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Carbon neutrality, social media, artificial intelligence, volume II

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Carbon neutrality, social media, artificial intelligence, volume II

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Waste management within the scope of environmental public awareness based on cross-sectional survey and social interviews

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Since the natural resources of the world are not unlimited, the effective use of resources and the access of future generations to these resources concern all societies on a global scale. From this point of view, waste management strategies should be examined in terms of medical, household, and other waste types. Thereby, this study aims to examine the level of public awareness in waste management by studying the perception, perspective, practice about waste's aspects. The survey in this study mentions questions on waste management knowledge, public awareness, and behaviors among social interviews of pharmacy students receiving laboratory training in the field of health. Internal consistency reliability is used to verify the uniformity of questions in this study. Pearson correlation, *t*-test, and the analysis of variance (ANOVA) are performed to study the differences between groups. The results of the data analysis show that public awareness and waste management knowledge, public awareness, and behaviors have a significant positive correlation, which provides us with a good basis for designing environmental strategies. The first module's outcomes of the questionnaire reveal a high degree of waste management among students. On the contrary, woman participants demonstrate a higher public awareness and application of the environment. Furthermore, there are significant correlations between the other modules and demographic factors with family education. According to the results, the public awareness of the participants who were members of an environmental organization is different from others. Finally, the participants state that the problem of not managing wastes effectively causes the most damage to the soil and all other natural resources after water.

KEYWORDS

public awareness, environmental citizenship, sustainability, waste management, social interviews, cross-sectional survey

1 Introduction

The COVID-19 pandemic has shown that many effects can easily occur, with direct and indirect effects on the sensitivity of human nature. It has emerged that medical waste management should be known not only by health professionals but also by all segments of society (Orazbayev et al., 2019; Ma et al., 2020; Zhumadillayeva et al., 2020). The scarcity of natural resources has begun to put pressure on the environmental sustainability of the world (Ince, 2018a). Short-term solutions like selling waste to underdeveloped countries or dumping it into the oceans are no longer acceptable. Because nature has started to show that it cannot handle the waste load with various disasters and results such as the depletion of clean water resources or the inefficiency of the soil (Ince, 2018b; Ingold et al., 2019). Waste management, which requires being a part of global businesses, states, and society, that is, a holistic perspective is starting from the design phase of any product. It is a discipline that covers the production, consumption, waste generation, recycling, and disposal of waste (Margallo et al., 2019).

Waste Management is an approach of management that includes reducing waste at its source, sorting according to its characteristics, collection, temporary storage, intermediate storage, recycling, transportation, disposal and post-disposal control, and similar processes (Minelgaitė and Liobikienė, 2019; Debrah et al., 2021). Today, where technological developments such as Industry 4.0, which consists of various stages such as the internet of things, internet services, and cyber-physical systems, are discussed, there are mobile and robotic systems developed for waste management (Singh et al., 2022). In the literature on waste management, it is seen that the issue is handled with various aspects in terms of different sectors (Chioatto and Sospiro, 2022; Koul et al., 2022; Ławińska et al., 2022). Studies that reveal the importance of education in waste management emphasize concepts such as environmental sensitivity and public awareness and make suggestions to increase it (Stojic and Salhofer, 2022; Owojori et al., 2022; Fan et al., 2021; Xiong et al., 2020; Liu et al., 2020; Tu et al., 2020; Yue et al., 2020; Bao et al., 2020).

Environmental public awareness is a consciousness around the natural environment and the choices that either promote its well-being or cause it more harm. It is also the public awareness that the Earth needs protection for its survival (Severo et al., 2021). The term, meaning knowledge of the natural environment and an understanding of how actions affect local and global well-being, can be greatly enhanced by education (Li, 2018). As a result of public awareness, environmental citizenship is formed by transferring this public awareness into practice. To become an environmental or ecological citizen, first of all, it is necessary to be literate. The first step of environmental literacy is public awareness, and then it is necessary to use this public awareness to solve problems for nature and to implement these solutions (Asilsoy and Oktay, 2018). So the starting point, public awareness, is just as crucial as the results. Cucu Cahyana et al. (2019) have addressed two key variables of environmental citizenship, emphasizing the important role of educators in raising public awareness:

- Major variables: Environmental sensitivity, investment, knowledge, and skill in environmental strategies.
- Minor variables: Knowledge of ecology, attitudes toward pollution, technology, and economies.

There are studies in the literature that action-oriented environmental education can increase environmental citizenship (Green et al., 2016). These research studies on the reflection of individual attitudes on behaviors show that if public awareness is raised through education, it can have a positive impact on environmental behavior and subsequently citizenship (Cobanoglu et al., 2021; Monte and Reis, 2021). The effect rate of public awareness on environmental outcomes can sometimes be lower than expected (Ince, 2014). Hence, models that explain the complex relationship between human behavior and the environment are also emphasized (Akintunde, 2017; Yue et al., 2021).

From this point of view, waste management is discussed in terms of environmental public awareness and citizenship in this study. The importance of the subject stems from the fact that it deals with the environment from different perspectives. Thus, it is aimed to show the relationship between attitudes towards the environment and expected behaviors. As the target population, students from a state university located in the Mediterranean region are selected (Figure 1) and it is limited to the department of pharmacy in the field of health since it is an applied education such as laboratory use. Thereby, it is requested to measure the public awareness, knowledge, and application levels of environmental variables, both medically and daily. Finally, the study offers the opportunity to analyze the current situation in waste management and environmental public awareness, both as a citizen and as a future health professional.

In the social media posts that raise awareness about Turkiye’s climate agenda this year, the roadmap to reach the 2053 net zero emission target, especially within the scope of the Paris climate agreement, is mentioned. In addition to social media, the legal outputs of the steps that are planned to be announced to large masses through online conferences are also on the agenda. It is stated that in order to reach net zero emissions by 2053, besides all legal processes, efforts will be made to disseminate social impacts (Aliabadi et al., 2022). The attitude of the country, which is considered in terms of the sample, towards carbon emissions and the way it handles technological developments in this respect are also important as it has the power to affect the social perspective. In 2022, it is seen that there is an increase in scientific studies that

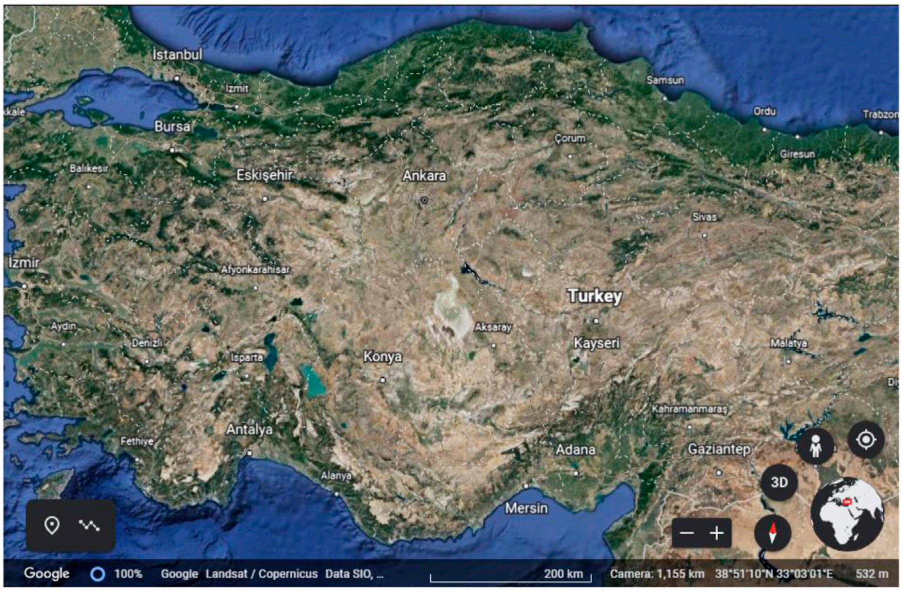

FIGURE 1
Geographic location of the study area in the Mediterranean region of southern Turkiye.

include model proposals on technology-oriented net zero carbon emissions. Cansiz et al. (2022) develop some prediction models for CO_2 emissions in the transportation sector. And according to their study, Artificial neural networks (ANN) give the best performance among simple membership functions and fuzzy rule generation technique (SMRGT), adaptive neuro-fuzzy inference system (ANFIS) methods, support vector machine (SVM), and multiple linear regression (MLR).

In another study focusing on combating regional climate change, these results are obtained in a study conducted in a single province. According to Kerem (2022), "while generating electricity with renewable energy sources, it has been determined that an average of 3,500,794 tons CO2, 3,024,120 tons CO_2, and 1,073,039 tons CO_2 carbon footprint savings were accomplished for 2019, 2020, and 2021". Such studies contribute to promoting research on renewable energy investments for local governments and investors in accordance with the Kyoto Protocols and the Paris Agreement. It also supports regional efforts to combat climate change. On the other hand, in Baş, (2022), building footprint extraction is carried out by a combination of high-accuracy Regularize Digital Topographic Map (RDTM) with LiDAR data in the urban areas to reveal the efficiency of orthophoto in building detection using the ANN method. Therefore, the reflections of technological developments on climate, environment, and waste management should be addressed from a social perspective. So, this study also draws attention to its sociological aspect.

FIGURE 2
Research model for the study.

2 Article types

The purpose of this study is to examine the level of pharmacy students' public awareness in waste management *via* the study of the perception, perspective, practice about many environment's aspects. A study sample (n:336) involving pharmacy students at a state university is evaluated. From January 2022 to March 2022, a cross-sectional survey is undertaken to collect data for the current research model (Figure 2). The survey has included questions on waste management knowledge, public awareness, and behaviors among pharmacy students receiving laboratory training in the field of health. However, the amount of medical and hazardous waste usage in this area is quite limited compared to other health areas. For this reason, waste management public awareness is also measured in terms of environmental citizenship. In the selected sample, interviews are performed, and a survey is conducted to examine the degree of public awareness, knowledge, and implementation of waste management and environmental citizenship amongst students. Responses from participants are collected using a carefully designed survey of closed-ended questions. Some studies have confirmed that awareness is an antecedent of the behaviour in question. That is, the formation of environmental awareness is an antecedent of environmental behaviour. Therefore, in this study, we focus on the correlation between environmental awareness and waste management.

Although the survey includes three scales, it consists of five parts. Scales, the first of which are waste management (Hacısalihoğlu, 2021), the second is environmental citizenship (WWF, 2008), and the third is environmental public awareness (Çetin and Yalçınkaya, 2018), have been previously developed and used in different studies (Nadeson and Barton, 2014; Yalçınkaya and Çetin, 2018; Çai et al., 2021). The model of the study can be seen in Figure 2.

The main hypothesis of the research is that there is a positive relationship between the modules which includes environmental variables and waste management. Then, as sub-hypotheses, it is examined whether there is a difference in the level of environmental variables in terms of demographic factors. To test the model, the questionnaire is tried to be comprehensive. The information about different variables have been included in the survey such as age, gender, family education level, childhood residence, and other details about waste handling, public awareness, knowledge, and implementation. The data collection tools are prepared in Turkish. Because the medical waste has become a major source of environmental pollution (e.g. disposable testing kits used for nucleic acid testing, etc.), especially since the COVID-19 pandemic, and then many lay people do not have the environmental awareness and expertise in this area (medical waste disposal). Therefore, considering that the people who are most exposed to medical waste in real life would be the group of people engaged in this profession of doctors, pharmacy students were chosen as the subjects for the study. The total number of students who voluntarily participated in the sampling to fill out the survey is 336 (134 males and 202 females, with an average age of 22.4 years). Participants in the study are guaranteed their anonymity and confidentiality. The survey is subdivided into three modules to collect information on various environment's areas. The first module is created to determine the level of waste management among students (Table 1). In addition, environmental citizenship is focused on the second module, which examined ecological implementation. Lastly, the third module has addressed environmental public awareness. In the second and third modules, the responses are classified as positive and negative to compare the variables (Dell-Kuster et al., 2014). For the second module, responses are given four different levels and divided into two levels of positive responses (often and always) and two levels of negative responses (never and rarely) (Figure 3). On the other hand, for the third module, responses are given in five different levels and divided into three levels of negative responses (strongly disagree, disagree, and neutral) and two levels of positive responses (agree and strongly agree) (Figure 4). Positive responses suggest that the participant has a high level of

TABLE 1 Frequency and percentage table of demographic factors.

Variable	Group	Frequency	Percent (%)
Gender	Female	202	60.1
	Male	134	39.9
Mother's/Father's education	Primary	200/133	59.5/39.6
	High school	90/115	26.8/34.2
	University	46/88	13.7/26.2
Childhood residence	Rural	54	16.1
	Urban	219	65.2
	Both	63	18.7
Total		336	100

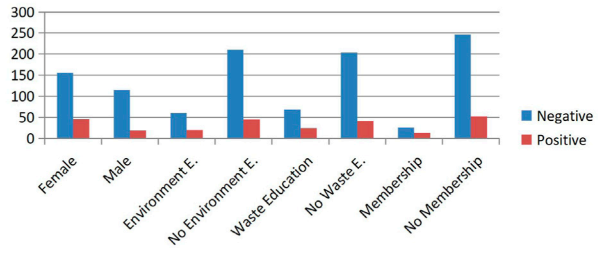

FIGURE 3
Module two additive sums of positive and negative answers.

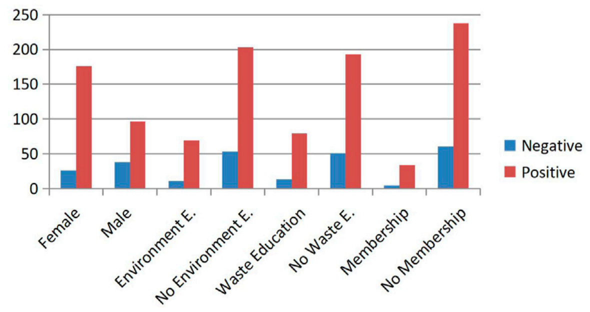

FIGURE 4
Module two additive sums of positive and negative answers.

knowledge and application of the subject of this topic, while negative responses indicate the reverse.

3 Data collection and analysis methods

Data from cross-sectional surveys conducted *via* social interviews at selected samples have been entered to evaluate the data acquired for item analysis, reliability, and validity of the produced instrument. In this study, we used SPSS 2.7 as the data analysis tool (McCrum-Gardner, 2008). Data characteristics were analysed through descriptive statistics; the relationship between the three main variables was verified through Pearson's analysis; and differences between sample groups were explored through analysis of variance. Descriptive statistics are employed to calculate frequency, percentage, average, and variance for study participants' demographic characteristics (Fisher and Marshall, 2009). The study's findings are shown in the form of figures, tables, and texts as needed. Internal consistency reliability (Cronbach's alpha coefficient) is used to verify the uniformity of questions in this study (Taber, 2017). Pearson correlation, *t*-test, and the analysis of variance (ANOVA) are performed to study the differences between groups (McCrum-Gardner, 2008).

4 Result of data analysis

The scales are valid since the reliability statistics of the items used in the survey are obtained above the statistically accepted level ($\alpha > 0.70$). The reliability statistics for each of the three modules and on the overall questionnaire are discussed as valid according to the levels of Cronbach's alpha coefficient. The first module's level of Cronbach's alpha coefficient is 0.797 while the second one is 0.797, and lastly, the third one is 0.877. Additionally, Cronbach's alpha coefficient level of the whole items is 0.895. Further, the analysis showed that removing any of the items would not significantly increase the alpha levels. According to George and Mallery (2010), "A kurtosis value between ±1.0 is considered excellent for most psychometric purposes, but a value between ±2.0 is in many cases also acceptable, depending on the particular application." Skewness is 0.259 (0.133) and kurtosis: 0.190 (0.265) for environmental citizenship, while skewness is -1,075 (0.133) for environmental public awareness, and lastly skewness is 0.565 (0.133) and kurtosis 0.320 (0.265) for waste management. Thus, it can be said that the data of the study refer to a particular statistical distribution named the normal distribution, which is symmetric continuous distribution defined by the mean and standard deviation of the data. According to Hair et al. (2018) "skewness measure of the symmetry of distribution; in most instances, the comparison is made to a normal distribution. A positively skewed distribution has relatively few large values and tails off to the right, and a negatively skewed distribution has relatively few small values and tails off to the left. Skewness values falling outside the range of −1 to +1 indicate a substantially skewed distribution."

Participants are asked where they spent their childhood to understand their perspective on the environment. This question is aimed to determine whether there is a difference between the perspective of an individual who grew up in a village and a city. The education level of the mother or father is also among the demographic factors that cause attitude differences in some studies (Pe'er et al., 2007; Oktaviani, 2017). However, the gender factor appears to be quite decisive in this sample. According to the general distribution in Table 1, the majority of the participants are women (60%) and grew up in the city (65%).

The questions measuring the attitudes, knowledge, and behaviors of the participants towards waste management, who were asked to choose one of four answers as yes, sometimes,no, total, are shown in Table 2. Responses to questions measuring recycling knowledge include a low yes rate and a high yes rate for water and electricity savings (74%). In the social interviews and some open-ended questions, the participants state that due to the high cost of living in the post-pandemic period, paying attention to expenditures is also effective in this saving trend. It is an accepted method in the evaluation of dishes with increased sensitivity to stray animals (67%). The campus environment, which includes small shelters for cats and dogs and allows them to roam freely in common areas, can also contribute to this trend.

The first module aims to find the level of knowledge and public awareness in waste management among participants. The second module is about environmental citizenship, and Figure 3 depicts the survey findings of several categories according to this module. The positive and additive negative responses are summarized in this bar graph. Different categories represent different replies to the questions such as gender, participation in environmental education, participation in a waste management project or education, and membership in an environmental organization. According to the positive response of environmental citizenship:

- Female has a higher positive rate than male (0.29 > 0.16).
- Participants who get educated about the environment have a higher positive rate than uneducated ones (0.33 > 0.21).
- Participants who get educated or volunteer about waste management have a higher positive rate than non-volunteers (0.35 > 0.17).
- Environmental organization members have a higher positive rate than non-members (0.52 > 0.21).

Environmental organization members have the highest value with a positive rate of 0,52 whereas male participants have the lowest positive rate with 0.16. The mean level of the second

TABLE 2 Percentage table of some of the waste management responses.

Questions	Yes	Some	No	Total
Do you know the meaning of the recycling signs on the packaging of the product you buy?	43.2	49.4	7.4	100
Do you throw plastic, glass, metal, and paper into designated recycling bins?	47.3	47.0	5.7	100
Do you pay attention to water consumption when using the bathrooms?	78.3	18.7	3.0	100
Do you unplug electronic devices when not in use?	74.1	20.5	5.4	100
Do you share your leftover food with stray animals?	67.9	27.6	4.5	100

TABLE 3 *t*-test results comparing gender groups on environmental public awareness and citizenship.

Variables	Female		Male				
	M	SD	M	SD	df	t	Sig
Environmental public awareness	4.57	0.54	4.34	0.58	334	3.57	0.000
Environmental citizenship	2.71	0.50	2.56	0.50	334	2.71	0.007

module is 2,65 out of 4, while the first module is 1,93 out of 3. A five-point Likert scale is used to evaluate module 3, the results are highly satisfying, with a mean value of 4.48 (Lange et al., 2020). In addition, Figure 4 depicts the survey findings of several categories according to this module. The positive and additive negative replies are summarized in this bar graph. According to the positive response of environmental public awareness:

- Female has a higher positive rate than male (6.76 > 2.52).
- Participants who get educated about the environment have a higher positive rate than uneducated ones (6.27 > 3.83).
- Participants who get educated or volunteer about waste management have a higher positive rate than non-volunteers (6.07 > 3.78).

Environmental organization members have a higher positive rate than non-members (8.50 > 3.96).

Environmental organization members have the highest value with a positive rate of 8,50 while male participants have the lowest positive rate with 2.52. These percentage rates are calculated as the ratio of positive responses to negative responses in each category. That is, when 176 female participants give positive answers and 26 female participants give negative answers, the positive response rate in the female group is around 6% (6.76).

According to the results of Pearson correlation analysis, there is a positive and significant relationship between the three modules that make up the research model. Although the correlation is low, this means that the main hypothesis of the research is accepted. The correlation coefficient r is 0.265 ($p < 0.001$) between environmental citizenship and environmental public awareness, while it is 0.239 ($p < 0.001$) between environmental citizenship and waste management. In addition, it is determined that environmental citizenship is also correlated with demographic factors as gender 0.147 (p: 0.007), environment education 0.144 (p:0.008), waste management education 0.154 (p:0.005), membership 0.144 (p: 0.009), mother' education 0.144 (p:0.008), and father' education 0.118 (p:0.031).

In the other module, environmental public awareness also has a low level of positive correlation with waste management 0.288 ($p < 0.001$) and other factors as gender 0.192 ($p < 0.001$), waste management education 0.113 and membership 0.113 (p: 0.039). Lastly, waste management has positive correlations with environment education 0.127 (p:0.020), membership 0.143 (p: 0.009), and childhood residence 0.117 (p:0.031).

The independent-samples *t*-test is conducted to compare environmental citizenship in female and male groups. As shown in Table 3 there is a significant difference in the scores for female (M = 2.7; SD = 0.5) and male (M = 2.5; SD = 0.5) groups; t (334) = 2.71, p:0.007. On the other hand, this significant difference applies to environmental public awareness as well. So, there is a significant difference in the scores for female (M = 4.5; SD = 0.5) and male (M = 4.3; SD = 0.5) groups; t (334) = 3.57 p:0.000. However, there is no statistically significant difference in waste management in terms of gender groups (F: 0.014; $p > 0.005$). Also, the *t*-test is not significant in terms of environmental education (F:0.304; $p > 0.005$), and participation a waste management project (F:0.130; $p > 0.005$). According to the environmental public awareness module, there is a significant difference in the scores for members (M = 4.6; SD = 0.3) and non-members (M = 4.4; SD = 0.5) groups; t (334) = 2.07 p:0.004.

TABLE 4 Percentage table of responses about waste bags.

Waste types	Black	Blue	Red	Yellow	Don't know	Total
Household waste	**40.2***	18.5	0.9	7.1	33.3	100
Hazardous waste	17.0	2.1	**34.2**	19.0*	27.7	100
Packaging waste	5.7	36.3*	4.2	11.3	**42.6**	100
Medical waste	8.3	19.3	**35.7***	11.0	25.6	100

Bold values indicates the largest share.

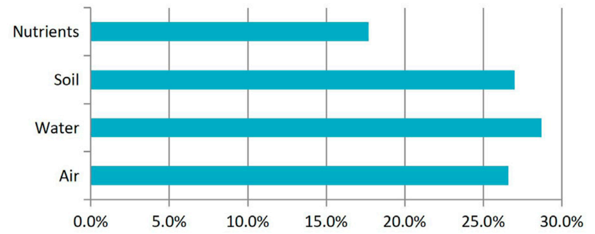

FIGURE 5
Natural resources damage assessment.

Although the difference is small, it is statistically significant, that is, those who are members of any environmental organization have a 0,2 higher mean value in terms of environmental public awareness. This means that the sub-hypotheses of the research are accepted too.

One-way ANOVA test results showed that there is not any statistically significant difference in the effect of mother's and father's education on environmental public awareness, citizenship, and waste management as well as childhood residence (F:0.706; $p > 0.005$). After the difference analyses, the data on the level of knowledge in terms of waste management can be examined in Table 4.

Regarding the level of knowing which bin or bag to put household waste in, 40% of the participants give the correct answer as black, followed by "I do not know" with 33%. The color of the hazardous waste bag is red with 34%, I do not know 27% and the correct answer is yellow with 19%. While the word danger is wrong by connoting the red answer, it may have promoted this answer to first place. In the color of recyclable waste bags such as packaging, medicine, and serum bottles, the answer "I do not know" ranked first with 42%, while the correct answer is blue with 36%. In the question about medical waste, the correct answer is the red waste bag color with 35%.

Finally, it is asked which resource wastes cause the most damage to measure public awareness of the impact of developments that threaten the environment on natural resources. Individuals are given the right to choose more than one source while answering this question (Figure 5). Thus, it can be determined to what extent the pressure on natural resources is felt.

When the responses received are carefully examined, it is noticeable that water scarcity has begun to be experienced as a result of developments such as drought, scarcity of precipitation, and the gradual decrease of clean water resources, and people can observe this scarcity in the current situation. Participants prefer primarily water (28.7), then soil (27.0), air (26.6), and nutrients (17.7) among the most pressing sources of waste. It is also stated as a comment that this pressure exists in all sources and if no precautions are taken, the seas and clean water resources will worsen in the future.

When the results of this study are compared with the studies in the literature, similar results are obtained. According to the study of Ince (2014), although individuals are concerned about the environment, they do not pay attention to this issue in their purchasing behavior. Severo et al. (2021) find a significant difference between gender and environmental public awareness in the country comparison study which they conduct during the pandemic period. Age and gender are strong variables that may differ between groups according to the subject studied (Ince, 2022). Also, the study of Li (2018) in six different departments of Minzu University emphasizes the positive relationship between environmental attitude, public awareness, and education. Lastly, Ahmad et al. (2012) highlight that the environmental issue should be kept on the agenda for public awareness, and action should be taken now in their research consisting of Malay, Chinese and Indian youths between the age of 18–25.

5 Conclusion

This paper aimed to draw attention by considering the issue with different dimensions, which deals with waste management in terms of environmental public awareness. So we can draw the following management conclusions.

Firstly, education, and living by seeing environmental problems can have dramatic effects. Thus, it would be useful to first look at how the research is structured and then interpret the results. The study deals with the subject of environment and waste management in three modules and includes detailed information supporting these models with various questions. . On the other hand, Our research tries to determine the level of environmental citizenship by measuring behaviors. Lastly, environmental public awareness is measured to understand environmental sensitivity in the third module.

Secondly, demographic factors such as family education level, childhood residence, and gender are also included to understand whether attitudes and behaviors towards the environment differ according to these factor groups. Further, the participants are asked whether they have received any training on the environment or waste management before, whether they are involved in a project on these issues and whether they are members of any environmental organization.

Thridly, The environmental awareness of practitioners needs to be strengthened. We found that there is a need for public awareness-raising training for the target audience and studies to increase sensitivity and desired behaviors on waste management. In addition to regular training, waste projects that combine fun and participation should be more widely.

Forth, Environmental behaviour is closely related to environmental knowledge and environmental citizenship. Although the participants state that they are sensitive to the environment in terms of environmental public awareness, these tendencies are relatively less reflected in behaviors in terms of citizenship and waste management. When the relationship between environmental variables and demographic factors is considered, statistically positive relationships are obtained. The difference analysis shows that female participants and those who are members of any environmental organization have higher environmental public awareness levels.

Fifth, People's educational background, family environment and other factors have a strong influence on their willingness and behaviour to become environmentally friendly. Considering the percentages of positive and negative responses to environmental citizenship and public awareness in the second and third modules, the results are highlighted. Thereby, decision-making authorities should support all social responsibility groups such as leading institutions of the society and voluntary organizations to implement some practices by paving the way for educators. International businesses that affect consumption also have responsibilities in this field. Their new management approaches towards the environment can also serve both future generations and the current society by organizing appropriate training, events, and public relations activities to increase environmental public awareness in the global arena. These competitive and sustainability-oriented businesses can profit in the long run by adopting perspectives that embrace society and nature.

The results show that in addition to planned, continuous and stable training on sustainable environment and waste management, participatory activities, fun activities, and projects should be done especially at early ages. A sustainable environment is a crucial issue that concerns all segments of society, from local to global. Therefore, new research on these issues can guide professionals as well as the literature. If the positive contribution of education and being a member of any environmental organization can change people's behavior, there is still hope for efficient use of resources and transfer them to future generations. So, it is recommended that the leading institutions in this field should be examined and brought to science to set an example for professionals as well as researchers on medical waste public awareness and practices, especially in special periods such as pandemics. Additionally, waste and environmental problems in different sectors such as agriculture, industry, and tourism can be examined, and comparisons can be made between different countries. For nature to continue living on its own, people must be willing to reduce its environmental impacts. Because while nature can live without humans, humans cannot live without nature. The sensitivity of the subject is due to its vital importance.

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

Conceptualization, YZ and JX; methodology, YZ and FI; validation, YZ, JX, HT, and MK; formal analysis, YZ, JX, and X-GY; investigation, YZ, JX, and FI; resources, YZ, JX, HT, and MK; data curation, YZ, JX, and X-GY; writing—original draft preparation, YZ, JX, and X-GY; writing—review and editing, YZ and FI.; supervision, YZ, JX, HT, and MK; project administration, YZ and JX; funding acquisition. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

JX was employed by VIPSHOP (China) 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.

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Risk assessment of cadmium pollution in selenium rich areas based on machine learning in the context of carbon emission reduction

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Machine learning is of great value for the situation analysis and scientific prevention and control of soil heavy metal pollution risk. In this paper, taking the selenium rich area as the research object, the improved Genetic Algorithm (GA)–Back Propagation (BP) algorithm was used to construct the risk assessment model of Cd pollution in this area. Firstly, the content of Cd and Se in the soil of the study area was statistically analyzed based on descriptive statistics and correlation analysis. Then, a three-layer BP neural network structure was designed and optimized by GA algorithm. The individual coding length was calculated by connecting weights and thresholds of Cd and Se elements. Based on 97 groups of field data in this area, the experimental results show that the BP model optimized by GA has faster convergence speed, maintains good generalization ability on the test sample points. Compared with multiple linear regression model (MLRM), GA-BP reduces RMSE by 64.84, 52.12, 49.53, and 63.18% compared with M5. The accuracy of estimating Cd pollution status in different areas by GA-BP neural network model is higher than the other three regression models on the whole. In the whole research region, the samples in the safe interval, relatively safe interval, light pollution interval, moderate pollution interval and severe pollution interval accounted for 4.12, 8.24, 42.26, 17.52 and 27.86%, respectively, and the prediction results of soil Cd pollution level showed that only 12.36% of the samples were in a safe state without the risk of Cd pollution, while most of the samples were in a mild state. Because of the huge potential of carbon sequestration and emission reduction in agriculture, planting se-rich and Cd-low crops in these areas can not only promote the development of local Se-rich industries but also achieve carbon sequestration and emission reduction.

KEYWORDS

Se, GA-BP, pollution risk assessment, Cd, carbon emission reduction

Introduction

Soil is an important part of the earth's ecosystem. The physical and chemical properties of soil affect the growth of plants, especially the heavy metal pollution in soil affects the growth of plants. Heavy metals in soil will enter plants or animals through the food chain, and then enter the human body for enrichment, affecting human life and health. According to the experimental results of the national survey of soil heavy metal pollution, the total over standard rate of soil heavy metal content in our country has increased to 16.1%, which damages the ecological environment, endangers human health and affects human life (Shi Jiangdan and Yangyang, 2022).

In some areas of China is rich in selenium rich soil resources. It is of great practical significance to develop selenium rich agricultural products based on selenium rich soil resources and increase selenium intake by daily diet for selenium deficient people. However, studies have shown that selenium rich soils are often associated with heavy metals such as cadmium and chromium, and the heavy metals in soil have the characteristics of small mobility, concealment, easy accumulation and high toxicity, which not only directly affect the quality of soil environment, but also affect the water source, animals and plants and human health (Hu Qing and Ying, 2022). And lead to selenium-rich areas of agricultural economic development in the face of resource shortages, environmental pollution and other related environmental problems, for high-selenium and high-cadmium areas can grow selenium and cadmium reduction crops, reduce the use of fertilizers, pesticides and so on, agricultural means of production also emit greenhouse gases in their production process, and using soil rich in selenium and cadmium to grow crops rich in selenium and low in cadmium can achieve a win–win situation of carbon sequestration and people's livelihood.

Therefore, how to obtain the pollution information of heavy metals in soil efficiently and quickly and provide basic support for soil treatment is an important research content in the field of Environmental Earth. At present, the soil heavy metal pollution investigation usually uses the ground object spectrometer (Qiuxia et al., 2017) or induced LIBS analysis technology (Ren et al., 2022) to study, and combined with the field measured a large number of soil heavy metal samples of laboratory physical and chemical data to estimate the soil heavy metal. Although the traditional geochemical methods have high detection accuracy, for large-scale pollution investigation, the field sample collection cost is high and time-consuming, and the comprehensive analysis ability of ecological environment information is weak, which makes it difficult for the traditional chemical method to become our high efficiency and has strong timeliness advantages to monitor environmental problems such as soil heavy metal pollution (Chen et al., 2018). Compared with the traditional assessment methods of regional soil heavy metal pollution, the artificial intelligence machine learning algorithm can accurately and quickly predict the regional soil heavy metal pollution status, which can play an auxiliary role in the prevention and control of soil heavy metal pollution. By analyzing the contribution of each heavy metal element to the soil pollution, the pollution source can be traced, so as to reduce the emission of source pollution and the cost of repairing the polluted land (Lijie et al., 2018; Yantao et al., 2022). For example, Dinpankar used Health hazard risk mapping (HHRM) to detect 14 different Health hazard factors from the Priuria area, which was mainly composed of hardy rocks (Ruidas et al., 2022). In another study, Ruidas used ANN and RF to quantify toxic substances in the Ramsar area of Lake Chilka with the help of 17 water chemistry properties of the lake water. Compared with the traditional assessment methods of regional soil heavy metal pollution, the artificial intelligence machine learning algorithm can accurately and quickly predict the regional soil heavy metal pollution status, which can play an auxiliary role in the prevention and control of soil heavy metal pollution (Pal et al., 2022).

In recent years, the methods of soil pollution risk assessment using artificial intelligence and machine learning methods have also begun to receive attention and research. The main research work focuses on the evaluation of soil environmental quality, prediction of soil characteristics, prediction of soil heavy metal content and so on. In the aspect of soil environmental quality assessment, Jiang et al. used the support vector machine method of statistical learning to evaluate the soil environmental quality, and had certain learning ability of small samples (Jiang Xue et al., 2014). In the aspect of soil properties prediction, Ma et al. (2016a) used machine learning method to predict soil total nitrogen, organic carbon and moisture values, and the data were obtained from spectral measurement instruments. In the aspect of soil heavy metal content prediction, Ma et al. (2016b) used the random forest model of machine learning to predict the heavy metal content of soil. Zhou et al. (2015) studied the hyperspectral inversion method of heavy metals in mining area soil based on transfinite learning machine, predicted the content of heavy metals in mining area soil using visible near infrared spectroscopy data, and analyzed and compared with support vector machine and other methods.

Therefore, this paper uses the improved GA-BP algorithm to build the cadmium pollution risk assessment model in the selenium rich area of the study area. Firstly, the correlation between soil samples is analyzed, and the missing or bad values of soil samples are interpolated to make the sample data more complete and accurate; After that, the Cd pollution under different pollution conditions was calculated, and the heavy metal pollution index of soil was quantitatively predicted, which is of great value for the spatial situation analysis and scientific prevention and control of soil heavy metal pollution.

Research status of soil pollution prediction based on machine learning

Dumedah et al. (2014) and Aydilek and Arslan (2012) used neural network algorithm to interpolate and predict the missing values of heavy metal elements in soil. They set the elements with missing values as category attributes, and other complete elements in the samples as description attributes. After that, they put the samples into the neural network for training, so as to predict the missing heavy metal values in the samples, and the prediction effect is good. Antonio (Sun and Sheng, 2016) took the information of relevant geographical environment elements as the input parameters of neural network, analyzes the correlation between various elements, so as to predict the regional soil heavy metal pollution index, and analyze the causes of soil heavy metal pollution. Gong et al. (2017) used the relevant data of heavy metals in soil as the input data of neural network, so as to predict the contents of heavy metals Cr, Cu, and Ni in soil, and the prediction effect was better. At the same time, the author compared the prediction results of BP neural network model with the prediction results of multiple linear regression and partial least squares regression, and the results showed that BP neural network was better. However, when traditional BP is used to solve the problem, its weight is usually changed due to local changes, which makes the derivation fall into local extremum easily, which makes the training fail. Meanwhile, due to the existence of flat area when the output of neurons is close to 0 and 1, the data deviation is smaller and the convergence process is slower.

Different from the traditional gradient derivation method, genetic algorithm (GA) is a more efficient method for global searching and solving problems (Deng et al., 2021). It can be realized not only by individual learning, but also by individual learning, which emphasis on the population and the strategy of searching among populations can overcome the nonlinear difficulties that other algorithms are difficult to solve. Considering that BP algorithm is easy to fall into local optimum and over rely on initial value, encoding BP parameters and Optimizing BP original data with genetic algorithm can improve BP learning quality and reduce the possibility of falling into local minimum data. In order to solve the problem of large data analysis error caused by background interference and signal interference of adjacent elements in XRF quantitative analysis and prediction of heavy metal elements in soil. Cheng et al. (2020) used GA algorithm to optimize the weights and thresholds of BP neural network, and quantitatively analyzed the spatial distribution and internal relationship of Pb, Mn, Cr, and Cu. Liu et al. (2021) analyzed the relationship between nine meteorological factors and soil moisture data measured by monitoring instruments. Considering the lag of meteorological factors, BP-GA model was used to predict soil moisture of eight meteorological data. The soil moisture of ecological slope can be well predicted, and the results have high prediction accuracy, which has a good application prospect in other fields.

To sum up, the artificial neural network has the ability to approximate any nonlinear mapping by learning, and its application in soil environment prediction is not limited by the nonlinear model, and has obvious advantages compared with the traditional nonlinear system prediction. At the same time, the topography of some research areas is complex and the sampling is difficult. The artificial neural network model can be used to reduce the sampling cost and analysis cost, and reduce the chemical pollution caused by the analysis samples. However, many studies are only limited to the prediction of different metal elements in the soil, and the research on the internal coupling relationship between different elements is relatively insufficient. This paper focuses on the area, where the soil Se content is relatively high, how to use unsupervised learning method to improve the adaptability and flexibility of spatial distribution modeling and explore the mechanism of Cd pollution in high Se content areas is an important research to be further studied.

Statistics of Cd and Se contents in soil of the study area

Some studies have shown that there are symbiotic and antagonistic relationships between selenium and cadmium in some areas. While some selenium rich agricultural products in some areas exceeds the standard of cadmium, which is mainly due to the symbiosis of selenium and cadmium in soil. Mingyi and Jing (2012) studied the characteristics and ecological effects of selenium and heavy metals represented by cadmium in the soil, which found that the reason for the simultaneous existence of selenium and cadmium was that the content of selenium and cadmium in the soil parent material was high, but there was no collective disease in the local population. The hair selenium content was high, and the hair cadmium content was low, suggesting that there might be some antagonistic relationship between selenium and cadmium. Therefore, due to the particularity of the study area, in order to quantitatively predict the Cd pollution index, it is necessary to carry out statistical and correlation analysis on Cd and Se contents.

Stratigraphic unit selection

There are differences in the distribution of elements in rocks of different strata. Therefore, the selenium and cadmium contents of seven rock samples in the study area were selected for statistical comparison, as shown in Figure 1.

The average content of Cd in rock samples is shown that Permian > Carboniferous > Triassic > Devonian > Cambrian > Ordovician > Silurian, which is consistent with the average selenium content of rocks in the main Se-rich strata in the study area. This area is a region with high Cd geochemical background under natural conditions. In different parent material units, the

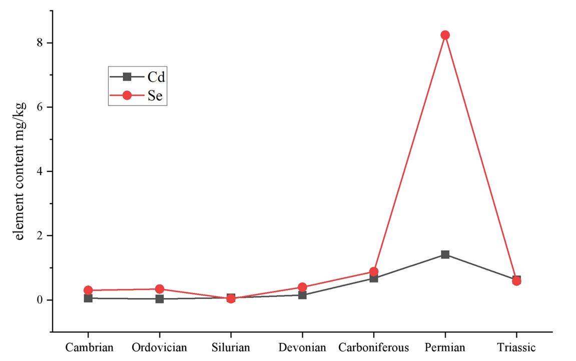

FIGURE 1
Comparison of Cd and Se contents in different stratigraphic units.

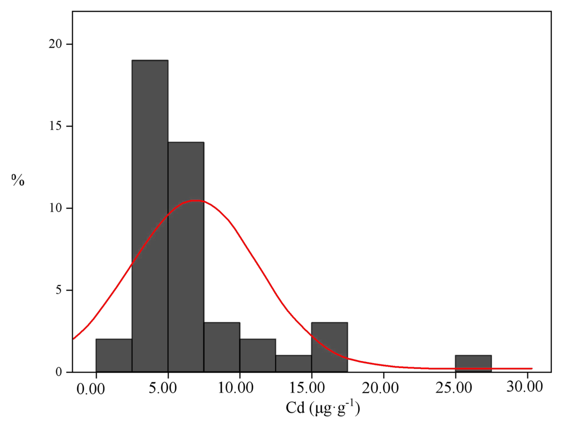

FIGURE 2
Histogram of soil Cd content in the study area.

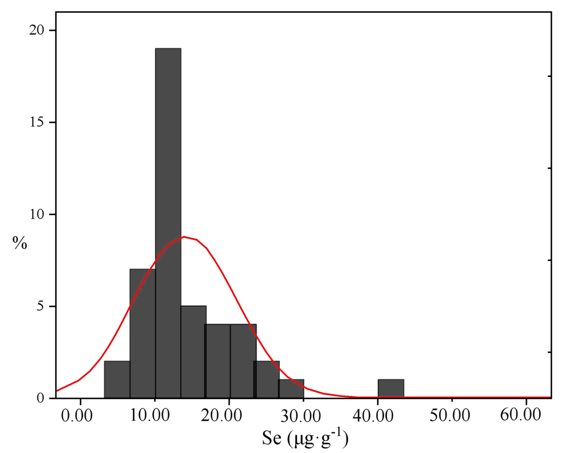

FIGURE 3
Histogram of soil Se content in the study area.

distribution of soil Cd is closely related to the geological attributes of the parent material, and the content of soil Cd is higher in the Permian parent material area, which is significantly higher than that in other strata. Therefore, this paper selected the soil data under the Permian system for training.

Descriptive statistics

Descriptive statistical analysis refers to the analysis of all aspects of the characteristic values of a group of data in the experiment. The purpose of this analysis is to more clearly describe and count the characteristics of the experimental samples and the overall characteristics that can be reflected. The 97 Cd and Se content sample values obtained in the study area are used for histogram statistics, as shown in Figures 2, 3.

It can be seen from the figure that there are some abnormal values of Cd and Se contents in soil. The existence of outliers has an impact on the accuracy of the estimation model of soil heavy metals, so the outliers of the two are eliminated. The content of Cd ranged from 0.44 to 29.6 μg/g, and that of Se ranged from 0.84 to 54.1 μg/g. We conducted histogram statistics on the sample data and eliminated the outliers. After elimination, the sample numbers of Cd and Se elements were 94 and 93, respectively.

Element correlation analysis

Correlation analysis is a statistical method that can measure whether there is a dependent relationship between two or more variables, and explore the degree of dependence between two variables. Pearson correlation coefficient method was used for correlation analysis in this study. Correlation coefficient is a non-deterministic relationship, which can measure the degree of correlation between two variables. If the absolute value of Pearson coefficient R is closer to 1, it means that the correlation between the two variables is greater. The calculation formula is shown in Formula (1).

$$R(X,Y) = \frac{\mathrm{Cov}(X,Y)}{\sqrt{\mathrm{Var}[X]\mathrm{Var}[Y]}} \tag{1}$$

Where, $\mathrm{Cov}(X,Y)$ is the covariance of X and Y, $\mathrm{Var}[X]$ is the variance of X, and $\mathrm{Var}[Y]$ is the variance of Y.

In order to facilitate the spatial prediction of soil metals, the correlation among the three target elements was analyzed based on the least square regression analysis method. The correlation analysis was carried out in SPSS software, and the results are shown in Table 1.

TABLE 1 Correlation matrix of Cd and Se.

Element	Cd	Se
Cd	1	
Se	0.5574**	1

$p < 0.01$ is a very significant correlation (**).

Although the correlation between the two elements showed significant correlation, but the correlation coefficient was not more than 0.7. In the construction of pollution estimation model, the two elements need to be analyzed and space estimated separately.

Risk assessment model of Cd pollution based on GA-BP

Back propagation topology

The core of BP neural network algorithm is to search for a group of weight vectors which can make the output error function of the network reach the minimum through the alternate iteration of the two propagation processes (Wang and Bi, 2021).

Forward propagation of data stream

As shown in Figure 4, the number of nodes in input layer, hidden layer and output layer of a certain network is n, q and m respectively, the weight matrix between input layer and hidden layer is V, the weight matrix between hidden layer and output layer is W, and the excitation functions of hidden layer and output layer are f_1 and f_2 respectively. The results of hidden layer and output layer of neuron model are as follows:

$$\begin{cases} Z = f_1(VX) \\ Y = f_2(WZ) \end{cases} \tag{2}$$

Thus, the network completes the overall mapping from n dimensional input data to m dimensional output data.

Backward propagation of error function

Set the number of training samples as p, and define the output error function for the i-th training sample:

$$E_i = \frac{1}{2}\sum_{j=1}^{m}\left(t_j^i - y_j^i\right)^2 \tag{3}$$

In Formula (3), t indicates the desired output.

According to the definition of error function, the global error of all training samples can be obtained as follows (Liang et al., 2019):

$$E = \frac{1}{2}\sum_{i=1}^{p}\sum_{j=1}^{m}\left(t_j^i - y_j^i\right)^2 = \sum_{i=1}^{p} E_i \tag{4}$$

The main purpose of this paper is to reduce the error of different levels by adjusting the weights of the different levels.

