, China became the world's largest online retail market, and in 2015, the "Internet Plus" initiative promoted the integration of e-commerce with traditional industries. The third stage (mid-2010s—present): In 2014, Alibaba launched the "Rural Taobao" project, and in 2016, Pinduoduo emerged as a major player. In 2017, the "Rural Revitalization Strategy" positioned rural e-commerce as a tool for poverty alleviation, and by 2018, rural online retail sales exceeded one trillion yuan. The fourth stage (late 2010s—future): In 2019, the new retail model matured, and in 2020, the COVID-19 pandemic accelerated the rise of live-streaming e-commerce. In 2021, cross-border e-commerce expanded significantly. Looking ahead, e-commerce will focus on AI, big data, and green logistics to promote sustainable development. These four stages highlight China's journey from the inception of e-commerce to its global leadership, reflecting continuous innovation and breakthroughs in technology, policy, and market dynamics.

The findings of this study can be further contextualized within the frameworks of the "digital divide" theory and spatial economics. The "digital divide" theory posits that disparities in access to digital technologies and infrastructure can exacerbate existing socioeconomic inequalities. Our results demonstrate that provinces with robust digital infrastructure, such as Zhejiang and Guangdong, exhibit significantly higher levels of rural e-commerce development. This aligns with the theory, as these regions benefit from enhanced information dissemination, improved digital literacy, and greater integration into the broader digital economy. Conversely, remote provinces like Qinghai and Tibet, which lag in digital infrastructure, remain on the periphery of the spatial linkage network, highlighting the persistent digital divide.

From a spatial economics perspective, the study reveals how geographical proximity and resource flows influence the formation of rural e-commerce networks. Spatial economics emphasizes the role of location and connectivity in economic development. Our analysis shows that central provinces such as Henan and Hubei serve as key hubs in the spatial linkage network, facilitating resource and information flows to less developed regions. This spatial spillover effect is crucial for understanding how regional disparities can be mitigated through enhanced connectivity and collaboration. The findings suggest that improving digital infrastructure in peripheral regions can reduce spatial inequalities by enabling these areas to better integrate into the national e-commerce network.

Moreover, the study's identification of two primary driving pathways—comprehensive and innovation-led—further underscores the interplay between digital infrastructure and spatial dynamics. The comprehensive pathway, driven by improvements in farmland scale, agricultural machinery, and technological innovation, highlights the importance of localized investments in digital and physical infrastructure. The innovation-led pathway, focused on technological advancements, demonstrates how innovation can transcend geographical barriers, enabling even remote regions to participate in the digital economy. These pathways align with the spatial economics theory, which suggests that targeted investments in infrastructure and technology can create positive externalities, fostering regional economic integration and reducing spatial disparities.

In conclusion, this study not only provides empirical evidence of the spatial patterns and drivers of rural e-commerce development but also contributes to the theoretical understanding of how digital infrastructure and spatial linkages can mitigate the digital divide and promote equitable economic growth. By integrating these theoretical perspectives, the study offers a more nuanced understanding of the mechanisms driving high-quality rural e-commerce development in China. China leads developing nations in rural e-commerce due to superior infrastructure (nationwide logistics/5G coverage), robust state policies (e.g., poverty alleviation subsidies), and scalable tech adoption (e.g., mobile payment). In contrast, peers face high logistics costs, spotty internet, and weak policy execution, hindering growth. China's model offers a replicable framework for emerging economies.

This study contributes to the theoretical understanding of rural e-commerce development by integrating spatial and systemic perspectives. Practically, it provides actionable insights for policymakers to enhance regional collaboration, allocate resources effectively, and design targeted interventions. By addressing both spatial dynamics and multi-factor configurations, the study offers a roadmap for fostering balanced and sustainable growth in China's rural e-commerce sector.

2 Materials and methods

2.1 The study area

The study area encompasses 31 provinces in mainland China, representing a diverse range of geographic, economic, and cultural contexts (Sun and Zhu, 2022; Sun et al., 2022). These provinces include economically advanced regions such as Zhejiang, Jiangsu, and Guangdong, which are characterized by robust digital infrastructure and mature e-commerce ecosystems. At the same time, the study also covers underdeveloped regions like Qinghai, Tibet, and Heilongjiang, where rural e-commerce faces challenges such as limited connectivity, low digital literacy, and fragmented supply chains (Sun and Li, 2022). This spatial heterogeneity provides a comprehensive basis for analyzing the disparities and interdependencies within China's rural e-commerce landscape (Su, 2020). Geographically, the study area spans from the eastern coastal areas, which serve as economic hubs, to the western and northern provinces, which are predominantly rural and agriculturally dependent (Su et al., 2024). The diverse socioeconomic and infrastructural conditions across these regions make them an ideal case for investigating spatial association networks and multi-factor configurations that drive high-quality rural e-commerce development.

2.2 Data collation

This study adopted a rigorous process to acquire data related to the development of rural e-commerce in China, providing a robust foundation for analyzing spatial correlation networks and configuration paths (Su et al., 2021). The research focuses on 31 provinces in China from 2018 to 2022. Data were sourced from authoritative statistical yearbooks and reports, including the "China Rural Statistical Yearbook", "China Population and Employment Statistical Yearbook", "China Social Statistics Yearbook", and reports from the Ali Research Institute and the "China Rural E-commerce Report" (Sun and Zhu, 2022; Table 1). Additionally, the inter-provincial spatial distance data were calculated using ArcGIS software by determining the straight-line distances between geometric centers of provinces.

During data preprocessing, missing values were filled using regression prediction, and the statistical criteria for all datasets were unified to ensure accuracy and consistency (Sousa et al., 2020). A comprehensive evaluation index system was constructed, incorporating 17 indicators across six dimensions: rural economic development, e-commerce scale, infrastructure, talent level, and brand building (Sotiriades et al., 2004; Song et al., 2024). The weights of these indicators were determined using the game

TABLE 1 Evaluation index system for rural e-commerce development in China.

Target layer	Element layer	Index layer	Formula	Data source	Weight		
					Objective weighting law	Subjective weighting law	Game theory and combination weighting method
China's rural e-commerce development Index	Rural economic development LEVEL	Rural per capita primary industry GDP	GDP of primary industry/rural population (ten thousand yuan)	/	0.011135	0.004982	0.016118
		Rural per capita disposable income	/	Obtained directly from statistical yearbook (yuan)	0.012132	0.017722	0.029854
		Engel coefficient of rural residents	Expenditure on tobacco and wine tasting/disposable income of rural residents (%)	/	0.004406	0.004202	0.008608
	Rural e-commerce development scales	Rural per capita of the province's e-commerce transaction volume	Provincial e-commerce transaction volume/rural population (yuan)	/	0.088314	0.018086	0.1064
		Retail sales of agricultural products	/	Obtained directly from rural e-commerce report (%)	0.047093	0.054258	0.101352
		Number of Taobao villages	/	Ali database	0.085996	0.162775	0.248772
		Number of enterprises with e-commerce activities	/	Obtained directly from statistical yearbook (one)	0.029906	0.018086	0.047992
	Rural e-commerce development capacity	Rural delivery routes	/	Obtained directly from statistical yearbook (km)	0.013667	0.007806	0.021473
		E-commerce demonstration village approved	/	Obtained directly from statistical yearbook (one)	0.018133	0.053489	0.071622
		Financial expenditure on rural agriculture, forestry, and water resources	/	Obtained directly from statistical yearbook (%)	0.008351	0.008491	0.016842
		Investment in fixed assets of agriculture, forestry, animal husbandry, and fishery	/	Obtained directly from statistical yearbook (%)	0.022019	0.021991	0.04401
	Rural e-commerce infrastructure	Number of rural mobile Internet users	/	Obtained directly from statistical yearbook (in person)	0.005954	0.008429	0.014384
		Rural network popularity	/	Statistics of Internet development in China (%)	0.008666	0.013381	0.022047
		Number of rural postal stations	/	Provincial postal industry development statistical bulletin (%)	0.016347	0.031861	0.048209

(Continued)

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TABLE 1 (Continued)

Target layer	Element layer	Index layer	Formula	Data source	Weight		
					Objective weighting law	Subjective weighting law	Game theory and combination weighting method
	Rural e-commerce talent level	Per capita years of education in rural areas	Number of illiterates * 1 + number of primary school education * 6 + number of junior high school education * 9 + number of high school and technical secondary school education * 12 + number of college degree or above * 16/total number of population over 6 years old (years)	/	0.003156	0.02471	0.027866
	Rural brand construction	Quantity of geographical indications of agricultural products	/	Obtained directly from statistical yearbook (a)	0.016809	0.024021	0.04083
		Integrity of the agricultural industry chain	/	Number of legal units in primary industry/total legal units (%)	0.013514	0.120107	0.133621

theory and combination weighting method, providing a composite measure of rural e-commerce development levels across provinces.