This paper constructs a three-layer neural network including input layer X_i, hidden layer and output layer Y_k. The number of input layer refers to the dimension of input vector, i.e., the

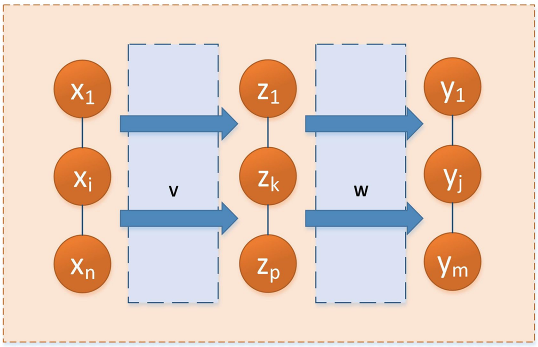

FIGURE 4
Forward propagation of data flow.

dimension of optimal influence factor set of heavy metal elements input from outside. Among them, the number of neurons in input layer of Se element participating in modeling is 6, and that of Cd element is 9;

Neuron Y_k in the output layer refers to the dimension of the output vector of the experiment, that is, the dimension of soil heavy metal training samples participating in the modeling. The selection of the number of hidden layer neurons has a great influence on the model accuracy of BP neural network. In this paper, the number of hidden layer neurons is determined to be 4 through trial and error method, the activation function of hidden layer is Sigmoid function, and the activation function of output layer is purelin function.

Genetic algorithm–back propagation model

BP neural network optimized by genetic algorithm mainly includes population initialization, fitness function and determination of genetic operation.

Population initialization

In this study, the coding method of individuals is real number method. The length of the encoding string is usually composed of four parts: the connection weight and threshold value between the input layer and the hidden layer, and the connection weight and threshold value from the hidden layer to the output layer. Assuming that the number of nodes in the input layer of BP neural network is m, the number of nodes in the hidden layer is p, and the number of nodes in the output layer is n, then the calculation formula of the coding length S is shown in Formula (5):

$$S = m \times p + p \times n + p + n \tag{5}$$

Where, $m \times p$ is the encoding length of the connection weight between the input layer and the hidden layer, $p \times n$ is the encoding

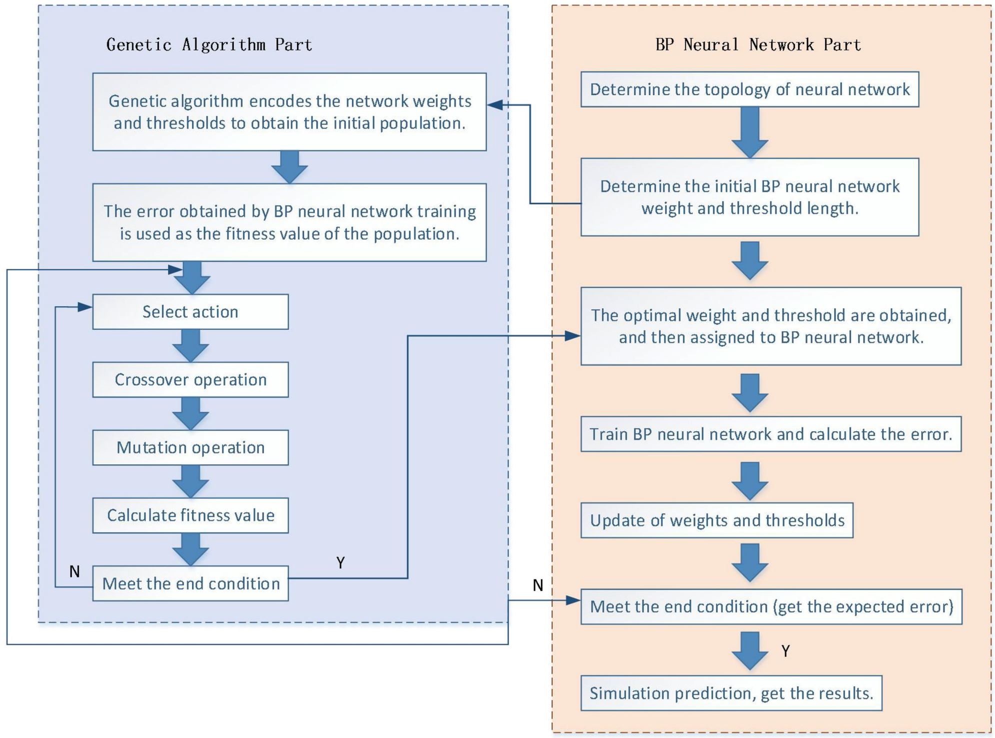

FIGURE 5
Algorithm flow of GA-BP.

length of the connection weight between the hidden layer and the output layer, p is the encoding length of the threshold of the hidden layer, and n is the encoding length of the threshold of the output layer. According to the connection weights and thresholds of Cd and Se elements, it can be calculated that their individual coding lengths are 45 and 33 respectively, and the calculation formula is shown in Formula (6):

$$S_{\mathrm{Cd}} = 9\times4+4\times1+4+1=45$$
$$S_{\mathrm{Se}} = 6\times4+4\times1+4+1=33 \quad (6)$$

Calculation of fitness value

The BP neural network is trained with training samples, and the error between the output obtained after training and the expected output is summed and calculated with the absolute value. The calculated F is the individual fitness value, and the calculation of F is shown in Formula (7):

$$F = k\left(\sum_{i=1}^{n}\mathrm{abs}\left(y_k - o_k\right)\right) \quad (7)$$

Where, n is the number of output nodes of neural network; y_k is the actual output of the neural network output layer; o_k is the expected output; If the individual fitness value of the calculated population is smaller, it means that the individual is optimal.

Crossover operator and mutation operation

In this paper, roulette method is used to select genetic operators. In this study, the real number method is used to initialize the population, so the operation of crossover operator is carried out by real number crossing method. When the crossover probability is set as 0.3, the real crossover operation is performed, and the mutation operation is performed when the mutation probability is 0.1.

After the parameters of genetic algorithm are determined, it is judged according to the optimization steps of genetic algorithm to see whether it can meet the accuracy of genetic algorithm or whether it can meet the maximum evolution algebra. If it is satisfied, the individual is decoded to obtain the optimal initial weights and thresholds, and then the initial weights and thresholds are assigned to the BP neural network, and the neural network is trained according to the flow shown in Figure 5.

Finally, the trained neural network is used to estimate the content of Se and Cd in the study area.

Risk assessment status

The single factor index method and Nemero comprehensive pollution index method are often used to evaluate the heavy metal

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TABLE 2 Selection criteria of pH influencing factors.

	$pH \leq 5.5$	$5.5 < pH \leq 6.5$	$6.5 < pH \leq 7.5$	$pH > 7.5$
α	0.11	0.29	0.43	0.57

pollution degree of a piece of land. The expression of single factor exponential method is shown in Formula (8).

$$P_i = \frac{C_i}{S_i} \tag{8}$$

where C_i represents the content of heavy metal i in soil, and S_i represents the standard content data of heavy metal i in soil.

In the screening of soil pollution risk in agricultural land, available cadmium in soil is closely related to pH value. The low availability of cadmium in acidic soil is not conducive to the absorption of selenium, while the high availability of cadmium in alkaline soil is more conducive to the absorption of cadmium. Therefore, the influence factor α is introduced into the above model to consider the influence of pH on the division of pollution degree, and the division basis is shown in Table 2. With the enrichment of cadmium, the effect of soil pollution is not linear, so the influencing factors are different at different pH. Meanwhile, the cadmium content in the model is the effective cadmium content.

Then, Formula (8) is optimized as

$$P_i = \alpha \frac{C_i}{S_i} \tag{9}$$

The pollution index was calculated according to Formula (10)

$$P_n = \sqrt{\frac{\left(\frac{1}{n}\sum_{i=1}^{n} P_i\right)^2 + \left[(P_i)_{\max}\right]^2}{2}} \tag{10}$$

Where P_i represents the single pollution index of heavy metal i in soil, P_n is the nemerow comprehensive pollution index of heavy metal in soil.

To obtain soil Cd content data in different pollution states, the content parameter of soil Cd in area A is defined as Z. Formula (9) is used to calculate the soil heavy Cd pollution state G (Safe state g1, relative safe state g2, mild Cd pollution state g3, moderate Cd pollution state g4, and severe Cd pollution state g5).

Experiment and analysis

Parameter settings

The transfer function of hidden layer is sigmoid function, and the learning rate is generally set between 0.01 and 0.8. If the learning rate is too large or too small, the network performance will be affected and the accuracy will decrease. The selection of training times and target errors determines the generalization ability of the model. Too little training times may lead to insufficient learning, and too much training times may lead to overfitting. The network learning rate set in this paper is 0.01, the maximum training times is 1,000, and the target error is 0.0001. The evolutionary algebra determines the change of individual fitness in the population. The appropriate evolutionary algebra can be determined according to the stability of the fitness function value. The maximum number of iterations selected in this paper is 100. After model debugging and comparison, the crossover probability value selected in this paper is 0.3, and the mutation probability value is 0.1.

Sample collection

Previous studies on the geochemistry of selenium and cultivation of selenium rich crops in the study area have found that the Cd content in the se rich soil in some area has reached a serious level, and the Cd content of rocks or soil in a large area of the Permian se rich strata in the study area exceeds the standard. Therefore, based on the collected data, 1,000 groups of data were randomly generated, and the data generated after annotation was used for algorithm training. Finally, 97 groups of data were used for algorithm verification.

Evaluation index

Pollution degree

Nemerow comprehensive pollution index P directly reflects the multiple of heavy metals exceeding standard and pollution degree in soil. According to the evaluation standard of Nemerow pollution index, when P is less than or equal to 0.7, the soil condition is safe (Level 1); when P range is (0.7,1.0), the soil condition is fair and safe (Level 2); when P range is (1.0,2.0), the soil condition is mildly polluted (Level 3). When P is in the range of (2.0,3.0), the soil is moderately polluted (Level 4); when P is greater than 3.0, the soil is severely polluted (Level 5) (Ying et al., 2019).

Model evaluation

In this paper, we use the experimental group samples to establish an estimation model to explore the changes of soil heavy metal content in the study area, and use the measured values of the remaining soil samples of the control group to evaluate the accuracy. This study mainly uses root mean square error (RMSE) and mean relative estimation error (MRE) to evaluate the accuracy of the study area, as shown in Formulas (11) and (12).

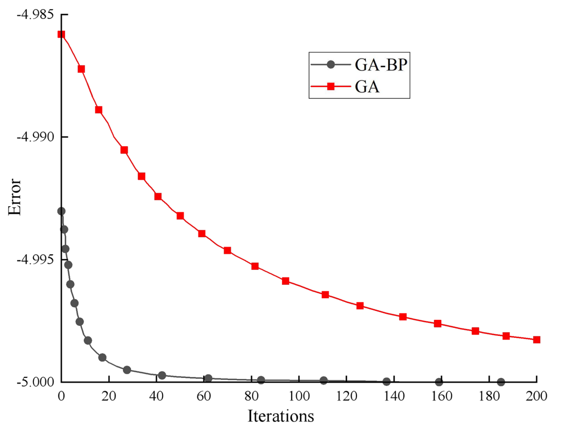

FIGURE 6
Model convergence.

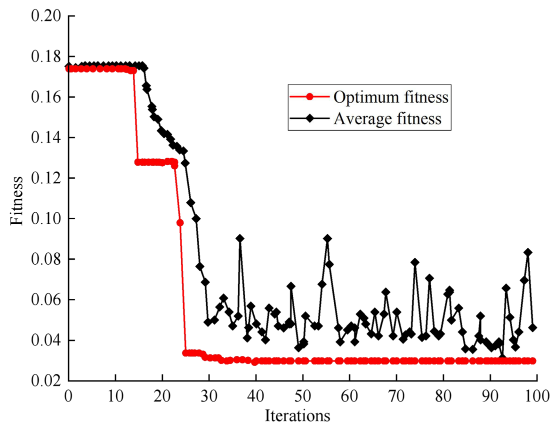

FIGURE 7
Fitness curve of the model.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(M_i - P_i)}{N-1}} \tag{11}$$

$$\mathrm{MRE} = \frac{\sum_{i=1}^{N}\left(\frac{|M_i - P_i|}{M_i}\right)}{N} \tag{12}$$

Where, M_i represents the measured value of the i-th soil heavy metal sample, P_i represents the estimated value of the i-th soil heavy metal sample; N represents the total number of soil samples. RMSE can measure the accuracy of the estimation model results. While MRE is the average value of relative errors of all test samples, which can measure the average reliability of model estimation results.

Results and analysis

Model convergence

In order to verify the effectiveness of GA-BP algorithm, the iterative process is tested, and the results are shown in Figure 6.

It can be seen from Figure 5 that after 200 iterations, the calculated value of GA-BP algorithm has been equal to −5. However, under the same calculation iteration times, the convergence speed of traditional BP algorithm is not as fast as that of GA-BP algorithm, which shows that compared with BP algorithm, GA-BP algorithm has better optimization effect in dealing with general function problems. The change trend of the model fitness curve after optimization is shown in Figure 7. After repeated genetic optimization of the model, the fitness index decreased and the adaptability increased. When the evolution reached about 24 generations, the fitness index gradually became stable.

Comparison of predicted values of Cd and Se

In order to directly reflect the overall trend of estimation error, the actual and predicted values of Cd and Se in the study area soil by GA-BP model were compared. The results are shown in Figures 8, 9.

It can be seen that GA-BP model has good training approximation accuracy, and the prediction of Cd and Se content is very accurate. Only a few sample points have relatively large error, but the overall prediction performance is good.

Prediction of pollution state

In order to verify the superiority of GA-BP neural network model, it was compared with multiple linear regression model (MLRM), BP network model and M5 decision tree model in different levels of Cd pollution samples. The results are shown in Table 3.

Compared with mlrm, GA-BP reduced the RMSE by 64.84, 52.12, and 49.53% respectively, and the estimation error of 63.18% was also significantly lower than that of M5. The distribution of soil Cd pollution level in the study area is statistically analyzed, and the results are shown in Figure 10.

Among the samples in the study area, 4.12, 8.24, 42.26, 17.52, and 27.86% were in the safe, relatively safe, slightly polluted, moderately polluted and heavily polluted areas, respectively.

Discussion

To sum up, GA-BP model maintains the good generalization ability in the new test sample points, and because of the fuzzy rule model expression, it has the interpretability and comprehensibility that the neural network model does not have. It has a significant

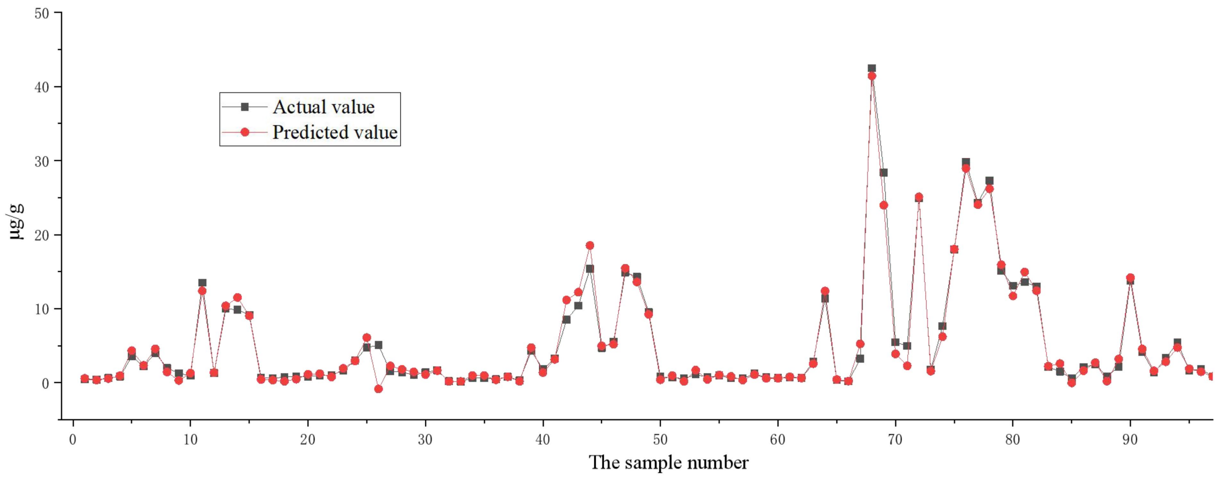

FIGURE 8
Comparison of predicted and actual values of Cd.

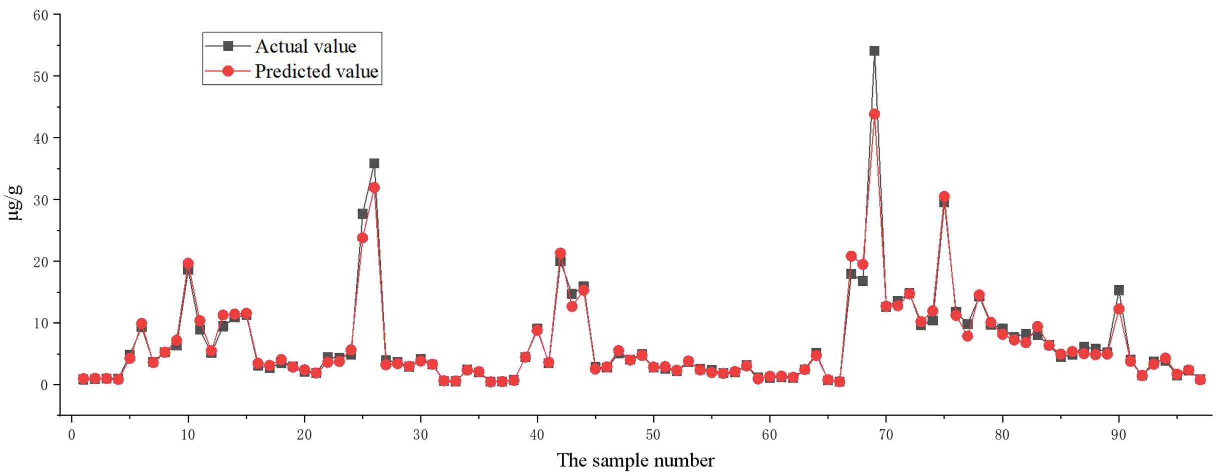

FIGURE 9
Comparison of predicted and actual values of Se.

TABLE 3 Comparison of estimation errors of different pollution states.

Level	RMSE				MRE			
	MLRM	BP	M5	BP-GA	MLRM	BP	M5	BP-GA
1	16.863	23.881	7.029	4.851	0.819	2.205	1.152	0.018
2	10.868	20.02	9.163	4.257	1.998	4.887	2.142	0.27
3	3.531	13.662	15.752	1.458	1.188	1.602	0.846	0.054
4	9.097	16.258	13.519	3.033	2.961	0.918	2.223	0.36
5	12.012	29.359	11.022	3.618	3.897	3.591	3.249	0.45

application value for the ecological risk analysis and assessment of soil heavy metal pollution. In addition, the accuracy of GA-BP neural network model in estimating Cd pollution status in different regions was higher than that of the other three regression models. At the same time, the prediction effect of this model for mild Cd pollution is better than other grades. Moreover, the

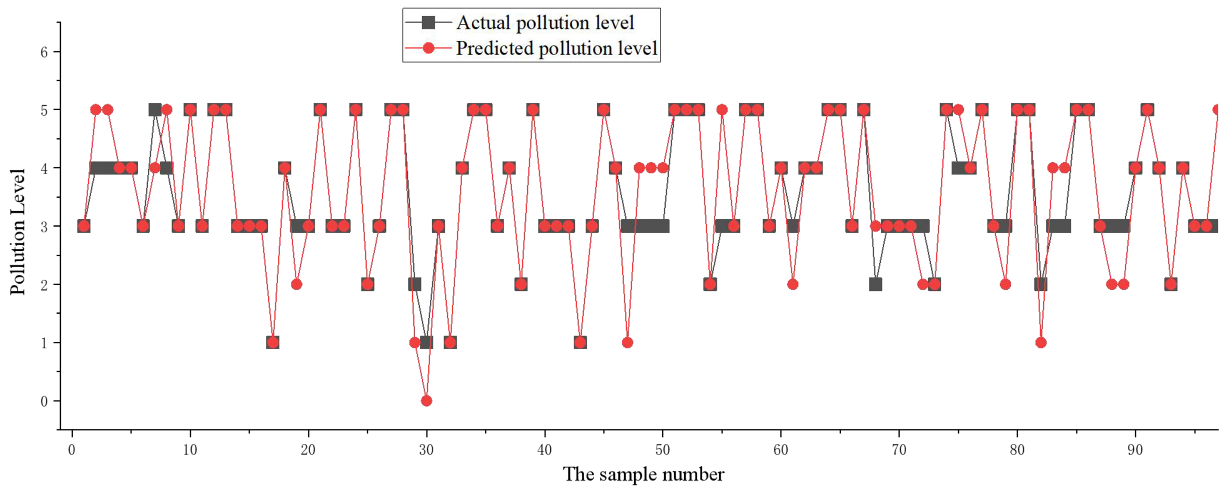

FIGURE 10
Cadmium pollution level.

Nemero pollution level predicted by GA-BP neural network model is close to the measured Nemero pollution level. In addition, it can be seen that soil Cd pollution in the study area is a serious problem. Only 12.36% of the samples are safe and have no risk of Cd pollution, while most of them are mildly polluted. Therefore, it is necessary to carry out risk control of Cd pollution in the study area. Because of the huge potential of carbon sequestration and emission reduction in agriculture, planting Se-rich and Cd-low crops in these areas can not only promote the development of local se-rich industries but also achieve carbon sequestration and emission reduction. Heavy metals in soil will enter plants or animals through the food chain and then enter human body for enrichment, affecting human life and health. This study has important value for the situation analysis and scientific prevention and control of soil heavy metal pollution risk.

Conclusion

In this paper, the improved GA-BP algorithm is used to build the cadmium pollution risk assessment model in the selenium rich are. The content of Cd in different pollution states was calculated and the soil Cd pollution index was used for quantitative prediction, which is of great value for the spatial situation analysis and scientific prevention and control of soil heavy metal pollution. The experimental results show that, compared with BP neural network, GA-BP has a significant optimization effect on the model, and its fitness index is gradually stable at lower iteration times. The accuracy of GA-BP neural network model to estimate Cd pollution status in different areas is higher than other models. In addition, this study has important value for the situation analysis and scientific prevention and control of soil heavy metal pollution. From the pollution level index, soil Cd pollution of the Permian in the study area is relatively serious, only 12.36% of the samples are in a safe state. In the global scale, soil Cd pollution or potential pollution in many areas is still very much studied. Heavy metals in soil will enter plants or animals through the food chain and then enter human body for enrichment, affecting human life and health. This study has important value for the situation analysis and scientific prevention and control of soil heavy metal pollution risk.

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

This study were reviewed and approved by Hubei Institute of Earth Sciences, Hubei Selenium Eco-Environmental Effect Testing Center and Huazhong Agricultural University. The participants provided their written informed consent to participate in the study.

Author contributions

WZ and JY were responsible for the conception of research ideas and the writing of the first draft. DW was responsible for data collection. YZ and CJ were responsible for the methodology design. LY was responsible for the analysis of the data. HC was responsible for the article chart. All authors contributed to the article and approved the submitted version.

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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.

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The evolution of public sentiment toward government management of emergencies: Social media analytics

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At present, social media have become the main media of network public opinion (PO) dissemination. By analyzing the trend of emotional development in public emergencies, we can explore the evolution law of PO and identify potential risks, which provide decision support for the guidance and control of government management. First, based on the concept of critical points in the complex system, this study established a public sentiment (PS) evolution model under public emergencies and proposed an algorithm to identify the critical points in PS based on microblog data analysis. In addition, the BC-BIRCH algorithm was used to construct a topic clustering model for public emergencies, which improved the effect of topic discovery by merging multiple topic clusters. The evolution of public emergencies was analyzed by calculating the emotional heat value of different topic events. Finally, experimental results showed that the emotion of netizens' fluctuates greatly in the initial stage of PO under different themes. The method used in this paper achieved good results in topic clustering, critical point prediction, and PO evolution analysis of public emergencies. The main contribution of this paper is to analyze the evolution of the internal mechanism of PS and to identify and predict key nodes such as the outbreak and extinction of netizens' sentiment based on data-driven methods so as to provide the basis and support to the government and related media as the main body of prevention and control to respond in advance and guide in time.

KEYWORDS

social media, public emergencies, BC-BIRCH, critical point, emotional evolution

Introduction

With the rapid development of social media, especially social information, the original public opinion (PO) of the single and linear networks has gradually developed to show more characteristics, such as wide source, complex content, fast spread, and diverse forms. Similarly, the real-time characteristics of the network ensure the timeliness of data collection and access, while its dynamic nature provides a theoretical basis for dynamic PO monitoring (Zhang and Chen, 2021). The rapid development of natural language processing and artificial intelligence (AI) technologies makes technological implementation for the discovery of online PO feasible.

At present, China's network equipment is rapidly popularized among more user groups, and network security and network PO become the key regulatory objects of government agencies and also aim to improve the quality of network public relation management services. Therefore, how to reasonably use the massive PO data on the internet in combination with a relevant text analysis technology to control PO is an inevitable problem for government agencies in public relation management services (The 13th Five Year Plan for the Construction of National Emergency Response System). As an important PO field and the PO center of many social events, the microblog has attracted the attention of governments at all levels and has increasingly become the main position of network PO governance. The essence of the microblog is a node sharing instant information network, which has the characteristics of instantaneity and sharing. The dynamic information dissemination network composed of the microblog is a dynamic development (Ma, 2022). Research on the social objectives of emergency management in case of major emergencies mainly focuses on the field of PO governance, among which emotion recognition is a hot spot (Zeng and Li, 2022). Accurate and effective identification of public sentiment (PS) is conducive for government departments to grasp the dynamics of PO and to formulate guidance strategies. However, there are still shortcomings in research on the governance of POs in public emergencies. In terms of prediction methods, many scholars developed semantic recognition and algorithms and optimized prediction methods, such as probability graphic pattern (Rui et al., 2017), deep rolling (Rong et al., 2019), damped oscillator model (Dong et al., 2020), and other newly developed models to predict PS, to achieve good prediction results, and to improve the prediction efficiency from different angles and levels. However, existing research on emotion prediction using machine learning algorithms only focuses on data performance or overemphasizes these algorithms. Meanwhile, most PS data obtained by existing research come from the network text, and many adverbs expressing emotional intensity are often ignored, which cannot truly reflect the change of PS. Indeed, the public in different regions have different emotional expression due to the difference in risk perceptions. Text and network information analysis, user behavior prediction, and other models can better explore the potential scale of network PO data and more accurately predict the emotional changes of users on PO topics so that relevant institutions can more effectively monitor the topic trend of network PO and correctly guide users to regulate their behavior on the network. Indeed, the public in different regions have different emotional expressions due to the difference in risk perception (Zeng et al., 2022).

In public emergencies, it is important to understand how to analyze the evolution of the internal mechanism of PS and to identify and predict the outbreak and decline of netizens' emotions based on data-driven method, to provide the basis and support for the government and relevant media as the main body of prevention and control to respond in advance and guide in time. Therefore, based on the concept of critical points in complex systems, this study combined the critical transition theories in the field of complex systems and established a PS evolution model under public emergencies, which analyzes the evolution and development stages of PS in public emergencies through the microblog text data.

Literature review

Emotional analysis

For some people, the expression of a variety of views is also the phenomenon of diversity. Everyone's expression differ in certain ways, and these differences are a result of different life experiences, different family environments, and diverse educational backgrounds. Emotional analysis on Twitter has achieved some progress and research results. Ruz et al. (2020) proposed a Bayesian factor measurement method and conducted experiments on two Spanish data sets. The results showed that, in comparison with the support vector machine and random forest, the Bayesian factor measurement method can solve emotional analysis problems (Ruz et al., 2020). Hassan conducted an automated web recycling through RStudio, collecting data on cryptocurrency tweets, extracting emotional states from users through machine learning methods, and explaining the social impact of the cryptocurrency phenomenon (Hassan et al., 2022). Jiang et al. (2013) optimized the algorithm by extracting more structural features based on the two-level classification structure of the emotional hierarchy. In the microblog emotional classification method, a two-step classification method is adopted, where the first step of the method is to filter the text content to screen out the emotional text, and then, the filtered text is classified into positive and negative emotions, and the classification accuracy can reach 60.1% (Jiang et al., 2013).

Machine learning on social media platforms to study user sentiment prediction research has been a major concern. For example, based on emotional analysis technology, scholars analyzed microblogs of local governments in the USA, studied the relationship between factors such as microblog intonation and citizen participation, established a prediction model of factors that influence the response rate of microblogs, tested a large number of facts, and found that specific emoticons can increase the possibility of answering, while tags negatively affect the response rate (Haro-de-Rosario et al., 2018). Some studies also found that, when dealing with disaster events, extracting the emotions of Twitter users can help emergency personnel to form a stronger situation awareness of the disaster area itself (Saputri et al., 2018). However, with the rapid growth in the volume of data and the increasing complexity of social network structures, traditional machine learning algorithms, such as logistic regression and Bayesian network of support vector machine, are facing challenges of model performance degradation and poor robustness (Wu et al., 2020). These methods are very effective for the test data set, but not for the source data.

PS under public emergencies

Emotional analysis and topic mining are combined to study network PO more comprehensively. Wu et al. (2021) proposed a Latent Dirichlet Allocation (LDA) short-text clustering algorithm based on the cooccurrence of emotional words and the feature extraction of knowledge pair to mine the distribution and connection of topics and emotions in comments. Among them, the cooccurrence of emotional words fully considers different short articles. Short microblog articles are endowed with emotional polarity. The knowledge pairs of topic-specific words and topic-related words are extracted and inserted into the LDA model for clustering (Wu et al., 2021). Gu et al. (2022) proposed a multisource domain transfer discriminant dictionary learning model to improve the effect of emotion recognition. This model can achieve fast clustering of microblog topics and quantitative calculation of emotional intensity (Gu et al., 2022). Fang et al. constructed the Gated Fully Fusion for network populism (GFF-NP) model to analyze and predict the evolution of netizens' opinions in internet populist events. Based on this, a creative expression based on populism is proposed to enhance group persuasion (Fang et al., 2019).

Most of the current research analyzes PS from the perspective of emergency, but a few studies on the evolution mechanism and development stage of PS itself. In addition, many scholars pay too much attention to the public panic mood but do not study the change of the topic content in the whole life cycle of PO events and analyze the emotional attitude and trend of netizens'. Meanwhile, in a few literature studies on emotional evolution, qualitative analysis is mostly used, and there is no determined theoretical basis.

PS evolution model under public emergencies

Stage division

This paper explored the critical transition of netizens' panic mood under public emergencies based on the emotion expressed by netizens' in social media. In social media, online communication of public emergencies belongs to the category of PO evolution analysis. Therefore, we can use the life cycle model of PO evolution and the evolutionary cycle model of public emergencies to explain the critical transition phenomenon of netizens' emotions.

First, the four-stage life cycle model (Ren, K. et al., 2019) was used to explain the critical transition of netizens' emotions under public emergencies. According to the temporal characteristics of the events, the evolution of netizens' emotions

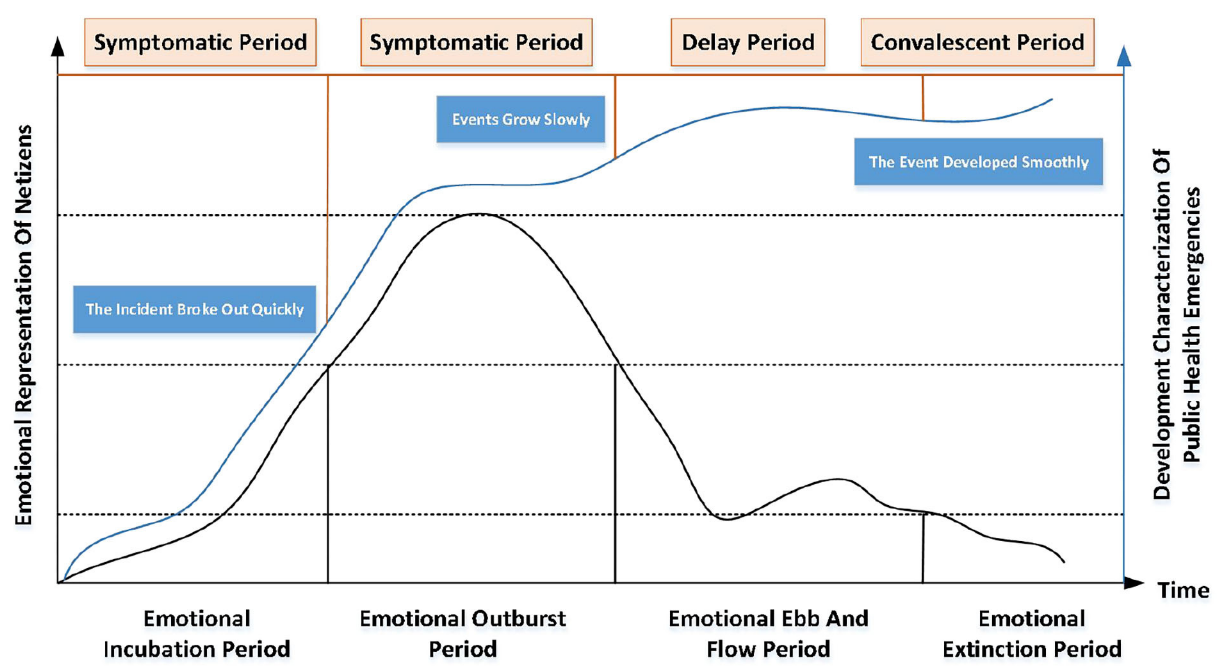

FIGURE 1
Evolution stage of public emergencies (Ren, K. et al., 2019).

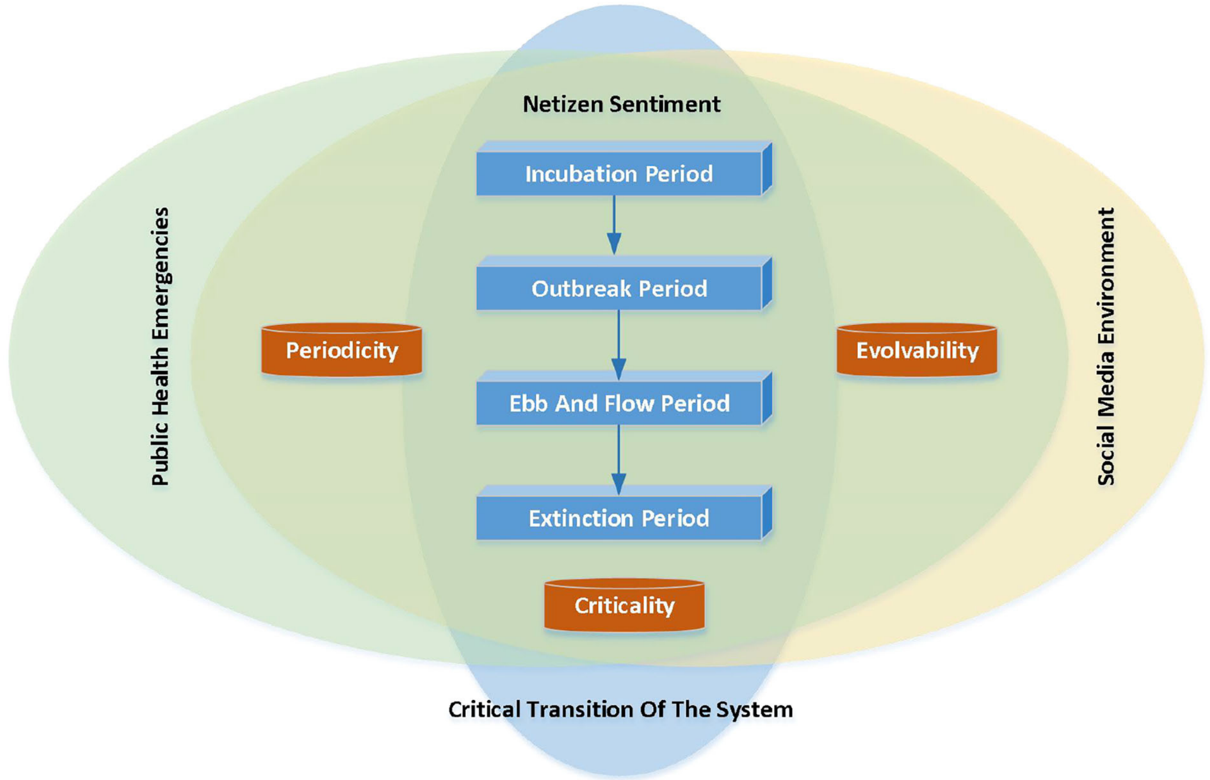

FIGURE 2
The critical transition of public sentiment (PS).

was compared with the development of public emergencies, and the characteristics of netizens' emotions with the development of public emergencies were analyzed, as shown in Figure 1.

The incubation period for netizens' emotions occurs after the public emergency begins to occur, when there is uncertainty about the nature, impact, and harm of the event, and when the public is unaware of the event. Therefore, bad emotions will gradually arise. However, due to the fact that the event is not widely known at this time, only a few netizens' on social media who are in the influence range of the event express relevant views, opinions, and comments. Therefore, the representation of netizens' emotion in the incubation period is very small.

However, with the rapid development of the incidence and the increase in the severity of public emergencies, information about them spread rapidly on social media, and more netizens' began to express their attitudes and spread information. As not only netizens' at the center of the incident but also those from other regions participate in the discussion of the incident, the overall panic of the netizens' starts to rise sharply into an outbreak of panic. The main reason for the beginning of netizens' emotional outbreak stage is that, due to the rapid outbreak of public emergencies, their wide spread makes netizens' emotional polarity (Ren, Z. et al., 2019). If the event itself does not break out quickly, then netizens' emotions will not enter the outbreak period and will gradually subside during the incubation period.

With the implementation of the government's prevention and control measures, the development of public emergencies began to slow down, the heat of online PO decreased, and PS began to decline through the highest point. Meanwhile, the increase in positive media reports reduced the uncertainty of information and rumors, and the public's understanding of the event was more accurate, where netizens' emotion was continuously reduced and began to enter the stage of emotional abatement. However, since the event is not completely over, some rumors or secondary events may spread on social media, so the panic mood may have certain volatility.

As shown in Figure 2, the development of public emergencies provides a stage for the critical change of netizens' emotions. The PO information in the social media environment provides the evolution of netizens' emotions, while the critical transformation characteristics of the system provide the criticality. Therefore, the evolution of netizens' emotions in the context of social media under public emergencies has the characteristics of stage, evolution, and criticality.

The identification of emotional critical points

According to the concept of critical points in a complex system (Truong et al., 2020), the concept of critical points can be expressed as follows when identifying the critical transition of time-series data: a token for time-series data of the system state $x = \{x_t\}_{t=1}^{T}$, some sets of time points $\tau = \{t_1, t_2, t_3, \ldots, t_k\}$ cause state changes in the sequence data at these positions and the time corresponding to these moments is called the critical point.

In a netizen emotion time series $x = \{x_1, x_2, \ldots, x_T\}$, the sequence x is assumed to be piecewise stationary, which means that some properties of the process change at some unknown time t_k. It can be generally used to calculate the critical points and the actual data of the critical point of difference in addition to the sample for evaluation, namely, $\forall k, \left|\widehat{t_k} - t_k{}^*\right| / T$. When the number of samples T is infinite, the error of the critical point identification algorithm should be wirelessly close to 0 so as to satisfy asymptotic consistency.

We are not aware of the actual critical point of netizens' emotion under public emergencies, the possible optimal segmentation τ^*, namely, the set of critical points, must be obtained by minimizing the quantitative criterion $V(\tau, x)$ (Truong et al., 2018).

$$V(\tau, x) := \sum_{k=0}^{K} c\left(x_{t_k \cdot t_{k+1}}\right) \quad (1)$$

Among them, $c(.)$ is a loss function, which lies in the degree sequence of quantum $x_{t_k t_{k+1}} = \{x_t\}_{t_k}^{t_{k+1}}$ on behalf of the goodness-of-fit of a specific model. The optimal split τ^* is the set of optimal critical points for the minimum of the criterion $V(\tau)$. Depending on whether we know in advance the number of critical points k^*. When the number of critical points is unknown, the critical point identification problem is to solve the following discrete optimization problem:

$$\min_{\tau} \sum V(\tau) + pen(\tau) \quad (2)$$

where $pen(\tau)$ is used to measure a proper division of the complexity of τ, namely, the penalty term.

Loss function $c(.)$ is a measure of equilibrium. If after-segmentation subsequence $x_a^b = \{x_t\}_{t=a}^{t=b}$ is homogeneous, which means that it does not contain any critical points, then $c\left(x_{t_a \cdot t_b}\right)$ should be smaller; if the child signal $x_a^b = \{x_t\}_{t=a}^{t=b}$ is heterogeneous, it means that it contains one or more critical points, then $c\left(x_{t_a \cdot t_b}\right)$ should be larger. Model drift, which is in response to changes in the statistical properties of the predictor variables, is adopted to prevent model training failures caused by changes in the underlying variables. For example, patterns in the data change due to seasonality. The loss function can be calculated as follows:

$$c\sum\left(x_{a,b}\right) = (b-a)logdet \overset{\wedge}{\sum_{a.b}} + \sum_{t=a+1}^{b}\left(x_t - \bar{x}_{a,b}\right)' \overset{-1}{\sum_{a.b}}\left(x_t - \bar{x}_{a.b}\right) \quad (3)$$

Among them, $\sum_{a.b}^{\wedge}$ is the empirical covariance matrix of the subsequence.

Emotion analysis model based on topic clustering

The topic discovery model based on the topic model combined with the hierarchical clustering algorithm is a fusion of the LDA algorithm and the BC-BIRCH algorithm. The topic model framework of PO in the microblog for public emergencies is shown in Figure 3.

Calculation of emotional intensity

First, for the sentence that contains emotion, we divided it into two parts. When the emotional words were found, it was checked whether there were degree adverbs and negative words before and after the emotional words. At the same time, the degree level of degree adverbs and the number of negative words should be considered. Finally, the emotional polarity value of the microblog text can be obtained by calculating the emotional polarity of a single sentence (Wu et al., 2021).

Text segmentation is the process of dividing every clause into single words according to certain rules, which is a key step in semantic understanding. In this paper, we used Jieba word segmentation toolkit in Python for Chinese word segmentation and retreived the data set after the word segmentation. Stop words refer to the words or words that have no real meaning for the follow-up work and the theme is not obvious, such as modal particles and special symbols. The comprehensive polarity weight of a sentence in the microblog text is used to judge the role of a single sentence in the text. The microblog text T is defined as being composed of several sentences Y, $T = \{Y_1, Y_2, \ldots, Y_n\}$, and then the sentiment value $P(Y_i)$ of a single sentence Y_1 *is calculated* to obtain the sentiment polarity value $P(Y)$ of T from the sentiment value of a single sentence, as shown in Formulas (4) and (5):

$$P(Y_i) = \sum Y_{w_i} \quad (4)$$

$$P(Y) = \sum P(Y_i), \quad (5)$$

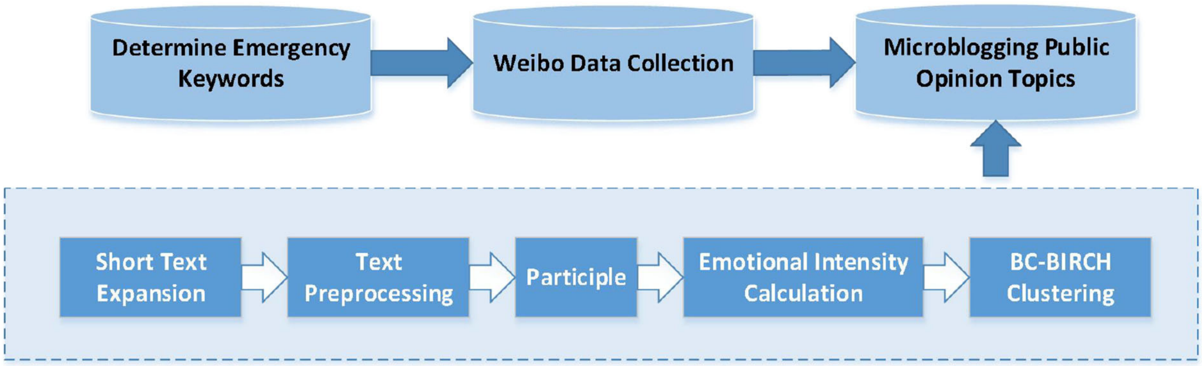

FIGURE 3
The structure of the topic clustering model for public emergencies.

where Y_w is the sentiment value of the sentiment word W_i in a sentence. If $P(Y)$ is >0, it means that the microblog is positive emotion. If $P(Y)$ is <0, it means that the microblog is a negative emotion. While if $P(Y)$ is equal to 0, it means that the microblog is neutral emotion.

Several sentences in the microblog text can be expressed by five sentence patterns: declarative sentence, rhetorical question, interrogative sentence, exclamatory sentence, and hypothetical sentence. Sentence patterns also affect the emotional value of a single sentence. For example, the emotional attitudes of the same sentence expressed by declarative and interrogative sentences are quite different. $P^1(Y_i)$ is defined as the sentiment value of a single sentence in the microblog after considering the sentence pattern characteristics (Yang, 2020). The sentiment value calculated by different sentence patterns is shown in Formulas (6)–(9):

$$Exclamatory\ sentence: P^1(Y_i) = P(Y_i) \times (1.5) \quad (6)$$

$$Hypothetical\ sentence: P^1(Y_i) = P(Y_i) \times (-0.2) \quad (7)$$

$$Interrogative\ sentence: P^1(Y_i) = P(Y_i) \times (-0.2) + (-0.5) \quad (8)$$

$$Rhetorical\ question: P^1(Y_i) = P(Y_i) \times (-0.6) + (-0.5) \quad (9)$$

Considering that the number of microblog comments will gradually decrease in the later stage of PO evolution, which may also lead to large emotional variance, this paper defines the formula of emotion hot as follows:

$$D = minmax\left(minmax(M)^{*}p\right) \quad (10)$$

In Formula (10), D is emotional heat, M is the number of comments, and P is the variance of affective propensity. Minmax is the standardized processing method. By standardizing the number of comments, we can avoid the problem of large emotional variance caused by the small number of published comments and make the two indicators of the number of comments and the variance of emotional tendency better perform in the analysis model of emotion evolution.

The BC-BIRCH clustering algorithm

Aiming at the defects of the BIRCH algorithm, the BC-BIRCH algorithm is proposed. The core idea of the algorithm is to combine related topics into a cluster as much as possible so as to reduce the number of clusters and to improve the accuracy of clustering. The algorithm process is shown in Figure 4.

The BC-BIRCH algorithm is an improvement of the BIRCH hierarchical clustering algorithm. The BIRCH algorithm has certain defects, that is, when a new data node needs to be inserted, the algorithm needs to calculate the distance between the new node and other leaf nodes, select the cluster with the shortest distance, and then merge and compare the diameter of the merged cluster with the threshold. If the diameter of the merged cluster is greater than the threshold value, the algorithm can calculate the distance between the new node and other leaf nodes. The new data point is split into a single cluster. In addition, the initial threshold value of the diameter threshold is fixed at the beginning of the algorithm, which can be tuned by continuous testing. In the process of inserting a new data node, the node is close to the center of the nearest cluster, but when the new node is merged with the cluster, the diameter of the merged node is greater than the threshold, which results in the new data node separated from the cluster as a single cluster. Finally, data from similar nodes cannot be combined well and the number of split clusters is too much, which leads to low clustering accuracy (Wang and Zhang, 2020).

The steps of BC-BIRCH are as follows:

Step 1. Initialize an empty tree and insert the first sample into the root node.

Step 2. Calculate the distance between the new sample and each child node of the node, iterate repeatedly to find the

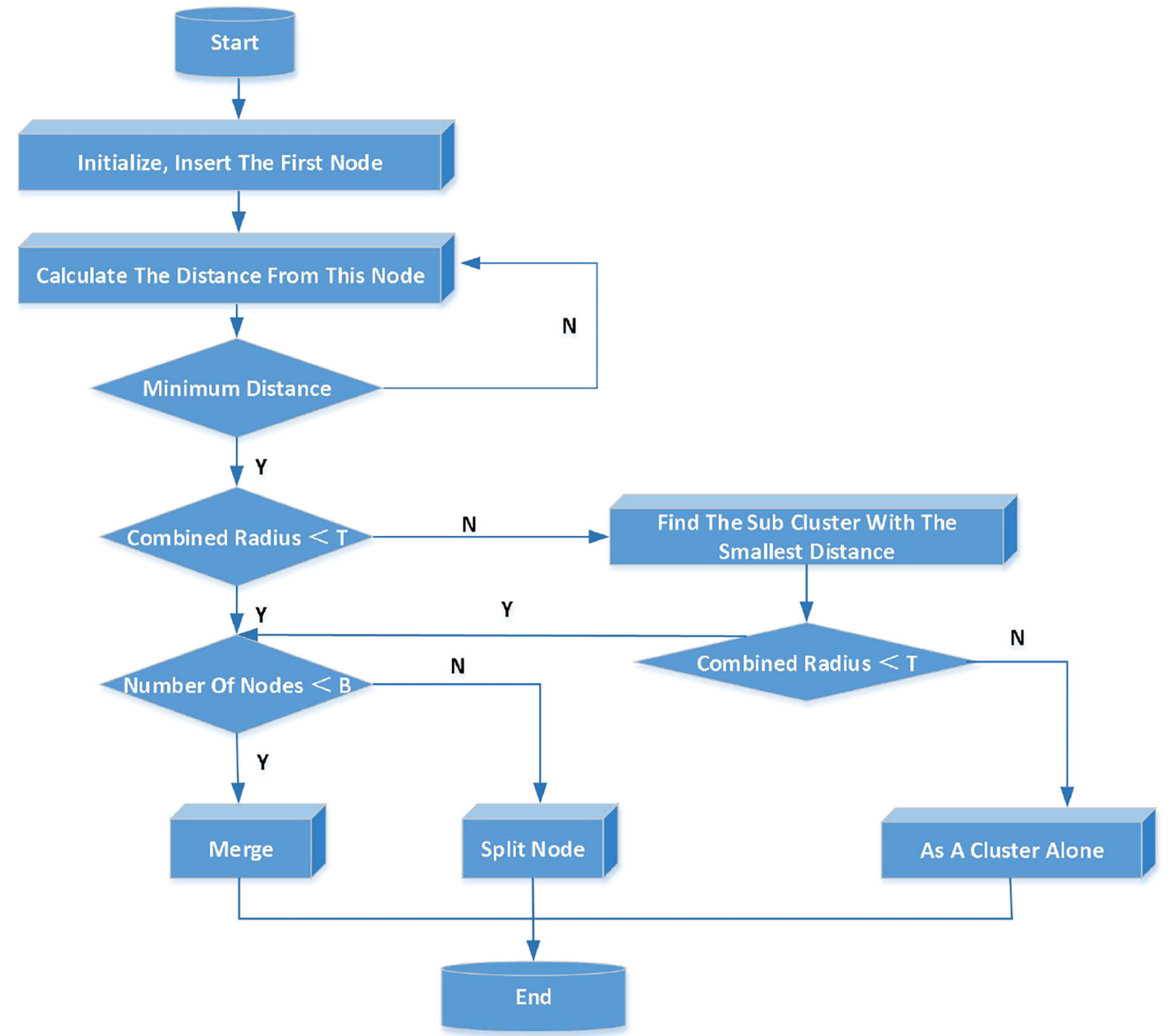

FIGURE 4
BC-BIRCH algorithm flow.

cluster with the smallest distance from the new sample, and continue if the radius is less than the threshold. Otherwise, the cluster with the shortest distance from the first merged cluster is found and merged to calculate the radius. If the radius is less than the threshold, it will be merged. If all the radiuses after merging are greater than the threshold, it will be regarded as a single cluster.

Step 3. If the number of CloudFlare (CF) nodes of the current leaf node is less than the threshold, create a new CF node, insert the new data, and then put the new CF node into the leaf node, update all CF nodes in the path, and the insertion is finished.

Step 4. Otherwise, the current leaf node is divided into two new leaf nodes. Among all CF tuples in the old leaf node, the hypersphere distance of any two CF tuples is calculated, and the two CF tuples with the farthest distance are selected and put into two new leaf sub-nodes, respectively, to calculate other tuples and new sample tuples.

Experiment and analysis

Data acquisition

Microblog text data were collected at https://www.sina.com.cn/. Different keywords such as "COVID-19" and "Epidemic" were input. Each search result includes 50 pages of data, and each page has 20 microblogs, that is, 1,000 pieces of data. Therefore, in

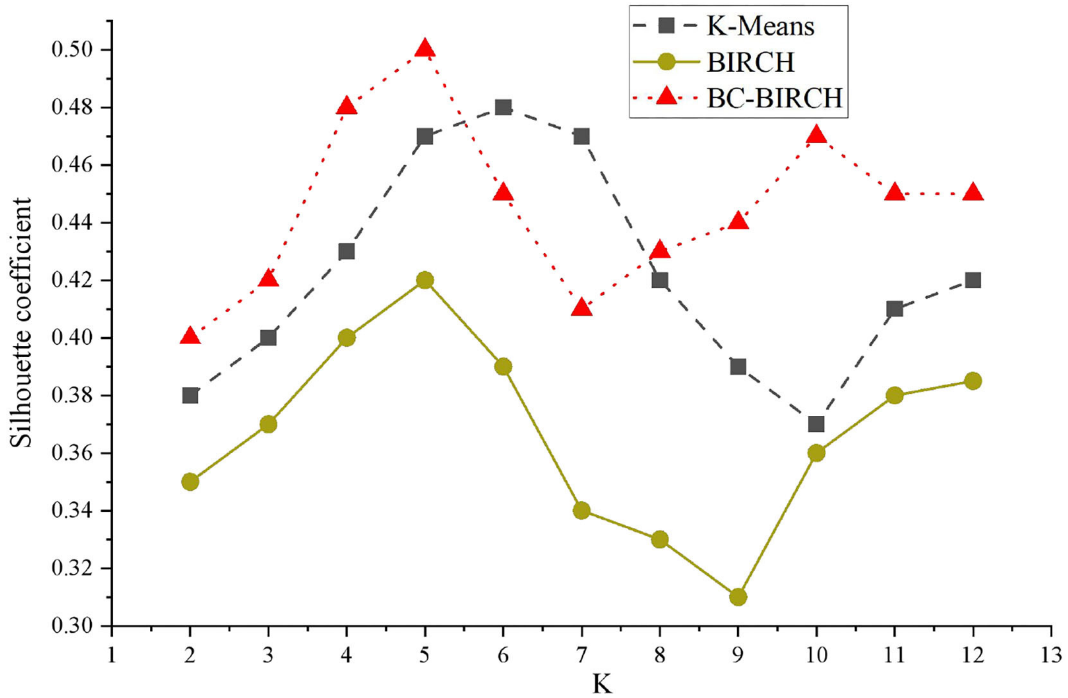

FIGURE 5
Comparison of the topic clustering effect.

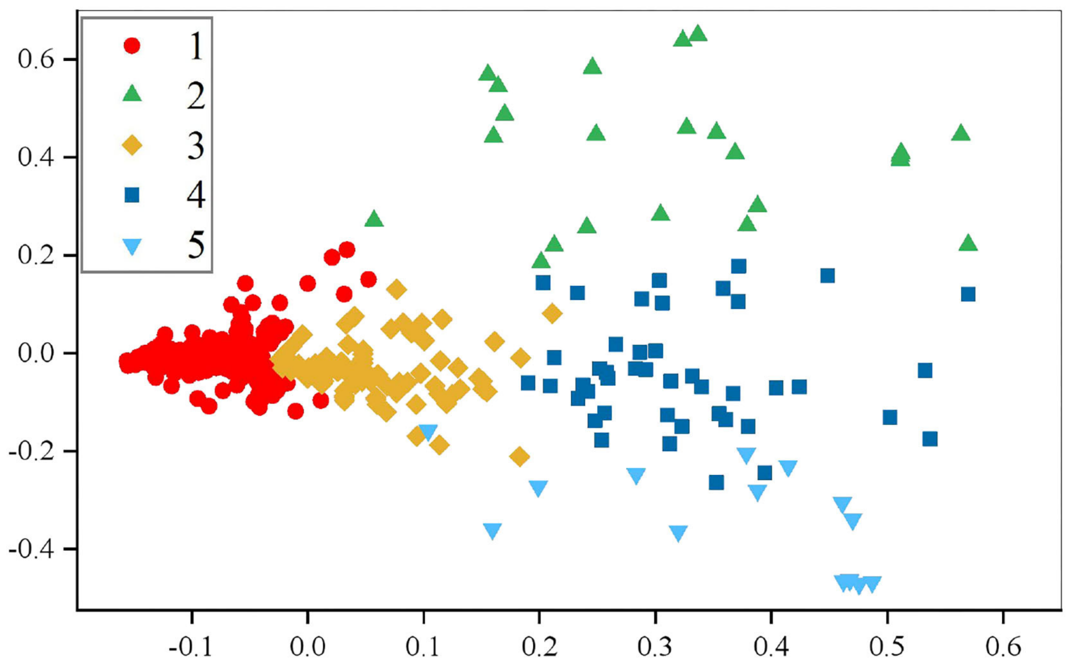

FIGURE 6
The clustering effect of different topics.

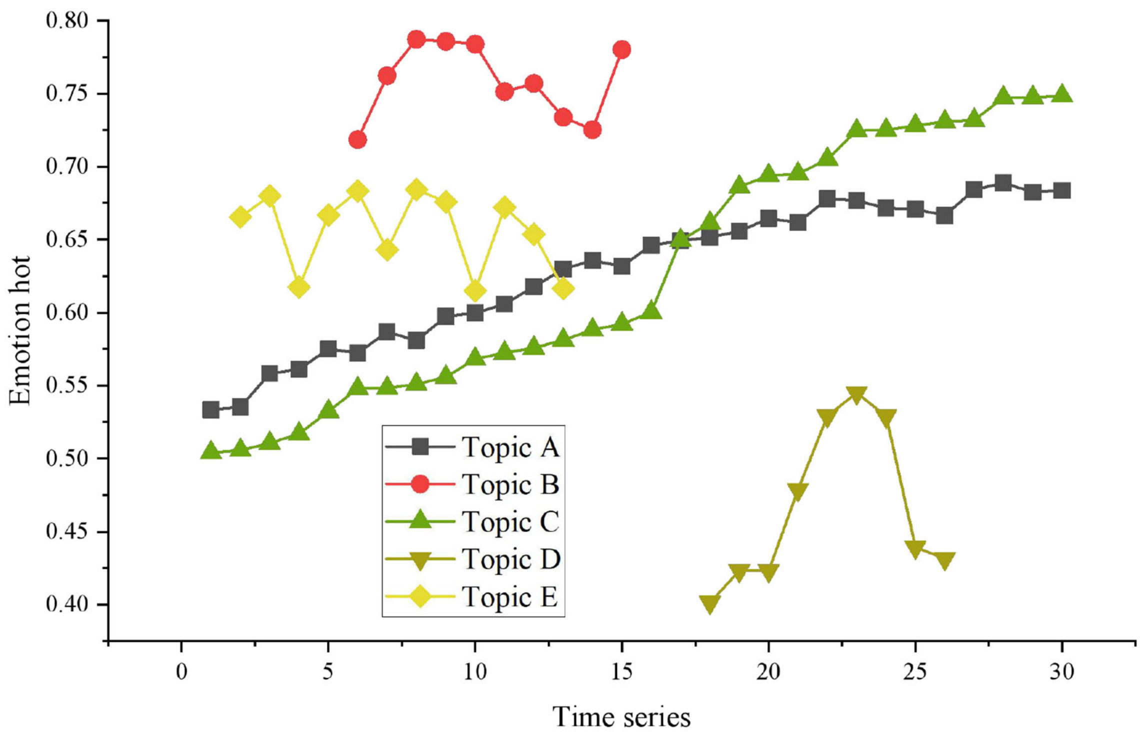

FIGURE 7
Analysis of the evolution trend of PS.

this study, the required time window was segmented to achieve all relevant microblog content searches. Then, using the web crawler technology, the Sina API interface was called to crawl all the microblog contents on the page.

A comparison of the topic clustering effect

In this paper, silhouette coefficient (*Si*) (Rezanková, 2018) was used to determine the number of clustering topics. If the number of clustering topics K is too small, the data itself will not be separated, which will affect the clustering effect. However, as the number of topics K increases, the value of Si will become smaller and smaller, and the clustering effect will become worse and worse. To verify the effectiveness of clustering results, the K-means, BIRCH, and BC-BIRCH algorithms used in this paper were selected for experiments. The comparison results are shown in Figure 5.

It can be seen from the comparison results that, when the BC-BIRCH algorithm is selected, and $K = 5$, Si has an optimal value, which is 0.55. At the same time, the clustering effect of the BC-BIRCH algorithm is the best under the same topic number. Therefore, the number of clustering topics is 5. In addition, the clustering effect of different topics is shown in Figure 6.

As can be seen from Figure 6, the clustering effect of topics A and C is better.

Evolution trend of PS

As shown in Figure 7, the emotional fluctuation of netizens' in the initial stage of PO under different themes is relatively large, where A–E represent different hot public emergencies. It is not easy to be affected by people's emotions. However, with the passage of time, after the official microblog announced the processing results, netizens' emotions gradually tended to be stable, and their emotions mostly turned from negative to positive. It can be concluded that each time the official government media publishes a microblog to explain, it will stimulate the enthusiasm of netizens' to participate in the discussion. In addition, official response behavior plays an important role in PO communication and is an important factor to stimulate the development of PO. Different response contents from official government media may lead to different PO trends. Therefore, relevant management departments should focus on the supervision and intervention of PO, and release authoritative explanations quickly and pertinently so as to avoid the adverse impact of erroneous and extreme PO on society.

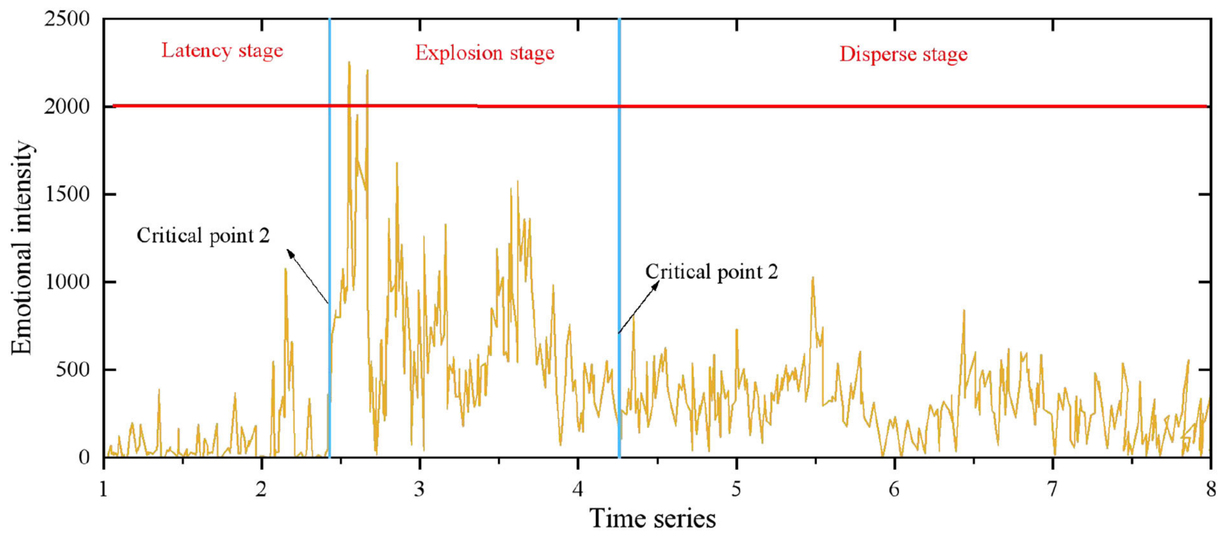

FIGURE 8
Critical transition in the evolution of PS.

Analysis of the evolution of PS

As mentioned earlier, topic A (COVID-19 event) with the best clustering effect was selected to verify the evolution analysis of PS.

The two critical points identified by this model are the boundaries, and the overall evolution of netizens' panic under the COVID-19 epidemic event during the study period is divided into three parts. According to the critical transition diagram in the evolution of PS (Figure 8), it can be seen that the two critical points divide the evolution of internet users' panic emotion under the COVID-19 epidemic event into three parts, and the overall variance change of internal emotions in each part is balanced. However, there is a big difference in the mean value (horizontal line) between all parts (among which the average value of stage 1 is 58.596, the average value of stage 2 is 782.715, and the average value of stage 3 is 374.689). It can be seen that, in the burst phase, the curve changes are more fluctuating and the jump between the peaks is more significant. Therefore, it can be concluded that there is a critical change of netizens' emotion under public emergencies.

In addition, the location of each critical point represents the change in the overall emotional state of netizens', that is, the occurrence of a critical transition. Critical point 1 represents the transition of PS from a low level of stable development to the state of a rapid increase of high outbreak under the new outbreak. Critical point 2 indicates the transition of netizens' emotion from a highly explosive and rapid growth state to a state of medium-level slow development. According to the life cycle model of netizens' emotions, we can regard these three periods as the three stages of netizens' emotions, namely, the emotional incubation period, the emotional outbreak period, and the emotional fluctuation subside period, which is roughly consistent with the previous stage analysis of netizens' emotions during public emergencies.

Figure 9 shows the model prediction results of the critical transition of PS.

In both positive and negative critical transitions, the predicted critical point is consistent with the actual critical point, and the predicted critical point and actual critical point are in the same position, which can accurately predict the occurrence of critical transition of netizens' panic emotion. In addition, it can be found that, in the reverse phase, the critical point predicted by the PS evolution model is two-time points ahead of the real critical point, but it is also close to the original critical point.

Conclusion

Due to the uncertainty and harmfulness of public health emergencies, they will have a serious impact on public physical and mental health and on social and economic development. First, based on the concept of critical points in a complex system, this paper proposes an algorithm to identify the critical points of PS based on microblog data analysis. The BC-BIRCH algorithm is used to cluster the topics of public emergencies and then the evolution model of PS under public emergencies is established. The experiment verifies an excellent clustering effect of the BC-BIRCH algorithm and selects the topic A event with the best clustering effect to analyze the evolution of PS. The results show that under this topic, the evolution of PS can be divided into emotional incubation period, emotional burst

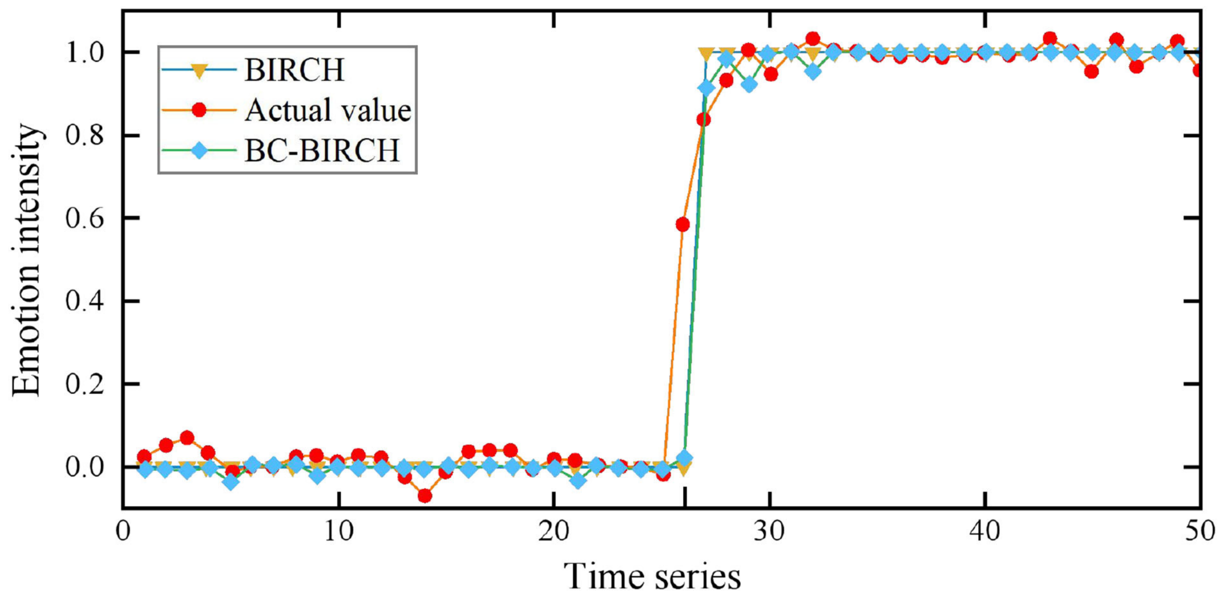

FIGURE 9
The evolution results of PS.

period, and emotional fluctuation fading period. Meanwhile, the credibility of official government media has a direct impact on the emotional polarity of netizens', which is helpful for relevant departments to obtain more in-depth information and solutions in PO events, and to provide suggestions for government departments in the management and decision-making of PO.

This study provides directions and strategies for the government and relevant departments to guide PS and manage emotional emergency. In the whole stage of public health emergencies, both the government and the media should reduce the risk and uncertainty of the event and reduce the harm caused by the public's emotions to society by suppressing the overall outbreak of internet users' emotions or promoting the transition of internet users' emotions to the fading period. However, due to the problem of the time span of the case data, only two critical points, namely, three evolution stages, were identified, while the extinction period of the evolution of panic among netizen was not identified. In the future, data samples with a longer time span can be selected to identify and analyze all critical points in the development of events. Therefore, in future research, more algorithms can be selected for comparison and verification, and different cases can also be studied experimentally to find the best model for internet users' emotion prediction under public health emergencies.

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

ZP contributed to writing—original draft preparation and data collection. HF contributed to data preprocessing and design of methodology. Both authors contributed to the article and approved the submitted version.

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Online or offline? The impact of environmental knowledge acquisition on environmental behavior of Chinese farmers based on social capital perspective

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With the development of mobile internet, Chinese farmers have started to access diversified information through social media, on one hand, based on breadth of information. On the other hand, as most farmers still live in rural areas, their socio-economic characteristics and lifestyles are in homogeneous acquaintance social network relationships, i.e. interpersonal interactions in offline homogeneous networks are still considered as the way for farmers to access homogeneous information (breadth of information depth). Based on social capital theory, social networks are structural social capital where trust and reciprocity are known as a relational social capital. Further, this study divides structural social capital into connective social capital (social media access to information) and bonding social capital (offline interpersonal interaction access to information) based on the differences in their information sources. The empirical study finds that structural social capital has a positive impact on farmers' environmental knowledge acquisition which influences their environmental behavior. In addition, relational social capital (trust and reciprocity) plays a mediating role in the influence of structural social capital on farmers' environmental behavior.

KEYWORDS

social capital, social media, environmental behavior, knowledge acquisition, farmer

1 Introduction

At the 75th UN General Assembly General Debate and Climate Ambition Summit, President Xi Jinping proposed that China should strive to peak its carbon dioxide emissions by 2030 and work towards achieving carbon neutrality by 2060 (Shiyong et al., 2022). This major strategic development and systemic change will inevitably force a green development and low-carbon transformation of the way of economic development, promote high-quality development of China's economy, and profoundly change the lifestyles of members of society at large towards a green and low-carbon direction (Wang et al., 2022). Agriculture is an important source of greenhouse gas emissions and environmental protection in agriculture (D Wu, 2021). Rural areas are considered as the top priority for achieving carbon peaking and carbon neutrality. As the year 2022 is the opening year of the 14th Five-Year Plan, the issue of environmental protection in rural areas has become a hot topic in China's agricultural development (Zhao J C et al., 2022).

In today's rural environmental issues, the level of awareness of farmers largely determines the development of rural environmental protection and implementation of national policies which is also related to the progress of a series of construction work in rural environmental protection (Davis L S et al., 2020). Due to the low level of education and environmental awareness of farmers, the level of awareness and toxicity of agricultural waste is low, resulting in agricultural waste not being effectively recycled and the rural environment not being effectively protected. Thus, this affects rural agriculture to a certain extent, causing pollution of the rural environment and increasing the burden on farmers, enterprises, government, and society (Zheng X Q et al., 2020). Therefore, it is increasingly important to work to effectively raise farmers' awareness of environmental protection, which is not only related to the development of environmental protection, but also closely related to the implementation of China's sustainable development strategy, and is more conducive to the construction of a harmonious socialist society (Jimenez-Navarro J P et al., 2020).

Awareness depends on having a certain level of knowledge about environmental protection (Minton, 2018). Therefore, access to knowledge and environmental education is the key in solving rural and farmer environmental problems (H Qasim et al., 2019). With the spread of social media, the way in which farmers acquire knowledge has changed (Joo. et al., 2018). Traditional offline face-to-face interaction is still a major way of acquiring information (Mouakket, 2015). However, the diversity of information available in social media has enriched farmers' knowledge of environmental protection. Research on the impact of information access methods on farmers' environmental behavior is still in its early stages (Danna Greenberg and Hibbert, 2020). Therefore, some interesting research questions are: Which information access methods are more effective in influencing farmers' environmental behavior? What are the underlying mechanisms? Those questions deserve special attention.

At present, academic research on rural environmental governance focuses on three areas: Firstly, policy changes, that can be mainly revolved around time (Zhao et al., 2005). Secondly, representational issues, including the characteristics, difficulties, and problems of rural environmental protection (Li Z G and Wang J, 2021). Thirdly, governance models, which mostly focus on socially interactive and participatory environmental protection models (Mallapaty, 2020). While academic research has focused on the government's leading role in environmental governance in terms of policy mechanisms, practical challenges, and governance models, which has contributed to the improvement of the rural environment at the macro level (Kang Y et al., 2020), there is little research on the participation of non-governmental actors in environmental governance at the micro level (Shiyong Z et al., 2022).

This study uses media as a tool and social capital as a theoretical framework to explore and investigate the impact of different types of social capital on farmers' environmental behavior and their underlying mechanisms (Wei W et al., 2020). This study contributes to the literature on rural environmental protection in several ways. Firstly, our study is one of the pioneering studies examining the role of social capital on environmental behavior. Secondly, we capture the significant effects of different types of social capital on environmental behavior, which provides new insights into the optimization of environmental strategies from the perspective of social capital characteristics. Thirdly, we propose the perceived risk as a mediator in the model to explain farmers' environmental awareness and behaviour by revealing their perceptions of different types of social capital and extending the current literature.

The people's desire is a prerequisite for promoting specific environmental behaviours (Zheng X Q et al., 2020). The farmers who work in agriculture are the ones who carry out and directly benefit from rural environmental protection behaviour (Jimenez-Navarro J P et al., 2020). Therefore, it is important to promote farmers' willingness to protect the environment in rural areas (Mallapaty S, 2020). The availability of appropriate knowledge is an important factor in the formation of behavioural awareness among individuals (He J K et al., 2020). So, when we focus on people's awareness of environmental protection behaviour, we consider their knowledge of environmental protection, which in turn influences their willingness and behaviour to protect the environment (Zhou Y et al., 2019). According to communication theory, in the process of information interaction, factors such as the object of communication and the way of communication affect the final communication effect (F Su et al., 2021). Therefore, this study analyses the influence of the type of knowledge source on the environmental protection willingness and behaviour of farmers in the process of focusing on the formation of their environmental protection awareness, and proposes corresponding environmental protection publicity strategies to assist the rural environmental protection cause.

2 Review of the literature

2.1 Social capital

The social capital dimension includes structural social capital, cognitive social capital, and relational social capital (N Wen, 2020). Structural social capital emphasizes the association between individuals, i.e. the formation of network relationships (M Oliver et al., 2020). Relational social capital emphasizes interactions based on associations, i.e. reciprocity and trust (Y Mou and Lin, 2017). Cognitive social capital emphasizes organizational norms such as a common language during interaction (Homero Gil De Zú Iga and Scherman, 2017).

2.1.1 Structural social capital—social networks

Structural social capital refers to the effect that the structure of a network has on the overall value of social capital (G Calado et al., 2017); factors such as the size and density of the network in which an individual is embedded, as well as the individual's own position in the network such as degree centrality and eigenvector centrality, all influence the amount of value that the network brings to the individual which can be influenced by the value that the structure of the group has created (A Zubiaga and Ji, 2014). Group convergent behaviour is more likely to occur when the network density within the group is high, meaning that individuals within the group interact more frequently (J Piyapong and Tsunemi, 2014). An individual's position in the network means that the person has direct or indirect access to resources, and if the person has more access to resources, other individuals are more likely to interact with the person for resource utilization motives (Berger, 2014).

In the age of mobile internet, people can interact online through social media. Some studies point out that online interaction can be achieved across time and space constraints (F Su et al., 2021). However, the authenticity and real-time characteristics of traditional offline interactions make offline interactions to be considered as one of the main ways for people to access information (D Agapito et al., 2013). According to some scholars, social capital can be further divided into bridging and bonding social capital according to the mode of interaction (online or offline) (Wei W et al., 2021, G. E Newman et al., 2017). In online interactions, users can relate to strangers (heterogeneous nodes) through the internet and gain access to a wide range of information, i.e., they gain access to information through bridging social capital (Ž Kolbla et al., 2018). In offline interactions, users are more likely to be dealing with networks of acquaintances (homogeneous nodes), and the information they receive is more credible, i.e., through bonding social capital (K. P Winterich et al., 2018).

As urbanization accelerates, urban dwellers are beginning to rely less on offline communication, and even acquaintances can share information through social media (S. T Fiske, 2018). Moreover, in underdeveloped areas, offline face-to-face communication is still one of the most common ways people interact with each other (H Chen et al., 2018). With the spread of social media, interpersonal interaction and social media use are two of the most common forms of farmer interaction in underdeveloped areas (e.g., rural areas), and can generate corresponding social capital (P Torres et al., 2017). Specifically, because of the simplicity of farmers' lives, offline interpersonal interactions are frequent and limited to a limited group of people (acquaintance networks—strong relationship networks) and have a higher potential to generate bonding social capital (G. E Newman and G Diesendruck, 2017). Social media social networks can connect users to the outside world and reach out to other users that they do not know (stranger networks—weak relationship networks), but these connections are mostly superficial and not deep, and are mostly connective social capital (M Mcgowan et al., 2017). Based on the daily habits of Chinese farmers, this study measures farmers' offline interpersonal communication and online social media use to represent their connective and bonding social capital (F Hayes, 2017).

2.1.2 Adhesive social capital

Rural China is a communication environment that has been characterized by homogeneous social capital for thousands of years, with bonding social capital in the form of interpersonal discussions in acquaintance societies (T. P Derdenger et al., 2017). As one of the key theoretical underpinnings of the homogeneous social capital interaction hypothesis, Andrei have derived the affective-interaction hypothesis as the Homophily hypothesis, which states that emotional friendship connections tend to be based on the principle of homogeneity, i.e, (A. G Andrei et al., 2017). the like-me hypothesis: social interactions tend to occur between individuals with similar economic and lifestyle characteristics (Y Wang and Wang, 2016). The Homophily hypothesis is based on the principle of like-me: social interactions tend to occur between individuals with similar economic and lifestyle characteristics (L Su et al., 2016). This homogeneity is found in the social network relationships of the farmers who are the mainstay of our countryside, who make their living from the land, and who have similar levels of education (C. L Newman et al., 2016). Social networks are more likely to be established among people with similar socio-demographics, or Status Homophily, because they share similar ideas, attitudes and values (D. J Li and Liu, 2016). In terms of the conditions under which the social capital homophily interaction hypothesis applies, this theory fits in many ways with the study of environmental communication in farmers' social networks in China (S Kazakova et al., 2016).

The homogeneity of our farmers in many ways, including their living environment, education level and daily activities, as well as the frequency of their daily interactions and their confinement to a small area, makes it easy to generate adhesive social capital (E Fang et al., 2016). Therefore, we use farmers' interpersonal communication behavior to measure their social capital (Song G J et al., 2021). In rural environmental communication in China, more inputs in a homogeneous social network will lead to more social resources, which in turn will lead to more scientific knowledge or scientific action by the inputters, which is the theoretical goal of this empirical study (Du H B et al., 2021).

2.1.3 Connective social capital

Social media use is a current emerging form of social capital for farmers, i.e., connected social capital on behalf of farmers (Kang Y et al., 2020). Electronic networking is an emerging form of social capital that carries resources beyond the mere use of information, bringing with it a new social capital and representing the advent of a revolutionary rise in social capital (Liu and Yang, 2020). The facilitation of information flows, the influence of social ties on the decisions of organizational agents, the use of social networks as proof to gain more capital, and the ability of social ties to enhance identity and recognition (Davis L S et al., 2020). In communication terms, the degree of information use and channel bias brings social capital to the user (Zheng X Q et al., 2020). However, the Internet is open, diverse, inclusive, cross-regional, cross-industry and cross-class, and is a heterogeneous interaction of social capital, or connective social capital (Chen C et al., 2019).

The social media environment allows farmers to connect with other users from different backgrounds and hence have easy access to diverse information (Jimenez-Navarro J P et al., 2020). Social capital theory suggests that individuals in the position of a broker will have access to a greater diversity of information, leading to the development of bridging social capital (Liu X P et al., 2018). The use of social media provides farmers with easy access to groups of people from different life experience backgrounds, thus creating bridging social capital (Han H et al., 2018). For farmers in an environment of homogeneous social capital, internet use is important for accessing environmental resources (Davis L S et al., 2020).

The internet is an emerging social capital that is particularly important in an environment of social capital homogeneity, and is a new form of access to resources for farmers that breaks the limits of geography, ethnicity and occupation (Xiao H et al., 2019). Some studies have compared online and offline access to information and found that social media use allows users to access more and newer information about different social connections in the process of obtaining information, and social capital that is easily overlooked or inaccessible offline (Chen C et al., 2019). There are also studies that focus on social media platforms, in the form of online questionnaires that measure the connected social capital or bonding social capital that respondents have through the content of social media platforms (Liu X P et al., 2018). However, these studies differ in their classification of social media and types of social capital, while there is no clear classification of the population surveyed (He J K et al., 2020). Unlike the above studies, this study has a clear target group and classification.

2.1.4 Relational social capital—trust and reciprocity

Baker defines the information conveyed during interpersonal interactions as relational social capital (Dranka and Ferreira, 2018). In contrast to structural social capital, which emphasizes the establishment of relationships and the position of individuals in a network, relational structural capital emphasizes the value of information during the interaction of individuals based on network relationships (Bekalu M A et al., 2018). This trust in others and reciprocity has a positive impact on the value creation of the group as a whole (Dunlop S M et al., 2010). When individuals feel that the organization and other individuals within it are trustworthy, in which they share a common value goal, and that it is a win-win situation, then individuals are more willing to help and give their resources to the organization and other individuals (Sarvary, 2011). However, they do not have the willingness to interact, and they do not add value to the resources available (Borrayo E A et al., 2016).

Organizational research suggests that trust is a psychological state of willingness to expose weaknesses, which is a state based on the trustor's positive expectation of the trustee's intentions and behaviors that are not expected to harm the trustor (Bekalu M A et al., 2018). Borrayo notes that reciprocity is also a manifestation of relational social capital, i.e., secondary interactions are more likely to occur when the interaction can benefit both parties to the interaction, which focuses on the analysis of group value in terms of short- and long-term interactions This is primarily an analysis of the magnitude of group value in terms of short- and long-term interactions (Borrayo E A et al., 2016).

Sociological research points out two main sources of value perception, trust, and reciprocity (Wang W et al., 2019). Trust refers to the expectation that the trusted person will act from the trustor's perspective, aiming to maximize the trustor's interests and fulfil the trustee's responsibilities and obligations (H Risselada et al., 2018). Reciprocity refers to the expectation that the recipient will give equal consideration to his or her own interests (S Pike and Lubell, 2018). In addition, trust and reciprocity are prevalent in areas such as science and technology innovation, environmental health, and financial investment (W Gong and Li, 2017).

Based on the above, this study will test the following hypotheses:

Hypothesis_1a: Farmers' communication through online social media increases their perception of trust in the information source.

Hypothesis_1b: Farmers' perception of reciprocity of information sources can be increased through online social media communication.

Hypothesis_1c: Farmers can increase their perception of trust in information sources through offline interpersonal interactions.

Hypothesis_1d: Farmers can increase their perceptions of reciprocity towards information sources through offline interpersonal interactions.

2.2 Environmental behavior

Environmental Protection Behavior (EPB) or Pro-environmental Behavior (PEB), for example, this is one of the key outcomes of social capital interactions, and this is an extremely important variable in environmental communication research (C. Y Chen et al., 2017). In the social capital paradigm, environmental behavior is an important dependent variable linking social network relationships, perceptions of trust and environmental knowledge, resulting in a model that is quite predictive of pro-environmental behavior (Baltas. et al., 2017). There is a clear causal mechanism in the social capital theory paradigm.

The interaction of networks of social relationships leads to information interaction and thus knowledge learning, which further influences user behavior (Y Yang et al., 2016). Stephens argues that social capital interactions result in knowledge, emotional support and behavior, i.e (Stephens et al., 2016). they emphasize that individuals have better behavioral outcomes as a result of access to social network resources (Kumar et al., 2016). The hypothesis of homogeneity of social capital comes in part from his understanding of Chinese society, particularly rural society, and there is a lack of empirical research to support the hypothesis of whether internet use and interpersonal discussions in a homogeneous environment can lead to changes in environmental behavior (He J K et al., 2020).

In recent years, there have been new developments in the quantitative study of social capital and environmental behavior in China (Zheng X Q et al., 2020). One study divided the core elements of farmers' social capital into three independent variables: trust, reciprocity norms, and civic engagement networks, and the dependent variable was farmers' willingness to invest in environmental protection (Wang W et al., 2019). This study examines farmers' willingness to engage in environmental behavior mainly from the perspective of financial investment (Y Jiang et al., 2016). In order to explore the relationship between farmers' social capital and environmental behavior, one study has empirically classified social capital in general into three independent variables: network media, external interaction, and village identity (S Hazari et al., 2016). The study is somewhat over-generalized and does not optimize the specific pathway of external interaction as an important variable of social capital, as internet use and interpersonal discussions play an extremely important role in farmers' lives (Wang et al., 2015).

Therefore, this study uses the theoretical paradigm of social capital as a framework and structural social capital as the independent variable to consider the role of farmers' offline interpersonal interactions (adhesive social capital) and online social media use (connective social capital) on their relational social capital (trust and reciprocity), and furthermore on their environmental behavior. The empirical approach provides a scientific basis for breaking the bottleneck of farmers' inherent capital in a homogenous social capital environment.

Based on the above, this study will formulate and test the following hypotheses:

Hypothesis_2a: Trust perception as a mediating variable explains the positive relationship between farmers' offline interpersonal discussions and environmental knowledge.

Hypothesis_2b: Trust perception as a mediating variable explains the positive relationship between farmers' online social media communication and environmental knowledge.

Hypothesis_2c: Perception of reciprocity as a mediating variable explains the positive relationship between farmers' offline interpersonal discussions and environmental knowledge.

Hypothesis_2d: Perception of reciprocity as a mediating variable explains the positive relationship between farmers' online social media communication and environmental knowledge.

2.3 Environmental knowledge

On the one hand, there is a correlation between environmental behavior and environmental knowledge (Han H et al., 2018). Several psycho-behavioral theoretical models confirm that behavior is mostly based on cognition, and the environmental behavior in this study is no exception (Zhou Y et al., 2019). Therefore, it is assumed that environmental behavior is based on environmental knowledge (He J K et al., 2020). On the other hand, social capital and knowledge are closely linked. In a knowledge society, the structure of knowledge determines to some extent the social network relationships, which drive the accumulation of social capital, and the process of networked social learning leads to new knowledge production, output and behavioral change (Jimenez-Navarro J P

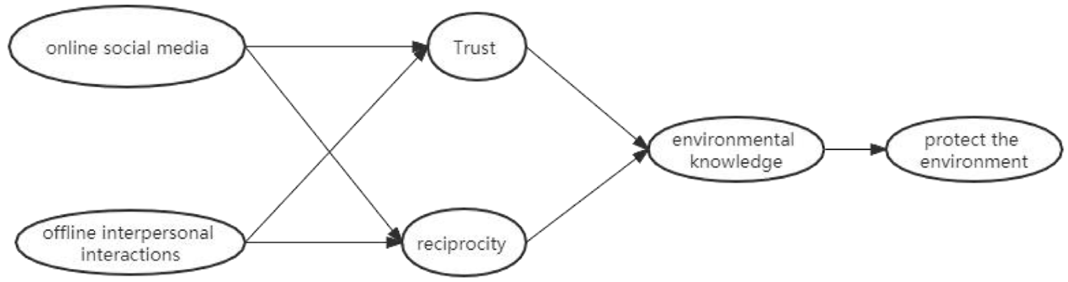

FIGURE 1
Diagram of the model for this study.

et al., 2020). Previous research has shown that the growth of environmental knowledge has a positive effect on environmental attitudes and behavior, and that environmental knowledge is a prerequisite for environmental behavior in certain environments or conditions (Dong F et al., 2018). In studies exploring urban residents' perceptions of environmental pollution in China, environmental knowledge was introduced as an important variable in the model and was found to have a significant mediating effect on perceptions of environmental risk (Dranka G. G and Ferreira P, 2018). However, differences in the external conditions and intrinsic subject traits of environmental knowledge and environmental behavior dictate that the growth of environmental knowledge does not always lead to environmental behavior, and a rather complex conditional relationship is required to maintain consistency between the two (Ooms J A et al., 2017). For example, in studies related to rural life and production experiences, it has been found that whether environmental knowledge is derived from direct or indirect experience has different effects on environmental behavior; individual attitudes, behavioral habits, social norms and cultural traditions all have an impact on environmental behavior (Bekalu M A et al., 2018).

Based on the above, this paper proposes and tests the following hypotheses, using the willingness of our farmers to protect the environment as the dependent variable:

Hypothesis_3: Farmers' knowledge of environmental protection is positively correlated with their willingness to protect the environment.

Based on this, the research model for this study is shown in Figure 1.

3 Research methodology

3.1 Sample selection

In this study, samples were obtained by Purposive Sampling combined with Stratified Sampling (Majchrzak A et al., 2013). Because of the need for social capital homogeneity theory, the samples were selected from representative rural areas for the study (Dranka G. G and Ferreira P, 2018), namely Longsheng County in Guilin, Guangxi, as an agricultural area in the south of China, Jili County in Hubei, as a traditional plain agricultural area, and Qinzhou City in Guangxi Zhuang Autonomous Region, as an agricultural area near the sea. Representative districts were then selected in the target cities and counties, and then representative villages were selected in the districts (Moran M B et al., 2016). Due to the presence of illiterate or literacy-challenged households in rural areas, the research team used primary and secondary school students, or assisted family members, neighbors or townspeople through primary and secondary school students to read in order to complete the questionnaires. Due to the special situation of media use in rural areas, the questionnaires were mainly distributed in paper form (Yang K et al., 2015; Laer T V et al., 2014).