The 17 indicators selected for measuring rural e-commerce development comprehensively cover five key dimensions: rural economic performance, digital infrastructure, e-commerce scale, talent level, and brand building. Each dimension reflects a distinct aspect of the rural e-commerce ecosystem, ensuring a holistic evaluation of its development. To derive and validate the weights of these indicators, we used a systematic approach, ensuring that each indicator was carefully selected based on its ability to capture critical characteristics essential for rural e-commerce growth.

The derivation of indicator weights began with the application of a game-theoretic combination weighting method, where each dimension was analyzed for its influence on rural e-commerce development. In this method, the interaction between indicators within the same dimension and across dimensions was considered. For example, economic performance indicators, such as rural per capita primary industry GDP and the Engel coefficient, reflect the economic health of rural areas. These indicators were assigned higher weights due to their direct impact on purchasing power and market potential. Similarly, infrastructure indicators like the number of rural mobile internet users and the length of rural delivery routes were weighted based on their crucial role in enabling seamless e-commerce transactions.

To validate the derived weights, we used a multi-step process. First, a sensitivity analysis was conducted to test the robustness of the weights by adjusting the weights and observing the consistency of the results across different scenarios. This helped confirm the stability and reliability of the derived weights. Additionally, expert validation was performed through interviews with professionals in the field of rural e-commerce, allowing us to refine the weights based on real-world insights and practical considerations. Finally, we compared the derived weights with empirical findings from existing literature, ensuring that the weights aligned with established research and accurately reflected the importance of each factor in rural e-commerce development.

To ensure the independence and relevance of the selected indicators, factor analysis was employed to identify any potential correlations or overlaps among them. This statistical method ensured that each indicator contributed uniquely to the composite index, enhancing the validity and robustness of the overall measurement framework. By addressing any redundancies, the analysis guaranteed that the indicator weights accurately reflected the multifaceted nature of rural e-commerce development. This rigorous process not only validated the weights but also provided actionable insights for policymakers and stakeholders.

To construct the spatial correlation network, a modified gravity model was employed, integrating factors such as GDP, rural population, and rural e-commerce development levels to quantify the spatial interaction strength between provinces (Liu et al., 2020). The initial gravity matrix was then binarized to form a spatial correlation network (Skordos et al., 2021). Furthermore, social network analysis (SNA) techniques were applied to evaluate network characteristics, including overall structure, node centrality, and clustering features. To validate the approach of filling missing values using regression prediction, we conducted a sensitivity analysis to examine how different methods for handling missing data might influence the results. Specifically, we compared the outcomes of regression imputation with other common techniques, such as mean imputation and k-nearest neighbor imputation, to assess their impact on the overall findings. The sensitivity analysis demonstrated that while different methods lead to some variation in the results, the regression imputation approach provided the most consistent and reliable estimates for the missing data.

This data acquisition and processing method ensured comprehensive and scientifically sound data, laying a solid foundation for exploring the structural characteristics and driving factors of the rural e-commerce spatial correlation network.

2.3 Methods

2.3.1 Calculation method for spatial correlation strength

To quantitatively measure the spatial correlation strength of high-quality rural e-commerce development in China, this study integrates the theoretical framework of the traditional gravity model with the specific characteristics of rural e-commerce development, resulting in a refined and optimized model. In the traditional gravity model, spatial correlation strength is typically determined by the economic scale (e.g., GDP) of two regions and the reciprocal of the spatial distance between them (Singh et al., 2023). However, the complexity and multidimensionality of rural e-commerce necessitate adjustments to the model to better capture the nature of inter-regional e-commerce interactions. Thus, a composite rural e-commerce development index is incorporated into the model, alongside rural population and economic factors, to enhance its descriptive power (Sindhu and Anilkumar, 2022). The modified model is expressed as:

$$G_{ij} = K \cdot \frac{E_i \cdot E_j}{D_{ij}^{\beta}} \tag{1}$$

where, G_{ij} represents the spatial correlation strength between provinces i and j, E_i and E_j? denote the rural e-commerce development indices (derived from a comprehensive evaluation model), D_{ij} is the straight-line distance between the geometric centers of the two provinces, β is the spatial resistance coefficient, and K is a constant. In the modified gravity model, the spatial resistance coefficient (β) plays a critical role in determining the strength of interactions between regions. To ensure the appropriateness of the selected β, it was calibrated based on empirical data reflecting key regional factors such as transportation costs, infrastructure development, and connectivity. These factors are integral to the flow of goods, information, and services in the rural e-commerce landscape. A sensitivity analysis was carried out to test the robustness of the model under varying values of β. The sensitivity test covered a range of β values from 0.5 to 2.0, with step increments of 0.5. The analysis demonstrated that while variations in β influenced the strength of spatial correlations, the structural patterns of the network, including the positioning of central provinces (e.g., Henan, Hubei) and peripheral regions (e.g., Qinghai, Tibet), remained stable. This confirms that the model's findings are not highly sensitive to the exact value of β, ensuring the reliability and generalizability of the results. The rural e-commerce development index integrates key indicators across six dimensions: economic performance, infrastructure, logistics efficiency, digitalization, talent support, and brand building, comprehensively reflecting the capacities and characteristics of rural e-commerce development in each province (Zhu, 2023).

This refined model enables precise characterization of the spatial correlation network of rural e-commerce development, quantifying the intensity of resource, information, and market flows between regions. Additionally, by binarizing the correlation matrix, the model supports further analysis of network centrality, density, and clustering features, providing a scientific foundation for exploring the spatial patterns and driving mechanisms of high-quality rural e-commerce development. In the modified gravity model, key parameters such as the spatial resistance coefficient and the constant play a crucial role in determining the spatial interaction strength. To ensure their accuracy and relevance, these values were determined through a combination of prior research, calibration, and sensitivity analysis. Specifically, the spatial resistance coefficient was calibrated based on empirical data to reflect factors such as transportation costs, infrastructure development, and regional connectivity that influence the flow of goods and information in rural e-commerce. The constant value was derived using sensitivity analysis, where its value was adjusted to ensure the model's fit and the meaningfulness of the results. Additionally, the selection of these parameter values is informed by previous studies that have employed similar approaches in the context of rural development and e-commerce. This detailed explanation of the parameter determination process will be included in the revised methodology section to improve the transparency and robustness of the model.

2.3.2 Overall network structure analysis

The overall network structure is analyzed using metrics such as network relationships, density, connectedness, hierarchy, and efficiency (Shi et al., 2023). Network relationships represent the number of actual connections, reflecting the scale of resource and information flows between regions. Network density measures the closeness of connections; higher density indicates stronger inter-regional collaboration. Connectedness assesses network stability, with a value of 1 suggesting all nodes are reachable, indicating robust structure (Shen et al., 2023).

Network hierarchy reflects reliance on core nodes. High hierarchy indicates key nodes play critical roles but increases vulnerability if these nodes fail. In contrast, low hierarchy enhances fault tolerance. Network efficiency measures the ratio of actual to potential connections; while lower efficiency may indicate longer pathways, it also increases resilience. These metrics collectively reveal the spatial correlation characteristics of rural e-commerce development, providing insights for optimizing network structures.

2.3.3 Individual network structure analysis

The individual structure of a spatial correlation network can be quantified using degree centrality, closeness centrality, and betweenness centrality (Zhu et al., 2021). Degree centrality is a key metric for evaluating the influence of nodes within the network, reflecting the number of direct connections a node has, indicating its connectivity and influence. Nodes with higher degree centrality are likely to play a significant role in facilitating resource flow and information transmission. Closeness centrality measures the proximity of a node to all other nodes, with higher values indicating that a node can transmit information and drive resource flow more efficiently (Zhu, 2023). Betweenness centrality reflects how much a node acts as a bridge between other nodes. Nodes with higher betweenness centrality are crucial for controlling and coordinating resource flows across the network, significantly influencing its overall functionality.

2.3.4 Clustered network structure analysis

The analysis of clustered network structures aims to uncover the modular characteristics, hierarchical organization, and functional roles within the spatial correlation network (Zhu and Chen, 2016). This study employs spatial clustering techniques, utilizing iterative association convergence based on the relationship matrix to divide the spatial correlation network of high-quality rural e-commerce development in China into several functional blocks (Zhu and Chen, 2013). These interactions are systematically analyzed using the α-density evaluation mechanism, revealing the following typical network modules, (1) Net Outflow Blocks, characterized by resource output exceeding input, signifying a strong external transmission function and resource support role for other blocks; (2) Bidirectional Outflow Blocks, maintaining tight external resource exchanges while fostering active internal interactions, functioning as cooperative hubs in the rural e-commerce network; (3) Net Beneficiary Blocks, where resource reception surpasses output, serving as resource aggregation points with critical absorption roles; (4) Broker Blocks, which facilitate both outward resource diffusion and external resource absorption but exhibit limited internal interactions, acting as bridges within the network (Zhu and Luo, 2024). Analyzing these block-specific functions and interrelations enhances the understanding of hierarchical structures and synergistic mechanisms within the rural e-commerce spatial correlation network (Zhou, 2022).

2.3.5 QAP regression method

To further investigate the factors driving changes in the spatial correlation network of high-quality rural e-commerce development, this study employs the QAP (Quadratic Assignment Procedure) regression method (Zhou et al., 2024). QAP regression is a statistical approach specifically designed for analyzing social network data and effectively addresses multicollinearity issues among network variables. By employing randomization and permutation tests, QAP regression ensures the robustness and statistical significance of model parameter estimation, making it a reliable tool for analyzing the dynamic mechanisms of spatial correlation networks.

Specifically, the QAP regression process involves repeatedly permuting the rows and columns of the independent and dependent variable matrices to generate random samples (Zhou, 2024). By comparing the correlations between the original network matrix and the permuted matrices, the method identifies the true effect size and statistical significance of independent variables on the dependent variable. In this study, QAP regression is used to evaluate the influence of factors such as economic performance, digital infrastructure, logistics efficiency, and policy support on changes in the spatial correlation network of rural e-commerce development (Zhou et al., 2021). The findings reveal that certain key variables, such as policy support and digital infrastructure, play significant roles in enhancing network connectivity and optimizing its structure. The application of the QAP regression method effectively identifies the core factors influencing changes in the spatial correlation network of high-quality rural e-commerce development. This provides a clearer understanding of the relative importance of these factors and offers scientific evidence for policy formulation and regional coordinated development.

2.3.6 The fuzzy-set qualitative comparative analysis

The fuzzy-set qualitative comparative analysis (fsQCA) method is a set-theoretic analytical tool that examines how multiple factors collectively produce specific outcomes (Zhou, 2023). As an improved version of QCA, fsQCA handles the membership degrees of fuzzy sets, addressing endogeneity challenges often encountered in traditional correlation analysis. It is particularly suitable for small-sample studies, requiring only 4–8 condition variables to analyze causal configurations across 12–50 cases. Its flexibility and explanatory power make it a valuable tool for investigating the driving factors behind high-quality rural e-commerce development.

The calibration of variables in fsQCA is a critical step that transforms raw data into fuzzy sets. In this study, we employed percentile-based calibration, a widely used method in the fsQCA literature, to define the thresholds for full membership, crossover point, and full non-membership. While this approach may appear somewhat arbitrary, it is particularly useful when theoretical or empirical anchors are not readily available. To ensure the robustness of our calibration, we carefully considered the distribution of our data and aligned the percentiles with the theoretical expectations of rural e-commerce development. For instance, the 95th percentile was chosen as the threshold for full membership to capture the top-performing cases, while the 5th percentile was used for full non-membership to identify cases with minimal development. The crossover point was set at the 50th percentile to reflect the median level of development. Sensitivity analyses were conducted to assess the impact of different calibration thresholds on the results, confirming that the core findings remain consistent across alternative specifications. This approach provides a transparent and replicable basis for our analysis, while also accommodating the unique characteristics of our dataset.

Certain variables, such as economic development differences, were excluded from the fuzzy-set qualitative comparative analysis (fsQCA) due to their lack of statistical significance in influencing the spatial correlation network. While these variables are theoretically important, their absence of a clear and significant effect in the context of this study led to their exclusion. This ensures that the fsQCA focuses on the most impactful factors driving high-quality rural e-commerce development. However, it is crucial to recognize the potential for omitted variable bias. Economic development differences, for example, could influence e-commerce adoption indirectly through factors such as financial capacity or access to technological infrastructure. Similarly, cultural factors—such as local attitudes toward technology, entrepreneurship, or innovation—are likely to influence e-commerce adoption but were not explicitly considered in this study. These omitted variables may vary across regions and potentially affect the outcomes of rural e-commerce development. To mitigate this potential bias, future research should consider integrating cultural factors and other omitted variables into the analysis. Qualitative data, such as surveys or interviews, could be utilized to better understand the socio-cultural dynamics at play. Additionally, comparative studies across different regions or countries would help clarify how these omitted factors contribute to the adoption and success of rural e-commerce in varying contexts.

3 Results

3.1 Evaluation of high-quality development level of rural e-commerce in China

This study selects the years 2018, 2020, and 2022 as key time points to analyze the spatial distribution characteristics of high-quality rural e-commerce development in China. Using ArcGIS 10.8 software and the natural breaks classification method, the development levels of rural e-commerce across 31 provinces were graded, and spatial distribution maps were created (Zhou, 2023; Figure 1). The results reveal significant differences in the spatial distribution of rural e-commerce development across different periods.

In terms of the high-quality rural e-commerce development index, 14 provinces exceeded the national average level in 2018, with the top five provinces being Zhejiang, Shandong, Sichuan, Guangdong, and Guizhou. In 2020, the number of provinces above the national average remained at 14, but the top five provinces shifted to Zhejiang, Guangdong, Shandong, Sichuan, and Jiangsu. By 2022, the number of provinces above the national average decreased to 12, with the top five provinces being Zhejiang, Guangdong, Shandong, Jiangsu, and Sichuan. Zhejiang consistently ranked first nationwide during the observation years, with development indices of 2.920 (2018), 4.144 (2020), and 5.393 (2022), demonstrating sustained and rapid growth. Guangdong showed strong growth momentum, with indices of 2.478, 3.734, and 4.805 in 2018, 2020, and 2022, respectively. By 2022, Guangdong firmly occupied second place nationwide, creating a significant gap with Zhejiang and other provinces.

Overall, the spatial distribution of high-quality rural e-commerce development in China exhibits a pattern of "stronger in the east, weaker in the west", with eastern provinces outperforming their central and western counterparts. The "stronger in the east, weaker in the west" pattern observed in the spatial distribution of rural e-commerce development levels can be attributed to several historical and cultural factors. Historically, eastern China has experienced earlier industrialization and urbanization, leading to more robust infrastructure, greater access to capital, and a higher level of technological adoption. In contrast, the western regions, which are more rural and geographically isolated, have lagged in these areas. Additionally, cultural attitudes toward technology and entrepreneurship differ across regions, with the eastern regions having a more entrepreneurial culture fostered by historical economic development. The contrast in regional policies also plays a crucial role, with the eastern provinces often receiving more investment in digital infrastructure as part of broader economic reforms.

3.2 Evolution and structural trends of China's rural e-commerce spatial correlation network

The study found that the overall connectivity of China's rural e-commerce spatial correlation network increased between 2018 and 2022. As shown in Figure 2, the actual number of connections rose from 244 in 2018 to 250 in 2019 but temporarily declined to 247 in 2020 due to the impact of the COVID-19 pandemic, before recovering to 250 in 2022. The network density increased from 0.262 in 2018 to 0.269 in 2022, indicating that the interactive spillover effects and inter-provincial collaboration were gradually strengthened over time.

The network hierarchy index decreased from 0.375 in 2018 to 0.181 in 2022, suggesting a shift from a centralized to a more decentralized structure, with more frequent interactions among provinces and a trend toward network equilibrium. The network connectedness index remained at 0.972 in 2018 and 2019 and reached 1.000 from 2020 to 2022, indicating closer and more cohesive inter-provincial connections, forming a highly connected network structure. Meanwhile, network efficiency declined slightly from 0.699 in 2018 to 0.662 in 2022. Although efficiency decreased, this trend reflects an increase in internal connections and enhanced network stability.