The following criteria were met (Zhang and Hanaoka, 2021): 1) The farming population was based on farming households, and no duplication of surveys was allowed; 2) Farming households had their own contracted land (including some farming households who rented out their farming land to others); 3) The place of economic activity was mainly rural; and 4) Farming households' living accommodation and living space was mainly rural. A total of 1,541 questionnaires were distributed and 1,216 valid questionnaires were obtained, with a valid return rate of 79%.

3.2 Measurement indicators

3.2.1 Dependent variable measurement: Design of farmers' environmental behaviour

The rural environmental behavior is the dependent variable and a total of 5 questions have been used to measure (α= 0.85), including: "Do you specifically collect plastic bags and other rubbish from your cultivated land, house site, etc." "Do you sort your rubbish", "Do you discuss environmental issues with relatives, neighbors, etc.", and many others (Kang Y et al., 2020). The Kalombach reliability analysis has met the criteria (α = 0.76). The first part of the questionnaire is about private EB, while the last two questions are about public EP such as "participation in environmental activities" and "environmental information" (Liu S and Yang J Z, 2020). The questionnaire is based on a 5-point scale, with 1 being 'never' and 5 being 'very often', and the final score is averaged (Zheng X Q et al., 2020). The design considers the actual environmental aspects of rural agricultural production and livelihoods, and balances all aspects (Chen A et al., 2020).

3.2.2 Independent variable measurement: Online social media use vs. offline interpersonal interactions

The social media use in rural areas is different from urban areas which is more akin to media exposure, where media is a life scenario in many cases (Liu X P et al., 2018). This paper draws on Lin and Li's Media Attention Scale, which is scored on a 5-point scale, with 1 being 'never' and 5 being 'very often' (Laer T V et al., 2014). The pre-test data shows that rural television use is the highest, with smartphone use also dominating. In order to optimize the measurement structure of media use in this study, traditional media (including magazines, newspapers, radio, and television, α= 0.78) and social media (including microblogs, WeChat, Jitterbug, etc., α= 0.81) have been combined and scored as a mean (Zhang R and Hanaoka T, 2021). Interpersonal discussions consisted of two questions measuring the frequency of "you discuss with your family" and "you discuss with your relatives and friends" on environmental health issues, both of which are very representative forms of communication in homogeneous social capital interactions (Du H B et al., 2021). A five-point scale was used (1 for 'hardly ever' and 5 for 'very often') and the scores for the variables were summed to form an indicator.

3.2.3 Mediating variable measurement: Farmers' environmental knowledge design

The design of rural environmental protection knowledge questions requires a certain degree of science and authority (Sorescu, 2008). This study draws on a resource for national rural environmental protection publicity, rural environmental protection tips, and incorporates local environmental protection practices to design a questionnaire on rural environmental protection knowledge, environmental risk perception, and environmental behavior (R Mugge and W Dahl, 2013). Targeting rural farmers in China, it provides a detailed information on some of the basic environmental knowledge and issues currently prevalent in China's rural areas, covering the range of knowledge on the decentralized, random, hidden, not easily monitored and difficult to quantify nature of pollution facing China's rural areas, while taking care to integrate environmental knowledge with China's agricultural production and life (M Zhao et al., 2014). The scale consists of 11 knowledge questions, which are dichotomous variables of single choice (1 = correct, 0 = incorrect), with each question being worth 1 point and all corrects adding up to a total of 11 points, with missing values being incorrect answers. There is no Kalombach reliability analysis because the variables are judged to be correct or incorrect (A. F Hayes, 2017).

3.2.4 Measurement of two parallel mediating variables: Trust and reciprocity

The trust perceptions have been designed to measure trust perceptions with four questions on a five-point scale (1 being totally disagree and 5 being strongly agree). The questions included "This information is reliable", "Your information is trustworthy", "I believe this information will be useful to me" etc. Scores for this part of the variable measure are scored according to summation into indicators (Minton, 2018).

The perception of reciprocity consists of 7 questions. A five-point scale of 1 (totally disagree) to 5 (strongly agree) was used. The questions include "I share correct and useful information when I come across it" and "I am willing to share my knowledge with others". The Karonbach value is achieved (α= 0.82) (K. P. Winterich et al., 2018).

3.3 Sample characteristics

The sample sizes for Longsheng, Jianli and Qinzhou were 384, 398 and 434, respectively, with a total valid sample of 1,216. In terms of sample characteristics, 62% were female and 38% were male, with an average age of 53 years (SD = 12.35), and the largest proportion, 36.4% of the total, was over 55 years old. The average number of household members was 4.41 (SD = 1.62), indicating that rural areas are still dominated by traditional households with several generations living together, and homogeneity is still evident. However, the use of social media scored 3.24 (SD = 1.26), second only to television at 3.51 (SD = 0.92), which is a traditional media. This suggests that social media has a very important role to play in the dissemination of information in rural areas (D Wu, 2021).

In terms of demographic variables (see Table 1), there is also a convergence in terms of educational attainment and economic attributes. The majority of rural inhabitants have primary and lower secondary education (73.2%), while those with no schooling (17.2%) and upper secondary education (7.9%) account for 26.8% of the total. In economic terms, those who consider themselves to be "average families" (61.4%) and "families in difficulty" (18%) make up the majority of the population, accounting for 79.4% of the total; poor families (10.4%) and "The lowest number of people, 0.9%, considered themselves to be from rich families. It can be seen that cultural education and economic attributes are important homogeneous features in the sample (Song G J et al., 2021).

TABLE 1 Basic background information on the sample population.

Variables	Probability (percentage)	Variables	Probability (percentage)
Gender		**Education level**	
Man	469 (38.6%)	No schooling	210 (17.2%)
Woman	747 (61.4%)	Primary education level	381 (31.3%)
Age		Lower secondary education	510 (41.9%)
Less than 18 years	2 (0.1%)	High school education	96 (7.9%)
18–25	15 (1.2%)	University level and above	19 (1.6%)
26–35	96 (7.9%)	Household economic attributes	
36–45	310 (25.5%)	Poor families	127 (10.4%)
46–55	350 (28.9%)	Families in difficulty	219 (18%)
Over 55 years old	443 (34.4)	General household	747 (61.4%)
		well-off families	111 (9.1%)
		Affluent Families	12 (0.9%)

TABLE 2 Correlation coefficients between the sample's social media use, interpersonal discussions and each variable.

	Offline interpersonal discussions	Online social media usage	Confidence	Reciprocity	Environmental knowledge	Environmental behaviour
Offline interpersonal discussions	1					
Online social media usage	0.255*	1				
Confidence	0.161*	0.131**	1			
Reciprocity	0.195**	0.042	0.144**	1		
Environmental knowledge	0.012	0.069*	0.255**	0.190*	1	
Environmental behaviour	0.348*	0.178**	−0.077**	0.089*	0.084***	1

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

4 Data analysis

4.1 Correlation analysis

The results of the correlation analysis of the independent and mediating variables using SPSS are shown in Table 2, where there was a significant correlation between farmers' offline interpersonal discussions and their online social media use ($r = 0.255$, $p < 0.05$) (Mallapaty S, 2020). Social media use was significantly and positively correlated with perceptions of trust ($r = 0.131$, $p < 0.01$), thus supporting Hypothesis 1a; with environmental knowledge ($r = 0.069$, $p < 0.01$) and with environmental behavior ($r = 0.178$, $p < 0.01$). On the other hand, there was no significant correlation between social media use and perceptions of reciprocity ($r = 0.042$, $p > 0.05$), thus negating Hypothesis 1b. Offline interpersonal interactions were significantly positively correlated with perceptions of trust ($r = 0.161$, $p < 0.05$), thus supporting Hypothesis 1c; a significant positive correlation with perceptions of reciprocity ($r = 0.195$, $p < 0.01$) further supports Hypothesis 1d. Among all the significant correlation coefficients, interpersonal discussion had the greatest correlation with environmental behavior ($r = 0.348$, $p < 0.01$), which is worth further exploration when examined in terms of homogeneous interaction outcomes (Jimenez-Navarro J P et al., 2020).

4.2 Demographic variables are significantly associated with environmental knowledge and behavior

The age of the rural population has a negative relationship with environmental knowledge and behavior. Currently, a significant proportion of the rural population is old, with the average age of the sample being 53 years (SD = 12.35), and the phenomenon of rural ageing is quite serious. Age is an important

TABLE 3 Table of correlation coefficients between sample age and environmental communication variables.

	Age	Confidence	Reciprocity	Environmental knowledge	Environmental behavior
Age	1				
Confidence	−0.032	1			
Reciprocity	−0.105*	0.144**	1		
Environmental knowledge	−0.126*	0.255**	0.190	1	
Environmental behavior	−0.198**	−0.077**	0.089	0.084***	1

Note: *p < 0.05; **p < 0.01; ***p < 0.001.

TABLE 4 Effect of educational attainment and household income on each dependent variable.

	Confidence		Reciprocity		Environmental knowledge		Environmental behaviour	
	F	sig.	F	sig.	F	sig.	F	sig.
Education level	1.64	0.163	7.12***	001	3.51**	0.009	22.12***	0.001
Household income	3.15*	0.010	5.12***	001	4.56***	001	4.27**	0.002

Note: *p < 0.05; **p < 0.01; ***p < 0.001.

indicator system to examine the homogeneity and homogeneous interaction of farmers' social capital (Cai A et al., 2021). Table 3 shows that the older a farmer is, the lower his or her environmental knowledge score is, and the two are significantly negatively correlated ($r = -0.126$, $p < 0.05$); on the other hand, the age of a farmer is significantly negatively correlated with his or her environmental behaviour ($r = -0.198$, $p < 0.01$). These statistical findings are generally in line with our common knowledge that rural environmental issues are closely related to the ageing of the rural population, as older people do not have responsive environmental knowledge, resulting in less environmental awareness (Zheng et al., 2019).

Further analysis from Table 3 revealed that age size was largely negatively correlated with trust and reciprocity, with a significant negative correlation with reciprocity ($r = -0.105$, $p <$ 0.05). These statistics suggest that older rural residents, to some extent, solidify the attribute of homogeneity of their social capital and do not easily trust others. Therefore, there is a need to consider how to overcome the negative effects of ageing in the rural environmental process (Jun et al., 2022).

As shown in Table 4, educational attainment and household income were also significant demographic variables. Statistically, education has no effect on perceptions of trust F (1, 1,216) = 1.64, $p > 0.05$; education has an effect on perceptions of reciprocity F (1, 1,216) = 7.12, <0.001; education has an effect on farmers' knowledge of environmental protection F (1, 1,216) = 3.51, <0.01; education has an effect on farmers' environmental behavior F (1, 1,216) = 22.12, <0.001, This suggests that more education is beneficial for acquiring knowledge about environmental protection. In the same way, a high level of education is not only motivated by self-interest in environmental protection, but also by reciprocity (Zheng Shiyong and Jiang Suping, 2019).

As shown in Table 4, household income had an effect on perceptions of trust, F (1, 1,007) = 3.15, $p < 0.05$, and reciprocity, F (1, 1,216) = 5.12, $p < 0.001$; household income had an effect on farmers' environmental knowledge, F (1, 1,216) = 4.56, $p < 0.001$; and court income had an effect on farmers' environmental behavior, F (1, 1,216) = 4.27, $p < 0.01$; This confirms the Chinese proverb: "When one has enough food and clothing, one knows what is honorable and disgraceful", and only when people have solved the problem of food and clothing will they pay more attention to environmental issues (Wang et al., 2022).

4.3 Cause and effect analysis

To further explore the relationships between the variables, this study uses structural equation modelling to clarify the effects of online social media use and offline interpersonal discussions on a range of environmentally relevant variables (Xiao et al., 2019). In the model, online social media use and offline interpersonal discussions were set as independent variables, trust and reciprocity were set as two parallel mediating variables, environmental knowledge was used as a subsequent mediator to link the two parallel mediating variables to the dependent variable environmental behavior, while age, educational background, religion, and household income were

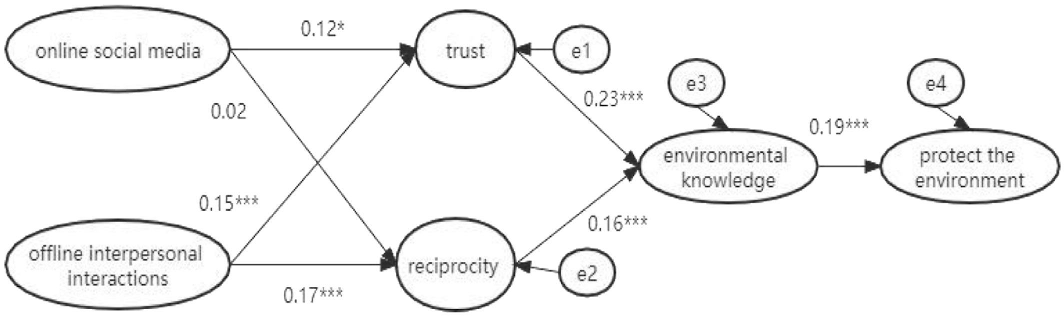

FIGURE 2
Data analysis results.

included as control variables in the model. After adjustment and modification, the new model showed a good fit with the data (see Figure 2) (Wang et al., 2022).

The results of the structural equation model showed that farmers' offline interpersonal discussions had a significant effect on reciprocity (β = 0.17, $p < 0.001$), which in turn significantly influenced farmers' environmental knowledge (β = 0.16, $p < 0.001$), thus supporting Hypothesis 2a. In addition, farmers' perceptions of trust positively influenced their environmental knowledge (β = 0.23, $p < 0.001$), while perceptions of trust were significantly influenced by social media use (β = 0.12, $p < 0.05$), thus supporting Hypothesis 2b. Both trust and reciprocity had a significant effect on environmental knowledge, but trust had a greater effect on environmental knowledge than trust; farmers' social media use did not have a significant effect on reciprocity (β = 0.02, $p > 0.05$), and thus did not support Hypothesis 2d. Interpersonal discussions had a significant effect on trust (β = 0.15, $p < 0.01$) and reciprocity (β = 0.01). This suggests that the main source of trust and reciprocity for farmers is offline interpersonal discussions, and that social media use is more for self-interest motives, to gain knowledge, rather than to provide benefits to other users. At the same time, it reflects the fact that offline interaction is still the main way of accessing information in rural areas, showing the practical utility of homogeneous interaction in rural areas (Shiyong Z et al., 2021).

Finally, we also found a positive correlation between environmental knowledge and environmental behavior (β = 0.19, $p < 0.001$), thus supporting Hypothesis 3. This suggests that environmental knowledge and awareness is necessary to improve farmers' environmental behavior (Shiyong Z et al., 2022).

5 Discussion and conclusion

This study, conducted in a representative sample of three rural areas in China, has found that offline interpersonal discussions and online social media use, as the main forms of social network interaction among farmers, had a positive effect on promoting trust and reciprocity in information acquisition, environmental knowledge and environmental behavior in an environment where farmers are relatively homogeneous in terms of social capital, while at the same time displaying different characteristics. The main findings are as follows:

(1) This study has found that farmers' adhesive social capital (offline interpersonal discussions) continues to play a greater role than connective social capital (online social media use). The positive effect of interpersonal discussions as bonding social capital in environmental communication among farmers in China is greater than that of social media use as connecting social capital. This is reflected in the relationship between the effect of social media use on the two parallel mediating variables in the structural equation, namely the insignificant effect on reciprocity (β = 0.02, p > 0.05) and the weak effect on trust (β = 0.12, p < 0.05); On the other hand, interpersonal discussion has a significant effect on trust (β = 0.15, p < 0.001) and reciprocity (β = 0.17, p < 0.001). In line with Lazarsfeld and Morton's hypothesis of homogeneous interactions in "affective-interaction", this study has verified that the effect of homogeneous interactions of affective friendship, bonding social capital (offline interpersonal interactions), was significantly stronger than the effect of connecting social capital (social media use) in environmental communication among farmers (Zhang et al., 2022). This suggests that in the field of environmental health topics, the effect of social media use in China's vernacular acquaintance social groups is still difficult to break through the homogeneous interaction effect of social network relationships characterized by 'emotion—interaction—resources'. In other words, in terms of social learning in environmental communication, the role of interpersonal discussion as a form of bonding social capital of rural residents is still deeply

rooted, and the influence of social media use as a form of connective capital is difficult to surpass for the time being.

(2) The impact of social media also plays a role in the communication of environmental protection in rural China in an environment of social capital homogeneity. However, the perceptions of trust play a major motivating role in this process, while perceptions of reciprocity do not. Due to the fact that farmers are generally less educated and have less knowledge about environmental protection, they use the internet more for self-serving motives to learn and obtain information. Since they have less valuable information, they use social media less for altruistic motives reciprocity (S Zheng et al., 2022). Most of the people that we meet during the online use of social media are strangers, and there are more differences between users, i.e. the online network is a heterogeneous network. In contrast, the scope of offline interpersonal interactions is usually limited to a certain geographical area. Farmers' offline interpersonal network relationships are a homogeneous network due to the similarity of their geographical characteristics, and therefore, it is easier to share environmental knowledge in a homogeneous network out of self-interest and altruistic motives.

(3) Environmental knowledge in rural areas is mostly derived from labor experiences and interpersonal discussions rather than heterogeneous interactions of social capital. From farmers in India to those in other developing countries, farmers' environmental knowledge comes from keen observation of their daily work and from communication and discussion between collaborators, which cumulatively leads to 'everyday knowledge'. The statistics (see Table 1) show that, although they all belong to the same large group of farmers, there is little difference in their cultural (mainly primary and lower secondary school levels) and economic levels (Zheng et al., 2022). In a homogeneous social network of socio-economic characteristics and lifestyles, characterized by similar types and amounts of resources, interactions tend to take place within this social network of similar or adjacent socially situated relationships; and access to resources is positively related to the number of interactions they have, with emotional friendship relationships playing an important connecting role. These specific claims are supported by the empirical results of this study.

6 Management implications

(1) Environmental knowledge dissemination and environmental activities should be primarily relied upon offline. This study found that the current sources of knowledge for farmers are still largely based on offline networks of acquaintances. The role of online social media has not been fully utilised (S Zheng et al., 2022). This finding is consistent with the loss of youth labour in the census data. It suggests that many of the young farmers with social media skills and higher education have moved to the cities. Older farmers, on the other hand, have certain thresholds and barriers to the use of social media. Therefore, offline campaigns should still be used as the main tool when conducting environmental campaigns in rural areas. At the same time, the use of social media should be actively promoted and popularised. Broaden the channels through which farmers can access knowledge and diversify their sources of knowledge.

(2) Social communication strategies should be chosen for environmental protection publicity based on trust mechanisms. Knowledge learning among farmers is more out of trust, so some social strategies in the marketing field, such as viral marketing strategies, can be used for environmental knowledge promotion. Choosing highly respected individuals as seed users makes other individuals have a higher response to the environmental knowledge promoted by the seed users and the environmental activities initiated by them due to their higher appeal and trust. This enhances the acceptance of environmental knowledge.

(3) A knowledge diffusion strategy of homogeneous networks should be used. Our study found that farmers' information sources mainly rely on information sharing from other users in homogeneous networks, which means that the identity of propagators in environmental knowledge diffusion should be positioned as peer nodes in homogeneous networks, not necessarily opinion leaders from heterogeneous networks. That is, the identity reduces the social distance between the information sharer and the receiver, which in turn enhances the persuasive effect.

7 Research limitations and future research directions

This study empirically validates some of the hypotheses in theories about the homogeneity of social capital. Social media use, as virtual social network relationships in electronic space, has become a new type of connected social capital for contemporary people to break out of the homogeneous environment of social capital such as geography, group, clan, and even social class, and still brings limited resources in the current communication of environmental protection in rural China. The revolutionary rise in social capital has been brought about by the internet and its heterogeneous reciprocal effects are not clearly highlighted in all elements of current rural environmental communication in China due to population loss and ageing issues in rural areas. In contrast, interpersonal discussions, a local, contextual-emotional form of communication that serves as bonding social capital, play an important role in communication among farmers with similar lifestyles, social-psychological proximity, and economic status.

However, the following limitations exist in this study:

(1) Limitations of the sample selection area of the research questionnaire. In this study, samples have been selected from representative rural areas for the study, namely Longsheng County in Guangxi Guilin as the southern agricultural area of China, Jili County in Hubei as the traditional plain agricultural area, and Qinzhou City in Guangxi Zhuang Autonomous Region as the sea-facing agricultural area. Representative districts have then been selected from the target cities and counties, and then representative villages have been selected from the districts. Overall, only three counties were selected, and of the 1,636 counties within China, we have selected only three with specific geographical characteristics. Therefore, in future studies, the area of research can be expanded.
(2) Differences between counties of the same type have been ignored. In this study, we have selected three geographical types of counties. However, even for counties of the same type, there is uneven development. With urbanisation, some of the counties that are traditionally agricultural and slow to develop have serious population loss and obvious ageing characteristics, which introduces some bias into the data sampling for this study. Therefore, in future research, it may be possible to conduct separate studies on environmental behaviour for areas with different levels of economic development.
(3) Social capital is used as a mediator in this study. The main consideration is the perception of differences in trust and reciprocity brought about by the source of information access. However, in practice the same phenomenon can be explained by different theories, for example offline networks of acquaintances are more of a fixed social norm; whereas online networks of strangers have access to more differentiated information, creating an informational influence. From this perspective, the use of social influence theory (informational vs. normative influence) also seems to explain the difference in persuasive effects brought about online and offline. Therefore, in future research, we can try to adopt more theories to explain the phenomenon in environmental behaviour and explore the underlying mechanisms.

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

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

Conceptualization, JZ; Writing—review and editing, SZ; Writing—original draft; SZ. Data curation, MK; Formal analysis, X-GY; Methodology, X-GY. Revising and funding provide—RC.

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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.

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Application of carbon emission prediction based on a combined neural algorithm in the control of coastal environmental pollution in China

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The marine ecosystem provides the environment, resources, and services necessary for the development of every human society. In recent years, China's coastal zone has been polluted to varying degrees, which has seriously affected its development. The characteristics of marine environmental data include the variety of data types, the complexity of factors affecting the marine environment, and the unpredictability of marine pollution. Currently, there are few studies applying the clustering analysis algorithm to marine environmental monitoring. Then, carbon emissions (CEs) from coastal areas are predicted using marine environmental data. Therefore, this paper mainly studies the spatial and temporal accumulation characteristics of marine environmental data and uses the fuzzy c-means (FCM) algorithm to mine the data monitored by the marine environment. Meanwhile, it has been focused on the prediction of coastal CEs, and the grey model-back propagation (GM-BP) algorithm has been developed to predict CEs from coastal areas, which solves the problem that the traditional back propagation neural network (BPNN) cannot fully learn data features, which leads to a decline in accuracy. The experimental results showed that the FCM algorithm can divide the marine sample data into corresponding categories to distinguish polluted and unpolluted samples. The improved neural network model has a higher degree of non-linear fit and lower prediction error than a back propagation (BP) neural network. The main contribution of this paper is to first study the spatial and temporal accumulation characteristics of marine environmental data. The academic contribution of this study is to substitute the predictions of the three gray models (GMs) with the neural network structure simulation to finally obtain more accurate predictions. From a practical point of view, this study is helpful to a certain extent in alleviating the pressure of climate change due to increased CEs in global coastal zones. This study can also provide a new method of measuring environmental governance for marine environmental regulatory authorities.

KEYWORDS

coastal zone, environmental governance, CE, FCM, GM-BP

1. Introduction

The coastal zone is a transitional zone between land and sea. It is a special zone extending from the coastline to both sides of land and sea, with a strong interaction between land and sea. It has the characteristics of two different environments: land and sea. With rich biodiversity and a comfortable climate, the coast is suitable for the survival and development of human beings and is the focus of the national economy and population. More than half of the world's coastal areas are related to the development of the human population, which is the key to the development of every human society. However, with the intensification of human activities, a large number of pollutants are discharged into the coastal zone in a variety of ways. The environmental pollution caused by high-intensity human activities has led to the degradation of the coastal zone, the earth's key zone. Therefore, exploring the current situation of coastal pollution in China and putting forward reasonable and effective pollution control measures will play an important role in ensuring the ecological security of coastal zones, ensuring public health, and maintaining the sustainable development of coastal zones. The global carbon cycle is constantly changing under the influence of natural changes and human beings, and the carbon cycle in coastal waters is also constantly changing. The diversity of carbon sources and carbon sinks and the interaction between them increase the complexity of research (Li, 2018; Liu et al., 2018). Experiments showed that increased temperature and decreased precipitation will slow down the decomposition of soil organic matter, thus slowing down the positive feedback effect of human-induced changes on the climate. Human impacts on the coastal zone and the ocean are becoming more and more intense, and some human activities have weakened the carbon sink in the coastal zone (Vondolia et al., 2020; Fu et al., 2021).

Data mining technology can be used for statistics and the analyses of data so as to guide the decision-making of practical problems in real life, discover the relationships between things, and predict the future work. The marine environment monitoring involves a wide range of sea areas, and a large amount of monitoring data will be obtained. It is also possible to monitor only a certain station or sea area, and the data acquisition may be a long-term series or a specific time period (Sun et al., 2018). Data mining technology is an application-oriented research field. When dealing with the marine environment, we need to know who the specific users are, and the knowledge obtained according to the needs of users is useful and valuable. Although data mining technology has achieved certain results in the processing of marine environmental monitoring data, the development of a data mining system is not perfect because of the particularity of marine environmental data, the diversity of data types, the complexity of factors affecting the marine environment, and the unpredictability of marine pollution. Some data mining methods still have some problems in marine data processing, such as unclear mining tasks, sensitivity to noise, and low efficiency (Zhang, 2018).

In this study, the spatial and temporal accumulation of marine environmental data is studied; at the same time, it focuses on the prediction of coastal carbon emissions (CEs) and uses the GM-BP algorithm to predict the CEs in coastal areas, which provides a new method for the marine environmental supervision department.

2. Literature review

2.1. Coastal environment management based on data mining

Some developed countries have achieved some theoretical research results in the fields of marine data management and marine information processing (Zhuang et al., 2016; Tanhua et al., 2019; Lou et al., 2021). The United States is one of the first countries to develop digital mapping products for deep sea areas. As early as 1990, the United States established the digital bathymetric data center of the international island survey organization. It is expected to establish a global digital bathymetric data warehouse to store, manage, and mine the data of areas deeper than 100 m. China has also gradually established the information system for sea area use and marine environmental protection management information system so as to make reasonable use of and store the information resources of the marine information center. In terms of data mining technology, more and more scholars use the characteristics of marine information data to further explore the data mining technology applied in the marine environment. Chen (2014) improved the clustering algorithm using the concepts of specified distance and reachable distance of sub-trajectories in a trajectory division, which solved the problem of the sensitivity of the algorithm to input parameters, and applied the improved algorithm to the clustering of hurricane tracks to obtain an internal clustering structure of hurricane tracks. Zhou puts forward a fuzzy clustering algorithm based on weight. By clustering the physical and chemical factors of red tide, the occurrence and development of red tide were divided into four stages (Zhou and Yang, 2016). Liu also analyzes the physical and chemical factors of red tide, designs an open-source, cross-platform marine environment data mining system, improves the fuzzy algorithm based on similarity relationships, and processes the marine data to obtain the main factors leading to the occurrence of red tide, which can give an early warning on whether red tide occurs (Liu L. et al., 2016). Geman et al. (2016) analyze the ecological environment remote sensing data of Bohai Bay using the *k*-means algorithm in cluster analysis and the Apriori algorithm in correlation analysis, respectively, to analyze and predict the environmental conditions of Bohai Bay and put forward reasonable suggestions (Geman et al., 2016). In addition to the application of data mining to the analysis of the marine environment at the algorithmic level, there is also the storage of massive marine environmental monitoring data at the technical level. Liu gridded the marine environmental monitoring data using spatial interpolation and a spatiotemporal difference algorithm, making it convenient for users to analyze data at multiple levels and dimensions (Liu L. et al., 2016).

The types of marine data samples are diverse. The marine monitoring data include the most basic environmental data, such as temperature, seawater salinity, and dissolved oxygen concentration, as well as remote sensing data, marine culture, and other statistical data related to the marine economy (Zhang, 2018). These categories can also be subdivided into many small categories, which leads to the fact that the data types of marine data samples are very complex and huge. At the same time, there is little research on the application of clustering analysis algorithms to marine environmental monitoring. This study considered the complex factors affecting the marine environment, with characteristics of diversity, suddenness, disorder, and randomness, which cause fuzziness in the marine data, and used the fuzzy C-means (FCM) algorithm to mine some basic monitoring data of the marine environment.

2.2. Prediction of CE

Carbon dioxide emitted by human beings mainly comes from urban areas. Approximately 50% of the world's population lives in cities, especially in economically developed coastal areas. At least 70% of carbon dioxide released by fossil fuels and a large amount of methane generated by human activities come from this source (Krause-Jensen and Duarte, 2016). In the construction of the smart ocean, with the continuous development of the shipping industry, there are an increasing number of ships on the sea, and CEs from ships has increased significantly, which is the main source of CE in the coastal zone. CEs from ships is based on the ship energy efficiency operation index, which represents carbon dioxide emissions per unit voyage and is directly related to the ship's fuel consumption. The index can be used as an objective calculation method for monitoring the energy efficiency of operating ships. Zheng et al. established the relationship between CE, fuel consumption, and ship Automatic Identification System (AIS) information. Through the obtained AIS data information, the variables needed to calculate the EEIO formula were converted into the data contained in AIS to estimate the value of CEs (Zheng et al., 2014). Yao et al. calculated CEs from ships according to the ship type, linked the length of the ship with the ship power, and directly calculated the CE value using the static AIS data (Yao et al., 2017).

Summarizing the current research on China's CE peak prediction and total amount control, it can be found that scholars mainly analyze the influencing factors of total CEs through the following methods (Chai et al., 2017; Dong et al., 2019), namely, the STIRPAT model, the logarithmic mean Divisia index (LMDI) factor decomposition model, the environmental Kuznets curve (EKC) curve, and other means, that were established to decompose CEs of energy consumption so as to put forward corresponding countermeasures and suggestions for China to eliminate backward production capacity and accelerate the upgrading of the industrial structure. For the prediction of total CEs, most of the existing studies used the partial least squares regression method, the STIRPAT model, and the scenario analysis method to predict the peak of China's CE, and some scholars combined various methods to predict China's CEs (Yang et al., 2018; Li et al., 2021). Jin et al. used the radial basis function (RBF) to predict the urban CE content in China from 2027 to 2032 (Jin, 2021). The experimental results showed that the number of samples will affect the prediction ability and network structure complexity of RBF, and the network is not suitable for large sample data prediction. Kashi et al. used a multilayer perceptron, RBF, and adaptive neuro-fuzzy inference system model to predict the dissolved oxygen, biochemical oxygen demand, and chemical oxygen demand levels of Iran's Karun river (Emamgholizadeh et al., 2014). Zhang et al. (2018) proved that the back propagation (BP) network can be used to predict the evolution of sea ice (Zhang et al., 2018). The experimental results showed that the BP algorithm is more satisfactory than the least squares method in predicting the ice melting process. Although research on the shallow neural network (SNN) in predicting marine data is quite effective, this kind of model has a single structure and can only capture simple data features, which is suitable for processing the mapping relationships of small sample data. In the face of marine environmental data with mass and diversity characteristics, SNN cannot fully learn the data features, which leads to a decline in accuracy (Jiang et al., 2018; Erichson et al., 2020).

Through the abovementioned analysis, it can be seen that, at present, neural networks have been widely used in predicting CEs, but most of them are for urban CEs. At the same time, the accuracy of SNN is reduced because it cannot fully learn the data features. Therefore, this study attempts to use the gray neural network prediction model to predict CEs in the coastal zone.

3. Clustering model of coastal environmental monitoring data based on FCM

3.1. Mining process of monitoring data

The types of coastal data samples are diverse. The marine monitoring data include the most basic environmental data, such as temperature, salinity, dissolved oxygen concentration, etc., as well as remote sensing data, marine culture, and other statistical data related to the marine economy. The whole data mining process can be divided into three parts: the data preparation stage, the data mining stage, and the pattern evaluation and knowledge representation stage. In the first stage, the data preparation stage mainly includes data cleaning, data integration, and data transformation. The specific process is shown in Figure 1.

3.2. FCM clustering algorithm

Fuzzy C-means algorithm can deal with the problem of difficult batch processing under the condition of ocean big data, and it can realize the optimization of clustering centers under the condition of ocean big data. FCM achieves data clustering by minimizing the objective function and determines the number of genetic centers under the condition of marine big data *via* piecewise processing of a specific analysis through the genetic population of individuals under the condition of marine big data, combined with the characteristics of marine big data.

Let the n-dimensional sample data set be $X = \{x_1, x_2, x_j, x_n\}$, and each sample data have a S-dimensional property $x_k = \{x_{k1}, x_{k2}, x_{ks}\}$. If the FCM algorithm is used to cluster the sample data into C classes, V is the cluster center matrix, and U is the fuzzy matrix, the corresponding objective function of the algorithm is as follows:

$$J_m(U, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m D_{ij}^2 \tag{1}$$

where u_{ij} represents the membership degree of some sample data j and the ith category, and $0 \leq j \leq n, 0 \leq i \leq c$.

$D_{ij} = \| x_j - v_i \|$ in Equation (1) is expressed as the Euclidean distance between the jth data sample and the ith cluster center. The biggest difference between fuzzy clustering and hard clustering lies on this m, which represents the fuzzy weighting index of membership degree. If the value of m is 1, then it becomes a hard cluster, and as the value of m becomes larger, it means that it is fuzzier. When the FCM algorithm achieves the best clustering effect, the objective function obtains the minimum value. Therefore, using the Lagrangian multiplier method on $m \in [1, \infty)$, when the objective function satisfies the constraint $\sum_{i=1}^{c} u_{ij} = 1$ to obtain the minimum value and the optimal clustering effect is achieved, the corresponding fuzzy matrix and clustering center can be obtained.

$$J_m^*(U, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m D_{ij}^2 + \lambda \left(\sum_{i=1}^{c} u_{ij} - 1 \right) \tag{2}$$

The meaning of u_{ij} and D_{ij} is consistent with what is described in Equation (1). The partial derivatives in Equation (2) are calculated, and the fuzzy matrix and cluster center corresponding to the minimum value of the objective function are obtained *via* simplification, as shown in Equations (3) and (4).

$$U_{ij} = \left[\sum_{k=1}^{c} \left[\frac{D(x_j, v_i)}{D(x_j, v_k)} \right]^{\frac{1}{m-1}} \right]^{-1} \tag{3}$$

$$V_i = \frac{\sum_{j=1}^{n} u_{ij}{}^m x_j}{\sum_{j=1}^{n} u_{ij}{}^m} \tag{4}$$

3.3. Algorithm implementation process

A specific clustering process of the FCM clustering algorithm is as follows: the input is the sample object data n, the number of clustering categories c, and the output is the cluster center matrix V and the fuzzy matrix U. The specific steps are as follows:

(1) Set the specific number of categories of the sample data to be clustered, and initialize a series of parameters: the number of iterations, the threshold of the objective function ε, and the fuzzy weighting exponent m. Given any fuzzy matrix of initial classification and C initial cluster centers, it should be noted that the initial fuzzy matrix only needs to satisfy the constraint $\sum_{i=1}^{c} u_{ij} = 1$.
(2) According to Equation (3) and the value of the initial cluster center, the distance between the sample data and the cluster center is calculated to obtain the fuzzy matrix.
(3) According to Equation (4), the cluster center is updated by the fuzzy matrix.
(4) Loop process judgment if the objective function difference is less than the set objective function threshold and then exit the loop. Otherwise, return to Step (2).

4. CE prediction model based on the gray neural network

4.1. Carbon balance analysis of coastal cities

Urban carbon balance in coastal zones studies the relationship between CEs and carbon absorption. When urban CEs are equal to its carbon absorption, it is in equilibrium. Carbon input and output include vertical and horizontal carbon flow. In addition, carbon will stay in the carbon pool for a certain time. Carbon inputs include plant photosynthesis, fossil fuels, food, and building material transport; the carbon pool includes plants, soils, buildings, furniture, books, and living

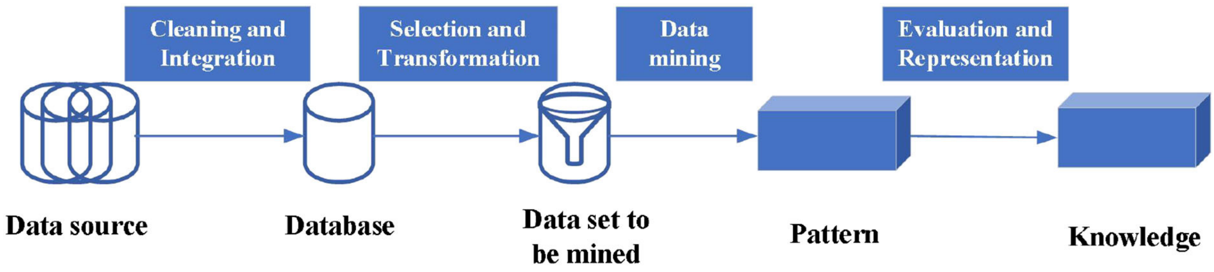

FIGURE 1
The mining process of coastal zone monitoring data.

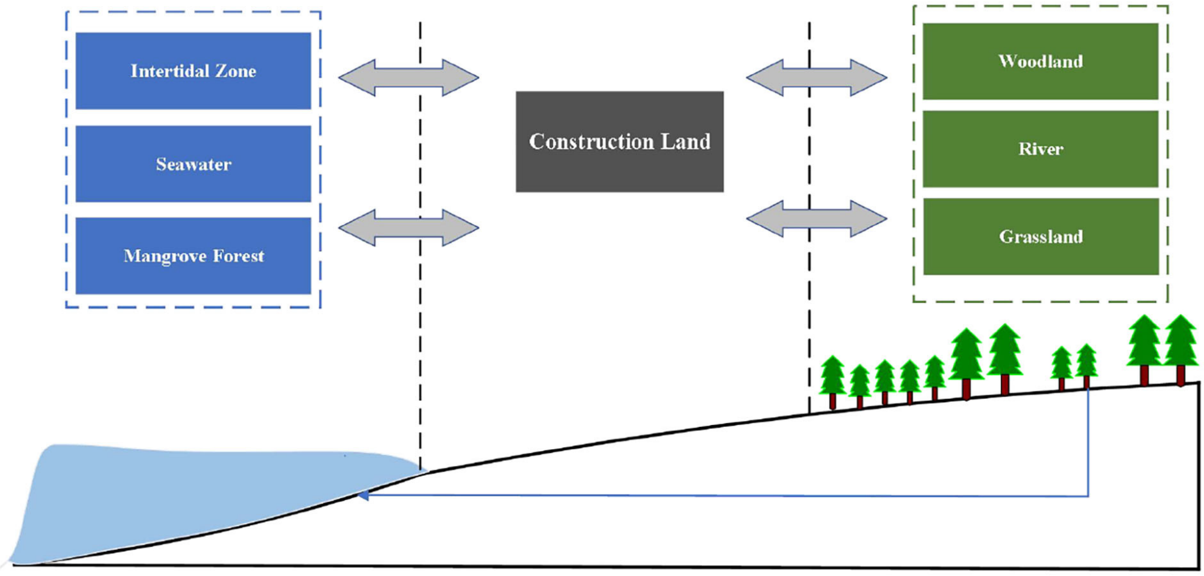

FIGURE 2
Carbon metabolism in the coastal zone.

organisms; and carbon output includes the respiration of plants, soils, and other living things, the burning of fossil fuels, and the decomposition of waste.

Carbon input and output can be divided into horizontal flow and vertical flow. The vertical flow of carbon includes vegetation and algae, among others, which is produced by the processes of carbon fixation by photosynthesis, fossil energy combustion, and biological respiration; the horizontal flow of carbon is the movement of carbon containing materials in the horizontal direction, such as the transfer of food and fiber from cultivated land, oceans, and forests to urban areas and the transfer of domestic waste from urban areas to land and sea landfill sites. Meanwhile, the horizontal carbon flow starts from or finally participates in the carbon cycle through the vertical flow. For example, organisms are transported to the market in a horizontal direction after being captured and then reemitted into the atmosphere through vertical biological respiration after being consumed. There is no carbon absorption or CEs in the horizontal direction. CEs studied in this study are vertical. The simplified carbon metabolism in coastal cities is shown in Figure 2.

4.2. Gray neural network algorithm

The gray prediction method can eliminate the influence of random interference *via* the accumulation of a small number of sample data, and the accumulated series show a monotonically increasing trend, which can better predict the overall trend (Liu C. et al., 2016; Zhuang et al., 2021). In the modern emerging technology of information processing, the combination of gray model (GM) prediction and the BP neural network prediction can effectively predict CEs. Based on GM (1, 1), unbiased GM (1, 1) (WPGM), unequal GM (1, 1), the weighted GM (1, 1)

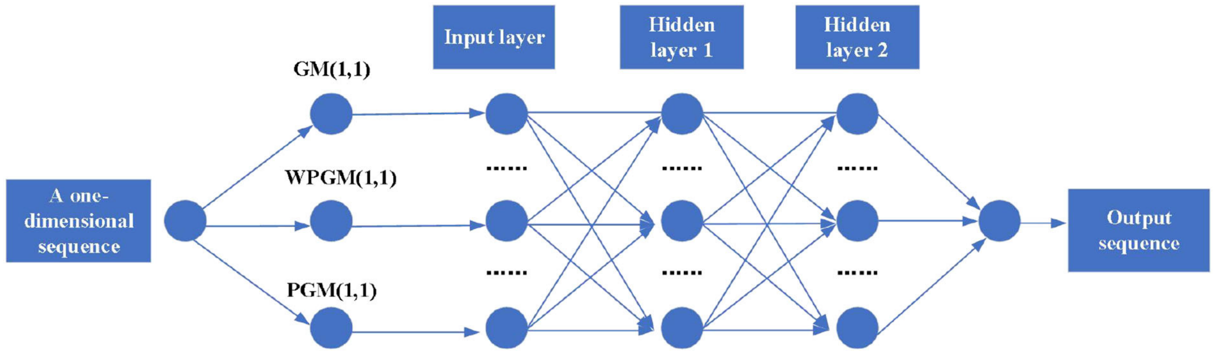

FIGURE 3
The topology of gray neural network prediction model.

(PGM), and BP neural networks, the GM-BP model is proposed in this study. The optimal neural network structure is obtained by training the three sets of simulated values obtained from the one-dimensional sequence through three GMs as the input mode and from the original sequence as the output mode. The predictions of the three GMs are substituted into the neural network structure simulation, and the predictions are finally obtained. In regression problems, the mean square error (MSE) loss function is used to measure the distance between sample points and the regression curve, and the sample points can fit the regression curve better by minimizing the square loss. The MSE loss function is adopted in the model in this study. The structure of the GM-BP prediction model is shown in Figure 3.

4.3. Modeling steps

Let m be the original sequence length and n be the predicted sequence length. The structure of the two hidden layers of a four-layer neural network is (p, q), where p is the number of nodes in the first hidden layer and q is the number of nodes in the second hidden layer.

(1) For a sequence, $GM\ (1,1)$, $WPGM\ (1,1)$, $and\ PGM\ (1,1)$, were used, respectively, to obtain m simulation values and n forecast;
(2) The preset structure of a neural network (p, q) is $(1, 1)$.
(3) The simulated values of the three groups of GMs were used as the input modes. The lumped error E of the corresponding neural network structure samples was recorded (Wang, 2020).
(4) Increase p and q by 1, respectively. If $p = q = 11$, continue to Step (5); otherwise, go back to Step (3).
(5) Select the (p, q) corresponding to the minimum value of the abovementioned E, denoted as (p_0, q_0).
(6) Respectively according to $(p_0, 1)$, $(p_0, 2)$, , $\cdots$, $(p_0, 10)$, $(1, q_0)$, $(2, q_0)$, $\cdots$, $(10, q_0)$, select the (p, q) corresponding to the minimum value of the abovementioned 20 E, denoted as (p_1, q_1).
(7) The three groups of n predictions in Step (1) are used as input modes, and the network simulation is carried out according to the structure of (p_1, q_1).

4.4. Prediction of CE

Suppose that it is necessary to predict the marine pollution at time t_A at a point $A\ (x_A, y_A, z_A)$ in the target sea area. Using the marine CE monitoring data of the target marine area at time t_1, t_2, $\cdots$, t_n, polyhedral models of the marine pollution situation at time t_1, t_2, $\cdots$, t_n, respectively, were constructed. The polyhedron model is used to interpolate the ocean CE data f_1, f_2, $\cdots$, f_n of point A. The above model is trained, the relevant parameters in the network are determined, $f_1, f_2, \cdots, f_n$ is taken as the input data, and the organic gray neural network model is the input, that is, the predicted value of the marine pollution at point A can be obtained.

Suppose that it is necessary to predict the Marine pollution status of the target sea area at time t_A. Taking a proper number of sampling points in the target area and ensuring the rationality of the spatial distribution of sampling points, the predictions of marine pollution at time t_A of each sampling point are solved one by one (Di Luccio et al., 2020). Using the sampling points to construct a three-dimensional (3D) polyhedral model, the status of CEs in the whole target sea area at time t_A can be described.