In the spatial network structure, provinces such as Henan, Hubei, and Shandong consistently occupied central positions due to their advanced rural e-commerce development levels and favorable geographic conditions. These core provinces played a critical leading role in driving other regions through resource spillover effects (Liu, 2020). The observed decrease in network efficiency can have several significant implications for rural e-commerce development. Lower network efficiency often correlates with increased transaction costs, as information is less readily available and transactions become more time-consuming. The inefficiency of the network structure can result in fragmented information flow, causing delays in decision-making, inefficient supply chain management, and limited access to market information. As a result, rural businesses may struggle to respond swiftly to market demands, leading to missed opportunities and stunted growth. Moreover, inefficiencies in network connectivity can also reduce the overall effectiveness of marketing efforts, limit access to customer feedback, and hinder the rapid scaling of e-commerce platforms. Therefore, enhancing network efficiency should be a key focus for promoting the growth and sustainability of rural e-commerce initiatives. Overall, the spatial correlation network of high-quality rural

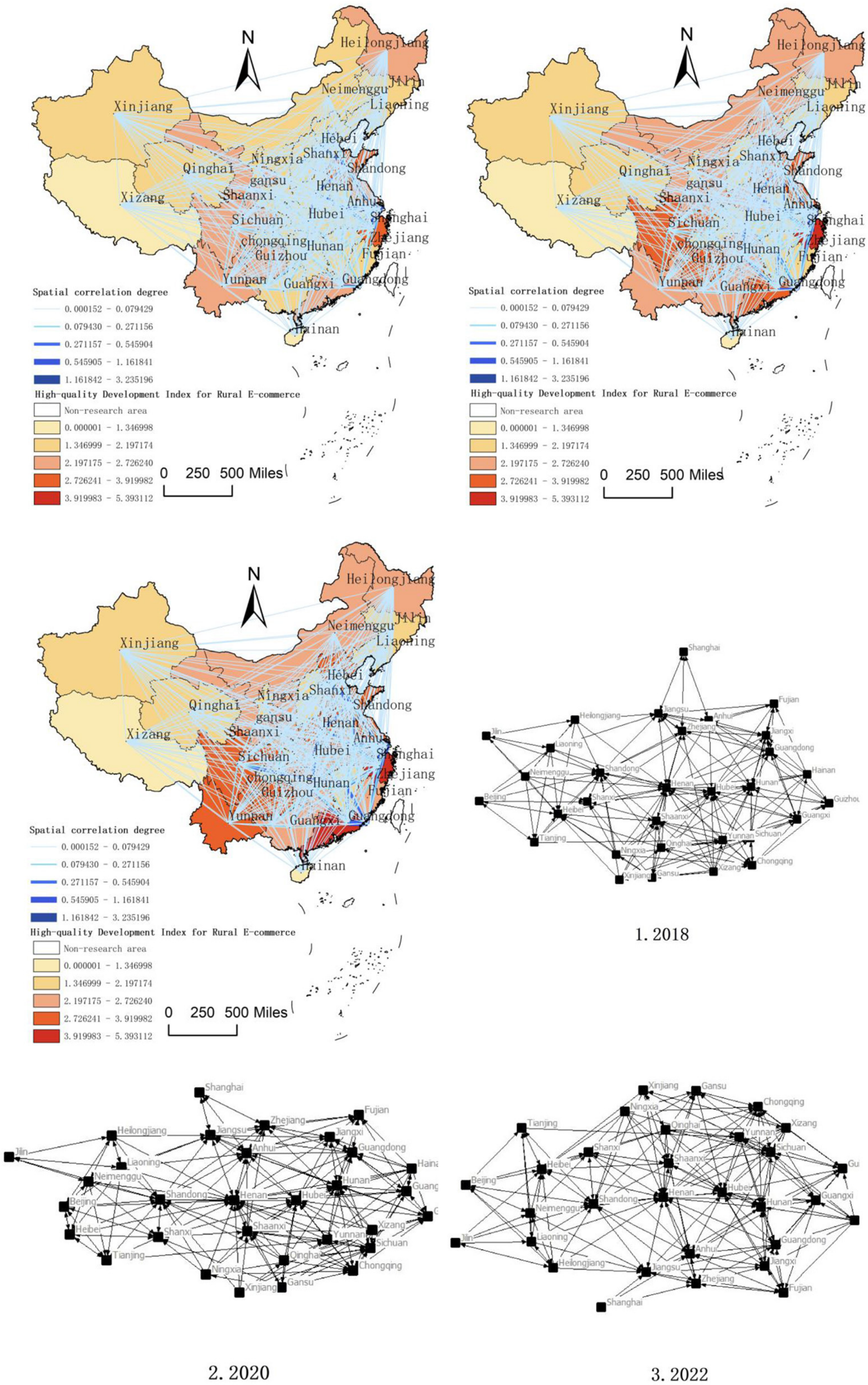

FIGURE 1
China's rural e-commerce development index map, spatial correlation network map, and network topology map. The map of this paper was based on the standard map of GS (2020) 4,619 standard map downloaded from the standard map service website of the Ministry of Natural Resources, and the base map was not modified.

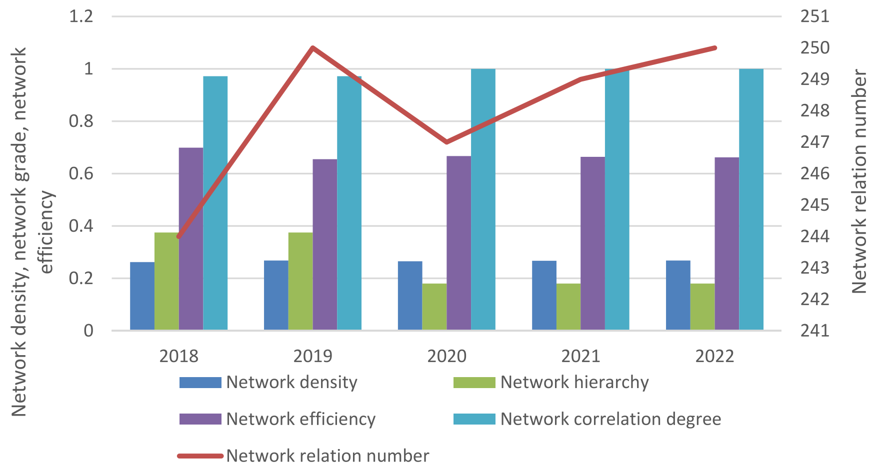

FIGURE 2
Overall network characteristics of rural e-commerce development space related network in China from 2018 to 2022.

e-commerce development in China exhibits a typical "strong center, weak periphery" pattern, forming a radiating network structure centered on central provinces. This trend provides important insights for optimizing regional coordination in rural e-commerce development.

The most significant barrier to e-commerce development in western provinces is the infrastructure gap. While eastern provinces benefit from robust digital infrastructure, efficient delivery networks, and better market access, western regions struggle with inadequate internet connectivity, fewer transportation routes, and less efficient logistics. These deficiencies limit the ability of rural businesses in the west to connect to broader e-commerce markets. The geographic isolation of western provinces, coupled with a reliance on traditional sectors like agriculture, further hampers the development of rural e-commerce. The difficult terrain and limited transportation infrastructure make it challenging to integrate these regions into the national e-commerce network. Future research could explore how tailored government policies, such as increased infrastructure investment or digital literacy programs, could support e-commerce development in western provinces. Additionally, qualitative research that examines local cultural and social factors could provide more detailed insights into the barriers that prevent the adoption of e-commerce in these marginalized areas.

3.3 Individual network characteristics and regional disparities in China's rural e-commerce

A higher degree centrality indicates that the node has stronger capabilities for resource flow and information dissemination (Figure 3). Overall, central provinces in China consistently occupy core positions within the spatial correlation network for high-quality rural e-commerce development, demonstrating their critical roles in the network structure (Liu et al., 2024b).

In 2018, the average degree centrality was 37.419, with 16 provinces scoring above the mean. The top five provinces were Henan, Hubei, Shandong, Hunan, and Sichuan, indicating their high level of network connections. The averages in 2020 and 2022 were 37.634 and 38.065, respectively, with little change in rankings; Henan and Hubei consistently remained at the top. Regarding in-degree centrality, the 2018 average was 7.871, with 16 provinces above the mean, led by Henan, Hubei, Shandong, Hunan, and Hebei. The averages in 2020 and 2022 were 7.968 and 8.065, respectively, and by 2022, the number of provinces exceeding the mean dropped to 13, with the top five being Henan, Hubei, Shandong, Hunan, and Anhui.

Regarding out-degree centrality, the 2018 average was 8.065, with provinces in western regions such as Qinghai, Tibet, Shaanxi, Guangxi, and Hainan exceeding the mean. In 2020, the average dropped slightly to 7.968, with top provinces including Tibet, Qinghai, Guangxi, Hunan, and Shaanxi. The average in 2022 rebounded to 8.065, with Tibet, Qinghai, Guangxi, and Shaanxi remaining in the lead, along with notable performances from Inner Mongolia and Hunan. This indicates that western regions hold certain advantages in resource output but generally exhibit weaker overall connectivity.