5. Experiment and analysis

5.1. Data acquisition

The data used in this study are from the National Marine Science Data Center of China (http://mds.nmdis.org.cn/), among which the indicators of marine monitoring data

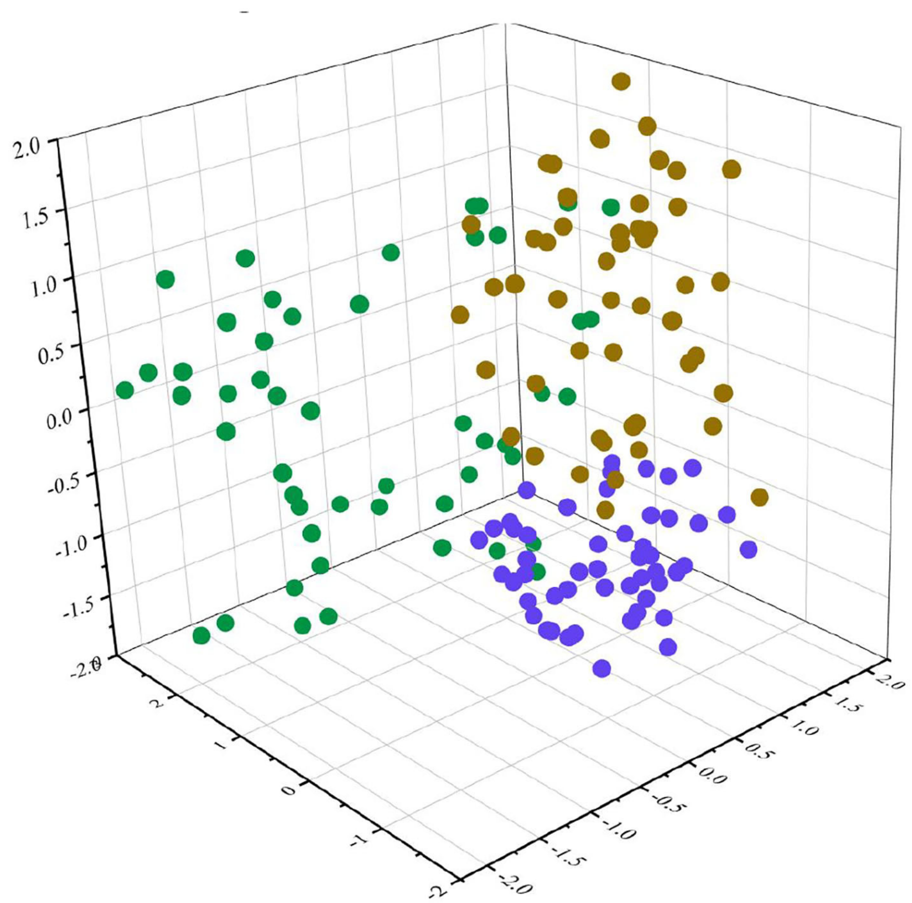

FIGURE 4
Fuzzy clustering results.

mainly include: seawater temperature, salinity, pH value, and dissolved oxygen concentration. The FCM algorithm was used to mine the marine environmental data by time and region.

5.2. Results and discussion

5.2.1. FCM clustering result analysis

Based on the fuzzy cluster analysis of 150 groups of marine environmental monitoring data from January to May, the influence of salinity on the clustering results can be ignored because there is no clear change in the salinity from January to May. The corresponding coefficient of the algorithm is set: clustering category $C = 3$, $m = 2$, and the maximum iteration number l is 20. The fuzzy clustering result is presented in Figure 4.

The coordinate axes in Figure 4 represent the values of seawater temperature, dissolved oxygen concentration, and P_H, respectively. As shown in Figure 4, the clustering effect of this algorithm for the marine monitoring data of the sea area is

TABLE 1 Comparison of clustering results.

	k-means	FCM
Accuracy/%	80.34	89.30
Execution time/s	0.190	0.034
Iterations	28	30

good, and it shows strong time characteristics. The same marine environmental data samples were selected, the FCM and *k*-means algorithms were used to cluster the marine monitoring sample data, and the execution efficiency and accuracy of the two algorithms were compared. The results are presented in Table 1.

The *k*-means and FCM algorithms were used to select and cluster the historical monitoring data of the marine environment into the corresponding sea areas. To a certain extent, there was a deviation. The reason may be related to a sudden change in the sea environment and the geographical location of the three sea areas. Some attributes of the nearby sea area

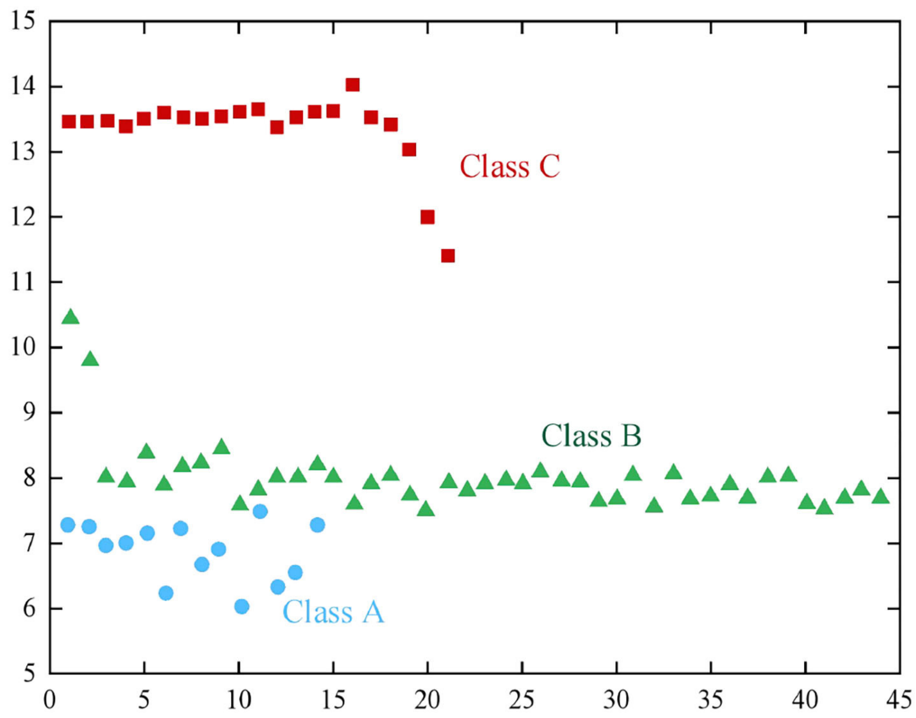

FIGURE 5
The clustering results of pH values of seawater.

were similar. However, when processing a large number of sea area monitoring data, the two algorithms can basically cluster the data from different sea areas in terms of accuracy. Compared with the *k*-means algorithm, the accuracy rate of the FCM algorithm for the data processing of different sea areas was 89.30%. Moreover, when a large number of marine environmental data are classified, the FCM algorithm can still achieve the desired effect, which shows that the FCM algorithm has more advantages in clustering marine environmental monitoring data.

In this study, the pH value of seawater in some historical monitoring data of a certain sea area was taken as the data sample, and some new historical monitoring data of pH value were added. The clustering results obtained by simulation are shown in Figure 5.

The coordinate axes in Figure 5 represent pH and temperature. From the simulation diagram, it is clear that the FCM algorithm divides the sample data into three categories according to the pH value, which corresponds to normal seawater (B), acidic polluted seawater (A), and alkaline polluted seawater (C). The pH of class A seawater is acidic, indicating that the content of carbon dioxide in seawater is high and that there is a great possibility of a jellyfish outbreak crisis in the sea area. Class C represents that there may be a large number of algal plants breeding. The growth of algae will consume a lot of carbon dioxide, which will lead to an increase in the pH value of seawater and make the seawater alkaline.

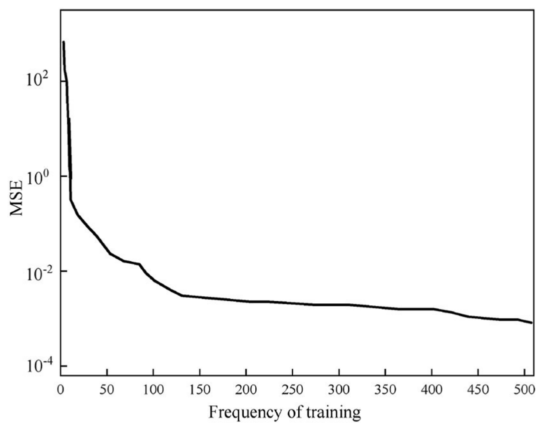

FIGURE 6
The results of training model.

5.2.2. Analysis of CE prediction results

The training process of the enhanced neural network model using the GM-BP model is shown in Figure 6. It can be seen from

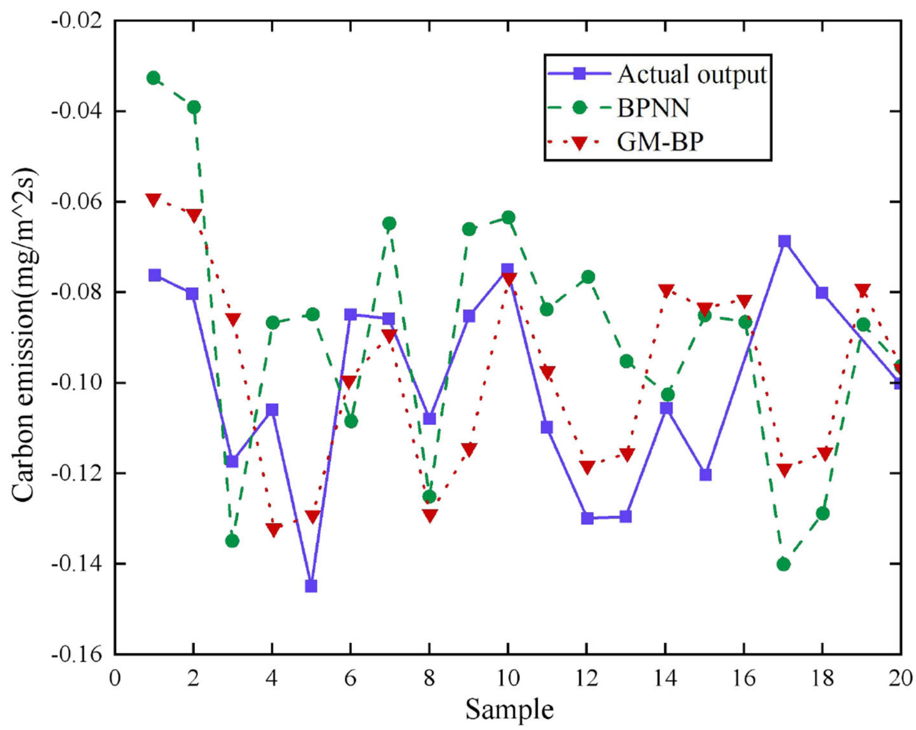

FIGURE 7
Comparison of the predicted and actual values of coastal carbon emission (CE). The prediction error of different algorithms is presented in Table 2.

TABLE 2 Comparison of carbon emission (CE) prediction errors.

	MSE	MAPE
BP	0.0264	19.532
GM-BP	0.0134	9.88

the figure that, after 510 times of training, the network stops training, and the network error reaches the goal of 0.001.

It can be seen from Figure 7 that the predicted value of CEs based on the GM-improved BP neural network algorithm is closer to the real value than that of the ordinary BP neural network algorithm.

The MSE and the mean absolute percentage error (MAPE) were used to analyze the CE errors of different models. From the test data, this algorithm can produce relatively accurate coastal CEs, while the BP neural network can only roughly predict the general trend. At the same time, from the perspective of prediction performance, the improved neural network algorithm based on GM has the best prediction effect. The maximum relative error is 0.4386, the root MSE of the prediction data is 0.0264, and the average relative error is 19.532%. It can be seen that the prediction error of the improved neural network is better than that of the ordinary BP neural network, which indicates that the model has a higher degree of non-linear fit and is scientific and feasible.

6. Conclusion

Coastal cities are the most densely populated and economically populated areas, as well as the most concentrated areas of CEs. The growth of CEs in the global urban areas will continue to exert pressure on climate change. The FCM algorithm is used to mine the monitoring of data of the marine environment, and the GM-BP algorithm is used to predict the CEs in the coastal area. By analyzing the sea area data in the first half of a year, the clustering results showed that the parallel FCM algorithm has a good clustering effect in processing a certain scale of historical marine monitoring data. The GM-enhanced neural network has a higher degree of non-linear fit, and its prediction error is lower than that of the BP neural network. This study focused on the effective prediction of CEs in the coastal zone, which can provide a new method of measuring environmental governance for offshore environmental regulatory authorities.

The status of marine pollution changes gradually and continuously. The change in the results obtained by the interpolation method occurs only at the boundary; that is, the results produced are abrupt at the boundary and homogeneous inside the boundary, i.e., unchanged. In the absence of sufficient sampling points, this assumption is not appropriate. In addition, future work will be devoted to studying the changes in carbon metabolism in coastal cities and mapping them onto the classified fine spatial data so as to analyze the spatial pattern characteristics of carbon metabolism in coastal cities more fully. New research (Yao et al., 2022) suggests that the use of social media data to clean up carbon pollution in the marine environment is also a good idea.

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

This study was reviewed and approved by the School of Shipbuilding and Ocean Engineering, Jiangsu University of Science and Technology. All participants provided their written informed consent to participate in the study.

Author contributions

BW contributed to the writing of this paper, data collection, and data pre-processing.

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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.

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Achieving carbon neutrality: How does the construction of national high-tech zones affect the green innovation of enterprises? Based on quasi-natural experiments in pilot areas in China

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From the standpoint of green patents, verifying the influence of the construction of national high-tech zones on the degree of green innovation of enterprises is of enormous theoretical and practical importance. We construct a multi-period two-difference model to assess the influence of the national high-tech zone policy's implementation on enterprises' levels of green innovation. The outcomes of the study show that: first, the establishment of national high-tech zones greatly increases the level of green innovation among enterprises. While the effect on green and practical patents is average, the effect on green invention patents is more obvious. Second, how enterprises in national high-tech zones promote green innovation varies significantly. Promotional effects are more prominent in Tier 1 and Tier 2 regions, non-state firms, and high-tech industries with significant economic development. State-owned enterprises, non-high-tech industries, and third-tier and lower-tier regions, on the other hand, fared brilliantly. Third, additional action mechanisms show that the establishment of national high-tech zones can contribute to the institutional environmental effects of enterprises and the concentration of green innovation elements, thereby realizing regional green innovation development. Thus, our research provides an empirical foundation for stimulating the formation of national high-tech zones, increasing firms' ability to innovate on their own, and nurturing the long-term growth of national high-tech zones and associated businesses.

KEYWORDS

carbon neutrality, national high-tech zone, corporate green innovation, double difference model, government policies

1. Introduction

China's economy has grown continuously and steadily, resulting in the awareness of green development becoming an important concept that influences contemporary social and economic development (Su and Fan, 2022; Wang and He, 2022). The green industry has become a major development trend with the continuous integration of green concepts into the development of the industry (Midttun et al., 2022). The national high-tech zone, which serves as a pilot zone to encourage technological innovation and green development, is a vital technical support for green development. To promote green development, scientific and technological innovation must be coupled (Xie et al., 2018; Lu et al., 2020). They complement each other, are mutually advantageous, are coupled and facilitated, and promote high-quality economic development together (Li et al., 2021; Wu et al., 2022).

The goal of green innovation differs from other forms of innovation in that it emphasizes resource allocation and organizational innovation. Besides the spillover effects of innovation activities themselves (such as technology spillovers and knowledge externalities), green innovation is also characterized by environmental benefits that distinguish it from general innovation. Externalities caused by external environmental costs are also referred to as externalities (Chava, 2014; Qiao et al., 2019). Green innovation outcomes meet the criteria of environmental, economic, and social performance, which has a dual externality (Wang et al., 2022). They have an impact not only on how successfully enterprises perform but also on how severely the environment is impacted (Takalo and Tooranloo, 2021). Furthermore, this may potentially have a positive effect on society, which would benefit everyone.

China's carbon neutrality target provides more effective impetus and support for green innovation and development. The national high-tech zone's resources for scientific and technological innovation serve to improve the environment and provide a solid support for fostering green growth. Given the development of the new normal, the study of how to use national high-tech construction as an important carrier for innovation-driven, and then enhance the green operation level and green competitiveness of local enterprises, is of considerable theoretical and practical value (Ding H. et al., 2022). This article begins by looking at enterprise green patents to see if the construction of national high-tech zones may improve the degree and role of green innovation in businesses in the process of boosting the implementation of innovative development strategies. This analysis is significant in terms of reference and illumination for further understanding the future development direction and positioning of national high-tech zone building.

2. Literature review

Several research findings on the connection between the growth of national high-tech zones and enterprise green innovation can be found throughout the body of current literature, with the following elements gaining the most attention.

First, a study of the impact of national high-tech zone development on implementation. Academics both domestically and abroad have studied the establishment of the national high-tech zone as an important step for the enhancement of the national innovation development and the promotion of regional economic transformation. The first step is to investigate the significance and purpose of the location. As an example, Hu et al. (2021) analyzed the influence of land use change at different stages of the life cycle. According to some scholars, allotting resources efficiently and improving innovation ability can be significantly improved by establishing high-tech industrial zones (Xi and Mei, 2022). From the perspective of urban innovation, the establishment of national high-tech zones is a choice that conforms to the times and has an important impact on improving the development of urban innovation system (Luo and Shen, 2022). The second step is to assess the impact on its development. Some scholars classified and expanded on the concept, status, authority, and functions of China's administrative management system for high-tech zones, and they recognized the path of innovation (Zheng and Li, 2020). We should build a scientific evaluation index system to support the growth of national high-tech zones, to develop a world-class science park (Xie et al., 2018). Last but not least, academics have performed substantial research on the construction effect. One example is the employment of a method based on dynamic network relaxation assessment to assess the performance of China's national high-tech businesses (Bai et al., 2015). From the aspect of industrial structure, the construction of national high-tech zones will have a substantial influence on the modernization and transformation of regional industrial structure, and this impact will have a varied growth cycle. Relevant academics' discussions of the influence of high-tech zones on the degree of urban innovation, enterprise innovation performance, and regional green economic growth improved relevant analysis on the establishment of national high-tech zones (Shafique, 2013; Kong et al., 2021; Zhao et al., 2022).

Second, research on the measurement and influencing factors of enterprise green innovation. Green innovation can also be achieved by emphasizing technological innovation, which is most intuitively reflected in improved enterprise productivity, which can be measured by enterprise production efficiency. In addition, enterprises' innovation activities differ in terms of input and generation of innovation due to their diversity. Researchers construct theoretical models to analyze the interaction between environmental regulation and corporate green innovation. At the same time, the number of enterprise green patents and green invention patents is used to reflect the strength of enterprises' green innovation capabilities. Through research, it has been found that environmental regulations can effectively play a role in promoting it (Qiao et al., 2022; Xie and Teo, 2022). Some scholars have studied the relationship between environmental regulation, enterprise green technology innovation and green management innovation from the perspective of strategic flexibility and regional differences, and have confirmed that the impact of different variables is also different (Zhou, 2006). Some scholars, however, take a breakthrough or progressive approach to innovation, which not only emphasizes the importance of breaking through existing products, technologies, and services to develop enterprises but also pays attention to the transformation of products and technologies (Lian et al., 2022). According to relevant scholars, enterprise green innovation is affected primarily by factors such as the market, environmental policy, government, and environmental regulation (Du et al., 2022; Su et al., 2022). A targeted analysis of enterprise green innovation development and solutions was conducted by Weng et al. (2022).

According to the research literature currently available, relevant research on the construction of national high-tech zones and enterprise green innovation is relatively fruitful, and some scholars look into how the creation of national high-tech zones affects the effectiveness of urban green innovation at the local level (Park and Lee, 2004). Few authors have looked at the effects of national high-tech zone policies on green transformation and enterprise innovation development from the perspective of green development, though some scholars have studied the effects of national high-tech zone establishment on enterprise innovation performance. The twofold difference approach is utilized to assess its impact on enterprise green innovation levels, and its mechanism of action to improve enterprise green innovation is examined. Consequently, utilizing panel data from China's A-share listed businesses and prefecture-level cities from 2005 to 2019, this research focuses on the green growth effect caused by the establishment of national high-tech zones.

Some of the potential contributions of this paper include: (1) Taking the pilot construction of the national high-tech zone as a quasi-natural experiment, starting from the perspective of green development and change, the impact of the national high-tech zone on the green innovation of enterprises is mainly considered, so as to enrich the relevant research work of micro-enterprises. (2) Enterprise green patent data is used to reflect the amount of green innovation in enterprises. For analysis, green patents are subdivided into enterprise utility model patents and green invention patents to illustrate the differences between different innovation outputs and inputs. (3) Make an effort to consider the innovation-driven influence of high-tech zone creation on business growth, and investigate how it influences enterprise green innovation from the standpoints of factor agglomeration, innovation-driven capability, and the impact of transaction costs imposed by the institutional environment. (4) In addition to an examination of the influence of various influencing factors on the growth of enterprise green innovation development, several effects of the establishment of national high-tech zones are examined.

3. Theoretical mechanisms and research assumptions

The creation of pilot national high-tech zones is crucial for fostering the adoption of creative development strategies and attaining high-quality regional development. It is a crucial component of the central development location-oriented policy. Enterprise innovation activities are inextricably linked to the promotion of regional high-tech development. Therefore, the creation of the national high-tech zone has improved the ability of businesses to innovate independently by creating a good innovation environment for them. It is also useful for expanding green production technology and carrying out innovative activities with the twin goals of economic and environmental benefits, to achieve low-carbon development in the area, as a result of utilizing creative technologies and methods (Petrescu et al., 2016; Wang and Zhi, 2016). The formation of high-tech zones, according to theory, can enable the flow of innovation factor resources between regions, have effects on enterprise development that are driven by innovation, and be managed at the institutional level, as indicated in the following parts (Wang et al., 2022).

3.1. Factor agglomeration and enterprise green innovation

The establishment of national high-tech zones may increase green innovation in enterprises by improving the agglomeration effect. The establishment of high-tech zones can provide regulatory benefits to high-tech enterprises, attract the necessary talent, capital, and other resources to construct a certain scale of agglomeration, and ultimately boost the rate of regional technological growth (Ding J. et al., 2022a,b). While high-tech zones are being developed, encouraging the growth of local green innovation by focusing on increasing human capital and information sharing is a more straightforward approach. The construction of the national high-tech zones can create an advantageous condition for the growth of both high-tech and non-high-tech industries, ensure the normal flow of resources between various business types, and boost the area's human capital stock while achieving the rational allocation of resources in various industries, thereby resolving the issue of the region's lack of stamina for enterprise development (Jiang et al., 2023). On the other hand, it helps to increase the efficiency with which enterprises use their resources, as well as to realize gains in talent development and labor quality by raising business levels of high technology and high knowledge. Finally, these zones contribute to the aggregation of elements and the exhibition of diverse industrial parks, which increases the level of technical advancement of firms (Liu et al., 2022).

As factor endowment rises, the influence of environmental regulation on company innovation efficiency will diminish. At the moment, China's misallocation of scientific and technology resources is most visible in three areas: first, a severe lack of investment in basic research, a low proportion of investment in enterprises, and insufficient investment in traditional sectors (Kuang et al., 2022). Second, despite China's overall abundant liquidity, the misallocation of financial resources makes it difficult and costly for small businesses to obtain capital (Morazzoni and

Sy, 2022). The financial sector does not efficiently support the capital required for the transformation and upgrading of old businesses, as well as the creation and expansion of emergent industries, making real-economy development challenging. Finally, the misallocation of human resources manifests itself in the phenomena of overinvestment in the financial and virtual economy industries. Pilot construction policy construction of high-tech zones effectively addresses the issue of low efficiency caused by factor mismatch, consequently improving company green innovation efficiency (Zhang et al., 2023).H1:The factor agglomeration effect generated by the construction of the national high-tech zone promotes the green innovation of enterprises.

3.2. Institutional environment and enterprise green innovation

The establishment of national high-tech zones may raise the amount of green innovation in enterprises by establishing institutional environmental implications. The foundation for the construction of the national high-tech zone, an industrial agglomeration park, was laid by the government's industrial policy, which is increasingly impacted by policy assistance (Liu et al., 2022). To function, develop, and compete in the market, related businesses must have accurate market information, and the resulting transaction costs will increase unproductive spending. The high-tech zone policy can stimulate the improvement and growth of the regional institutional environment, as well as an improvement in innovation efficiency and collaborative invention development, resulting in lower business transaction costs and production costs (Zhou et al., 2021). The creation of high-tech zones has boosted the competitiveness of high-tech enterprises and encouraged commercial potential for green innovation. However, to promote the influence of the institutional environment and achieve green innovation and development across the entire region, non-high-tech industries must continue to fully exploit the policy dividends provided by the high-tech zone policy (Lu et al., 2022).

Only endogenous independent innovation, according to the notion of innovation-driven economic growth, is the major driver of technological advancement and economic prosperity. Exogenous technology introduction and imitation cannot become a long-term stable driver driving economic growth (Qiao et al., 2022). To address China's severe resource and environmental issues, high-tech zones were established as an institutional guarantee of the country's autonomous innovation and to assist in the greening of the economy more quickly and cheaply. The creation of the national high-tech zone has significantly increased China's green technology and industry's international competitiveness with the aid of a steadily improving green innovation guarantee system and supporting policy system. Green innovation is the integration of the two development concepts of green and innovation. Furthermore, by developing high-tech zones, a strong government can effectively mitigate the consequences of market demand and return rate uncertainty, while also increasing company enthusiasm for green innovation (Xie et al., 2022). This is primarily because establishing high-tech zones reduces the cost of enterprise end-to-end governance and production legality, as well as the environmental impact of manufacturing. Furthermore, fewer resources are used at the source, immediately reducing the number of pollutants discharged.H2:Optimizing the high-tech zone's institutional environment promotes enterprises' green innovation.

3.3. Economic development and enterprise green innovation

Green innovation has a public attribute due to its stronger emphasis on the characteristic of resource allocation than other firm innovation activities (Hu et al., 2021). This is accomplished by emulating a strategic sense of corporate social responsibility and principles. Economic development will unavoidably have an influence on company green innovation because it is the primary component of economic activity. While manufacturing generates huge wealth, the traditional economic development model also presents several difficulties such as resource depletion, environmental degradation, and the greenhouse effect (Li et al., 2022). Carbon emissions are principally caused by the use of energy and materials at each stage. As a result, under the normal economic development model, enterprises' efforts to innovate in a greener manner will be hampered (Wang et al., 2022).

In some ways, China's economic development success comes at the expense of the environment, resource scarcity, and environmental pollution, exacerbating concerns with fragile environments, lengthy economic growth models, and environmental oversight during the Chinese economic development process. As a result, the disparity between resource and environmental constraints and economic expansion has grown more pronounced (Zhang et al., 2020). Green manufacturing through corporate green innovation is a significant goal and development paradigm for achieving sustainable and high-quality development. Green manufacturing practices are used to ensure a product's functioning, quality, and cost, as well as its overall environmental effect and resource efficiency. Finally, ensure that the product's entire life cycle produces no pollution or produces as little as possible (Lin and Ma, 2022). The National High-tech Zone has achieved high-quality innovation-driven economic development, promoting the establishment of innovative firms, through a variety of governmental supports and a comprehensive infrastructure. In addition to stimulating and promoting environmental protection production technology in enterprises, the establishment of high-tech zones can provide new opportunities for green transformation and business development, as well as achieve coordinated development of economic and environmental benefits in the process of ongoing innovation and development.H3:The positive correlation between the construction of national high-tech zones and the level of green innovation of enterprises gradually increases with economic development.

The specific research logic of this paper is shown in Figure 1.

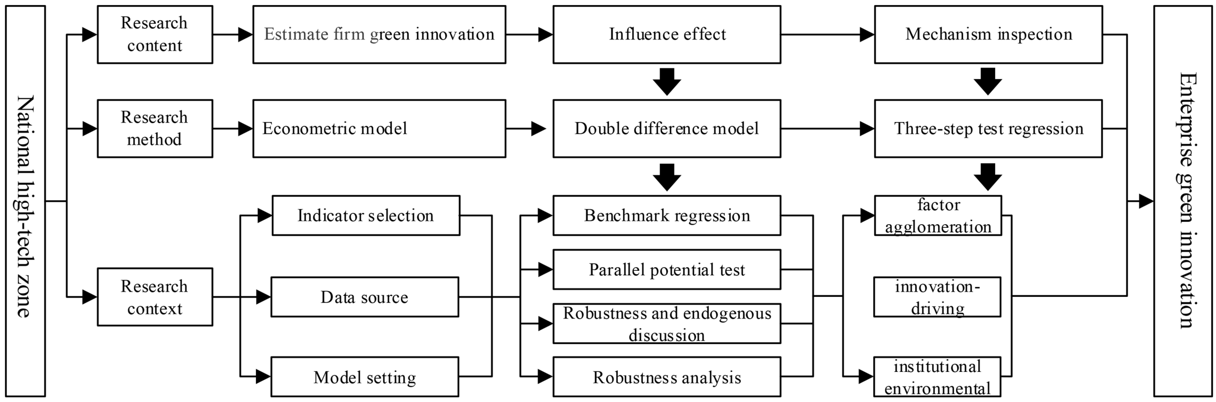

FIGURE 1
The research logic of this article.

4. Research design

4.1. Two-difference model

To assess the influence of policy implementation on company green innovation, this study employs a double difference model based on establishing national high-tech zones. The experimental and control groups were formed using the criterion "if the policy is implemented, "and the policy's implementation was treated as a dummy variable. Because the national high-tech zone pilot is built in batches, using a single time point twofold difference model may result in incorrect experimental results. Using predecessors' research approaches, a multi-period twofold difference model is developed for in-depth examination (Beck et al., 2010). Here is the precise model:

$$\ln \text{patent}_{it} = \alpha_0 + \alpha_1 du \times dt + \alpha_2 \text{Control}_{it} + \mu_{it} + \lambda_{it} + \varepsilon_{it} \quad (1)$$

where i and t reflect the corresponding enterprise and year, patent_{it} reflects the company green innovation, and $du \times dt$ is a dummy variable for policy implementatio. Control_{it} reflects control variables that affect the variable being explained, $\propto$ and λ represent individual and year fixed effects and ε represents random error terms.

Furthermore, there is no direct comparison between established and unestablished areas of the national high-tech zone. To avoid the estimation error caused by the use of the double difference model and to enhance the comparability of the two, the establishment of a national high-tech zone in the location of the enterprise and the location of the enterprise without the establishment of a national high-tech zone are thus matched using the double differential tendency score matching method. This work refers to previous research methodologies to set the PSM-DID regression model (Holtz, 2012; Zhang et al., 2022).

$$\ln \text{patent}_{it}^{PSM} = \beta_0 + \beta_1 du \times dt + \beta_2 \text{Control}_{it} + \mu_{it} + \lambda_{it} + \varepsilon_{it} \quad (2)$$

4.2. Description of the relevant variable

Explanatory variable: Corporate Green Innovation (*pat*). This study refers to the International Patent Commission's (IPC) classification of environmentally friendly patented technology and draws on forerunners' research tactics to reflect the firms' level of green innovation. Improving enterprise green innovation can lower the amount of input created by polluting intermediates (Zhou and Qi, 2022). It is further subdivided for study into green utility model patents (*pat-ut*) and green invention patents (*pat-in*).

Core explanatory variables: policy dummy variables ($du \times dt$). The policy dummy variable in this study is the location of pilot areas, the experimental group is businesses in the high-tech zone, and the corresponding dummy variable is 1; businesses in non-high-tech zones are employed as control groups, and their corresponding dummy variables are 0. This conforms to the standards of national policy papers. To reflect the entire impact of policy implementation, the policy dummy variable interaction items are generated concurrently following the national high-tech zone's establishment time.

Control variables: This article chooses variables that have a strong link with enterprise green innovation to minimize the influence of missing variables on model regression findings. (1) The company's size as assessed by total assets in the most recent fiscal year. (2) Return on net assets (*roe*), calculated by dividing the current fiscal year's total net assets by the after-tax earnings. (3) The asset-liability ratio is calculated by dividing the company's total liabilities by its total assets for the current fiscal year (*lev*). (4) The company's age, as evidenced by its formation date. (5) The enterprise's intensity of R&D investment (*rd*) is defined by the proportion of R&D spending in total operating income in the current year.

4.3. Data source

Given the difficulty in getting micro-enterprise data, this research draws its sample from Chinese A-share listed enterprises from 2005 to 2019. The relevant data for listed firms is primarily sourced from the Guotai An (CSMAR) database, while the patent data is derived from the State Intellectual Property Office's patent databases and the China Urban Statistical Yearbook, among other sources, and is manually collected. Simultaneously, the listed enterprise registration location information is matched with the regional information involved in the establishment of the national high-tech zone to get correct sample matching data. During the sample data processing, the relevant data of ST, *ST listed firms, and financial institutions were eliminated, and some of the sample data with missing financial information and research variables were excluded, yielding a total of 32,505 sample observations. Furthermore, for the sake of research, the sample data in 2005 were treated at constant valence, and all data were logarithmized to lessen the volatility of the regression results.

5. Analysis of empirical results

5.1. Benchmark regression analysis

The double difference approach is used in this study to empirically examine the net effect of the implementation of the pilot policy before employing the strategy of gradually adding control variables to perform regression. Table 1 displays the regression results under the theoretical analysis and empirical model development discussed previously.

The two-difference model's fundamental regression findings are shown in Table 1, The regression coefficient of the policy dummy variable is initially importantly positive regardless of whether the control variable is included in the regression model, and it rises with the addition of the control variable, showing that the creation of the national high-tech zone plays a role in fostering regional green growth and thereby enhancing enterprise levels of green innovation. Green patents are further divided into green invention patents and green utility model patents to explicitly investigate the impact of the establishment of national high-tech zones on firms' capacity for green innovation. While the implementation of the national high-tech zone policy is significantly beneficial for green utility model patents at the 10% level, it is not significantly beneficial for green invention patents at the 5% level, demonstrating that the influence of national high-tech zone creation on internal enterprise green innovation is not uniform. This could be because the current system emphasizes the volume and intensity of innovation input while allowing little room for the transfer of innovation input from theory to practice. Furthermore, this indicates how invention-based patent innovation can be used to stimulate corporate innovation and growth more efficiently.

The firm's scale and return on net assets are two crucial control variables that have a substantial influence on how innovatively green an enterprise is. This means that as a company's development scale grows, so do its productive benefits and labor force profitability, ensuring that the company has the resources it needs to engage in innovative activities. Corporate R&D investment is also an important factor in supporting corporate green innovation, green utility model patents, and green invention patents. This emphasizes the need of investing in innovation. The asset-liability ratio and enterprise age both harm corporate green innovation.

5.2. PSM-DID-based inspection

Given that there may be variances in the sample data due to changes in regional conditions during the execution of the national high-tech zone program. It is critical to compare the experimental and control groups' sample data, compute the required propensity score value using the Logit regression model,

TABLE 1 Regression results of the baseline model.

Variable	*pat*		*pat-in*		*pat-ut*	
	(1)	(2)	(3)	(4)	(5)	(6)
du×dt	0.143*** (2.68)	0.112*** (3.31)	0.191** (1.99)	0.225** (2.05)	0.526* (1.75)	0.048* (1.83)
lnsize		0.258** (2.35)		0.148*** (2.88)		0.089** (2.18)
lnroe		1.248** (2.40)		0.948* (1.80)		1.496** (2.30)
lnlev		−0.585*** (−3.36)		−0.080*** (−2.63)		−0.108** (−2.18)
lnage		−0.325* (−1.82)		−0.093** (−2.37)		−0.175** (−2.07)
lnrd		0.105** (1.98)		0.148* (1.78)		0.082** (2.42)
Time	YES	YES	YES	YES	YES	YES
Individuals	YES	YES	YES	YES	YES	YES
N	32,505	32,505	32,505	32,505	32,505	32,505
R^2	0.692	0.718	0.725	0.705	0.882	0.792

***, **, and * indicate passing the significance test of 1, 5, and 10%, respectively, and the *t*-value in parentheses is the *t*-value.

and run the related balance test with the covariate. From Table 2, the overall findings of the sample data after matching suit the balancing assumption, and the lack of substantial disparities between the matched variables further supports the accuracy of the matching results. As can be shown after matching the sample data, the execution of the national high-tech zone policy has a considerable influence on raising the degree of green innovation among firms. The significant coefficient is likewise noticeably higher, and the promotion effect on green invention patents is stronger than the promotion effect on green utility model patents. This supports the veracity of the previous findings.

5.3. Robustness test and endogeneity discussion

Various strategies are used to measure robustness to corroborate the veracity of previous empirical results. The percentage of enterprise green patents in total patent numbers is used as a substitution variable to quantify enterprise green innovation, which allows the influence of major explanatory variables on the numerator and denominator to be separated. This substitution variable method is first used, based on predecessors' research concepts (Popp, 2006). The regression test results are shown in column (1) of Table 3, and it reflects that even after adjusting for substitution variables, the implementation of the national high-tech zone policy still has a high promotion influence on the level of green innovation of enterprises, confirming the rationality of variable selection. As a result, the explanatory variables will be treated with a lag period and regressed again. The test results are shown in column (2) of Table 3, and the regression results demonstrate that the coefficient between the lagging period of the national high-tech zone policy's dummy variables and the green innovation level of enterprises is positive. Finally, regression is performed using the Tobit model, and analysis is performed using the approach of substituting the econometric model. The regression data is shown in column (3) of Table 3, demonstrating that the research results are still credible. The study's findings were determined to be trustworthy.

The issue of missing data and the reverse causal link between variables are the two main points of controversy regarding the model's endogeneity. As a result, the model's endogeneity is further assessed using the two-stage least squares method (2SLS). Lagging panel data can be used to process tool variable choices. The lag periods of the national high-tech zone policy's dummy variables and two lag period data are chosen as the paper's tool variables. The regression results of the model are shown in column (4) of Table 3, and both the LM and F statistics show significant findings. Furthermore, the results of Hasen's test illustrate the utility of the instrumental variables, overcoming the model's endogeneity problem.

TABLE 2 Regression test results of PSM-DID.

Variable	*pat*	*pat-in*	*pat-ut*
$du \times dt$	0.412*** (3.48)	0.247** (2.23)	0.178* (1.94)
Control variables	YES	YES	YES
Fixed time	YES	YES	YES
Fixed individuals	YES	YES	YES
N	32,086	32,086	32,086
R^2	0.869	0.789	0.825

***, **, and * indicate passing the significance test of 1, 5, and 10%, respectively, and the *t*-value in parentheses is the *t*-value.

TABLE 3 Robustness test and endogenous regression results.

Variable	Enterprise green innovation			
	(1)	(2)	(3)	(4)
$du \times dt$	0.312*** (2.59)	0.258*** (2.92)	0.418** (2.05)	0.104** (2.17)
LM statistics				6.705* (1.88)
F statistic				40.361*** (15.01)
Hasen				20.125*** (10.23)
Control variables	YES	YES	YES	YES
Fixed time	YES	YES	YES	YES
Fixed individuals	YES	YES	YES	YES
N	32,505	32,505	32,505	32,505
R^2	0.728	0.826	0.792	0.814

***, **, and * indicate passing the significance test of 1, 5, and 10%, respectively, and the *t*-value in parentheses is the *t*-value.

TABLE 4 Test results of heterogeneity of economic development strength.

Variable	First- and second-tier cities			Third-tier and below cities		
	pat	*pat-in*	*pat-ut*	*pat*	*pat-in*	*pat-ut*
	(1)	(2)	(3)	(4)	(5)	(6)
$du \times dt$	1.125*** (3.67)	0.751*** (2.85)	1.245** (1.99)	0.471* (1.9)	1.027* (1.75)	1.042 (1.53)
Control variables	YES	YES	YES	YES	YES	YES
Fixed time	YES	YES	YES	YES	YES	YES
Fixed individuals	YES	YES	YES	YES	YES	YES
N	21,525	21,525	21,525	10,980	10,980	10,980
R^2	0.826	0.847	0.853	0.782	0.794	0.804

***, **, and * indicate passing the significance test of 1, 5, and 10%, respectively, and the *t*-value in parentheses is the *t*-value.

5.4. Further heterogeneity analyzes

Due to disparities in economic development strength, geographic location, and enterprise type across regions, it is vital to focus on high-tech zone implementation in the subsequent research of the influence of national high-tech zone establishment on green innovation of firms. This is because high-tech zone laws vary based on the type of firm. As a result, this heterogeneous effect is further discussed below.

5.4.1. Heterogeneity of economic development strength

Because of the variance in economic growth strength between areas, this study divides the sample data into first- and second-tier cities, third-tier cities, and below, and divides the associated enterprise samples accordingly. Individual regression results are shown in Table 4.

Table 4 columns (1)–(3) shows the regression findings for first- and second-tier cities, and columns (4)–(6) provide the regression results for third-tier and below cities. It has been discovered that the establishment of pilot areas plays a vital role in boosting the improvement of companies' green innovation levels in first- and second-tier cities, as well as third-tier cities and below. While the national high-tech zone policy's implementation plays a stronger role in enhancing both first- and second-tier cities when it comes to green invention patents and green utility model patents, the impact on businesses in developed cities is greater. The positive significance level for third-tier cities and below is not high, and among them, the regression coefficient of green utility model patents is not obvious. The creation of pilot areas will encourage companies to enhance their level of technological innovation and continuously innovate the production process department to improve industrial competitiveness in those developed regions due to geographic location, infrastructure construction, technological capital, and other resource advantages. However, the undeveloped regions' economic development strength is weak, and there is a lack of financial assistance and factor resource flow. In the short term, the formation of pilot areas has minimal influence on the degree of green innovation of connected firms, and it is important to raise awareness of independent innovation and increase the region's innovation capability.

5.4.2. Heterogeneity of enterprise ownership

The extent to which an enterprise's level of green innovation improves will be determined by the type of enterprise as well as the strength of the area's economic development. Direct government management or intervention is the hallmark of state-owned enterprises, and the location of the business must take into account the government's strategic objectives and development plans. Non-state-owned enterprises are more cognizant of market developments. To that end, this study evaluates the levels of green innovation and examines the consequences of creating pilot areas on enterprises with diverse ownership structures. Although it is not immediately evident from the regression findings in Table 5, there is an important positive promotion effect on non-state-owned firms from the execution of the national high-tech zone plan on state-owned enterprises' development of green innovation. On the one hand, whether or not national high-tech zones are developed, state-owned businesses have a relatively solid infrastructure basis and it is very easy for them to obtain money and favorable regulations. Therefore, it is uncertain how the construction of the pilot areas would affect the linked enterprises' ability to innovate more sustainably. On the other hand, non-state-owned businesses urgently need to draw in foreign investment through the creation of national high-tech zones and create a favorable business climate, so that the impact of pilot areas on green innovation is more apparent.

5.4.3. Industry heterogeneity

The varied effects of the construction of pilot areas on enterprise green innovation were investigated from the perspectives of economic development strength and firm ownership heterogeneity. The establishment of high-tech zones will be focused on the growth of high-tech industries, and the direction and pace of development of different industry types will affect the enhancement of local green innovation. As a result, this paper leans on the preceding classification of high-tech businesses to divide the sample data into high-tech and non-high-tech industries, and the specific regression results are provided in Table 6. It reflects that the execution of the pilot areas policy plays a larger role in promoting the level of green innovation in high-tech sectors. This also demonstrates the efficacy of policy execution. It demonstrates that the creation of the pilot areas has obvious industrial variations in the improvement of firms' green innovation level.

5.5. Mechanism of action analysis

According to the empirical data, the pilot building of the pilot areas has a significant influence on encouraging enterprises to increase their level of green innovation. But how exactly does this promotion work? The approach of establishing national high-tech zones to encourage enterprise green innovation needs to be investigated further to provide solutions to the concerns stated above. The implementation of the high-tech zone policy drives the factor agglomeration effect, innovation-driven effect, and institutional environment effect in the process of promoting the level of green innovation in enterprises, to better improve the level of regional low-carbon development. Hence, two more models are added to the model (1), and then the mediation effect model is built for in-depth investigation, and the specific model development technique is as follows:

$$\text{Mediation}_{it} = \theta_0 + \theta_1 du \times dt + \theta_2 \text{Control}_{it} + \mu_{it} + \lambda_{it} + \mu_{it} \quad (3)$$

$$\ln \text{patent}_{it} = \varphi_0 + \varphi_1 du \times dt + \varphi_2 \text{Mediation}_{it} + \varphi_3 \text{Control}_{it} + \mu_{it} + \lambda_{it} + \varepsilon_{it} \quad (4)$$

In the formula, mediation is a collection of mediating variables. The OP approach is used to estimate the factor agglomeration effect (*fac*) by determining the total factor productivity of firms (Ren et al., 2022). The Innovation Index of publicly traded companies is used as a proxy variable for measuring the innovation-driving effect (*inv*; Hao et al., 2022). The institutional transaction cost in firm transaction costs is used as a proxy variable in this study to quantify the institutional environmental effect (*env*; Fan et al., 2019). In addition, when performing the mediation effect test, it is necessary to ensure that the regression coefficients α_1 , θ_1 , and φ_1 in the policy dummy variables in the model (1), (3), and (4) all meet the significance level. Simultaneously, when the coefficient φ_1 in equation (4) is not significant, it is indicated that the intermediary variable plays a complete mediating role of the explanatory variable affecting the explanatory variable. When the coefficient φ_1 is less than α_1 , it indicates that the intermediary variable plays a partial mediating role in promoting it, and the specific influence mechanism is shown in Table 7 through the corresponding model regression test.

TABLE 5 Results of the heterogeneity test of enterprise ownership.

Variable	State-owned enterprises			Non-state-owned enterprises		
	pat	*pat-in*	*pat-ut*	*pat*	*pat-in*	*pat-ut*
	(1)	(2)	(3)	(4)	(5)	(6)
$du \times dt$	1.205* (1.67)	1.014 (1.45)	0.275 (1.39)	0.782*** (2.66)	1.147** (2.30)	0.082* (1.75)
Control variables	YES	YES	YES	YES	YES	YES
Fixed time	YES	YES	YES	YES	YES	YES
Fixed individuals	YES	YES	YES	YES	YES	YES
N	11,985	11,985	11,985	20,520	20,520	20,520
R^2	0.71	0.642	0.628	0.802	0.814	0.852

***, **, and * indicate passing the significance test of 1, 5, and 10%, respectively, and the *t*-value in parentheses is the *t*-value.