Specifically, Henan had degree centrality values of 80.000, 83.333, and 76.667 in 2018, 2020, and 2022, respectively, significantly outperforming other provinces. Its central location within China's economic geography, coupled with a large rural population, grants it substantial resource spillover effects. Hubei consistently ranked second, with degree centrality of 66.667 across all observation years. Its advantageous position as a transportation hub facilitates logistics, talent mobility, and commercial interactions, driving rural e-commerce development. Shandong and Hunan demonstrated strong resource attraction and exchange capacities due to their advanced economies,

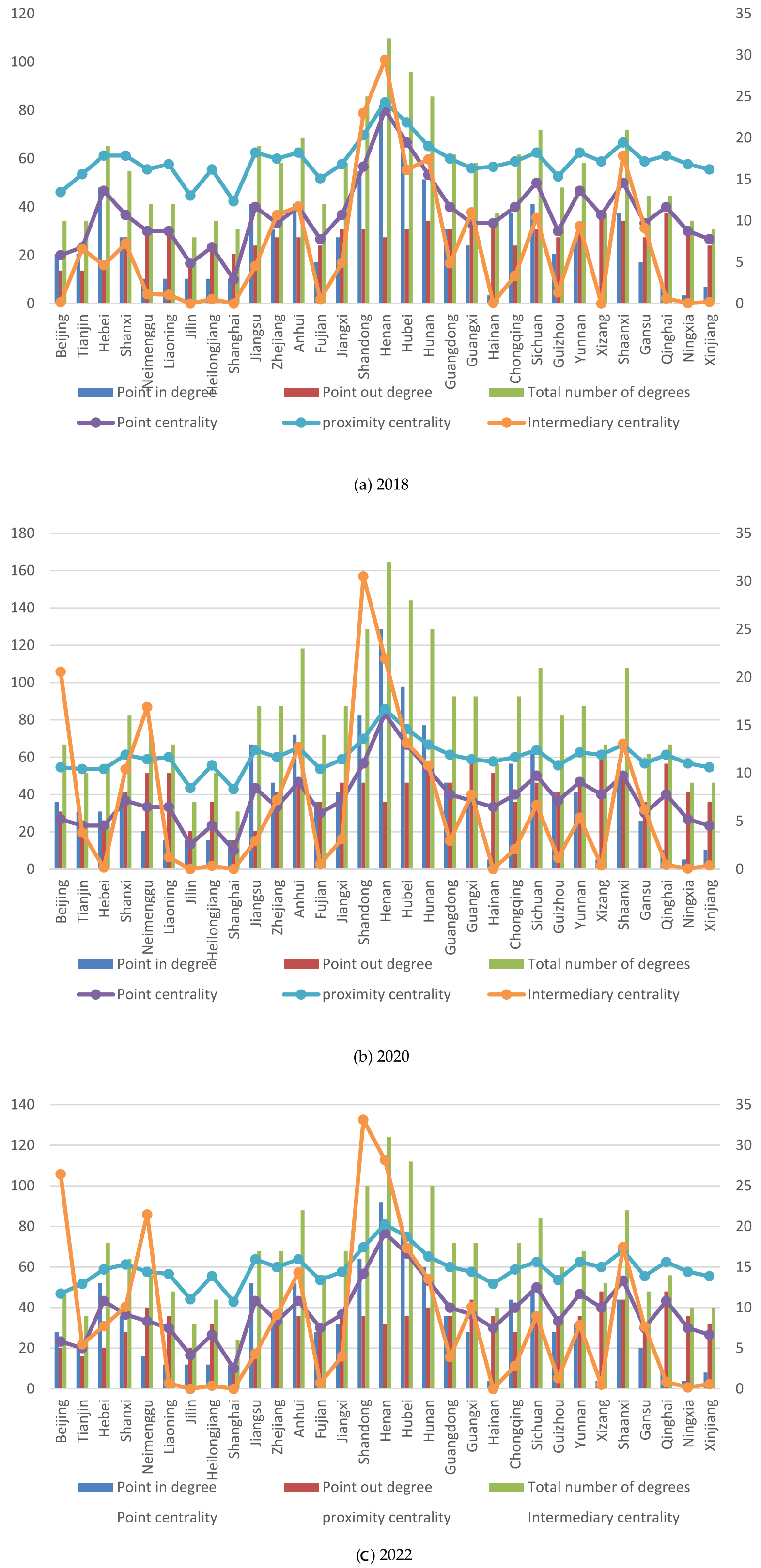

FIGURE 3
Individual network characteristics of the development space of rural e-commerce in China from 2018-2022. **(a)**, **(b)**, and **(c)** are the calculation results for 2018, 2020, and 2022, respectively.

convenient transportation, and dense rural populations. In contrast, western provinces such as Qinghai and Tibet, constrained by sparse populations and remote locations, exhibited weaker connections with other provinces and faced significant limitations in rural e-commerce.

3.4 Centrality analysis of China's rural e-commerce spatial correlation network

A higher value indicates greater advantages in information transmission and resource flow. In the spatial correlation network of high-quality rural e-commerce development across 31 provinces in China, the average closeness centrality was 59.148 in 2018, 59.958 in 2020, and 59.089 in 2022. The number of provinces exceeding the average was 14, 15, and 14, respectively, during the observation years. Provinces consistently ranking high included Henan, Hubei, Shandong, Shaanxi, Hunan, Sichuan, and Yunnan, with minimal changes in rankings over time.

Betweenness centrality measures the ability of a node to act as a bridge between other nodes. A higher value indicates greater capacity to regulate connections between other nodes in the network. In 2018, the top five provinces in terms of betweenness centrality were Henan, Hubei, Shandong, Shaanxi, and Hunan. By 2020, the rankings shifted significantly to Shandong, Henan, Beijing, Inner Mongolia, and Hubei. In 2022, the top five were Shandong, Henan, Beijing, Inner Mongolia, and Shaanxi. These dramatic changes indicate that these provinces served as key "bridges" in the spatial correlation network during different years, significantly influencing inter-provincial connections while also reflecting the instability of their roles (Liu et al., 2024a).

Additionally, some provinces, such as Shanghai and Jilin, consistently recorded a betweenness centrality of zero during the observation years. This indicates their minimal influence on other nodes within the spatial correlation network, likely due to their lower levels of high-quality rural e-commerce development, relatively peripheral geographic locations, and weaker rural development potential.

3.5 Cluster characteristics and block spillover effects in China's rural e-commerce spatial correlation network

Using the CONCOR module in Ucinet software with a depth of 2 and a convergence criterion of 0.2, this study conducted a block division analysis of China's rural e-commerce high-quality development spatial correlation network for the years 2018, 2020, and 2022 (Jinsong and Hexiang, 2021; Table 2). The results show that the network can be divided into four typical blocks: the "Net Beneficiary Block", the "Broker Block", the "Bidirectional Spillover Block", and the "Net Outflow Block". In 2018, the "Net Beneficiary Block" included Zhejiang, Jiangsu, Anhui, Shanghai, Fujian, Henan, Guangdong, Hunan, Jiangxi, and Hubei, characterized by a greater number of outgoing relationships than incoming ones and stronger inter-block connections compared to intra-block ones. The "Broker Block" comprised Gansu, Sichuan, Guizhou, Yunnan, Hainan, Guangxi, Chongqing, Tibet, Qinghai, and Shaanxi, featuring significant outgoing and incoming relationships. The "Bidirectional Spillover Block" included Shanxi, Tianjin, Shandong, and Hebei, with stronger external than internal relationships, demonstrating notable bidirectional connectivity. The "Net Outflow Block" consisted of Heilongjiang, Xinjiang, Jilin, and Liaoning, characterized by a significantly higher number of outgoing than incoming relationships. By 2022, the composition of the blocks changed substantially. The "Net Beneficiary Block" was reduced to Zhejiang, Anhui, Shanghai, Fujian, Guangdong, Hunan, Jiangxi, and Hubei. The "Bidirectional Spillover Block" shifted to Gansu, Guizhou, Sichuan, Yunnan, Guangxi, Chongqing, Hainan, Shaanxi, Qinghai, and Tibet. The "Broker Block" included Tianjin, Heilongjiang, Hebei, Inner Mongolia, Jilin, Beijing, and Liaoning. The "Net Outflow Block" expanded to include Jiangsu, Ningxia, Shandong, Henan, Shanxi, and Xinjiang.