TABLE 6 Heterogeneity test results of different industries.

Variable	High-tech industries			Non-high-tech industries		
	pat	*pat-in*	*pat-ut*	*pat*	*pat-in*	*pat-ut*
	(1)	(2)	(3)	(4)	(5)	(6)
$du \times dt$	1.105*** (3.02)	1.045*** (2.9)	1.042** (2.06)	0.893** (2.35)	0.127* (1.88)	0.422* (1.89)
Control variables	YES	YES	YES	YES	YES	YES
Fixed time	YES	YES	YES	YES	YES	YES
Fixed individuals	YES	YES	YES	YES	YES	YES
N	9,060	9,060	9,060	23,445	23,445	23,445
R^2	0.817	0.804	0.882	0.824	0.739	0.756

***, **, and * indicate passing the significance test of 1, 5, and 10%, respectively, and the *t*-value in parentheses is the *t*-value.

TABLE 7 Test results of the influence mechanism of mediation effect.

Variable	*fac*	*lnpatent*	*inv*	*lnpatent*	*env*	*lnpatent*
$du \times dt$	0.109** (2.18)	1.247*** (2.81)	0.042*** (2.62)	0.858*** (3.18)	0.188* (1.89)	0.362*** (2.81)
fac		0.241*** (3.60)				
inv				0.217*** (3.28)		
env						0.205** (2.37)
Control variables	YES	YES	YES	YES	YES	YES
Fixed time	YES	YES	YES	YES	YES	YES
Fixed individuals	YES	YES	YES	YES	YES	YES
N	32,505	32,505	32,505	32,505	32,505	32,505
R^2	0.807	0.854	0.79	0.745	0.71	0.893

***, **, and * indicate passing the significance test of 1, 5, and 10%, respectively, and the *t*-value in parentheses is the *t*-value.

Table 7 shows that the formation of the pilot areas has a significant intermediate role in driving the augmentation of businesses' green innovation levels because of the factor agglomeration impact, innovation-driven effect, and institutional environment effect. The adoption of a national high-tech zone strategy can first foster collaboration and the sharing of factor resources, which can enhance firms' production technology level. The contribution of the pilot areas to innovation is mostly due to the information exchange and knowledge transfer that it encourages among various innovation subjects, which results in the progress of manufacturing technology. The construction of the national high-tech zone will allow high-tech industries and surrounding linked firms to benefit from preferential policies, institutional guarantees, and so on, which will be more conducive to increasing enterprises' innovative potential. As a result of the enterprise's operation, the institutional environment effect will generate a variety of transaction costs. The three major effects of factor agglomeration, innovation drive, and institutional environment generated during the construction of the pilot areas are simultaneously found to importantly enhance the enterprises' green innovation level, and the significance coefficient gradually increases, confirming the validity of the previous research hypothesis. This is because all three effects were included in the regression model.

6. Conclusion and revelations

6.1. Research conclusion

This paper develops a multi-period double difference model based on micro-enterprise panel data from A-share listed companies in China, from 2005 to 2019 to validate the influence and mechanism of the national high-tech zone policy implementation on green innovation of enterprises. The implementation of the high-tech zone policy, in particular, has a more obvious promotion influence on companies' green invention patents, although the promotion effect of enterprises utilizing utility model patents is broad. (1) The establishment of the pilot areas plays a significant role in increasing the level of green innovation among firms. (2) The heterogeneity study results show that the formation of national high-tech zones has a greater influence on green innovation in first- and second-tier cities, whereas the significance level of the regression coefficient in third- and lower-tier cities is low. This is because of the disparity in economic development strength. The adoption of the national high-tech zone strategy favors non-state-owned enterprises more in terms of increasing their level of green innovation while having little impact on state-owned businesses. The establishment of national high-tech zones has a bigger impact on green innovation than on non-high-tech industries. (3) The mechanism of action analysis demonstrates that pilot areas implementation essentially increases the degree of green innovation of businesses by fully utilizing the effects of factor agglomeration, innovation-driven effect, and institutional environment.

6.2. Policy recommendations

Based on the preceding conclusions, the following policy recommendations are offered in this study:

To encourage the potential for green innovation among businesses, actively encourage the creation of national high-tech zones, develop innovative methods and mechanisms, and better utilize the leading role of high-tech zones in innovation. In this paper, we further demonstrate from the perspective of green development through empirical research that the implementation of high-tech zone policies will have a positive influence on the level of green innovation of enterprises. On the one hand, a large number of research results show that the construction of national high-tech zones has a significant role in promoting the innovation and development of enterprises. Therefore, it is essential to encourage the creation of pilot areas logically. To ensure long-term innovation and development in the area, it is necessary to establish and enhance the intellectual property protection and R&D management system in the national high-tech zone, raise enterprise awareness and level of R&D investment, and attach importance to the quality of innovation for patent applications. Improve high-tech zone enterprises' ability to innovate autonomously, use innovation as a long-term company growth engine, and design the national high-tech zone's construction to best serve the interests of green business innovation. To improve the flow of factor resources, the government has raised the level of green technology in high-tech firms by passing environmental regulatory measures such as harsher penalties and higher technical standards. On the other hand, it has spurred corporations to invest more in green development. Reduce the negative impact of technical barriers on corporate green innovation by communicating and sharing information. On the other hand, to reduce corporate transaction costs, it is critical to establish an environment that stimulates innovation and to implement preferential policies such as policy subsidies and tax exemptions. To support the long-term development of pilot areas, it is also necessary to fully capitalize on the motivating power of high-tech enterprises on park development and to raise enterprise understanding of and accountability for attaining the aim of carbon-neutral development.

Plan the establishment of pilot areas logically, taking into account all important factors such as the nature of firms and other regional variances. To construct high-tech zones that accomplish overall high-quality development while leaving a tiny footprint, it is critical to carefully analyze the economic development potential of various locations, the nature of enterprises, and whether or not they fall under the scope of high-tech industries. In addition, we should create a green innovation structure for firms that is adaptable to local situations.

6.3. Limitation and future research

This article, which starts with the notion of creating pilot areas for the development of green businesses, offers recommendations and references for the implementation of high-tech zone policies to support the level of green innovation of businesses through empirical testing and analysis. After careful research and analysis, it was determined that there are still some areas that could be expanded upon and further investigated. These include: (1) Because the pilot areas are being developed from a global standpoint, businesses in the surrounding areas may be affected by interaction. Future research can now focus on the effects of the pilot areas policy's implementation on spatial spillover effects. (2) Several factors could have an influence on the expansion of enterprise green innovation. Consequently, future research might focus on developing a more thorough system of assessment elements to analyze how enterprises can develop their green innovation. (3) Regarding the influencing factors of green innovation, the influencing role of the implementation of other industrial policies can also be considered.

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

XJ, ZL, JX, and PZ performed the material preparation, data collection, and analysis. BL wrote the first draft of the manuscript. All authors contributed to the study conception and design, commented on previous versions of the manuscript, and read and approved the final manuscript.

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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.

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Network attention and carbon dioxide emission performance of agricultural enterprises: Empirical evidence from China's baidu search index

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Based on the network attention data of China's agricultural listed companies from 2012 to 2020, this paper uses the IV model to measure and investigate the impact of network attention on the carbon dioxide emission performance of China's agricultural listed companies and its mechanism. The findings are as follows: 1) The carbon dioxide emission intensity of listed agricultural companies in China is generally decreasing year by year and the carbon dioxide emission performance is improving; 2) The increasing network attention has significantly reduced the carbon dioxide emission intensity of agricultural listed companies and brought about better carbon dioxide emission performance; 3) The relationship between network attention and carbon dioxide emission performance of agricultural listed companies has network, regional and property heterogeneity; 4) The investment in environmental protection has strengthened the inhibition effect of network attention on the unit carbon dioxide emissions of agricultural listed companies. The research conclusion enriches the literature on "network concern - environmental governance", and also provides ideas for developing countries to exert the environmental governance effect of network concern in the process of carbon neutrality.

KEYWORDS

carbon neutralization, network attention, carbon dioxide emission intensity, environmental protection investment, IV model

1 Introduction

China is a large agricultural country and the largest carbon dioxide (CO2) emitter in the world. In the process of agricultural modernization, the agricultural sector is an important source of carbon dioxide emissions in China. According to the statistics of the Food and Agriculture Organization of the United Nations (FAO), China's agricultural sector's generalized carbon dioxide emissions reached 663 million tons in 2019, accounting for 11.1% of the global agricultural sector's total emissions. The Chinese government attaches great importance to how to reduce the intensity of carbon dioxide emissions from agricultural enterprises and achieve the goal of carbon neutrality. In recent years, the Chinese central government has continuously strengthened the construction of ecological civilization, actively promoted carbon neutrality in various fields, including the agricultural sector, and released a strong signal of concern about environmental protection, resource recycling, carbon reduction, and carbon reduction (Hansen et al., 2018). In 2015, China adopted the new Environment Protection Law. In 2021, the work report of the central government made clear for the first time the overall goal of carbon emission reduction of carbon peak in 2030 and carbon neutrality in 2060. The above has greatly enhanced the binding force of formal environmental regulations on environmental pollution behavior, and the cost of agricultural enterprises for pollution control and operation has also increased (Yu and Morotomi, 2022). Moreover, in addition to the formal environmental regulations implemented by the government, the public's attention to the network should not be underestimated. Under the background that environmental protection is increasingly valued by society, Chinese people have been paying close attention to the environmental pollution problem of agricultural enterprises, and have made a voice in the network to form a strong network attention, to provide support for the green development of agricultural enterprises. However, as an informal environmental regulation that complements formal environmental regulation, whether and how network attention affects the carbon dioxide emission performance of agricultural enterprises has not received enough attention from the academic community (Chen and Wu, 2021). In particular, there remain some academic differences in the relationship between network attention and the performance of companies' carbon dioxide emissions. The "irrelevance theory" (Hart and Ahuja, 1996; Ziegler et al., 2008), "promotion theory" (Kathuria, 2007; Zheng et al., 2018; Han, 2022), and other views have been put forward. The lack of direct empirical evidence makes it necessary to systematically investigate and analyze the impact and mechanism of network attention on the carbon dioxide emission performance of agricultural listed companies under the Chinese scenario. Given this, this paper takes China's agricultural listed companies from 2012 to 2020 as a sample to systematically investigate the possible impact of network attention on carbon dioxide emission performance and its impact mechanism.

Compared with the previous literature, the marginal contributions that this study may bring are as follows: First, because of the controversy of "network attention and carbon dioxide emission performance", we use the data generated by the largest search engine in China to systematically investigate the impact of network attention on carbon dioxide emission performance; Second, focus on the agricultural sector, which has been less involved in previous studies, analyze and examine the impact mechanism of network attention on the carbon dioxide emission performance of agricultural listed companies, and thicken the mechanism literature of "network attention - environmental governance" in developing countries; Third, the conclusions of this paper also provide ideas and suggestions for promoting the green development of agriculture in developing countries and strengthening the carbon neutral governance under the network media.

2 Literature review

Carbon dioxide emission performance is a beneficial result of the ecological restoration and protection of environmental pollution by the emission subject (Hou et al., 2021), which shows the positive action on the prevention and control of greenhouse gases such as carbon dioxide (Nkhata and Breen, 2010). It is worth noting that existing studies have shown that network attention as a non-environmental regulation can bring direct and indirect effects on the performance of carbon dioxide emissions (Sissenwine, 2007). Focusing on the issue of network attention and carbon dioxide emission performance, existing studies have focused on the impact of formal environmental regulations on carbon dioxide emission performance, and the impact and mechanism of network attention on carbon dioxide emission performance.

The first piece of literature is about the relationship between formal environmental regulation and carbon dioxide emission performance. Most of the existing studies believe that formal environmental regulations such as environmental protection laws can help promote carbon dioxide emission performance. On the one hand, the traditional hypothesis is that there is a mutual constraint between the environmental objectives and the objectives of the enterprise. Meeting the objectives of one party will inevitably negatively affect the objectives of the other party, which could have a negative impact on the performance of carbon dioxide emissions (Johnson, 2010). For example, Gray and Shadbegian (1995) took the U.S. pulp and paper industry, petroleum refining industry, and steel industry as the research object, and found that the increase of environmental costs inhibited the growth of productivity level, that is, the productivity level and growth rate of enterprises subject to stricter environmental control were significantly lower than those subject to less environmental control. Yang et al. (2012) also show that it is difficult to improve the performance of companies' carbon dioxide emissions solely through spontaneous market behaviour. Cui et al. (2015) analyzed the carbon dioxide emissions performance of the U.S. manufacturing industry and found that there was an inverse relationship between enterprise productivity and carbon dioxide emissions per unit output. On the other hand, in recent years, more and more scholars believe that formal environmental regulation led by the government can significantly improve the performance of carbon dioxide emissions (Shen, 2016). Zhao and Luo (2017) have shown that official regulations, including emissions monitoring and the implementation of standards, are key factors in promoting the reduction of carbon dioxide emissions. Wang et al. (2020) found that formal environmental regulations such as environmental supervision have a positive effect on the reduction of carbon dioxide emissions in Chinese provinces. Jia and Lin (2021) proposed that under China's "carbon neutral" policy scenario, formal environmental regulations should play a moderating role in reducing the intensity of carbon dioxide emissions.

The second literature on the relationship between network attention and the performance of carbon dioxide emissions, but there are also a few arguments. First, a small number of studies have found that informal environmental regulation such as network attention, has no correlation with carbon dioxide emission performance. Hart and Ahuja (1996) found that environmental protection measures taken by non-governmental organizations or markets do not clearly correlate with the performance of carbon dioxide emissions. Ziegler et al. (2008) found that informal environmental regulation could not achieve an obvious response to environmental governance. Second, informal environmental regulations such as media pressure and network pressure can significantly improve the performance of carbon dioxide emissions. Kathuria (2007) found that the pressure of news reports significantly reduced the pollutant emission intensity of enterprises according to the research on media pressure and environmental governance performance in India. Zheng et al. (2018) found that online media attention will put greater pressure on companies' environmental governance, forcing them to respond to improve the performance of carbon dioxide emissions. Han (2022) proposed that the pressure from the media and public opinion supervision becomes the power of enterprise environmental protection, which can imperceptibly change the enterprise's environmental protection ideas, from environmental end treatment to cleaner production, and bring a positive impact on enterprise environmental governance.

The third literature discusses the mechanism of the influence of network attention on carbon dioxide reduction. Most scholars focus on the pressure mechanism, which can be subdivided into reputation pressure, disciplinary pressure, and market pressure. First of all, network attention will bring reputation pressure to pollution-discharging enterprises, and affect carbon dioxide emissions and governance behavior. Lesser (2008) pointed out that network attention would bring reputation pressure to enterprises, forcing enterprises to make decisions to fulfill environmental protection responsibilities and improve environmental performance. Khaqqi et al. (2018) believed that for the consideration of future development and enterprise value, enterprises often attach importance to their reputation in the network. The media pays attention to environmental protection issues such as carbon dioxide emissions of enterprises, puts them under reputation pressure, and promotes enterprises to increase investment in environmental protection and improve environmental performance. Moreover, higher network attention will attract the attention of regulatory authorities, especially the unofficial negative environmental protection information disclosed by the network, which is easy to bring administrative punishment pressure and risk to enterprises and urge them to improve their carbon dioxide emission behavior. Cheng and Liu (2018) found that network information would increase regulatory attention and the likelihood of penalties for heavily polluting corporations. Zhang and Xie (2020) found that the supply of public opinion and other information increases the cost of pollution and the fear of environmental punishment, which helps to form external constraints on environmental pollution behavior. In addition, media and network attention have brought market pressure to enterprises and promoted enterprises to reduce carbon emissions. For example, Cai et al. (2020) believed that media and network attention would bring strong market pressure to listed companies in the capital market and stimulate listed companies to adopt green technology to reduce environmental risks. Lei et al. (2022) pointed out that under the network focus scenario, listed companies have the motivation to respond to market green development expectations and improve environmental competitiveness.

To sum up, although many pieces of literature believe that enterprises will improve the performance of carbon dioxide emissions due to the pressure of network attention, there are still some conclusions to the contrary. In particular, the existing literature has not explored the relationship between the agricultural sector's network concern and carbon dioxide emissions performance, and there is little direct evidence from the agricultural sector in developing countries, which requires systematic analysis and investigation. Accordingly, this paper focuses on the impact of the network attention of agricultural listed companies, the main body of pollutant emissions in non-industrial sectors ignored by the academic community, on the performance of carbon dioxide emissions, to strengthen the academic understanding of "the mystery of network attention and agricultural carbon reduction".

3 Measurement models and data

3.1 Instrumental variable model (IV model)

The instrumental variable model is an effective estimation model to solve the endogenous problem, and it has strong applicability to alleviate the self-selection of samples and overcome the high correlation between independent variables and random disturbance items (Amemiya, 1985). Compared with other estimation models, the instrumental variable model makes the causal relationship evaluation between independent variables and dependent variables more objective by looking for instrumental variables that are highly related to independent variables and not related to random error terms (Cragg and Donald, 1993). formula (1) shows the IV model:

$$\begin{gathered} y_{i,t} = \beta_0 + \beta_1 x_{i,t} + u_{i,t} \\ Cov(Z_{i,t}, u_{i,t}) = 0 \\ Cov(Z_{i,t}, x_{i,t}) \neq 0 \\ y_{i,t} = \beta_0 + \beta_1 z_{i,t} + u_{i,t} \end{gathered} \tag{1}$$

In Eq. 1, $y_{i,t}$, $x_{i,t}$, $z_{i,t}$ uit respectively represent dependent variable, independent variable, instrumental variable, and random disturbance term. Cov represents the covariance between variables. β_0, β_1 represent the estimated coefficient. In the original estimation model, there is often a high correlation between the independent variable $x_{i,t}$ and the random disturbance term $u_{i,t}$, resulting in biased estimation. The endogenous problem of the original model can be effectively solved by introducing the tool variable z_{it} instead of the independent variable $x_{i,t}$.

The IV model is the basis for us to examine the relationship between network attention and the carbon dioxide emission performance of agricultural enterprises. Next, based on Eq. 1, the exogenous instrumental variable model is used to examine the impact of network attention on the carbon dioxide emission performance of agricultural enterprises. At the same time, it is effective to use lag-independent variables to construct tool variables, which is helpful to estimate consistent estimators of parameters (Koop et al., 2012). The specific model 2) is constructed, as shown in Eq. 2:

$$Emp\_intensity_{i,t} = \beta_0 + \beta_1 Media_{i,t-1} + \beta_2 Cotrollers_{i,t} + Year + \delta_{i,t} \tag{2}$$

In Eq. 2, $Emp\_intensity$ represents the performance of carbon dioxide emissions, $Media$ refers to the instrumental variable of network attention in the lag period, including two specific instrumental variables, namely, the total amount of annual network attention ($Media\_total$), annual total urban broadband access users ($Access\_user$). Theoretically, these instrumental variables are highly correlated with network attention and have exogenous characteristics. *Controllers* represent other control variables that may affect carbon dioxide emission performance, and *Year* represents the annual fixed effect. δ is a random disturbance term, i represents the individual of agricultural listed company, and t represents time.

3.2 Variables

3.2.1 Dependent variable

Carbon dioxide emission performance ($Emp\_intensity$): Carbon dioxide emission performance reflects the main achievements of economic organizations in environmental protection, including whether they meet the environmental protection standards and the intensity of unit carbon dioxide emissions. However, for the agricultural listed companies studied in this paper, as the enterprises concerned with the public and the network, they have reached the basic environmental protection standards stipulated by the state, and it is difficult to fully reflect the environmental governance results by using relevant variables. Referring to the practice of Patten (2005), Zhang and Cao (2015), the six broad carbon dioxide (CO_2, CH_4, N_2O, HFCs, PFCs, SF_6) defined in the Kyoto Protocol is used as the statistical caliber, and the unit carbon dioxide emission intensity is used as the specific measurement index.

3.2.2 Independent variable

Tool variables of network attention (*Media*): Network attention refers to the degree of the public's attention to the enterprise based on the internet media, which is measured by the search index. In the context of the Chinese internet, the public first chooses Baidu Search, the largest local search engine, to focus on relevant enterprises and express their opinions online. With reference to the practice of McCreery (2010), based on the number of internet users searching in Baidu, define the first tool variable, the total annual network attention (*Media_total*). Furthermore, to avoid the error in the estimation of a single indicator, based on Kitty (2011) and other ideas, the second instrumental variable - the annual total number of urban broadband access users (*Access_user*) is set.

3.2.3 Control variables

Environmental protection administrative punishment (*Epap*): Formal environmental regulation is an important external factor driving enterprises to improve environmental protection behavior. A strong administrative sanction to protect the environment will limit companies' carbon emissions behaviour and correct their inappropriate behaviour in environmental governance. In order to control the impact of administrative power on the performance of carbon dioxide emissions, referring to the practice of Ding and Shahzad (2022), the intensity of formal environmental regulation is measured based on the annual environmental protection administrative punishment of agricultural listed companies.

Financial leverage (*Lev*): Since carbon reduction itself is a high investment, long cycle process, enterprises need to raise necessary funds for environmental protection equipment upgrading, emission reduction technology upgrading, etc. through financial leverage. The ratio of total liabilities to total assets of agricultural listed companies is used to measure the level of financial leverage.

Enterprise size (*Size*): In addition to the capital factor, another factor closely related to the performance of carbon dioxide emissions is enterprise size. Larger enterprises tend to emit more greenhouse gases, and the corresponding greenhouse gas emission intensity will also be affected. We refer to the practice of Shao et al. (2016) and introduce the enterprise scale variable. The logarithmic measurement of enterprise asset scale is intended to control the change of environmental protection governance effect brought by enterprise scale.

Development status (*Growth*): Enterprises at different stages of development will present different environmental governance motivations. When enterprises develop rapidly, their carbon dioxide emissions will increase. They will face greater pressure on environmental governance and may invest more funds in the field of environmental governance to promote the improvement of carbon dioxide emissions performance. We learn from Soltani et al. (2021). The growth rate of business income is used to measure the development status, so as to control the impact of development status on carbon dioxide emission performance.

Age of establishment (*Firmage*): The operation and management activities of enterprises that have been established for a long time are relatively standardized, and they are motivated to implement more strict environmental governance behaviors, thus causing changes in the performance of enterprises' carbon dioxide emissions. Refer to Cole et al. (2015) and measure the above indicators by taking logarithms of the company's establishment years.

Board governance (*Board*): The board of directors is the core organization for business decision-making, and the governance of the board of directors determines the corporate environmental governance behavior to a large extent. A larger board size means more directors participate in environmental governance decisions. In order to control the decision-making behavior of the board of directors on environmental governance, referring to the practice of Okoye (2010), we measure the governance variables of the board of directors by taking logarithms of the size of the board of directors.

3.2.4 Regulated variable

Environmental protection investment (*Epinvest*): Listed agricultural companies under the pressure of network media have the motivation to increase environmental protection investment and improve environmental performance. At a time when environmental protection is becoming increasingly important, network attention may stimulate enterprises to pay attention to environmental protection, force them to invest more funds in the field of environmental protection, and bring about changes in the carbon dioxide emission performance of agricultural listed companies. With reference to Liu et al. (2022), it is measured by the annual environmental protection investment of agricultural listed companies. Table 1.

3.3 Sample selection and data source

This paper selects China's A-share agricultural listed companies from 2012 to 2020 as the initial sample, and

TABLE 1 Variable definitions.

Variable		Variable symbol	Variable declaration
Dependent variable	Carbon dioxide emission performance	*Emp_intensity*	Broad carbon dioxide emissions of agricultural listed companies (tons)/operating income (100 million yuan)
Independent variable	Total annual network attention	*Media_total*	Annual Baidu search total index, taking logarithms
	Annual broadband access user	*Access_user*	Annual broadband user access users (thousands) in the city where the company is located, then logarithm
Control and regulation variables	Environmental protection administrative punishment	*Epap*	The administrative penalty for environmental protection in the current year is 1, otherwise 0
	Financial leverage	*Lev*	Total liabilities/assets
	Enterprise size	*Size*	Asset scale, then logarithm
	Development status	*Growth*	(Operating income of the current year - operating income of the previous year)/ operating income of the previous year
	Age of establishment	*Firmage*	The number of years of establishment of the company, then logarithm
	Board governance	*Board*	Number of directors, logarithm
	Environmental protection investment	*Epinvest*	Annual environmental protection investment (ten thousand yuan), then logarithm
	Year	*Year*	Set the year dummy variable, 1 for the current year, 0 for other years

(source: China Finance and Economics database).

TABLE 2 Descriptive statistics of the main variables.

Variable	Sample size	Mean value	Standard deviation	Minimum	Maximum
Emp_intensity	324	3.552	11.853	0.000	116.755
Media_total	324	12.329	0.837	4.094	14.036
Access_user	324	7.276	0.774	4.593	9.126
Epap	324	0.006	0.078	0.000	1.000
Lev	324	0.443	0.213	0.050	1.249
Size	324	21.765	1.033	19.478	25.532
Growth	324	0.114	0.466	-0.751	4.383
Firmage	324	2.842	0.328	1.609	3.611
Board	324	2.103	0.228	1.609	2.773
Epinvest	324	15.545	1.527	7.507	18.848

(source: China Finance and Economics database).

standardizes the sample as follows: 1) exclude the sample of agricultural listed companies that are specially treated by the CSRC and have delisting risks; 2) Remove the samples of agricultural listed companies with more missing data; 3) Exclude the sample of agricultural listed companies that have been listed for less than 2 years. In addition, in order to supplement panel data, some missing values are supplemented by the industry average. After sorting out, 324 sample observations were obtained. The Baidu search index is derived from the data disclosed by the Baidu search engine, and other variable data is derived from the China Finance and Economics (CSMAR) database.

4 Data analysis and discussion

4.1 Descriptive statistics

Table 2 reports the descriptive statistics of the main variables. The mean value of *Emp_intensity* is 3.552, the standard deviation is 11.853, the minimum value is 0.000, and the maximum value is 116.755, which indicates that there are obvious differences in carbon dioxide emission intensity of Chinese agricultural listed companies. Combined with the time series distribution data in Table 3, from the data on carbon dioxide emission intensity of listed agricultural companies in China from 2012 to 2020, the

TABLE 3 Time series distribution of carbon dioxide emission performance (*Emp_intensity*) and network attention (*Media*).

Variable	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
Emp_intensity	2.800	2.366	0.025	0.104	0.017	13.589	3.573	6.220	2.228	3.552
Media_total	11.984	12.135	12.384	12.974	12.468	12.083	11.974	12.374	12.523	12.329
Access_user	6.822	6.915	6.944	7.002	7.263	7.374	7.549	7.669	7.734	7.276

(source: China Finance and Economics database).

annual average of carbon dioxide emission intensity during the statistical period is 3.552. The decline in carbon dioxide emission intensity after 2017 is very obvious. It should be noted that before 2017, although the carbon dioxide emission intensity of Chinese agricultural listed companies was at a low level, it was mainly due to the small scale of non-modern agriculture and low carbon dioxide emissions. In 2017, the central government of China put forward the concept of "agricultural modernization" in the government work report for the first time, and actively advocated the development of "green agriculture". Later, a group of large agricultural listed companies with modern characteristics and practices to reduce carbon dioxide emissions grew rapidly. Therefore, the carbon dioxide emission intensity of agricultural listed companies shows the characteristics of the decreasing year by year and improving carbon dioxide emission performance.

Among the independent variables of network attention, the average value of *Media_total* is 12.329, and the standard deviation is 0.837, indicating that China's agricultural listed companies have more widespread network concerns. Another independent variable, *Access_user*, is 7.276, with a standard deviation of 0.774, which also shows that there are many network users in the cities where agricultural listed companies are located, which brings a certain scale of network attention. Combined with the temporal distribution description of network attention in Table 3, *Media_total* and *Access_user* values are increasing year by year, which shows that Chinese agricultural listed companies are increasingly concerned by the network. From the perspective of control variables, the mean values of *Epap*, *Lev*, *Size*, *Growth*, *Firmage*, and *Board* variables are 0.006, 0.443, 21.765, 0.114, 2.842, and 2.103 respectively, and the standard deviations are 0.078, 0.213, 1.033, 0.457, 0.328, and 0.228 respectively. This conveys the real information that China's agricultural listed companies have less environmental protection punishment, use financial leverage, relatively large scale, rapid development, long establishment time, and considerable internal governance. As an adjusting variable, the average value of *Epinvest* is 15.545, and the standard deviation is 1.572, indicating that there are certain differences in the environmental protection investment of different agricultural listed companies. In general, the results of the descriptive statistics are basically in line with the realistic characteristics of environmental governance and network concerns of China's agricultural listed companies. In addition, before the benchmark test, we also conducted a correlation coefficient test. The variance inflation factor was significantly lower than 10, and there was no serious multicollinearity problem among the main variables.

4.2 Benchmark test

Due to the pressure of reputation, punishment, and market caused by network concern, agricultural listed companies are sensitive to green development issues and are prone to make more environmentally friendly behaviors, reduce environmental risks of enterprises and improve the competitiveness of carbon dioxide emissions. This makes network attention help to promote the performance of carbon dioxide emissions. Table 4 reports the results of the benchmark test based on model 2). Columns 1) and 2) examined the overall impact of the network attention of China's agricultural listed companies on the performance of carbon dioxide emissions. In order to judge the effectiveness of the lag instrumental variables, we first test the insufficient identification and weak instrumental variables of the two instrumental variables. The total amount of network attention in the lag period *Media_total(-1)* and the total number of urban broadband users in the lag period *Access_user(-1)* is a tool variable, and the *p*-value of the under-identification test (Kleibergen-Paap rk LM statistic) is 0.026 and 0.000 respectively. The estimated results reject the original hypothesis, indicating that the instrumental variables are related to the original explanatory variables. In addition, the test results of weak instrumental variables (Cragg-Donald Wald F statistic) of the two instrumental variables are greater than 10, which are 97.218 and 158.535 respectively, indicating that the selection risk of instrumental variables is low. From the overall regression results, in column 1) and column 2), the estimated coefficients of *Media_total* and *Access_user* are significantly negative, indicating that the increasing network attention has significantly reduced the carbon dioxide emission intensity of agricultural listed companies and brought about better carbon dioxide emissions performance.

4.3 Heterogeneity test results and analysis

Table 5 reports the results of the heterogeneity test. Columns 1)–4), 5)–8), and 9)–(12) examined the impact of network attention on carbon dioxide emission performance of agricultural listed companies based on the heterogeneity of network, region, and property rights. Columns 1) to 4) are divided into PC concerns and mobile internet concerns according to the main sources of the total number of network searches. The network heterogeneity test results show that the independent variable *Media_total* and *Access_user* are only significantly negative in column 3) and column 4), with estimated coefficients of -4.921 and -2.086 respectively, indicating that the network focus mainly on mobile internet search has a more significant effect on the improvement of carbon dioxide emission performance of agricultural listed companies. From the regression of regional heterogeneity of column 5)–8) subsamples, the

TABLE 4 Results of benchmark regression.

Variable	*Emp_intensity*	
	(1)	(2)
Media_total(-1)	-4.511* (-1.75)	
Access_user(-1)		-0.985*** (-2.97)
Epap	1.049 (0.57)	0.893 (0.59)
Lev	-2.603 (-0.49)	-4.851 (-0.77)
Size	-3.623*** (-3.03)	-5.018*** (-3.02)
Growth	-1.307** (-2.00)	-2.012* (-1.68)
Firmage	2.647* (1.67)	1.442 (1.07)
Board	5.659* (1.94)	4.027 (1.57)
Constant	118.317*** (2.76)	106.208*** (3.02)
Year	control	control
Observations	324	324
Adj R-squared	0.367	0.301

Note: 1) * * *, * *, and * respectively represent significant levels of 1%, 5%, and 10%; 2) The T values are in parentheses; 3) The regression results in the table have been corrected by the cluster at the regional level. The same is below.

independent variable *Media_total* and *Access_user* are significantly negative in column 6), column 7), and column 8), and the estimated coefficients are -1.086, -6.051 and -0.573 respectively. At the same time, the coefficient difference test of variable *Access_user* in column 6) and column 8) shows that there is a significant difference in the estimated coefficient of independent variables, that is, the estimated coefficient of independent variables in the central and western groups is more significant. The above shows that network attention has a more significant impact on the carbon dioxide emission performance of agricultural listed companies in the central and western regions. From the regression of property right heterogeneity of subsamples 9) to (12), the independent variable is significantly negative in columns 9) and (10), and the estimated coefficients are - 7.397 and - 1.864 respectively, indicating that network attention has a more obvious impact on the environmental governance behavior of state-owned agricultural listed companies. Therefore, there is the network, regional, and property heterogeneity in the promotion of China's network attention on the carbon dioxide emission performance of agricultural listed companies.

In fact, with the rapid development of the internet, the external governance effect of network attention on environmental protection is increasingly obvious (Schrlau et al., 2011). Compared with the PC's attention, using mobile internet can get rid of location restrictions and search more convenient and accurate, which makes the attention from mobile internet not only far exceed the PC's attention in magnitude, but also exert more obvious and focused network pressure (Wang et al., 2022), bringing more powerful carbon dioxide emission control effect than PC's attention. In addition, the eastern coastal provinces are the regions where China opened up earlier and changed to a market economy. The agricultural enterprises in this region have a strong concept of green environmental protection. However, agricultural enterprises in the central and western regions are often inferior to those in the eastern coastal regions in terms of environmental protection awareness and behavior performance (Komarek et al., 2015), which makes the improvement effect of network attention on the carbon dioxide emission performance of agricultural enterprises in the central and western regions more obvious. Finally, the nature of property rights of Chinese enterprises includes state-owned and private enterprises, and there are significant differences in the motivation and motivation of corresponding emission reduction (Wu et al., 2019). Compared with private agricultural listed companies with the primary goal of chasing profits, state-owned agricultural listed companies also shoulder the goal of fulfilling political tasks and social responsibilities. It has more power to actively respond to network concerns and public expectations by reducing other greenhouse emissions per unit product, making the network focus more significant in improving the carbon dioxide emission performance of state-owned agricultural listed companies.

4.4 Mechanism test results and analysis

In recent years, promoting green and low-carbon transformation has been regarded as an important direction for enterprises to move towards high-quality development and has attracted the attention of Chinese netizens. In this context, agricultural listed companies will pay more attention to environmental protection issues and have the motivation to respond to network concerns, to invest more costs to promote environmental protection, which makes environmental protection costs play a mechanistic role for the network to focus on improving the performance of carbon dioxide emissions. On the one hand, a higher degree of network attention can help alleviate the degree of environmental information asymmetry of agricultural listed

TABLE 5 Results of heterogeneity regression.

Variable	*Emp_intensity*				*Emp_intensity*				*Emp_intensity*			
	PC		Mobile internet		East		Midwest		State-owned		Private-owned	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Media_total(-1)	-0.714 (-0.95)		-4.921** (-1.85)		-0.145 (-0.34)		-6.051*** (-2.68)		-7.397*** (-4.73)		0.786 (1.52)	
Access_user(-1)		-0.261 (-1.63)		-2.086** (-2.50)		-1.086* (-1.79)		-0.573** (-1.97)		-1.864*** (-2.93)		-0.657 (-1.58)
Epap	0.000 (0.00)	0.000 (0.00)	1.208 (0.64)	0.639 (0.41)	0.000 (0.00)	0.000 (0.00)	1.521 (0.59)	2.014 (0.93)	2.123 (0.81)	1.443 (0.92)	0.000 (0.00)	0.000 (0.00)
Lev	-4.231 (-1.00)	-5.180 (-1.09)	-2.540 (-0.46)	-4.919 (-0.78)	1.306 (0.42)	0.181 (0.07)	-5.376 (-0.78)	-7.370 (-0.92)	-11.735* (-1.72)	-14.494* (-1.90)	2.175 (0.62)	2.812 (0.84)
Size	-2.576*** (-2.87)	-2.640*** (-3.10)	-3.623*** (-2.89)	-5.430*** (-3.07)	-1.651** (-2.45)	-2.132*** (-2.64)	-4.006** (-2.39)	-5.974*** (-2.98)	-2.465** (-2.47)	-6.342*** (-3.58)	-3.863*** (-3.10)	-3.893*** (-3.12)
Growth	-5.808*** (-3.41)	-5.112*** (-2.85)	-0.963 (-1.35)	-1.963 (-1.60)	-0.387 (-0.54)	0.095 (0.07)	-1.004 (-1.28)	-2.199 (-1.54)	-2.372** (-2.19)	-4.476*** (-3.37)	-0.319 (-0.35)	-0.299 (-0.34)
Firmage	-0.930 (-0.87)	-1.412 (-1.33)	3.428* (1.95)	2.287* (1.65)	1.878 (1.04)	1.462 (1.11)	5.777** (2.36)	3.138 (1.40)	-2.442 (-0.81)	-4.667 (-1.45)	3.138 (1.59)	3.203* (1.67)
Board	-0.881 (-0.43)	-1.438 (-0.61)	6.684** (2.05)	4.403 (1.49)	2.764* (1.79)	1.359 (1.44)	8.793** (2.05)	6.514* (1.85)	5.391 (1.47)	4.495* (1.77)	4.233 (1.40)	4.107 (1.44)
Constant	73.176*** (2.77)	70.136*** (2.99)	117.734*** (2.86)	121.973*** (3.07)	28.147** (2.44)	49.740*** (2.79)	131.126*** (3.47)	115.323*** (3.33)	148.155*** (3.93)	156.633*** (3.31)	57.967*** (3.20)	73.482*** (3.47)
Year	control	control	control	control	control	control	control	control	control	control	control	control
Access_user(-1) coefficient difference test	-	-	-	-	-	-24.440*	-	-24.440*	-	-	-	-
Observations	35	35	289	289	118	118	206	206	149	149	175	175
Adj R-squared	0.627	0.640	0.373	0.310	0.369	0.422	0.430	0.330	0.500	0.344	0.352	0.354

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TABLE 6 Results of mechanism testing.

Variable	*Emp_intensity*	
	(1)	(2)
Media_total(-1)	31.326** (2.16)	
Access_user(-1)		3.083 (1.48)
Epinvest(-1)	27.939** (2.29)	2.376** (2.18)
*Media_total(-1)*Epinvest(-1)*	-2.215** (-2.21)	
*Access_user(-1)*Epinvest(-1)*		-0.260* (-1.95)
Epap	1.145 (0.74)	0.742 (0.52)
Lev	-2.878 (-0.64)	-4.182 (-0.70)
Size	-3.757*** (-3.25)	-5.081*** (-3.06)
Growth	-1.423** (-2.48)	-2.022 (-1.61)
Firmage	2.836* (1.86)	1.547 (1.13)
Board	4.044* (1.71)	3.732 (1.59)
Constant	-327.731** (-1.96)	70.609* (1.92)
Year	control	control
Observations	324	324
Adj R-squared	0.402	0.306

companies, enable them to detect and fill gaps while enhancing environmental awareness (Lo et al., 2012), and help enterprises reasonably increase environmental protection investment expenditure; On the other hand, highly concerned enterprises have a higher exposure probability of environmental protection news, which will make agricultural listed companies fully feel the public's environmental protection requirements, and to alleviate the pressure on environmental protection (Hu et al., 2019), increase the investment in environmental protection costs, enhance the "carbon reduction and consumption reduction" efforts, to meet the social environmental protection requirements.

Based on model 2), add the *Epinvest* regulatory variable representing the environmental protection cost input. Via *Media_total(-1) * Epivest(-1)* and *Access_user(-1) * Epinvest(-1)* two interaction terms are used to test the possible mechanism of environmental protection investment. Table 6 reports the mechanism test results. In column 1), the estimated coefficient of *Media_total(-1) * Epivest(-1)* is -2.215, and it is significantly negative at the level of 5%. This shows that the investment in environmental protection has adjusted the relationship between network attention and carbon dioxide emission intensity of agricultural listed companies, and has significantly promoted the reduction of carbon dioxide emission intensity of agricultural listed companies. In addition, in column 2), the estimated coefficient of *Access_user(-1) * Epinvest(-1)* is also significantly negative, which further confirms the above conclusion. To sum up, the investment in environmental protection costs will strengthen the inhibition effect of network attention on the unit carbon dioxide emissions of agricultural listed companies.

4.5 Robustness test

In the part of the robustness test, we focus on mitigating possible estimation bias caused by variable selection and model setting. The robustness regression by replacing key variables, adjusting the model, and deleting the samples of special years. First, replace variables and models. Considering that network attention is not

TABLE 7 Robustness test results.

Variable	*Emp_intensity*		
	Replace variables and models	Non-linear model regression	Delete special year regression
	(1)	(2)	(3)
Pc_total(-1)	-4.619* (-1.67)		-2.050** (-2.00)
Pc_total(-1)2		-0.329 (-1.34)	
Epap	-1.592*** (-2.85)	-1.610** (-2.57)	-1.110 (-1.59)
Lev	-7.846*** (-2.96)	-7.402*** (-2.63)	-6.722* (-1.77)
Size	-1.319 (-0.77)	-1.761 (-1.10)	-3.946 (-1.50)
Growth	-3.063*** (-3.56)	-3.473*** (-2.83)	-2.127** (-2.09)
Firmage	7.792** (2.48)	9.114*** (2.79)	18.279** (2.50)
Board	-0.334 (-0.09)	-0.521 (-0.14)	-3.150 (-0.67)
Constant	39.432 (1.49)	30.386 (1.15)	59.081 (1.52)
Fixed Effect	control	control	control
Observations	324	324	245
Adj R-squared	0.137	0.102	0.075

only reflected in the annual search volume based on mainstream search engines, but also reflected in the amount of attention from computers and mobile internet. Therefore, referring to Francesca et al. (2017), we set into the computer side annual network attention (*Pc_total*) alternative indicators for regression; Second, transform the model. Due to the possible non-linear relationship between the network attention and the carbon dioxide emission performance of agricultural enterprises, referring to Shakil (2020), the original model introduced the quadratic term of the independent variable (*Pc_total2*) to test again; Finally, delete the special year regression. Since 2019, the central government of China has issued the "Regulations on the Supervision of Central Ecological Environment Protection" and implemented a more explicit ecological environment protection supervision system. The government's increased environmental protection supervision may have a disturbing impact on the carbon dioxide emission performance of agricultural enterprises. Referring to the practice of Zhan et al. (2022), the samples in 2019 and 2020 were excluded from robustness testing. From the results of the robustness test in Table 7, in column 1), after replacing the variable and model, the variable *Pc_total* estimated coefficient is still significantly negative. In column 2), after non-linear model regression, there is no significant non-linear relationship between annual PC network attention (*Pc_total*) and carbon dioxide emission performance (*Emp_intensity*), indicating that the original linear regression results are reliable. In column 3), after deleting the special year sample, the variable Pc_total estimated coefficient is still significantly negative. The above tests show that the previous conclusions are relatively robust.

5 Conclusion and suggestions

China is the largest developing country in the world and the country with the largest number of internet users. The environmental governance effect of its network attention deserves attention. This paper focuses on the agriculture sector, which has been neglected in the past and uses the unique network attention data in China to study the impact of network attention on the carbon dioxide emission performance of agricultural listed companies. The research found that: 1) By measuring the carbon dioxide emission intensity of China's agricultural listed companies, it is found that the overall carbon dioxide emission intensity is decreasing year by year and the carbon dioxide emission performance is improving; 2) Based on the instrumental variable model, the impact of network attention on the carbon dioxide emission performance of agricultural listed companies was examined. It was found that the increasing network attention significantly reduced the carbon dioxide emission intensity of agricultural listed companies, and brought better carbon dioxide emission performance; 3) Based on the heterogeneity analysis, it is found that there are network, regional, and property heterogeneity in the promotion of China's network attention on the carbon dioxide emission performance of agricultural listed companies; 4) Taking environmental protection investment as the potential mechanism, the test found that environmental protection investment will strengthen the inhibition effect of network attention on carbon dioxide emissions per unit of agricultural listed companies.

The research conclusions provide useful ideas and wisdom for China and other developing countries to promote carbon-neutral action, tap the potential of emission reduction in the agricultural sector, and give full play to the emission reduction effect of network governance. We suggest that: 1) developing countries should give full play to the role of informal environmental regulation in environmental governance in carbon neutral action, encourage non-governmental organizations to participate in environmental protection publicity, open channels for the public to express suggestions related to environmental protection issues, and increase the network attention and response to pollution issues; 2) Local governments should earnestly fulfill the obligations of the first responsible unit for implementing the carbon neutrality task in the region, scientifically design the system and mechanism for regional coordinated control of carbon dioxide emissions, encourage the green and low-carbon development of agriculture, and other sectors, and do good in guiding the public opinion of the carbon neutrality network; 3) Agricultural listed companies should pay attention to the carbon dioxide governance effect of network concern, actively look at the environmental pressure brought by network concern, actively respond to the environmental protection opinions of network concern and increase the investment in environmental protection costs, promote the improvement of carbon dioxide emission performance, and promote the green and high-quality development path.

Finally, this paper may have limitations in the following aspects, which need to be deepened in the future: First, according to academic practice and data availability, this paper uses carbon dioxide emission intensity as an alternative variable of environment-related performance. If more sufficient data can be obtained in the future, it can be further expanded to other environmental pollution performance levels such as soil and water; Second, based on the characteristics of China's online reality, this paper examines the impact of online attention on carbon dioxide emissions performance based on Baidu Search Index. In the future, we can try to use other online social media data to enrich research.