The analysis highlights three key findings. First, coastal regions such as Zhejiang, Anhui, and Shanghai have consistently belonged to the "Net Beneficiary Block", leveraging abundant agricultural resources, high levels of economic development, and significant research investment to exert strong resource attraction over other regions (Liu et al., 2024c). Second, central provinces such as Hubei, Hunan, Sichuan, and Henan frequently shifted between blocks, reflecting their dynamic roles as transportation hubs with active resource flows and intense competition. Third, western provinces such as Ningxia and Xinjiang have remained in the "Net Outflow Block" due to limited rural e-commerce development and high logistics costs, leading to significant resource outflows. Furthermore, by binarizing the density matrix, the study revealed the spillover effects and correlations between blocks (Table 3). The results show that Blocks I and II exhibit the strongest internal connectivity and spillover effects, with Block II demonstrating prominent external spillover effects. Block III showed significant spillover effects on Block IV, while Block IV exhibited strong spatial correlations with both internal and external blocks. The geographic isolation of regions like Tibet poses significant logistical challenges for e-commerce. The government should offer targeted subsidies and low-interest loans to businesses investing in logistics infrastructure such as warehouses, distribution centers, and transportation networks. This would improve the connectivity between remote areas and urban markets, lowering transportation costs and enhancing the efficiency of rural e-commerce. Digital infrastructure is another key factor. The government should incentivize investments in high-speed internet and mobile networks for rural areas. Public-private partnerships could be established to expand connectivity, while grants for training local technicians and digital literacy programs would ensure a skilled workforce capable of supporting e-commerce growth. E-commerce hubs in peripheral regions could serve as central points for processing goods, warehousing, and connecting local businesses with larger markets. These hubs would also provide training and support services to help businesses leverage e-commerce platforms effectively, improving their capacity to reach customers nationwide. These findings reveal the disparities and complex spillover dynamics among blocks

TABLE 2 Spatial links between rural e-commerce development plates in China.

Year	Plate	Member of the plate	Number of members	Receive relationships	Overflow relationship number	Expect internal relationship ratio (%)	Actual internal relationship ratio (%)	Plate characteristics
2018	I	Zhejiang, Jiangsu, Anhui, Shanghai, Fujian, Henan, Guangdong, Hunan, Jiangxi, Hubei	10	55	14	33.33	81.33	Net Beneficiary
	II	Gansu, Sichuan, Guizhou, Yunnan, Hainan, Guangxi, Chongqing, Xizang, Qinghai, and Shanxi	10	16	48	33.33	48.39	Broker
	III	Shanxi, Tianjin, Shandong, Hebei, and Beijing	5	31	11	16.67	57.69	Two-way overflow
	IV	Ningxia, Neimenggu, Heilongjiang, Xinjiang, Jilin, Liaoning	6	3	34	20.00	26.09	Net overflow
2020	I	Zhejiang, Jiangsu, Anhui, Shanghai	4	27	12	13.33	50.00	Net Beneficiary
	II	Heilongjiang, Shandong, Shanxi, Neimenggu, Tianjin, Liaoning, Jilin, Beijing, Hebei	9	12	19	30.00	69.84	Broker
	III	Guangdong, Hainan, Hunan, Fujian, Guangxi, Hubei, Jiangxi, Henan, Guizhou	9	51	32	30.00	60.00	Two-way overflow
	IV	Qinghai, Gansu, Sichuan, Ningxia, Xizang, Xinjiang, Yunnan, Shanxi, Chongqing	9	15	42	30.00	47.50	Net overflow
2022	I	Zhejiang, Anhui, Shanghai, Fujian, Guangdong, Hunan, Jiangxi, Hubei	8	27	12	26.67	76.92	Net Beneficiary
	II	Gansu, Guizhou, Sichuan, Yunnan, Guangxi, Chongqing, Hainan, Shanxi, Qinghai, Xizang	10	12	19	33.33	70.31	Broker
	III	Tianjin, Heilongjiang, Hebei, Neimenggu Jilin, Beijing, Liaoning	7	51	32	23.33	46.67	Two-way overflow
	IV	Jiangsu, Ningxia, Shandong, Henan, Shanxi, Xinjiang	6	15	42	20.00	25.00	Net overflow

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TABLE 3 Analysis of the spillover effect of the spatial correlation network of rural e-commerce development in China.

Year	Plate	Density matrix				Image matrix			
		I	II	III	IV	I	II	III	IV
2018	I	0.678	0.08	0.120	0.000	1	0	0	0
	II	0.380	0.500	0.140	0.050	1	1	0	0
	III	0.180	0.040	0.950	0.00	0	0	1	0
	IV	0.133	0.133	0.600	0.400	0	0	1	1
2020	I	1.000	0.056	0.278	0.000	1	0	1	0
	II	0.222	0.611	0.111	0.025	0	1	0	0
	III	0.444	0.037	0.667	0.160	1	0	1	0
	IV	0.083	0.086	0.395	0.528	0	0	1	1
2022	I	0.714	0.087	0.000	0.354	1	0	0	1
	II	0.387	0.511	0.029	0.267	1	1	0	0
	III	0.000	0.014	0.667	0.405	0	0	1	1
	IV	0.250	0.183	0.190	0.467	0	0	0	1

TABLE 4 Selection of variables for QAP analysis.

	Variable	Explanatory variable	Data sources
Dependent variable	Rural e-commerce development regional difference	Rural e-commerce the development level	The author calculated
Argument	Geo-spatial proximity relationship	Space adjacency matrix	National Geographic information Network
	Agricultural mechanization level regional difference	Farm machinery production	The China Rural Statistical Yearbook
	Logistics basis regional difference	Population served by the postal service per site	The National Statistical Yearbook
	Agricultural land scale regional difference	Agricultural acreage	The National Statistical Yearbook
	Agricultural productivity regional difference	Agricultural output value of agriculture, forestry, animal husbandry and fishery	The National Statistical Yearbook
	Rural human resource regional difference	Proportion of rural employed personnel	The National Statistical Yearbook
	Scientific and technological innovation and transformation regional difference	Technology turnover	The National Statistical Yearbook
	Economic development regional difference	Regional GDP per capita	State Statistics Bureau

within China's rural e-commerce high-quality development spatial correlation network, providing theoretical insights for optimizing regional collaboration.

4 Discussion

4.1 Analyzing the driving factors of rural e-commerce spatial correlation using QAP

This study uses 2022 data as a sample to explore the driving mechanisms behind the spatial correlation network of high-quality rural e-commerce development (Jing and Jie, 2021). Variables such as economic development, agricultural technology, transportation, land scale, human resources, and geographical proximity were selected as research factors to analyze their impact on the spatial correlation network (Zhu and Luo, 2024; Table 4). A QAP regression analysis was conducted to examine the relationship between the variable matrices and the spatial correlation network. After 24,322 random permutations, the R^2 value was 0.242, and the adjusted R^2 was 0.237, indicating an explanatory power of 23.7% for the model in explaining the rural e-commerce spatial correlation network (Jin et al., 2020; Jin and Li, 2022). As shown in Table 5, the coefficients for geographical proximity, regional differences in mechanization levels, agricultural productivity, and technological innovation were positive, with geographical proximity and technological innovation showing significance at the 1% level, highlighting their strong influence on the spatial correlation network (Jiaqin et al., 2007). Conversely, the coefficients for land scale differences and rural human resource differences were negative, with land scale differences being significant at the 1% level, indicating that smaller differences in land scale facilitate the formation of spatial correlation networks (Jiang et al., 2019, 2020). Logistics

TABLE 5 QAP correlation and the analysis and regression analysis.

Argument	QAP correlation analysis		QAP regression analysis		P price
	Correlation coefficient	P price	Unstandardized regression coefficients	Standardized regression coefficient	
Geo-spatial proximity relationship	0.555	0.000	0.214630	0.451792	0.000
Agricultural mechanization level regional difference	0.074	0.112	0.000007	0.112976	0.060
Logistics basis regional difference	−0.028	0.390	−0.027344	−0.015149	0.441
Agricultural land scale regional difference	−0.103	0.032	−0.000004	−0.080232	0.064
Agricultural productivity regional difference	0.060	0.136	−0.000000	−0.005198	0.768
Rural human resource regional difference	−0.056	0.192	0.016134	0.009617	0.876
Scientific and technological innovation and transformation regional difference	0.159	0.006	0.000000	0.138082	0.003
Economic development regional difference	0.001	0.471	0.000000	0.008000	0.255

infrastructure and economic development differences did not pass the significance test, suggesting a weaker impact on the network.

Further analysis reveals that geographical proximity has a significant positive effect on the spatial correlation network, with geographically adjacent provinces more likely to form connections (Jiang et al., 2022). Differences in mechanization levels also show a significant positive effect, with higher agricultural machinery power correlating with stronger inter-provincial connections. Although the coefficient for logistics infrastructure differences is negative, it lacks statistical significance, likely due to uneven distribution of logistics infrastructure (Ji et al., 2023, 2024). Land scale differences have a significant negative effect, suggesting that similar land scales between provinces promote tighter spatial networks. Agricultural productivity differences positively affect spatial correlations, with smaller gaps fostering stronger connections. Rural human resource differences positively influence network formation, with differences in rural employment numbers and proportions contributing to spatial connectivity (Jayanthi and Rau, 2019). Regional differences in technological innovation have a highly significant positive effect at the 1% level, indicating that higher levels of technological innovation drive better rural e-commerce development. Economic development differences show a positive but insignificant effect, possibly due to interference from multiple factors such as logistics, human flow, and capital flow (Jagoda et al., 2016).

Although this study covers a 5-year period, it is important to consider the dynamic nature of rural e-commerce development and how the identified driving factors and spatial linkages may evolve in the future. Emerging trends such as advancements in digital technologies, including artificial intelligence, big data, and blockchain, are expected to play a significant role in transforming the e-commerce landscape. These technologies could enhance the efficiency and scalability of rural e-commerce, improve data-driven decision-making, and enable more personalized services for rural consumers. Additionally, potential policy shifts, such as increased government investment in digital infrastructure and support for rural entrepreneurship, could further accelerate the growth of rural e-commerce. The interaction between these emerging factors and the existing spatial linkages will likely shape the future trajectory of rural e-commerce development, leading to new opportunities for regional collaboration and economic integration. Therefore, future studies should examine how these evolving trends may influence rural e-commerce in the coming years.

In our spatial network analysis, we recognize the potential endogeneity issue arising from the bidirectional causality between e-commerce development and infrastructure. Specifically, while improved infrastructure may promote the growth of e-commerce, the expansion of e-commerce can, in turn, drive further infrastructure development. To address this, we applied several methods. First, we used instrumental variables (IV) to mitigate endogeneity, selecting external variables, such as government policy support and historical infrastructure investment, that are related to e-commerce development but not directly influencing infrastructure. Additionally, we conducted lagged variable analysis by including lagged values of infrastructure indicators in the model, which helps isolate the long-term impact of infrastructure on e-commerce development. Finally, we employed a two-way fixed effects regression model to control for regional fixed effects and time-series variations, thus addressing potential biases in the analysis. These methods allow for a more accurate estimation of the causal relationship between infrastructure and e-commerce development, reducing the risk of endogeneity.

In conclusion, geographical proximity, smaller differences in land scale, and agricultural productivity facilitate the formation of rural e-commerce spatial correlation networks, while larger differences in rural human resources and technological innovation also play a significant role in driving network development (Islam and Doyle, 2008; Isabel Polo Pena et al., 2016). These findings provide theoretical support for optimizing the construction of spatial networks in rural e-commerce.

4.2 Configurational path analysis of high-quality rural e-commerce development in China based on fsQCA

This study applies fuzzy-set qualitative comparative analysis (fsQCA) to explore the configurational pathways and antecedent conditions for high-quality rural e-commerce development in China. Based on QAP analysis, logistics infrastructure differences and economic development differences were found to have insignificant impacts on rural e-commerce development and were excluded from the fsQCA analysis (Wang and Huo, 2012; Huaraca aparco et al., 2022; Huang et al., 2024c). Six variables—geographical proximity, mechanization levels, land scale, agricultural productivity, rural human resources, and technological innovation—were selected as conditional variables, with high-quality rural e-commerce development serving as the outcome variable.

fsQCA is suitable for analyzing set conditions where variable values range from 0 to 1. Therefore, continuous variables were calibrated based on the 5th, 50th, and 95th percentiles as full non-membership, crossover, and full membership points, respectively (Table 6). Consistency scores are used to evaluate the necessity of conditions, with a threshold of 0.9 set for this study. The results indicate that no single condition variable has a consistency score above 0.9, demonstrating that high-quality rural e-commerce development depends on a combination of multiple factors rather than being driven by any single factor.

Configurational analysis focuses on identifying multi-factor pathways leading to the outcome. A case threshold of 1 and a consistency threshold of 0.8 were set to analyze the conditions for both high-quality and non-high-quality rural e-commerce development, with each configuration pathway named accordingly (Table 7). Two main pathways for high-quality development were identified: (1) The "Land Scale-Mechanization-Agricultural Productivity-Technological Innovation" pathway (H1), characterized by abundant land resources, advanced mechanization, strong agricultural productivity, and high levels of technological innovation. These factors can drive rural e-commerce development even in the absence of sufficient human resources (Huang and Ye, 2022). (2) The "Agricultural Productivity-Technological Innovation" pathway (H2), where strong agricultural productivity and advanced technological innovation, combined with higher levels of economic development, facilitate high-quality rural e-commerce. Both configurations highlight the importance of agricultural technology and land resources as foundational factors (Huang et al., 2024b).

Configurational analysis focuses on identifying multi-factor pathways leading to the outcome. A case threshold of 1 and a consistency threshold of 0.8 were set to analyze the conditions for both high-quality and non-high-quality rural e-commerce development, with each configuration pathway named accordingly (Table 8). Two main pathways for high-quality development were identified: (1) The "Land Scale-Mechanization-Agricultural Productivity-Technological Innovation" pathway (H1), characterized by abundant land resources, advanced mechanization, strong agricultural productivity, and high levels of technological innovation. These factors can drive rural e-commerce development even in the absence of sufficient human resources. (2) The "Agricultural Productivity-Technological Innovation" pathway (H2), where strong agricultural productivity and advanced technological innovation, combined with higher levels of economic development, facilitate high-quality rural e-commerce. Both configurations highlight the importance of agricultural technology and land resources as foundational factors (Huang, 2021). The two main pathways identified for high-quality rural e-commerce development provide valuable insights for policymakers seeking to foster e-commerce growth in different regions. In regions where the first pathway, characterized by factors of Pathway 1, is prevalent, policymakers should focus on specific interventions based on these factors. For instance, investing in specific resources or infrastructure could enhance aspect of development, thus strengthening the pathway and boosting rural e-commerce outcomes. In contrast, for regions aligning with the second pathway, where Pathway 2 dominate, interventions should be tailored to address these specific conditions. Policies such as targeted infrastructure investment could effectively support the growth of rural e-commerce in these areas. Furthermore, combining elements from both pathways, depending on local characteristics, may allow policymakers to create more nuanced interventions that address the diverse needs of rural communities. These strategies will not only improve e-commerce development but also contribute to long-term rural economic sustainability.

For non-high-quality rural e-commerce development, two configurational pathways were also identified: (1) NH1, where poor land scale, mechanization, agricultural productivity, and technological innovation prevent high-quality development; (2) NH2, where severe deficiencies in agricultural productivity and technological innovation hinder development, even with high mechanization levels and ample land resources. These findings emphasize that agricultural technology and land productivity are critical factors for achieving high-quality development. To ensure robustness, the consistency threshold was adjusted from 0.8 to 0.75, following relevant studies, while keeping all other analytical procedures unchanged. The results showed that the adjusted configurations remained consistent with the original ones, confirming the robustness of the study's findings (Huang et al., 2024a).

The findings of this study are closely linked to key theoretical frameworks, particularly digital divide theory and spatial economics. Our results show that provinces with better digital infrastructure, such as Henan, Hubei, and Shandong, exhibit significantly higher rural e-commerce development levels. For example, by 2022, these provinces consistently ranked among the top five, with Shandong achieving a development index of 5.393, far surpassing other regions. This supports the digital divide theory, which posits that regions with superior digital resources experience faster growth, while less developed areas, like Qinghai and Tibet, lag behind with lower indices (e.g., Tibet had a development index of just 1.2 in 2022). Moreover, our findings highlight spatial spillover effects, where central provinces act as "brokers" in facilitating resource flows to neighboring regions. For instance, Henan's degree centrality value remained the highest (80.000 in 2018, 83.333 in 2020), indicating its pivotal role in the network. These central provinces, with advanced logistics and digital infrastructure, transfer technological and economic benefits to peripheral provinces, fostering more balanced development. The spatial network analysis shows that provinces like Hubei and Henan contribute significantly to the overall network connectivity, with the clustering coefficient increasing from 0.262 in 2018 to 0.269 in 2022. This suggests

TABLE 6 Variable calibration.