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

JC: Original writing, Editing and Revise paper HS: Original writing, Editing and Revise paper, Supervision, Data collection and analysis.

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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.

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Supplementary material

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Heterogeneous impact of artificial intelligence on carbon emission intensity: Empirical test based on provincial panel data in China

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Introduction: Energy conservation and emission reduction, as a major policy of China for a long time, has been put on the key strategic position. Based on the panel data of 30 provinces, cities and districts in China from 2006 to 2019.

Methods: This paper uses fixed effect model and spatial Durbin model to explore the effect and mechanism of artificial intelligence (AI) on regional carbon emission intensity (CEI).

Results: The results show that: (1) there is a significant inverted U-shaped between AI and CEI, that is, with the deepening of the development of AI, CEI first increases and then decreases. (2) There is a significant spatial correlation between the development of AI and CEI in China. (3) AI has a significant spatial spillover effect on CEI of adjacent regions, and it shows an inverted U-shaped track-from promoting to restraining.

Discussion: The conclusion provides policy implications for the formulation of AI development strategy and so on during the specific period.

KEYWORDS

AI, carbon-emission, spatial spillover effect, spatial Durbin model, energy conservation

1. Introduction

In view of the world energy statistical yearbook 2021, from 2011 to 2020, Chinese total carbon-emission has increased by nearly 1 billion tons, which is one of the few in the world. This also means that China's emission reduction situation is extremely severe under the situation of global warming and continuous large-scale greenhouse gas emissions. This is not only related to the current social and economic development, but also closely related to the survival of future generations (Liu et al., 2022). In 2020, President Xi promised to achieve carbon peaking and carbon neutralization by 2030 and 2060, respectively, at the UN General Assembly (Zhang et al., 2020). Since then, carbon reduction and emission reduction has been listed as a priority and become one of the core policies to promote China's high-quality development (Xu et al., 2021).

At the same time, with the wide application and continuous innovation of big data, Internet of things, and large machine production, AI has become a direct response to the great changes of internal endowments and external environment in China's high-quality development stage by virtue of its technology effect, scale effect, and network effect (Jia et al., 2021). According to the data released by International Federation of Robotics (IFR), it can be seen that the application scale of robots is on the rise, with an installed capacity of 140,000 units in 2019, ranking the first in the world. With the strong support of the state, it has penetrated into all walks of life. With the continuous improvement of the contribution of AI to the national economy, the rapid development of AI has been widely and continuously concerned by the academic community, especially the environmental improvement effect of the development of AI. Those effects can be divided into the following three views. The first is Acemoglu and Restrepo (2018), who believed that relying on the extensive application of AI, the industry production and carbon-emission reduction technology can be integrated with each other, and then change the production and consumption mode, so as to improve energy utilization efficiency. Meanwhile, the use of in-depth learning network and sensor equipment of AI for effective monitoring of carbon-emission can also optimize the carbon reduction decisions of government and enterprises, making the environmental improvement effect of AI more prominent (Batty, 2018; Henderson et al., 2020). The second is that the rise, maturity and wide application of AI will inevitably bring about changes in energy use types and utilization methods, leading to a large increase in power demand and a significant increase in CEI (Salahuddin and Alam, 2015). The third is that the development of AI has a complex and uncertain impact on Carbon-emission due to the degree of technological progress, regional development differences, depth of mechanization, and environmental policies (Bhujabal et al., 2021; Guo et al., 2021). In short, different from the policy level and the vigorous development of practice level, there is still no unified scientific cognition on whether the development of AI can reduce CEI (Milojevic-Dupont and Creutzig, 2021; Lu et al., 2022).

This study systematically investigates the effect and mechanism of the development of AI on CEI. The literature related to this study is how the development of digital technology affects carbon-emission. This kind of literature focuses more on the impact of informatization and digitization on carbon-emission through industrial change under the effect of technological progress. Some studies found that the Internet industry leads to the rapid growth of power consumption, which will enhance the total and intensity of carbon-emission (Hamdi et al., 2014). Other studies have proved that the information technology can reduce greenhouse gas emissions (de Bézenac et al., 2019; Haseeb et al., 2019), especially in the long term, increasing Internet penetration (Shobande, 2021) have significant effects on reducing CEI.

To sum up, it can be found that the existing studies have carried out detailed exploration, intensity, and AI development, but there are still some deficiencies. First of all, most of the existing studies focus on qualitative research, lack of empirical research support of AI on carbon reduction effect, and there is no scientific cognition of the impact of AI development on CEI (Yang, 2021). Secondly, the existing research on the spatial correlation of AI on carbon reduction effect is lack of detailed mechanism discussion and empirical proof. Finally, China is a vast country with unbalanced development among regions and large differences in industrial structure, which will bring regional heterogeneity to the application of artificial intelligence and regional carbon reduction and emission reduction (Li et al., 2019; Liu and Chen, 2021).

Based on this, the main contributions of this paper are as follows:

1. The inhibitory effect of artificial intelligence on regional carbon emission intensity is studied.
2. The regional differences of the impact of artificial intelligence development on carbon emission intensity are discussed.
3. The spatial spillover effect of artificial intelligence development on regional carbon emissions is clarified.

Therefore, based on the long panel data of 30 provinces, municipalities, and regions in China, this paper establishes a theoretical analysis framework for artificial intelligence and regional carbon emission intensity, explores the influence and mechanism of artificial intelligence on regional carbon emission intensity, enriches relevant studies, and provides theoretical inspiration for the development of artificial intelligence and the implementation and promotion of emission reduction policies in China.

2. Theoretical analysis and research hypothesis

The development of AI has entered the stage of technology explosion and large-scale application along with the breakthrough of basic technologies such as big data algorithm. Under this trend, the modes and means also present diversified changes. This paper analyzes the influence mechanism of AI on CEI from two aspects of direct mechanism and spatial effect transmission path, and puts forward corresponding research hypotheses (Lee and Lee, 2014).

Artificial intelligence has been in the process of dynamic evolution from low to high, so there will be dynamic differences in the impact on CEI (Yu et al., 2020). In the initial period, the wide application of AI and the large-scale construction of big data network center will aggravate the regional power consumption and energy consumption. With the popularization of machine learning system, AI language processing system will produce a lot of carbon-emission. Although it promotes the improvement of energy utilization efficiency, but it also intensifies more energy consumption, thus offsetting the effect of carbon-emission reduction and even increasing the CEI (Strubell et al., 2019). Meanwhile, the progress of AI technology will also promote the development of communication technology and related industries, as well as the development of Internet industry increases the demand for energy consumption, which leads to the growth of regional carbon-emission (Amiri et al., 2021). In the mature development stage, first of all, the rapid development of AI has led to the vigorous development of e-commerce industry and Internet industry, where a large number of intelligent machines replace programmed labor. As an environment-friendly industry, they can squeeze the development space of high energy consumption through crowding out effect. So that can accelerate the transformation and sustainable development of regional structure. Secondly, the technological progress brought about by the breakthrough development of AI can be developed and explored through intelligent devices to replace alternative energy sources, so as to reduce the use of traditional carbon-emission energy and achieve the goal of reducing CEI. Finally, the progress of AI can be used for fine management. Through the informal environmental regulation generated by the amount of pollution search data in the network platform, the environmental quality of the city can be improved. Moreover, the digital media communication can maximize the guidance of the public to form green environmental protection concept. It also provides new solutions for solving environmental governance problems such as dynamic supervision of environmental pollution and cross regional environmental management, avoids the negative impact of AI in the early stage of large-scale application (Xu et al., 2019; Pan et al., 2020). Based on this, the following assumptions are proposed:

> H_1: the impact of AI development on CEI is inverted U-shaped.

The economic activities of different regions in China show more and more strong correlation, and many scholars have confirmed that AI technology has obvious positive spatial agglomeration effect (Xu et al., 2022). Therefore, AI may also have spatial spillover effect. In the initial stage, due to the differences of natural endowment and social development among different regions in China, the allocation and utilization efficiency of industrial resources in different regions are uneven, which provides space for the release of polarization effect. Under the guidance of market-oriented profit, the scarcity and profit-making characteristics of economic resources will automatically concentrate from backward regions to high marginal yield regions. At the same time, the application of intelligent large machines and the continuous innovation of digital technology have broken the traditional regional restrictions. They can spread through the channels of factor flow and economic cooperation with neighboring regions, and have scale effects on economic growth. They not only drive a new generation of information industry, but also can drive the growth of related industries through the industry spillover effect. In the mature development stage, the application scenarios of AI are becoming more and more abundant. Each production department will produce strong low-carbon technology spillover effect through intelligent upgrading and transformation. In this process, a large number of highly polluting industries were replaced by service industries, and the industrial structure was gradually advanced. The structure dominated by fossil energy has also been greatly improved (Al-Ghandoor, 2010). Through the demonstration effect and industrial correlation effect, the regional carbon-emission and intensity were reduced. Based on this, this paper proposes hypothesis 2:

> H_2: the spatial spillover effect of AI on regional carbon-emission has an inverted U-shaped trajectory.

3. Research design

3.1. Model design

3.1.1. Panel benchmark model

In order to verify hypothesis 1, that is, the effect and mechanism of AI on CEI, this paper constructs the following panel benchmark model:

$$co2 = \alpha + \beta_0 rob_{it} + \beta_1 rob_{it}^2 + \beta_2 X_{it} + \mu_i + \rho_t + \varepsilon_{it} \quad (1)$$

In the Formula (1), $co2_{it}$ is the CEI, rob_{it} is the development level of AI, rob_{it}^2 is the square term of AI, i represents the region, t represents the year, X represents a series of control variables, $\propto_i$ means individual effect, ρ_t means time effect, $\varepsilon_{i,t}$ as a random disturbance term, this paper focuses on the coefficients β_0 and β_1 of the development level on AI, which is the core explanatory variable.

3.1.2. Spatial Durbin model

Spatial metrology models mainly include spatial autoregressive model, spatial error model, spatial autocorrelation model and spatial Dubin model. The spatial Dubin model attributes the generation of spatial effects to explained variables and explanatory variables, and includes the spatial lag term of explanatory variables, which helps to reduce the bias caused by missing variables in the empirical analysis. Therefore, in order to further explore the spatial spillover effect of artificial intelligence development on regional carbon emission intensity, the following model is constructed in this study based on the practice of Yu and Su (2022):

$$\begin{aligned} co2_{it} = {} & \beta_0 + \rho W co_{i,t} + \beta_0 rob_{i,t-1} + \beta_j X_{i,t} \\ & + \theta_1 W rob_{i,t-1} + \theta_j \beta_j X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \end{aligned} \quad (2)$$

In Formula (2), ρ is the spatial lag coefficient, $W \cdot rob$ represents the spatial lag variable of AI, W represents the spatial weight matrix. Formula (2) contains both the explained variables and the spatial terms of the explanatory variables. The spatial Durbin model can improve the robustness of the estimation results and be more comprehensive. At the same time, this paper uses geographic distance matrix and economic geography matrix to represent the spatial weight matrix, wherein the geographic distance matrix ($W1$) is constructed by calculating the distance (d_{ij}) between the city i and the city j according to the longitude and latitude of the city, the specific Formula (3) is as follows:

$$w_{i,j} = \begin{cases} 0, i = 1 \\ \dfrac{1}{d_{i,j}^2}, i \neq j \end{cases} \quad (3)$$

The economic geography matrix can better reflect the spatial relationship of adjacent areas from two aspects of geographical distance and economic distance. Referring to the practice of Lin et al. (2005), this paper uses the difference of real GDP *per capita* between cities to measure the economic distance between regions. The economic distance measures the closeness of economic ties between cities, and introduces it into the spatial weight matrix to construct the economic geography matrix $W2 = W1 \cdot E$, E is the economic distance matrix, and the calculation Formula (4) is as follows:

$$w_{i,j} = \begin{cases} 0, i = 1 \\ \dfrac{1}{\left|Y_i - Y_j\right|}, i \neq j \end{cases} \quad (4)$$

Y_i is the average of *per capita* real GDP for city i in the sample period.

3.2. Variable selection

3.2.1. Explanatory variable: AI

There are many measurement methods of AI, and the common methods are to use AI patents, investment amount of related industries and multi-index comprehensive method to measure, but these methods have some limitations and cannot truly reflect the actual application of AI. Therefore, this paper follows the practice widely used in academic circles (Cheng et al., 2019; Acemoglu and Restrepo, 2020), and indirectly reflects the practical application of AI by measuring the installation density of robot. The original data are from the national industry level robot stock data provided by IFR. Because the industry classification standard adopted by IFR is different from that in China, the practice of Yan et al. (2020) is used to unify the industry classification, and the development level of AI at the provincial level is calculated by the following Formula (5):

$$rob_{it} = \sum_{j=1}^{i} \frac{L_{ijt}}{L_{it}} \times \frac{rob_{jt}}{L_{jt}} \quad (5)$$

In Formula (5), L_{ijt} represents the number of employees in industry *j* of region *i* during period *t*, L_{it} represents the number of employees in area *i* during period *t*, rob_{jt} represents the stock of industrial robots in the period *t* of industry *j*, and L_{jt} is the number of employees in *j* industry in China.

3.2.2. Explained variables: CEI

Based on the practice of Liu et al. (2022), this paper uses the carbon-emission coefficient method to calculate the CEI, which is expressed as per 10,000 yuan of carbon-emission, the specific calculation method is as follows:

$$co2_i = \sum_{j} e_{ij} \times \sigma_j \quad (6)$$

In Formula (6), $co2_i$ is the total carbon-emission of area *i*, σ_j is the carbon-emission coefficient of the *j* energy, and e_{ij} is the consumption of the *j* energy in area *i*. Six energy sources including coal, oil, natural gas, coke, gasoline, and diesel are selected to calculate carbon-emission. The emission factors refer to the greenhouse gas emission list provided by IPCC.

3.2.3. Control variables

In order to reduce the impact of missing variables, based on the existing literature, the level of economic development, industrial structure, and the level of opening up are set as control variables.① *GDP*: take the logarithm of regional GDP to measure. ② *UNE*: expressed by registered urban unemployment rate; ③ *Indust*: measured by the proportion of industrial added value in GDP. ④ *Open*: expressed by the proportion of total import and export to GDP; ⑤ *urb*: expressed by the ratio of urban population to regional total population; and ⑥ *es*: expressed by energy consumption elasticity coefficient.

The research data are the panel data of 30 provinces, cities, and districts in China from 2006 to 2019. The original data are from China's provincial statistical yearbook, China's energy statistical yearbook, and IFR. The details of the main variables are as shown in Table 1.

4. Empirical analysis

4.1. Regression analysis benchmark

Table 2 shows the benchmark regression results of the CEI affected by the development of AI. Through the Hausmann test, the benchmark regression adopts the spatiotemporal double fixed model. Column (1) is the regression result of only adding AI; column (2) is the regression result of economic development level, urbanization level, and industrial structure; column (3) is the regression result of comprehensive consideration of AI, industrial structure, economic development level, urbanization level, regional unemployment rate, level of opening to the outside world, and energy structure. The purpose of adding control variables step by step is to observe whether the regression coefficient of AI changes. According to the regression results in column (1) of Table 2, when only considering the influence of AI on CEI, the first and second estimation coefficients are 0.0519 and − 0.0252 respectively, which are significant at 1 and 5% statistical levels. From column (2) and (3), after adding some and all control variables successively, the estimation coefficients of the first and second terms of AI are still positive and negative, and both pass the 5% confidence level test. It can be seen that there is an inverted U-shaped relationship between AI and CEI, that is, the CEI first increases and then decreases with the improvement of AI development level, and hypothesis 1 is proved. In addition, in the control variables, the improvement of opening-up level and economic development level can provide sufficient space for the optimal utilization of AI technology, and promote the reduction of CEI. However, the improvement of energy structure and the adjustment of industrial structure have increased the CEI at this stage, which shows that the current production and living are divorced from the traditional fossil energy, and the demand for electric power is greatly increased.

4.2. Spatial regression analysis

4.2.1. Spatial autocorrelation analysis

Before the spatial analysis, the global Moran'I index is selected to measure the spatial autocorrelation between the development of AI and regional carbon-emission. As can be seen the Table 3, there has been a significant positive correlation between AI and CEI in the geographical distance matrix. Therefore, it is necessary to further explore the relationship between the two.

4.2.2. Spatial econometric regression

In order to determine the specific form of the spatial metrology model, LM test, LR test, and Hausman test were carried out successively in this paper, and the results showed that the explained variable co passed the LM test. The LR test was continued, and the null hypothesis was significantly rejected, indicating that the spatial error model and the spatial lag model could be used only to investigate the spatial spillover effect of regional carbon emission intensity, so the spatial Dubin model was chosen. At the same time, in order to determine the specific form of the spatial Dubin model, the Hausman test is carried out, showing that the spatial and temporal dual fixed space Dubin model under fixed effects should be selected. In order to verify hypothesis 2, this paper conducts spatial Durbin regression on regional carbon-emission, and the regression results are shown in Table 4. As can be seen from Table 4, the estimated coefficients of both the primary term and the secondary term of artificial intelligence pass the significance test of 5% regardless of whether it is based on the geographical distance matrix or the economic geographical distance matrix, indicating that the development of artificial intelligence will significantly affect regional CEI on the basis of considering the spatial correlation [see column (1) of Table 4] or the economic geographic distance matrix [see column (2) of Table 4]. The coefficient of the

TABLE 1 Descriptive statistics of variables.

Variable symbol	Observations	Mean value	Standard deviation	Minimum value	Maximum
co2	420	2.7867	1.9764	0.326	12.754
rob	420	0.6196	1.3436	0.0014	14.3562
gdp	420	9.5001	0.9586	6.4747	11.5868
urb	420	0.5503	0.1381	0.275	0.938
indust	420	0.3811	0.0866	0.1109	0.5304
open	420	0.3086	0.355	0.0128	1.7117
une	420	3.4207	0.6799	1	5.1
es	420	−3.9907	2.4722	−10.69	10.86

TABLE 2 Benchmark regression results.

	(1)	(2)	(3)
rob	0.0519***	0.2373***	0.2066***
	(5.85)	(4.23)	(3.68)
rob^2	−0.0252**	−0.012**	−0.0112**
	(−2.37)	(−2.60)	(−2.47)
gdp		−1.4896***	−1.7308***
		(−11.58)	(−11.27)
urb		−2.4866**	−1.4248
		(−2.19)	(−1.14)
indust		0.4955	1.2001*
		(0.76)	(1.78)
open			−0.6502**
			(−2.39)
une			−0.2493***
			(−2.91)
es			0.0437***
			(3.94)
N	420	420	420
R^2	0.081	0.731	0.747

***, ** and * represent significant levels of 1%, 5% and 10% respectively.

primary term is positive, and the coefficient of the secondary term is negative, indicating that there is a significant inverted U-shaped relationship between the two, that is, with the deepening of the development of artificial intelligence, the spatial spillover effect of regional CEI presents a feature of first rising and then declining. There may be the main reasons for this phenomenon, in the early, has been heavily promoted by the development of artificial intelligence the expansion of related industries, so as to make the regional carbon emissions intensity ascend, technological progress although produce certain economic benefits, but has paid a huge price, so as to make the development of regional carbon emissions intensity of artificial intelligence in terms of space to promote the role; With the continuous deepening and skilled application of artificial intelligence technology, the diffusion effect and demonstration effect become prominent, and the environmental cost between different regions is minimized or even improved by the benefits brought by AI technology. Thus, the development of AI inhibits the spillover of CEI in the region. In general, China's developed cities have entered the downward period of regional CEI caused by AI development, but most cities are still in the first half of the inverted "U" shaped curve and the AI development level is also low. Therefore, China's AI development level should be further deepened.

4.3. Robustness test

4.3.1. Marginal effect test

Considering the sustainability of the development of AI, this paper makes a benchmark regression on the development level of AI after two periods of lag (Yang and Lu, 2023). The results are shown in columns (1) to (2) of Table 5. There is no significant difference in absolute value and significance between lag regression result and benchmark regression result, which indicates that the conclusion of benchmark regression is robust and reliable.

4.3.2. Replace the explained variable

In order to avoid the deviation of the regression results caused by the measurement method of CEI mentioned above, and ensure the reliability of the benchmark regression results, the CEI is expressed by logarithm of the total carbon-emission of each province by referring to the practice of Xue et al. (2022). According to column (3) of Table 5, the estimated coefficient of AI changes from positive to negative at the level of 1% when the explained variables are replaced, which indicates that the impact of the development of AI on CEI has changed from promoting to restraining.

4.3.3. Replace regression method

In order to prevent the measurement error of regression methods, random effect maximum likelihood estimation (MLE) is used for re-regression. From the regression results, the estimation coefficient of AI and its quadratic term is still from positive to negative, and it is significant at the level of 1%. Compared with the benchmark regression result, only the size of the coefficient is slightly different.

4.3.4. Tail shrinking treatment

In order to eliminate the influence of extreme values, all variables were subjected to 1% tailing and then fixed effect regression was performed again. The positive and negative sign of AI (0.0938) and its quadratic term (−0.0321) did not change and was still significant at 1% level.

TABLE 3 Moran index.

co2		Year	rob	
Moran'I	p		Moran'I	p
0.052	0.010	2006	0.051	0.012
0.061	0.006	2007	0.058	0.007
0.083	0.001	2008	0.059	0.007
0.078	0.002	2009	0.049	0.012
0.079	0.001	2010	0.054	0.009
0.077	0.001	2011	0.068	0.003
0.085	0.001	2012	0.079	0.001
0.081	0.001	2013	0.023	0.049
0.080	0.001	2014	0.020	0.054
0.072	0.002	2015	0.021	0.051
0.075	0.002	2016	0.018	0.057
0.079	0.001	2017	0.020	0.051
0.078	0.001	2018	0.020	0.045
0.086	0.001	2019	0.022	0.038

TABLE 4 Regression of spatial Durbin model.

	(1)	(2)
rob	0.2175***	0.1579***
	(3.09)	(2.74)
rob^2	−0.012**	−0.0114**
	(−2.35)	(−2.54)
gdp	−0.0491***	−0.0403**
	(−2.73)	(−2.34)
urb	−4.2261***	−5.3138***
	(−3.40)	(−4.48)
indust	−0.7304	−0.7997
	(−0.89)	(−0.97)
open	−0.5794**	−0.8783***
	(−2.10)	(−3.21)
une	−0.1032	−0.1532*
	(−1.21)	(−1.88)
es	0.0542***	0.0403***
	(4.41)	(3.31)
$w \times rob$	0.5166***	0.3849*
	(2.70)	(1.93)
$w \times rob_2$	−0.0368**	−0.0709**
	(−2.38)	(−2.05)
ρ	0.01448*	0.8791***
	(1.66)	(3.66)
N	420	420
R^2	0.244	0.110

***, ** and * represent significant levels of 1%, 5% and 10% respectively.

4.3.5. Endogeneity

In the benchmark regression, variables affecting regional carbon emission intensity have been added to the model as much as possible, but omitted variables may still be unavoidable, resulting in endogeneity problems. Severe endogeneity will lead to biased and inconsistent estimated coefficients, so it is necessary to deal with the endogeneity problem that may exist in the benchmark regression results. Considering that the development of AI is sustainable, the application level of artificial intelligence in the previous period will have an impact on the current period, but will not have an impact on the disturbance term, so the lag phase of AI is taken as an instrumental variable in this paper. The specific methods of endogeneity test are as follows: first, instrumental variables are added to carry out two-stage least squares (2SLS) regression; The results of the Hausman test rejected the null hypothesis of "all explanatory variables are endogenous" at the significance level of 1%, indicating that the core explanatory variable artificial intelligence has endogeneity and meets the prerequisite of using the least squares method (2SLS). Third, the validity of instrumental variables is tested. The results show that the null hypothesis of "weak instrumental variables" is strongly rejected. According to the endogeneity test results in column (6) of Table 5, which takes the lag of one stage of artificial intelligence as an instrumental variable, the sign and significance level of the estimated coefficients between the regression results of the instrumental variable and the benchmark regression results have not changed, indicating that the benchmark regression results have strong robustness.

4.4. Heterogeneity analysis

China has the problem of unbalanced regional development during a long time. Although all regions attach great importance to the development of digital technology, there are still great differences in the development level of AI among different regions due to factors such as factor endowment, location factors and development foundation, which will cause regional heterogeneity of the impact of AI on regional carbon-emission. According to Table 6, this differential effect does exist, that is, in the eastern region, AI promotes and then suppresses the CEI, followed by the western region, but has no obvious effect in the central region. This situation can be considered from the following aspects: first, as the most developed region of China's economy, various emerging technologies and products originate and spread here, with strong inclusiveness, high level of regional openness, government services and supervision, far ahead of the development and application of AI. Therefore, AI has the most significant effect on carbon reduction in eastern China. Second, in recent years, although the central region has a high latecomer potential, policy support and continuous transformation and upgrading of industrial structure have laid a solid foundation in the central region, the digital elements siphon seriously among the central regions, and a large number of manufacturing industries are still dominant, and the CEI is still large. Third, the western region is remote and sparsely populated. For many years, affected by geographical factors, industrial upgrading has not achieved significant results. However, AI has a great penetration in the region by virtue of its digital network foundation, and has a greater role in promoting the regional industrial upgrading, which makes the

TABLE 5 Results of robustness test.

	(1)	(2)	(3)	(4)	(5)
rob	0.1847***	0.1112**	0.00057***	0.0057***	0.0928***
	(3.08)	(2.40)	(4.92)	(4.92)	(3.05)
rob^2	−0.0073*	−0.0021**	−0.0841***	−0.0835***	−0.0321***
	(−1.93)	(2.39)	(−5.79)	(−5.81)	(3.75)
gdp	−1.5233***	−1.2873***	−0.2706***	0.0013	−1.6246***
	(−11.00)	(−10.19)	(6.65)	(0.07)	(−12.30)
urb	−1.7916*	−2.1238**	1.20002***	−12.4453***	−0.7129
	(−1.65)	(−2.21)	(3.59)	(−14.10)	(−0.66)
indust	0.7614	0.1334	0.6665***	−1.2112	0.8594
	(1.30)	(0.27)	(3.81)	(−1.59)	(1.51)
open	−0.5254**	−0.4349*	−0.0509	0.8824***	−0.678***
	(−2.15)	(−1.89)	(−0.70)	(3.29)	(−2.79)
une	−0.1409*	−0.057	−0.0199	0.1659*	−0.1327*
	(−1.93)	(−0.92)	(−0.87)	(1.86)	(−1.75)
es	0.0305***	0.0273***	0.0153***	0.0511***	0.0471***
	(3.37)	(3.66)	(5.17)	(4.03)	(4.48)
N	390	360	420	420	420
R^2	0.764	0.767	0.695	—	0.778

***, ** and * represent significant levels of 1%, 5% and 10% respectively.

carbon-emission reduction of human intelligence achieve certain results.

5. Conclusion and countermeasures

5.1. Conclusion

Under the background of AI and carbon-emission in China, based on the benchmark of the impact and the panel data from 2006 to 2019, this paper analyzes the effect and mechanism of AI on CEI. Dynamic and marginal effect analysis, substitution variable, and regression method were used to test the robustness. The results show that: (1) there is a significant inverted U-shaped between AI and CEI, that is, with the deepening of the development of AI, CEI first increases and then decreases. (2) There is a significant spatial correlation between the development of AI and CEI in China. (3) AI has a significant spatial spillover effect on CEI of adjacent regions, and it shows an inverted U-shaped track—from promoting to restraining. (4) There are significant regional differences in the impact of AI on CEI. This series of studies helps the government to formulate more targeted AI development policies in sub-regions and periods, and effectively promote the implementation of low-carbon emission reduction strategies. And studying the spatial spillover effect of AI on carbon emission intensity can help localities pay attention to the coordination of related policies and promote coordinated and sustainable regional development.

5.2. Policy implications

So far, the development of AI has penetrated into all aspects of social life. Intelligence in the field of economic life and industrial mechanization have become the main development direction in the future, and the new technology has played a significant role in energy utilization. Based on the empirical research results, this paper draws the following theoretical implications:

TABLE 6 Heterogeneity analysis.

	East	Central	West
rob	2.0669***	0.4059	0.0724*
	(2.94)	(1.12)	(1.69)
rob^2	−0.7755**	−0.0873	−0.0024***
	(−2.19)	(−0.80)	(−2.75)
gdp	−2.0949***	−2.0571***	−0.864***
	(−5.16)	(−5.77)	(−6.05)
urb	−5.1696	0.1991	−1.9834**
	(−1.40)	(0.06)	(−2.04)
indust	−0.8569	1.7687	1.8071**
	(−0.48)	(1.32)	(2.41)
open	−1.2993	5.3651***	−0.0057
	(−1.08)	(2.77)	(−0.03)
une	−0.6038***	−0.2681	0.1214
	(−2.80)	(−1.49)	(1.41)
es	0.0601***	0.0747***	0.027*
	(3.17)	(2.96)	(1.75)
N	168	126	126
R^2	0.800	0.773	0.802

***, ** and * represent significant levels of 1%, 5% and 10% respectively.

1. Strengthen the foundation of AI and improve the emission reduction effect of AI. Promote a new generation for information infrastructure, accelerate the realization of higher-quality interconnection. Provide solid information technology infrastructure support for the development of AI, release and enlarge the dividend of the machine age in a broader range, and combine with the governance mode to realize the coverage penetration of intelligent equipment and communication platform. So that can promote efficiency change and reduce the consumption of manufacturing resources (Zhang and Zhou, 2019).
2. Give full play to the carbon reduction effect of AI in China. In the early stage of the development of AI, the popularization is not only difficult to inhibit carbon-emission, but also may cause the intensity of carbon-emission to increase. Therefore, on the one hand, it is necessary to strengthen the research and development of key technologies of AI, especially in the field of green and low-carbon R&D, to promote the deep integration of AI and green low-carbon industry (Wang et al., 2021). On the other hand, we should improve the energy consumption assessment system of new infrastructure such as AI and digital center, carry out the evaluation and construction of green data center, strengthen the research and development of key technologies of zero-carbon data center, and optimize the energy efficiency scheme of low-carbon data center.
3. Break the space barrier, pay attention to the spillover effect of AI development. We should give full play to the structural optimization effect, technological innovation, and resource allocation of AI on social production and life, seize the positive spatial correlation, and reduce CEI.
4. We should face up to the differences in regional development and implement heterogeneous governance strategies (Zhuang, 2021). In the central region, we should accelerate the transformation of energy consumption structure. For the eastern region, AI should be used to carry out low-carbon, digital and intelligent transformation of modern industrial chain to improve the level of green industrial development. After crossing the turning point of carbon-emission reduction, the low-carbon technology should be combined with regional development. In the western region, it is necessary to maximize the use of AI to modernize traditional industries.

5.3. Deficiencies and prospects

This paper has the following shortcomings: ① Due to the lack of micro-enterprise level for AI application data, it is not able to comprehensively and multi-perspective study the impact of AI development on CEI; ② Due to the limitation of data availability and utilization, this paper only uses the data of provincial level in China for empirical analysis, and the research conclusion may have some limitations; ③ The influence of population aging, government behavior, and other variables on AI and carbon-emission behavior is not comprehensively considered. Therefore, in the future, both micro and international aspects should be taken into account to explore the carbon-emission reduction effect, and refine the combined research of energy structure and industrial structure.

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 were reviewed and approved by School of Investment and Construction Management, Dongbei University of Finance and Economics, School of Land Science and Technology, China University of Geosciences, and School of Business, Wenzhou University. The participants provided their written informed consent to participate in this study.

Author contributions

HD is responsible for the design of article research methods and writing. MD is responsible for article data analysis. XZ is responsible for data collation. YZ is responsible for completion of revision of the paper. All authors contributed to the article and approved the submitted version.

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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.

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Research on the path of practical cooperation between China and European Union countries under the environment of carbon neutrality and peak carbon dioxide emissions

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Globalization is increasing daily with the development of the world economy and society. International conflicts, cooperation, and interdependence in international environmental relations have become increasingly prominent, laying a theoretical and practical basis for international environmental cooperation. The ecological protection industries of China and the EU (European Union) are facing great development opportunities. Many EU member states have advantages in developing the environmental protection industry, which facilitates all-around cooperation in the environmental protection industry with my country. Based on the target policy background of PCDE (peak carbon dioxide emissions) and CN (carbon neutrality) and domestic and foreign research, this paper proposes a study on the practical cooperation path between China and EU countries. Based on international input–output data, an economic output CDE (carbon dioxide emission) matrix is constructed to characterize countries' economic and CDE correlation, thus forming a global CDE network. The analysis shows that the contribution rate of energy structure effect and energy intensity fluctuates slowly, indicating a positive and negative alternation; Our government should adopt an active energy optimization policy, speed up the formulation of macro policies such as carbon tax on energy-consuming industries, continuously optimize the energy structure and reduce the CDE intensity. By 2023, China's unit GDP will remain the same by 40–50% compared with 2022. Furthermore, the practical cooperation path proposed in this paper can provide valuable insights for policymakers and stakeholders in both China and the EU to promote the development of the environmental protection industry and achieve the common goal of carbon neutrality. The findings of this study can be used to inform the design and implementation of policies and initiatives aimed at reducing carbon emissions, improving energy efficiency, and promoting sustainable economic growth. Additionally, the international CDE network constructed in this study can serve as a useful tool for monitoring and evaluating the effectiveness of environmental policies and initiatives at the international level. Overall, this paper contributes to the scientific understanding of the complex relationship between economic development and environmental protection and provides practical guidance for promoting international cooperation in the environmental protection industry.

KEYWORDS

carbon neutrality, peak carbon dioxide emissions, carbon emissions, China, EU

1. Introduction

As the largest developing country in the world, climate change poses a severe threat to China's food security, water security, ecological security, energy security, infrastructure security, and people's lives and property security. CDE (carbon dioxide emission) involves all aspects of production and life of human economic activities, including production scale and population, energy structure, industrial structure, technical level, urban and rural structure, and consumption structure (Li et al., 2019, 2020). China's product exports depend heavily on the markets of developed countries such as the EU (European Union), with mechanical and electrical products, raw materials and textile products, miscellaneous products, base metals, and their products accounting for a relatively high proportion. CDE grows at the same time as the economic aggregate. China has become the largest CDE dioxide country in the world. Socialism with Chinese characteristics has entered a new era, and high-quality development has gradually become the main idea of China's development. Electricity sector emission reduction is the key driving factor of CDE decline in European and American countries. Its main driving force is that natural gas and renewable energy replace coal for power generation on a large scale. In this process, market behavior plays a significant role. Therefore, to solve the climate problem, on the one hand, international cooperation is needed. On the other hand, national interests should be considered, and appropriate adjustments should be made. If the actors (sovereign countries) only pursue their interests and do not consider the interests of other actors, competition will arise.

Global warming will not only destroy the whole natural ecosystem but also bring losses to other fields, such as the social economy. Some studies have explored the impact of renewable energy consumption on CDE in BRICS countries. However, the method has yet to fully consider the possible cross-section correlation and heterogeneity in panel data of BRICS countries (Montoya Lupita et al., 2017; Thapa et al., 2017). Because of the slow development of new energy in China, backward clean energy technology, and low energy utilization efficiency, it is particularly urgent to change the coal-dominated energy structure. The contradiction between the economy, energy demand, and environment is becoming increasingly severe, which has become a major issue in front of our country. As a regional international organization with the highest degree of integration in the world today, the EU is the top priority of China's environmental diplomacy (Konemann et al., 2017). In order to seek common interests, China and the EU have taken necessary joint actions and measures to solve environmental problems, and activities on which both sides have had an ordinary impact in the spirit of cooperation and achieved remarkable results. Despite the baptism of the financial crisis and the European debt crisis, the EU's economic foundation is still there, its economic vitality is still strong, investment opportunities and challenges coexist, and it still has a broad prospect of attracting foreign investment.

It must be recognized that PCDE (Peak Carbon Dioxide Emigration) and CN (carbon neutrality) can not only promote the transformation of China's economic structure but also trigger geopolitical changes, thus strengthening the game between big countries (Fernandez et al., 2018). The proposal of China's CN goal has released a positive signal that China will firmly follow the green and low-carbon development path and lead the global ecological civilization and beautiful world construction. Studying the path of pragmatic national cooperation will help us understand the achievements and problems of environmental cooperation between the two sides, find solutions, promote further cooperation between the two sides in the environmental field, and protect the earth on which human beings depend. At the same time, the research on this topic will enrich the theory of international environmental diplomacy and promote the development of this discipline.

2. Related work

2.1. Economic development and CDE-related research

Environmental Kuznets Curve (EKC) means an inverted U-shaped relationship between economic growth and CDE. In the initial stage of economic development, CDE increases with economic growth, but when economic development reaches a certain threshold, CDE is inversely proportional to economic development. Many scholars have tested the applicability of this theory in various countries. Qin et al. (2019) pointed out that the EKC hypothesis did not fully consider the two-way influence between economic growth and CDE and only included the one-way influence of economic development on CDE in the model, which led to endogenous problems in the model and used traditional Granger test to test the causality between economic development and CDE. Clarke et al. (2017) applied the global vector autoregressive method to incorporate the two-way relationship between economic growth and CDE into the model, focusing on the dynamic impact of China's economic growth on international CDE and major economies. Shi and Lee (2017) considered the transmission path of the dynamic relationship between economic growth and CDE under different openness. The results showed that expanding China's trade openness would increase its CDE, aligning with China's pollution paradise hypothesis (Shi and Lee, 2017).

McGrath and Liam (2017) comprehensively analyzed the characteristics of cargo arrival time, carbon dioxide emission, and line reconstruction ability. They set up an optimization model of long and significant cargo multimodal transport path expansion (McGrath and Liam, 2017) to minimize cost and CDE amount. Cosmas et al. (2019) explored the influence of four factors, such as energy consumption in BRICS countries, on CDE and found that increasing renewable energy consumption is conducive to carbon emission reduction (Cosmas et al., 2019). Naminse and Zhuang (2018) think that the service industry is immaterial and knowledge-intensive, so the shift of economic structure to the service industry is conducive to carbon emission reduction. Hao and Huang (2018) established multivariate economic growth models such as capital, labor, and energy consumption. They selected data on energy consumption and economic output to make a panel analysis of the relationship between energy consumption and economic growth in 16 Asian countries (Hao and Huang, 2018).

2.2. Research on panel data analysis method

The research on the impact of energy economic structure is mainly based on long-term and short-term panel data analysis, and the analysis of non-stationary panel data is more common. The appropriate panel data analysis methods are constantly developing and improving.

Takeuchi et al. (2021) think that due to some differences in economic data of different countries, heterogeneity should be fully considered in the research, and the panel method that allows heterogeneity to exist is used to explore the relationship among global energy consumption, economic growth, foreign direct investment, and financial development. Yu et al. (2018) used the traditional estimation method based on the assumption of cross-section independence, and the research results obtained will be biased.

Xiao-Jun et al. (2018) took the three factors of transportation cost, transportation time, and total CDE in transportation activities as the main influencing factors of multimodal transport route optimization. They established a Sino-European container multimodal transport route optimization model (Xiao-Jun et al., 2018). The manufacturing industry is divided into the low-carbon manufacturing industry and the high-carbon manufacturing industry. The research of Li and Bell (2017) shows that carbon leakage mainly occurs in the high-carbon manufacturing industry. At the same time, there is no carbon leakage problem in the manufacturing and low-carbon manufacturing industries (Li and Bell, 2017). Cheng et al. (2017) proposed a network optimization model of multimodal transport based on the principle of objective programming and can handle multi-objective and conflicting objective functions. Sensitivity analysis explores several non-dominant transport situations and analyzes potential competitiveness (Cheng et al., 2017). Qiu et al. (2017) think that if active measures such as industrial structure adjustment, technological progress, and emission reduction policies are taken simultaneously, the peak time can be advanced to 2026. Achieving carbon neutral requires a comprehensive understanding of the effect of different key factors on carbon emissions. To this end, this study investigates the effect of trade openness, human capital, renewable energy and natural resource rent on carbon emissions within the framework of the environmental Kuznets curve (EKC) hypothesis (Wang et al., 2023b). The traditional environmental Kuznets curve (EKC) hypothesis explains the inverted U-shaped relationship between the economy and the environment. This study expands the traditional EKC theory by adding social indicator, which also corresponds to the three aspects (social, economic, and environmental) required for sustainable development in 2030 (Wang et al., 2022). At the sub-regional level, trade openness favors carbon neutrality in rich countries, but not in poor countries. Thus, achieving carbon neutrality requires free trade, and fairer free trade needs to benefit countries of different income groups (Wang et al., 2023a).

3. Research method

3.1. Characteristic analysis of international CDE network

The realization of PCDE and CN is the inherent requirement of building a beautiful China where man and nature coexist harmoniously and promote high-quality development. It should be pushed forward unswervingly, but it is only possible to accomplish some of the work in one battle. It should be done simultaneously and steadily. The Paris Agreement will officially enter the implementation period after 2020, and the global green and low-carbon transformation will be significantly accelerated. The economic and social development and international trade and investment will undergo significant changes in the future, which is an improvement and a change. When the economic growth rate is moderately slowed, China will achieve the maximum CDE by 2035. After the realization of PCDE, China entered the CN period. At present, some domestic scholars have put forward suggestions on the realization path of CN from different angles, such as production mode and industrial sector, to help achieve the goal of CN as soon as possible.

However, the principles of common but differentiated responsibilities, fairness, and respective capabilities are the basic principles that global climate governance should follow. Due to the different industrial stages and division of labor, China exports many high-carbon products to the EU, leaving greenhouse gas and pollutant emissions at home, becoming a "pollution refuge" for developed countries. Even if the EU gives the default value of the carbon content of products, the differences in production processes and raw materials in different countries will make the default values different, which cannot cover the same kind of goods in all countries (Zheng et al., 2021). The EU still needs to clarify whether to consider the hidden carbon price brought by policies such as standards or regulations. Even considering the hidden carbon price, how quantifying the carbon emission reduction cost of such policies is a technical problem to be solved in the future.

China and the EU have gradually formed various cooperation mechanisms in continuous cooperation. All kinds of cooperation mechanisms have gradually played an enormous role in continuous improvement and have built a good cooperation platform between the two sides in the environmental field. In order to guide and coordinate the implementation of the cooperation plan, sum up the achievements, exchange experiences and adjust the plans and actions of the project in time, a steering committee of the China-EU cooperation plan on environmental management, jointly headed by the Ministry of Commerce and the European Mission in China, has been set up, which is of positive significance to the development of the plan.

When binarizing the international CDE matrix, the critical step is to select the threshold value, keep the carbon transfer links higher than the threshold value in the matrix, and remove the carbon transfer links lower than the threshold value. For example, with the increasingly close production relations and economic ties among countries, the network density reflecting the integrity of the international CDE matrix should gradually increase. The relative position of the matrix density each year will change slightly for different threshold values. In the binary international CDE network, enough connections are kept, and weak CDE connections are omitted, which is convenient for analyzing the prominent structural characteristics of the CDE network.

According to the CDE C_j, consumption standard quantity e_j and consumption structure proportion s_j of the j energy caused by fossil energy combustion, it is calculated as follows:

$$C_j = AD_j \times N_j. \tag{1}$$

$$e_j = AD_j \times P_j. \tag{2}$$

$$s_j = \frac{e_j}{\sum_j e_j}. \tag{3}$$

where: AD_j represents the physical quantity of the j -th energy consumption; N_j represents the CDE coefficient of the j th energy source; P_j is the discounted coal coefficient of the j energy source.

PCDE and CN goals effectively empower China's ecological civilization construction and comprehensively promote upgrading social cognition to a green and low-carbon perspective, reflecting the first enabling form of dual-carbon goals. At the same time, this development path harms the realization of PCDE and CN in China. Reducing pollution and improving environmental quality is one of the goals of PCDE and CN. Double carbon targets can effectively enhance the vitality of enterprises, enhance the technical level, and effectively promote the implementation of China's innovation-driven strategy. See Figure 1 for the internal logic of PCDE and CN, enabling high-quality development.

The innovation of CDE and CN is reflected in the following aspects:

(1) The introduction of dual carbon targets: The introduction of carbon peaking and carbon neutrality as targets for enterprise development was pioneered by China on a global scale. The achievement of this goal not only helps reduce greenhouse gas emissions and protect the global environment but also promotes the transformation and upgrading of enterprises to a green and low-carbon direction, enhancing their competitiveness and sustainable development.

(2) Comprehensively promote the upgrade of social cognition to a green and low-carbon perspective: The launch of CDE and CN is not only the goal of enterprise development but also a sign of upgrading social awareness. Through publicity and education, more people can be made aware of the importance of environmental protection and carbon emission reduction, thus forming a good atmosphere for the whole society to promote the construction of ecological civilization jointly.

(3) Promote the implementation of the innovation-driven strategy: Realizing the dual carbon goal requires enterprises to innovate, improve technology, and promote industrial upgrading continuously. This coincides with the innovation-driven strategy proposed by China, which can effectively promote the implementation of this strategy and the high-quality development of China's economy.

In conclusion, the innovation of CDE and CN lies in introducing the dual carbon target into enterprise development, promoting social cognition to upgrade to the green and low-carbon direction, facilitating the implementation of the innovation-driven strategy, and injecting new momentum into the construction of ecological civilization and sustainable economic development in China.

The application and diffusion of emission reduction and carbon control technology in China can also break the western technology blockade and achieve technological independence. At the same time, as a world economic power, the improvement of China's energy structure will help to improve the world's energy structure, gradually reduce the world's dependence on oil and gas resources, and promote the world's energy consumption revolution. The realization of PCDE and CN goals will help to show China's role as a big country, improve China's international status, strengthen China's right to speak in the international community, break the blockade of political, economic, and moral public opinion in western countries, and also help China's strategic communication with other economies, to truly achieve all-round and high-quality development based on the double-cycle new development pattern.