Variable	Completely non-subordinate	Cross point	Fully subordinate
Rural e-commerce development	1.26963982	2.482475039	4.362357469
Farmland scale	247	3,654.21	9,548
Agricultural mechanization level	245.95	2,805.71	9,553.9
Agricultural productivity	276.05	4,908.71	10,406
Rural human resources	0.1455	0.405	0.5295
Scientific and technological innovation transformation level	236,066.5	7,338,839.01	39,191,063

TABLE 7 Analysis of the necessary conditions.

Pre-cause conditions	High-quality development		Non-high-quality development	
	Consistency	Coverage	Consistency	Coverage
Farmland scale	0.740534	0.753632	0.547233	0.618446
~Farmland scale	0.625077	0.554210	0.782001	0.769951
Agricultural mechanization level	0.777778	0.779714	0.513695	0.571873
~Agricultural mechanization level	0.572936	0.514780	0.802124	0.800335
Agricultural productivity	0.844817	0.814970	0.493013	0.528144
Rural human resources	0.739913	0.697892	0.657350	0.688525
~Rural human resources	0.669770	0.637707	0.711571	0.752364
Scientific and technological innovation transformation level	0.728740	0.742568	0.466182	0.527514
~Scientific and technological innovation transformation level	0.5366313	0.474986	0.772499	0.759758

TABLE 8 Conditional configuration of rural e-commerce development and non-high-quality development.

Pre-cause conditions	High-quality development of the conditional configurations		Non-high-quality developmental conditional configuration	
	Configuration H 1	Configuration H 2	The group of NH 1	The configuration of the NH 2
Land scale	•	⨂	⨂	•
Agricultural machinery level	●	⊗	⊗	●
Agricultural productivity	•	●	⨂	⨂
Rural human resources		⊗		
Scientific and technological innovation transformation	●	●	⨂	⊗
Consistency	0.928496	0.945892	0.948523	0.946483
Original coverage	0.548107	0.292986	0.556177	0.346033
Unique coverage	0.306642	0.0515208	0.316378	0.106205
Consistency of the overall solutions	0.927063		0.949519	
Coverage of the overall solution	0.599628		0.662381	

● Indicates that the core condition exists, ⨂ represents the condition is missed, • means the edge condition exists, ⊗ represents the edge condition is missed.

that inter-provincial cooperation has strengthened over time, with central regions leading the way in reducing the digital divide by facilitating connections between urban and rural areas. From a spatial economics perspective, these findings align with the theory that geographic proximity and resource flows are crucial for regional economic development. The central provinces, acting as hubs, create a spillover effect that boosts e-commerce in neighboring regions. For instance, areas with better infrastructure and higher levels of digital engagement, such as Guangdong (development index of 4.805 in 2022), enhance the overall functionality of the network by providing access to markets, information, and technological advancements. As these hubs continue to grow, their economic benefits ripple outward, demonstrating how targeted investments in central regions can reduce spatial inequalities and promote more inclusive economic growth.

While this study is focused on China, it is important to consider the potential transferability of the findings to other regions or countries with different economic, social, and geographical contexts. The unique characteristics of China, such as its rapid digital infrastructure development, strong government policies supporting rural revitalization, and large rural population, may limit the direct applicability of the results to other countries. However, the principles of spatial linkages, e-commerce development, and regional collaboration explored in this study may offer valuable insights for other developing countries with similar rural-urban disparities and emerging digital economies. The findings highlight the importance of digital infrastructure and inter-regional cooperation in promoting rural e-commerce, which could be relevant in contexts where rural areas are seeking to integrate more fully into the digital economy. Future research could explore the transferability of these results through comparative studies in other regions to better understand the varying impacts of local economic, social, and geographic conditions. While this study relies on data from authoritative statistical yearbooks and reports, it is important to recognize that these data sources may have certain limitations. Specifically, rural-specific data collection methods may have evolved over time, and variations in data quality or consistency may exist between different regions or years. For example, data collection methods may have shifted due to changes in government policies, technological advancements, or regional reporting practices. Additionally, inaccuracies in rural data collection, such as underreporting or sampling biases, could affect the precision of the results. We acknowledge these potential limitations and suggest that future research consider integrating additional data sources or employing methods to account for data discrepancies to further validate the findings.

While China has made significant progress in rural e-commerce development, it faces unique challenges compared to other developing countries. One of the primary advantages China holds is its extensive infrastructure investments, particularly in rural digital connectivity and logistics networks. The widespread rollout of internet access and mobile payment systems has been crucial in facilitating e-commerce growth. In contrast, many other developing countries struggle with limited infrastructure, especially in rural areas, which significantly hinders the expansion of e-commerce. Additionally, while China benefits from a large market size, enabling scale and market penetration, many smaller developing countries face the challenge of limited market size, which restricts the potential for e-commerce platforms and cross-border trade. These differences highlight China's unique position in rural e-commerce development and provide valuable insights for other developing countries looking to overcome similar infrastructure and market-related obstacles.

Policy intervention plays a critical role in the development of rural e-commerce, and this study measures it through several key indicators. First, we consider financial support, including government subsidies and funding for infrastructure such as logistics networks and digital connectivity. Second, policy frameworks and regulations, such as the "Rural Revitalization Strategy" and "Internet Plus" initiative, are evaluated for their impact on promoting rural e-commerce. Third, infrastructure development is measured by examining government-led projects aimed at expanding digital access and e-commerce platforms in rural areas. Additionally, training and capacity-building programs that enhance digital literacy and e-commerce skills are considered. Finally, regional development policies targeting underdeveloped provinces are assessed based on the intensity and scope of governmental efforts to support e-commerce. These factors are integrated into a policy intervention index to quantify the government's role in shaping rural e-commerce growth.

China has emerged as the world's largest e-commerce market, surpassing the U.S. in both user base and total sales. This growth has been fueled by vast market potential, high consumer acceptance of digital commerce, and the rapid release of rural consumption demand. Unlike many developing nations constrained by smaller markets and weaker purchasing power, China leverages advanced technologies—such as mobile payments, big data, and AI—to enhance rural e-commerce efficiency and accessibility. These innovations, coupled with robust infrastructure and policy support, have narrowed the urban-rural divide and empowered small businesses. Globally, China's e-commerce boom has redefined digital trade standards, influencing cross-border logistics, payment systems, and inclusive growth models. Its success offers valuable insights for emerging economies seeking to bridge gaps in infrastructure, technology, and policy to unlock rural e-commerce potential.

5 Conclusions

Using game theory-based weighting, a modified gravity model, social network analysis, and configurational analysis, this study examined the spatial correlation network and pathways of high-quality rural e-commerce development in China (Hou et al., 2024). Results indicate that from 2018 to 2022, development levels improved overall but regional gaps widened. Coastal provinces like Zhejiang, Jiangsu, and Fujian remained far ahead, while inland areas lagged. The spatial correlation network exhibited a multi-linear structure, with Henan, Hubei, and Shandong as central nodes and Qinghai and Tibet on the periphery. Key provinces like Shandong, Henan, and Sichuan acted as "brokers" in the network. Technological innovation and agricultural productivity were identified as core drivers of high-quality rural e-commerce development, with resource-attracting provinces characterized by advanced technology and agriculture (Hou and Liu, 2024).

To promote high-quality rural e-commerce, regional collaboration should be strengthened by encouraging coastal provinces to partner with inland regions through technology transfer and talent exchange (Hou et al., 2022). Greater support should be provided to peripheral areas like Qinghai and Tibet to improve logistics infrastructure and network participation (Hossein et al., 2017; Hong, 2021). Key provinces like Shandong and Henan should leverage their broker roles to facilitate resource sharing. Investments in technology and agricultural productivity should be prioritized, promoting smart agricultural technologies to improve e-commerce efficiency while cultivating specialized talent to drive the digital transformation of rural economies.

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

LF: Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Conceptualization, Software, Validation, Writing – review & editing. WB: Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Conceptualization, Funding acquisition, Project administration, Validation, Writing – review & editing. WXu: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Validation, Writing – original draft, Writing – review & editing. WY: Formal analysis, Investigation, Validation, Writing – review & editing, Resources, Software. WXi: Formal analysis, Investigation, Resources, Software, Validation, Writing – review & editing. SD: Formal analysis, Investigation, Resources, Software, Writing – review & editing, Data curation, Methodology, Supervision. HL: Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Writing – review & editing. ZD: Data curation, Formal analysis, Investigation, Methodology, Resources, Supervision, Writing – original draft.

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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

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2025.1557395/full#supplementary-material

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