We can achieve high-quality energy development through energy conservation and efficiency improvement, energy structure optimization, and technological innovation (Xiao-Jun et al., 2018). Regarding import and export, China needs to work with other economies to maintain the ecological environment and promote the global development of low-carbon life. The country must formulate a strict import and export supervision system to ensure the low-carbon and environmental protection of imported and exported products. We can appropriately introduce high-end foreign talents to strengthen the innovation vitality, jointly devote ourselves to the research and development of low-carbon environmental protection technologies, promote the low-carbon development of the industrial chain, and lay a sound technical foundation for PCDE and CN.

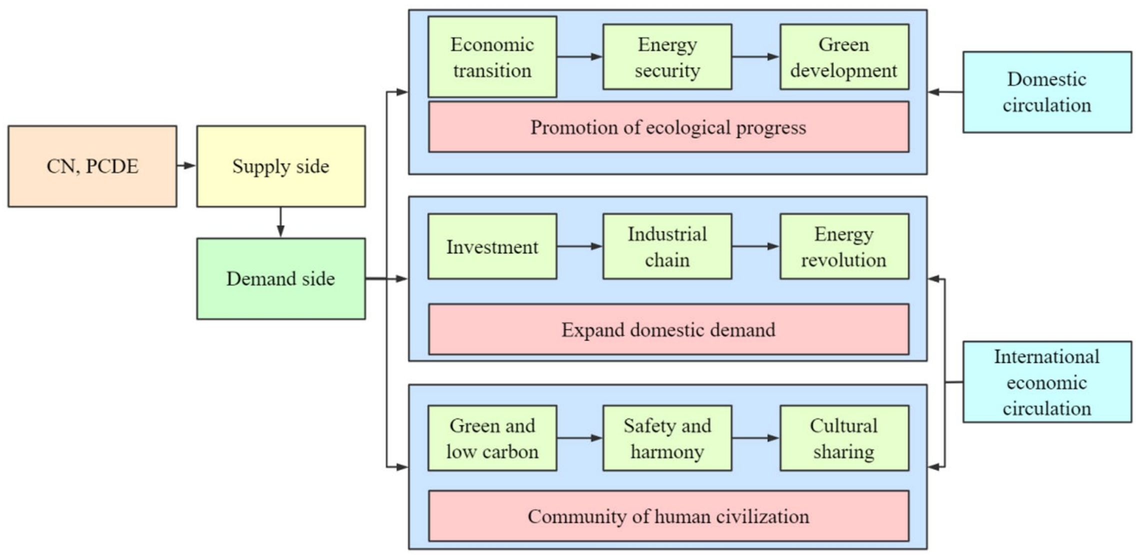

FIGURE 1
Peak carbon dioxide emissions (PCDE) and CN empower the internal logic of high-quality development.

Furthermore, product and energy service demand constraint means that for a given industrial product or transportation and construction service, the product of all equipment operation quantity and unit equipment product or service output quantity must be greater than or equal to the demand of the product or service, thus reflecting the actual process of fixed production according to demand. The expression is:

$$\sum_{d}^{D} OT_{i,d,j,t} \cdot OQ_{i,d,j,t} \cdot \left(1 - EFF_{i,d,j,t}\right) \geq DS_{i,j,t}. \tag{4}$$

Among them, $OT_{i,d,j,t}$ ——The unit output of equipment d in industry i producing products or energy services j in year t ;

$OQ_{i,d,j,t}$ ——Operation number of equipment d for producing products or energy services j in industry i in year t ;

$EFF_{i,d,j,t}$ ——The technological progress rate of equipment d in industry i producing products or energy services j in year t ;

$DS_{i,j,t}$ ——Total demand of products or energy services j of industry i in the t year.

Network density is an index that reflects the density of carbon transfer relationships among countries in the international CDE network, and reflects the overall characteristics of the network. The more relationships among countries in the CDE network, the greater the network density. It is defined as the ratio of the actual number of carbon connections between countries to the maximum number of carbon connections possible in the whole network. The network density D_{nt} of the international CDE matrix in the t year is:

$$D_{nt} = \frac{\sum_i \sum_j d_{ijt}}{n(n-1)}, 0 \leq D_{nt} \leq 1, i \neq j. \tag{5}$$

Among them, n is the number of countries in the international CDE network, $\sum_i \sum_j d_{ijt}$ is the actual number of carbon associations in the network in the t year, and $n(n-1)$ is the most possible number of carbon associations in the network.

From the perspective of cost–benefit, any calculation of carbon tax rate should be equal to the marginal loss of global warming, that is, at a certain point, the marginal loss is equal to the marginal control cost. In addition, if benefit evaluation is not pursued, the tax rate should be equal to the marginal control cost aiming at emission reduction.

Therefore, the carbon tax rate is calculated as follows:

$$C_e = \sum_{0}^{t} D_t (1+\lambda)^{-1}. \tag{6}$$

Formula C_e represents carbon tax; D_t represents the damage value in the t year caused by a ton of CDE, and λ represents the discount rate.

3.2. Carbon density and energy structure

It supports the national economy but is also the primary source of environmental pollution. The traditional industries with high pollution and energy consumption urgently need to adjust the industrial structure, reduce energy consumption and emissions, carry out cleaner production, and move towards the sunrise. Produce food beneficial to human health, and realize the sustainable development of agriculture to protect the soil structure and ecological balance. Consumers' awareness of health has increased, and they are willing to buy environmentally friendly products, such as fluorine-free refrigerators and phosphorus-free laundry detergent, especially children's products. The sales volume of green and pollution-free environmentally friendly products is better than that of ordinary children's products. Suppose our products want to enhance international competitiveness. In that case, we must take the development of the environmental protection industry as the premise, take environmental protection technology as the support, get rid of the traditional situation of high energy consumption, high emissions, high pollution, low labor cost, and export of primary products, and increase the export of green products and environmental protection products.

Establishing a long-term, stable, equal partnership between China and the EU is conducive to world peace and development. The development of China-EU environmental cooperation can complement each other's advantages, positively promoting the China-EU partnership. The scope of application has also expanded rapidly, from domestic environmental problems to global environmental problems. EU has rich experience in environmental tax, investment and financing, environmental funds, and ecological tax reform. Cleaner production has been mainly implemented by supply strategy in the world in the past 10 years. In recent years, the research on establishing a demand implementation model with the government as the propeller, enterprises as the main body, and the market as the guide has been intensified. The cooperation between China and Europe in the environment and sustainable development field will be further developed, and win-win results will be achieved. The prospect of cooperation is comprehensive.

Carbon density is the ratio of carbon dioxide emissions to energy consumption. Therefore, carbon density can reflect the energy consumption structure of the industry. Because different energy sources release different carbon dioxide while providing energy, on the one hand, the demand for rising energy prices will decrease correspondingly, and the prices of energy-intensive products will rise correspondingly, and the energy intensity will decrease accordingly. On the other hand, energy becomes more expensive compared with other factors of production, and producers will choose to improve production technology to reduce energy consumption, leading to a decline in energy intensity. The fierce competition has also become the pressure of technological advancement of enterprises. Low-level expansion and other issues. These industries can make good profits only by relying on traditional technology. This caused a lack of motivation and motivation for technological advancement in enterprises during this period.

The circular economy is essentially an ecological economy, which is the concrete embodiment and realization way of the concept of sustainable development. It requires following ecological and economic laws, rationalizing natural resources and environmental capacity, and developing the economy on the principle of "reduction, reuse and recycling." Developing a low-carbon economy will vigorously promote the development of low-carbon energy. Modern transportation fuels such as gasoline and diesel and crucial primary chemical products such as olefins and aromatics all use petroleum as their primary raw materials. The dependence of human economic activities on petroleum has formed the so-called petroleum economic model. The framework of the low-carbon economic development model is shown in Figure 2.

Reconstruct the economic system according to the law of material circulation and energy flow in the natural ecosystem so that the economic system can be harmoniously incorporated into the material circulation process of the natural ecosystem and realize the colocalization of economic activities to establish an ecological socio-economic system in harmony with the structure and function of the ecological environment system. This spiral structure contains four spirochetes, namely financial institution spirochetes, government spirochetes, scientific research institutions spirochetes, and enterprise spirochetes. The common interests of these spirochetes can promote the improvement of the carbon financial system, realize the "linkage effect" between carbon finance and a low-carbon economy, and then promote the development of the low-carbon economy.

In this paper, based on EKC theory modeling, in order to ensure the robustness of the estimation results, the *per capita* GDP and its square term are selected as independent variables and CDE as dependent variables, and the basic model is established as shown in formula (7):

$$\ln\left(TC_{it}\right) = a_0 + a_1 \ln\left(GDP_{it}\right) + a_2\left[\ln\left(GDP_{it}\right)\right]^2 + \varepsilon_{it}. \quad (7)$$

where i represents EU countries, and t represents the number of years included in the sample interval. $\ln(TC), \ln(GDP)$ measure CDE and economic growth, respectively. a_0 is a constant term, a_1, a_2 is the regression coefficient of $\ln(GDP)$ and its square term respectively, and ε_{it} is a random error term.

China's energy intensity, the amount of energy consumed per unit GDP, is decreasing, but there is still a big gap with the world average. Given China's current economic development and energy consumption, the situation of energy conservation and emission reduction in China could be more optimistic. It is necessary to mobilize the whole society to make joint efforts. Kaya identity is widely used in the research of CDE, and it is a well-recognized and commonly used method in current academic circles. Kaya identity decomposes CDE quantity into various driving factors, which can be expressed explicitly as:

$$CO_2 = \frac{CO_2}{EN} \times \frac{EN}{GDP} \times \frac{GDP}{POP} \times POP = C \times E \times P. \quad (8)$$

CO_2 represents CDE, EN represents primary energy consumption, GDP represents gross domestic product, and POP represents the total population in China. Correspondingly, C stands for "energy structure effect" and E stands for "energy intensity," that is, the amount of energy consumed per unit GDP; Y represents economic factors, and P represents population factors, that is, the total population.

In addition, this study defines φ_i as the total damage function of greenhouse gas emissions in country 1. The total greenhouse gas emission damage function of the importing country is the sum of the cross-border emission damage $m_{10}q_1$ caused by the exporter 1 and the cross-border emission damage $m_{20}q_2$ caused by the exporter 2, as shown in the following formula:

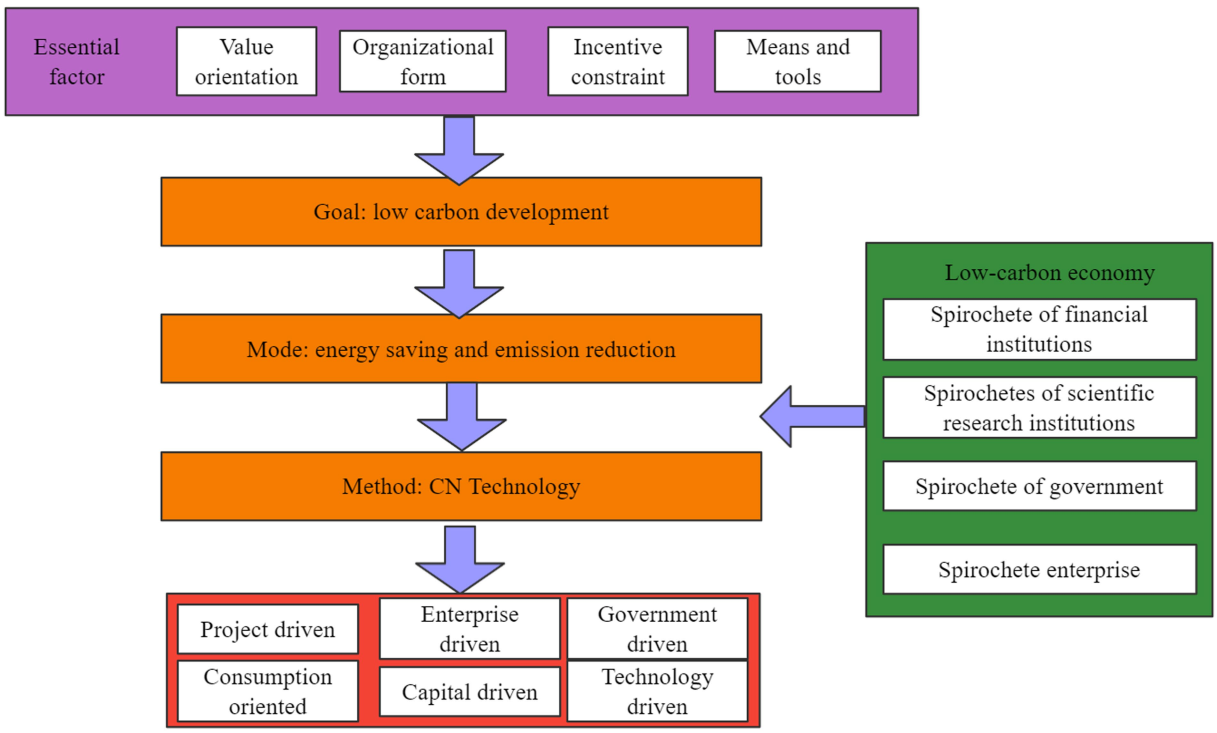

FIGURE 2
Low-carbon economic development model framework.

$$\varphi_0 = m_{10}q_1 + m_{20}q_2. \quad (9)$$

The total damage function of greenhouse gas emissions from exporting country 1 is the regional emission damage $m_{11}q_1$ from exporting country 1 and the transboundary emission damage $m_{21}q_2$ from exporting country 2 to exporting country 1, as shown in the following formula:

$$\varphi_0 = m_{11}q_1 + m_{21}q_2. \quad (10)$$

The above formula shows that the optimal tariff rate levied by the importing country on the two exporters is positive, because the importing country guides the two exporters to tax the transboundary emissions emitted by the importing country. It also means that the effect of increasing tariff revenue and reducing environmental greenhouse gas emission damage is greater than that of decreasing consumer surplus. Therefore, the importing country guides two foreign exporters to levy import tariffs.

4. Result analysis

Energy intensity directly reflects the utilization rate of energy and the efficiency of production. Generally speaking, developed countries improve energy utilization and output through technological progress and innovation. The energy intensity is low; *Per capita* GDP reflects a country's average living standard and macroeconomic situation. On the one hand, the economy needs energy consumption to promote it; on the other hand, economic development drives technological innovation and progress, contributing to the research and development of clean energy and improving production technology. Especially with the acceleration of urbanization, the increase in urban population will increase CDE by increasing energy consumption.

In this paper, the data from 2000 to 2021 are selected and decomposed according to the formula, and each driving factor's contribution value and contribution rate to CDE variation are obtained. The calculation results are shown in Figures 3, 4.

As seen in Figure 3, in the past 20 years, economic factors have played a positive role in promoting the change of CDE, which is significantly greater than other factors. Population factors have also played a positive role in promoting the change of CDE. However, the effect is far less than that of economic factors and is balanced, with little change in value. Nevertheless, generally speaking, the energy structure effect plays a positive role, and energy intensity plays a role in reducing emissions. Economic prosperity needs to be driven by energy, and improving people's material living standards also increases the demand for energy consumption. Economic factors always positively impact the increase of CDE changes.

As can be seen from Figure 4, on the whole, the fluctuation of the driving contribution rate of energy structure effect and energy intensity to CDE change is relatively consistent, with a sizeable annual fluctuation, and the fluctuation tends to be stable since 2003. The energy structure effect and intensity both decrease and when the total amount of CDE increases, the energy structure effect, and energy intensity inhibit it. From 2001 to 2009, the contribution rate of energy structure effect and energy intensity fluctuated slowly, showing a

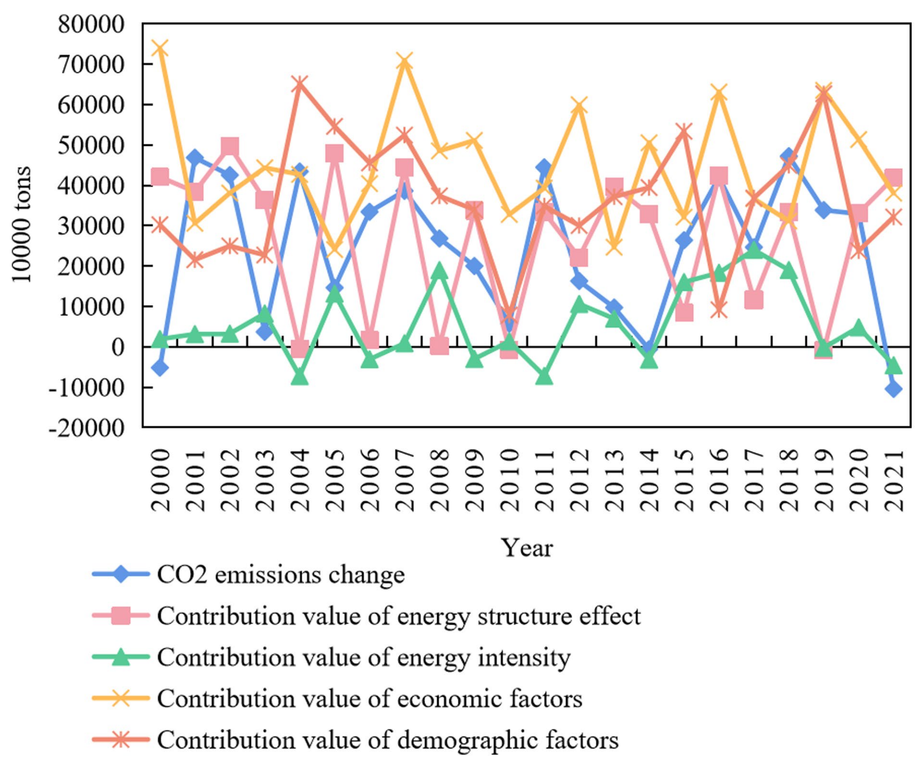

FIGURE 3
Carbon dioxide emission (CDE) driver decomposition results.

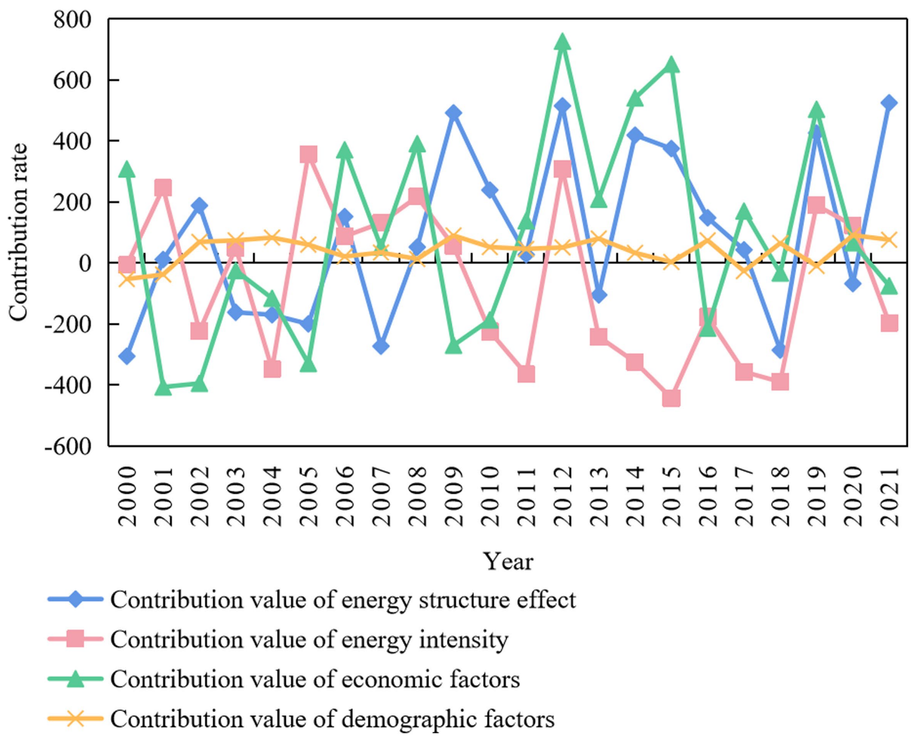

FIGURE 4
Contribution rate of CDE change.

TABLE 1 Annual GDP growth forecast.

Stage	Low speed	Intermediate speed	High-speed
2021—2025	3.74	2.22	4.91
2026—2030	1.94	2.54	4.36
2031—2035	3.9	5.73	4.97
2036—2040	3.6	5.54	5.27
2041—2050	2.74	3.05	5.05
2051—2060	2.13	5.16	4.98

positive and negative alternation. The increase in CDE showed that the driving effect of these two factors on CDE also changed positively and negatively.

Economic factors, energy structure effect, and energy intensity have a changing trend of offsetting each other, especially in the year when the extreme value appears, so the contribution rate of economic factors, energy structure effect, and energy intensity always show a reverse changing law. Generally speaking, the positive driving effect of CDE change of population factor is small, and with the change of time, this positive driving effect is still weakening.

The factors and processes each industry considers in forecasting the demand for products or services are quite different. Therefore, here, only each industry's standard parameters of demand forecasting are explained. The future economic growth rate of China is shown in Table 1.

With the continuous development of the manufacturing industry, independent design, R&D capability, and manufacturing level have been continuously improved, and large quantities of high-quality products have been delivered to the retail industry, which improves the position of the global value chain. Retail products are more competitive in the international market. With the increase in the ratio of capital to labor remuneration, more capital is used in low-end links but not in high-end links, such as improving production efficiency and saving energy, which will still promote the growth of CDE. Therefore, at this stage, upgrading the technical level of the retail industry is only an attempt to improve the convenience of the retail industry. However, it cannot be matched with the energy conservation and emission reduction goal in a short time. To achieve the goal of energy conservation and emission reduction, the retail industry needs to adopt more sustainable practices. This can involve various measures, such as reducing packaging waste, promoting the use of reusable bags, and implementing energy-efficient lighting and heating systems in stores. Additionally, the retail industry can explore the use of eco-friendly materials and products in their operations, which can help reduce their overall carbon footprint (Yuan et al., 2022). However, these measures may require significant investments and changes in business practices, which may not be immediately feasible for all retailers. In this regard, government policies and incentives can play a crucial role in encouraging the adoption of sustainable practices in the retail industry. For example, tax incentives can be provided to retailers who adopt energy-efficient practices, and regulations can be implemented to encourage the use of sustainable materials and products (Li et al., 2022; Naqvi et al., 2022).

TABLE 2 Conversion coefficient of CDE quantity.

Energy category	CDE coefficient (kg/GJ)	Standard coal conversion coefficient	Calorific value (kj/kg)	Oxidation rate (%)
Coal	3	0.3	23,031	0.95
Petroleum	3	0.23	21,368	0.91
Natural gas	19	1.32	11,107	0.92
Petroleum products	13	0.48	5,081	0.92
Coke	15	1.34	10,472	0.97
Power	8	1.55	18,415	-
Fuel gas	8	1.17	4,950	0.95

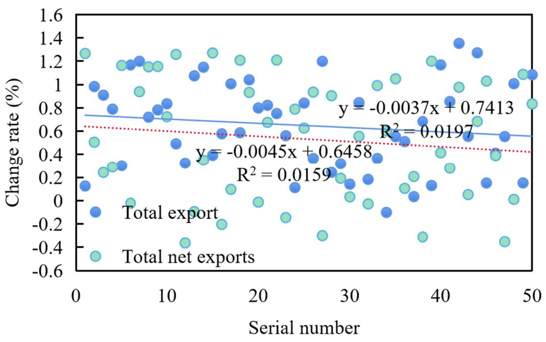

FIGURE 5
Changes of China's exports by industry under the carbon tariff rate of $100.

In the model, carbon tariff is the cost of export products and is included in the price of export products. This paper also assumes that the world price is constant and fixed, and individual countries will not affect it. When the world price is fixed, the increase in the cost of export means that some profits of products are obtained abroad. The calculation of the unit CDE quantity of a product needs to convert all kinds of energy necessary for the production of a product into standard coal consumption by converting it into standard coal coefficient and then calculate the CDE quantity in the production of a product by using calorific value, CDE, oxidation rate and other coefficients. Specific values are shown in Table 2.

The most direct impact of carbon tariffs is the restriction on export profits. Foreign countries have plundered many carbon tariffs from China's foreign trade by levying carbon tariffs. With the continuous improvement of carbon tariffs, foreign countries' total amount of carbon tariffs levied constantly increases. The profits lost in China's foreign trade will also be transferred like those of developed countries. As a result, China's exports have shrunk, resulting in huge losses.

After foreign countries' imposition of carbon tariffs, China's exports and trade surplus have been adversely affected. China's exports have been greatly affected by the continuous increase of carbon tariffs. This is because, after the reduction of export prices, the profit per unit product of China's exports has also decreased, resulting in the shrinking of exports. Then the sharp drop in total exports has led to the continuous decline of trade surplus.

Among the trade with EU countries, China's exports to the United States are most affected by carbon tariffs, with the most significant drop in export value. In contrast, its exports to other countries are less affected. The impact of carbon tariffs on China's exports of various industries is shown in Figure 5 below.

The results show that carbon tariff significantly influences China's exports, including the fuel processing industry; Coal mining and washing industry; Metal products industry; Printing industry, manufacturing of cultural and educational articles; Textile industry; Cement, lime, and gypsum manufacturing industries, etc. Therefore, our government should adopt active energy optimization policies, speed up the formulation of macro policies such as carbon tax on energy-consuming industries, continuously optimize energy structure and reduce CDE intensity.

In this paper, China's real GDP is positively impacted by a standard deviation, and the response function values of CDE quantity of four representative economies are obtained. The results are shown in Figure 6.

The impact of China's economic growth on some emerging economies in the EU also presents an inverted U-shaped trend. However, the impulse response function of the two countries is always greater than zero, which does not show the characteristics of positive and negative alternation of CDE growth. China's economic growth has achieved complementary advantages and positive interaction with the economical production of some emerging economies, prompting the increase of CDE.

In addition, due to China's economic growth, CDEs of nine representative economies have differences in response size and response time lag. The EU CDE impulse response function's fluctuation amplitude and response speed are the most prominent. China is at the middle level of the global value chain, while the EU is at the high end of the global value chain. The impact of China's economic output is conducted from bottom to top along the global value chain channel, resulting in apparent fluctuations of EU CDE.

According to the above settings for each factor, we predict the growth rate of each factor. From the predicted data, it can be seen that the change in carbon density in China by 2023 is not very obvious. However, the energy density change is significant, showing that China's technical level has improved. Figure 7 shows the CDE prediction results in four scenarios.

The analysis results predicted by Scenario 3 and Scenario 4 cannot reach the emission reduction target of 40% to −50% of China's unit GDP in 2023 compared with 2022. In the next 10 years, China will still be under heavy industrialization.

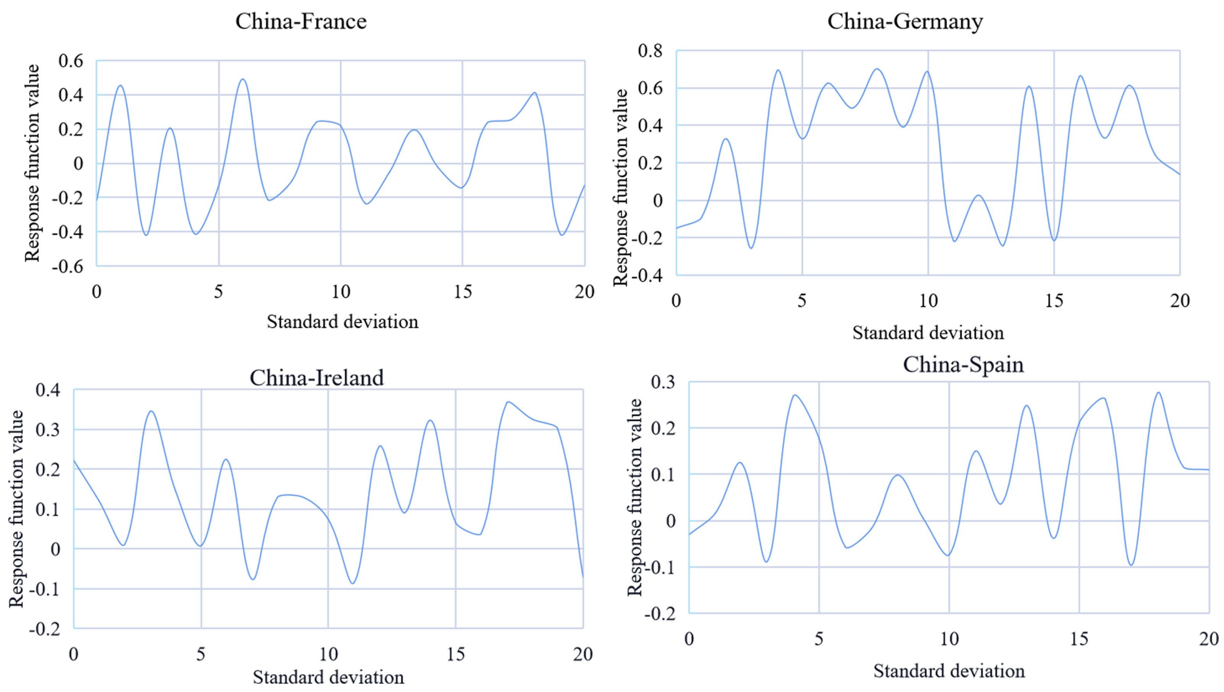

FIGURE 6
The influence of China's economic growth on CDE, a representative economy.

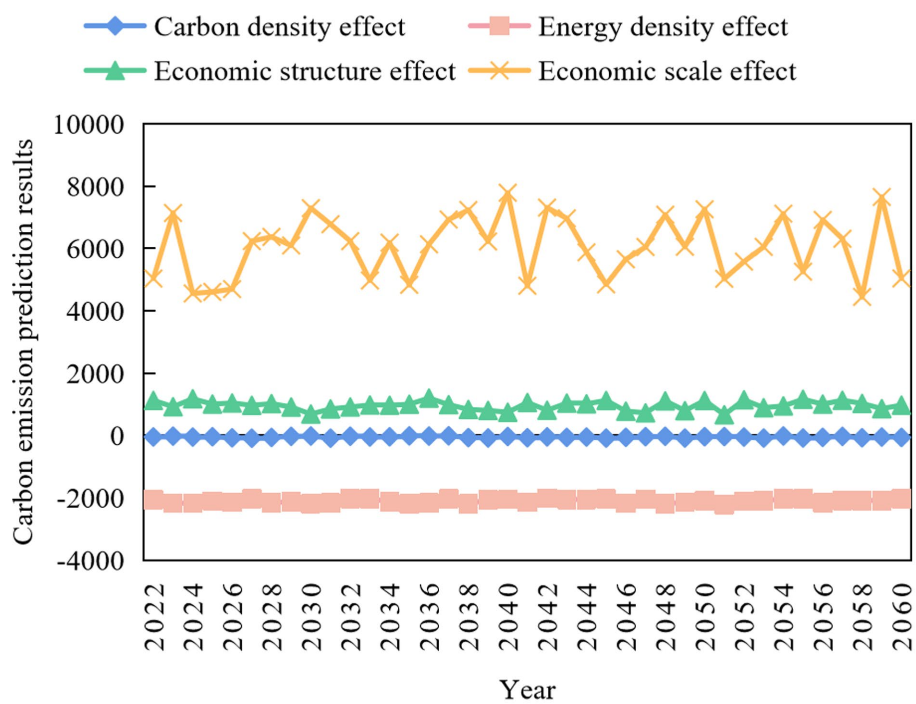

FIGURE 7
Carbon dioxide emission prediction results.

However, if the industrial sector develops at a growth rate of 7%, China will not be able to achieve the emission reduction target by 2023. It shows that China has dramatically improved its technical level and economic structure adjustment while developing its economy, which has played a role in curbing carbon dioxide emissions. However, the effect of carbon density is minimal, which shows that there is still much room for China to improve its energy structure.

5. Conclusion

Developing the environmental protection industry under the environment of PCDE is the general trend, and cooperation between China and the EU environmental protection industry is the inevitable choice. This paper concludes the pragmatic cooperation path between China and EU countries using relevant economic theory, EKC theory, and Kaya model analysis. After research, the specific conclusions of this paper are as follows: Economic factors always have a positive impact on the increase of CDE changes. The positive driving effect of CDE change of population factor is small, and with the change of time, this positive driving effect is still weakening. Among the trade with EU countries, China's exports to the United States are most affected by carbon tariffs, with the most significant drop in export value. In contrast, its exports to other countries are less affected. The predicted analysis results cannot reach the emission reduction target of a 40–50% reduction of China's unit GDP compared with 2022 by 2023.

The main contribution of this study is to propose a new pathway for achieving dual carbon goals-CDE and CN goals, which has achieved effective promotion in the construction of ecological civilization in China. Our findings show that CDE and CN goals can effectively promote technological innovation and transformation and upgrading of enterprises and effectively promote the upgrading of social cognition to a green and low-carbon perspective. In addition, our study reveals the limitations of PCDE and CN realization in China, which is an essential guideline for future dual carbon goal realization.

Our findings have a solid practical and replication value. Our results can provide references and insights for other countries and regions to achieve the dual carbon goal. In addition, our findings also provide necessary theoretical and practical support for the construction of ecological civilization and green low-carbon transition in China.

Of course, our research results also have certain limitations. Our study only focuses on the situation in China, and further research may be needed for the practice in other countries and regions. In addition, our findings need further empirical studies to verify their effectiveness and feasibility.

Future research directions can be carried out in the following aspects: first, the paths and mechanisms for achieving the dual carbon targets can be further studied in depth to explore practice models that are more suitable for different countries and regions; second, the synergistic mechanisms for achieving the dual carbon targets can be explored from the perspectives of enterprises and governments to promote the green and low-carbon transition further; finally, the evaluation and monitoring of the achievement of the dual carbon targets can be strengthened to provide Finally, the assessment and monitoring of the triumph of double carbon targets can be supported to provide more scientific guidance for practice.

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

WC was responsible for designing the framework of the entire manuscript from topic selection to solution to experimental verification.

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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.

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Design of a low carbon economy model by carbon cycle optimization in supply chain

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Introduction: Concerning economic globalization, enterprises must work with the cooperative partner to obtain more profits and overall planning of the supply chain has become a new focus for enterprise development. This paper studies the joint emission reduction of the supply chain in green low-carbon economy development and achieve joint emission and economic cost reduction through the optimization of carbon emission and economic dispatch.

Methods: The paper firstly uses the multi-agent model to complete the fullcycle modeling of carbon emission and economic cost; Secondly, the simulated annealing-adaptive chaos-particle swarm optimization (SAACPSO) method is used to optimize various parameters in the model to achieve emission and cost reduction

Results: The results show that after the optimization, the economic cost is reduced by 0.07 and the carbon emission is also reduced by 0.16; Finally, the practical test of the model is conducted with the collected data from the local company. The results show that the multi-objective optimization model of a joint enterprise supply chain is significantly better than single optimization in terms of emission reduction.

Discussion: It provides new ideas for a green economy and technical support for the global planning of supply chain integration.

KEYWORDS

carbon emission reduction, supply chain carbon optimization, economy dispatch, PSO optimization, economic development

1. Introduction

With the deterioration of the environment, the greenhouse effect has become an important issue that hinders sustainable economic development. Balancing economic development and environmental protection has become an important issue for all countries across the world (Golpîra and Javanmardan, 2022) "Carbon peaking" and "carbon neutrality" have emerged, and various countries have responded to develop low-carbon economies. At present, the main sources of carbon emissions are developing countries, which have a late start in carbon trading, backward industrial structure, and insufficient linkage between various links, resulting in more unnecessary carbon emissions in their trading process (Eslamipoor, 2023). Therefore, promoting research and development (R&D) in low carbon technology innovation in developing countries is vital to achieving a low carbon economy. While some new low-carbon emission reduction technologies require continuous large-scale investment, which leads to high costs. This requires the government to mobilize enterprises by providing them with subsidies for R&D and to guide their investment toward the optimal level that can be achieved. According to the experience of developed countries, government carbon subsidy policy has a great influence in promoting enterprises to conduct R&D and promote emission reduction technologies (Chen et al., 2018).

In addition to strengthening government subsidies and supervision, enterprises should also fully combine their own characteristics to actively adjust their strategies to achieve low-carbon economic development. In today's globalized economy, the development of each enterprise does not rely on its own, but needs more cooperation through a large number of supply chain enterprises. How optimize each part of the supply chain to realize the maximum economy and minimum carbon emission simultaneously is the final goal (Tully and Winer, 2014). Each enterprise in the supply chain is interdependent. It is a chain structure that integrates business flow, logistics, capital flow, and information flow. It integrates procurement, manufacturing, and distribution, and creates value for the end customer. Therefore, it is essential to optimize each link in the supply chain through smarter means. With the continuous development of computer science, complete deductive reasoning of the carbon emission process through mathematical modeling has become possible (Heiskanen et al., 2010). Using artificial intelligence techniques to quantify the various links in the supply chain using supervised, semi-supervised and unsupervised learning (Fritzke, 1994; Le et al., 2013) methods to form intelligent models makes it possible to save energy and reduce emissions. In the economic scheduling process of low-carbon development of an enterprise's multiple supply chains, the overall process is shown in Figure 1, and it can be seen that the process can be abstracted as a regression problem based on multi-source data fusion, with the ultimate purpose of achieving low-cost while minimizing carbon emissions. Therefore, supervised learning using a large amount of historical data to achieve an artificial intelligence-based (AI) classification model is a key to solving this kind of problem, which is also the current development trend of the smart economy and green economy. The optimization of model parameters by meta-heuristic algorithm after the model is built is the key to further improving the model performance and generalization.

The external factors mainly considered in the modeling process include the policies of relevant government subsidies and department regulations. Internal factors mainly include supply chain deployment, including personnel deployment and product transportation. Efficient economic dispatch and low-carbon development can be achieved through joint analysis of internal and external factors (Rezaee et al., 2017). There are many factors involved in the establishment of the model. How to quantify these contents and determine the optimization of its internal parameters to achieve an efficient allocation of each link is the focus of research on the establishment of a low-carbon economy smart model.

Therefore, this paper investigates the cooperation strategy and economic scheduling model of supply chain enterprises. After completing the modeling of enterprise economic scheduling and carbon emission by the multi-agent method, the model optimization is completed by meta-heuristic algorithm to improve the enterprise supply chain management and achieve the win-win situation of reducing carbon emission and lowering economic cost. The specific contributions of this paper can be concluded as follows.

(1) In this paper, the multi-agent method is used to improve the traditional carbon emission model to achieve the establishment of the model with the optimization goal of enterprise carbon emissions and economic scheduling.
(2) The optimization of model parameters was achieved based on the SA-ACPSO method, and results showed that the model performance was substantially optimized.
(3) After the optimization of the model, a practical test was also conducted, and the results showed that the model can optimize the carbon emission and economic scheduling of the operation of the enterprise, to reduce the operating cost and reduce carbon emission at the same time. Results showed that the economic operating cost was reduced by 0.07 and carbon emission was reduced by 0.16 after the optimization.

The remainder of the investigation is organized as follows. In section 2, the related works for the carbon emission reduction and model construction methods are introduced, section 3 introduces the methods used, section 4 describes the experiment and result analysis of model optimization, where the model application is also discussed. In section 5, we discuss the result and the notice that should be paid in the enterprise development and carbon concerning the supply chain.

2. Related works

2.1. Research on carbon cooperative emission reduction

Concerning low carbon economy, it is vital to ensure the low carbon emission of the supply chain for its future market development and supply chain green schedule. However, low carbon scheduling is not easily achieved by itself and requires the cooperative efforts of several enterprises and sectors. Ji et al. (2017) studied the online to offline (O2O) supply chain in a low-carbon environment and found that the government is the key. Liu et al. (2021) explored the possibility of cooperative emission reduction in agricultural supply chains through game theory and found that the environment can be protected when a centralized supply chain is established. Li et al. (2021) investigated the joint emission reduction problem of government

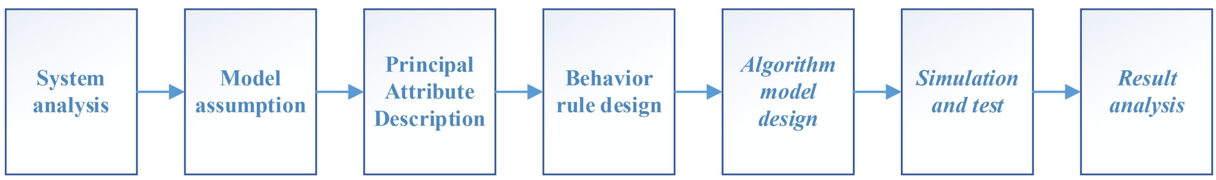

FIGURE 1
The framework for the construction of the economic dispatch model.

subsidies and supply chains under the cap-and-trade mechanism. Three mathematical models considering green technology investment and two types of subsidies were developed. It was found that government subsidies do not guarantee the total amount of carbon emission reduction by firms. Compared to subsidies based on the cost of green investments, subsidies based on emission reductions have greater emission reductions, but also larger total carbon emissions. Fang et al. (2012) compared the effects of two types of emission reduction subsidies, product innovation subsidies, and R&D subsidies, on the profits and social welfare levels of supply chain firms. Product innovation subsidies were found to be more likely to motivate firms to invest in R&D and enhance total social welfare. Both government subsidies are found to lead to supply chain coordination, especially for low-carbon technology subsidy policies. Peng et al. (2018) investigated the impact of cap-and-trade policies on supplier and manufacturer supply chain systems. They considered the impact of uncertainty on manufacturers' production capacity to improve system performance. Sun et al. (2020) studied the transfer of carbon emissions between suppliers and manufacturers and considered the lag time of green technology and consumer green awareness. Chen et al. (2018) indigenized emission reduction subsidies into a research joint venture and derived an equilibrium strategy for the level of innovation effort and cost-sharing rate.

According to the above study, it is not difficult to find that in the current low carbon research of enterprises, from the supply chain of enterprises and market product sales, multi-faceted efforts to achieve carbon reduction and environmental protection in the whole cycle of enterprises is the current consensus reached by the academic and business sectors.

2.2. The research on the carbon reduction model and optimization

In the theoretical research, the scientists established the relevant theoretical model fundamentally by analyzing the low-carbon behavior of enterprises in an all-around way. Du et al. (2015) analyzed the possibility of coordination and cooperation between manufacturers and suppliers to reduce emissions under aggregate control and emissions trading policies. Huang et al. (2016) proposed a game model with multiple suppliers. They apply GA (generic algorithm) to maximize the profit of each party and minimize the manufacturer's carbon emissions. For the emission reduction strategy, by constructing a cooperative emission reduction revenue allocation scheme, Wang et al. (2019) gave the emission reduction revenue allocation coefficients and the initial revenue allocation matrix of each subject in the region to improve the cooperation of entities in emission reduction. In addition, the role of carbon cap-and-trade policies is also discussed. For more complex engineering problems, intuitive representation through multi-Agent modeling approaches has become a focus of current research. Multi-Agent approaches have a wide range of applications (Ajitha et al., 2009), which include the stock markets prediction and epidemics spread model, and the range can be expected from small model simulations to large decision support systems. Models are based on a set of idealized assumptions designed to capture the most salient features of the system (Musa et al., 2015). Also, methods based on multi-objective regression and parameter optimization have important applications in low carbon emission reduction models, and such problems are ultimately accomplished by multi-objective optimization regression using machine learning (Wang and Chen, 2020), deep learning (Lee and Shin, 2019) and statistical learning methods to form appropriate carbon cycle models and optimize their parameters have become the focus of research in such work. As a class of multi-objective regression problems, how to improve the parameter generalization and complete the corresponding parameter modification to enhance the model capability becomes the focus. In the current research on model parameter optimization, the use of metaheuristic algorithms, i.e., GA methods, PSO, and other methods have some advantages in the optimization of model parameters due to their simplicity and low computational load. Soumaya et al. (2021) collected the speech of Parkinson's patients, Alzheimer's disease, and depression patients by processing the speech signals into a dataset and optimized the important parameters of support vector machines using genetic algorithms with recognition accuracy 91.18%. Wang et al. (2022) used PSO to improve SVM (support vector machine) parameters based on grid search and K-fold crossover and did prediction on the heart disease standard dataset of UCI and got 84.04% accuracy. Through the above research, it can be found that for the emission reduction analysis based on supply chain scheduling, the optimization of the model is generally completed by considering environmental factors, supply chain factors, and the market behavior of related enterprises to achieve efficient economic scheduling and carbon emission reduction of the supply chain. The multi-agent method is used to realize the modeling of observable data, quantify, and confirm these parameters, and through an intelligent algorithm optimization model, transform it into a traditional multi-objective regression model for parameter optimization, to efficiently complete the win-win of enterprise economic scheduling and carbon emission reduction.

3. The economic dispatch model construction using the supply chain information

3.1. Multi-agent model establishment

The basic model used in the modeling process of this paper is based on the multi-agent supply chain enterprise carbon emission model, which is a system model that follows the multi-agent-based model framework shown in Figure 2 and is completed with improvements based on the existing standing model[1] (Cucuzzella, 2017). The SA-ACPSO method in Section 3.2 is used for optimization to complete the final use of the model. If building the model, the main factors concerned can be abstracted into two goals, namely, the lowest cost and the lowest carbon emissions. The objective function can be expressed as

$$F(t) = \min \sum_{t=1}^{T} \left(F_1(t) + F_2(t) + F_3(t) + F_4(t) \right) \tag{1}$$

1 https://github.com/LantaoYu/MARL-Papers

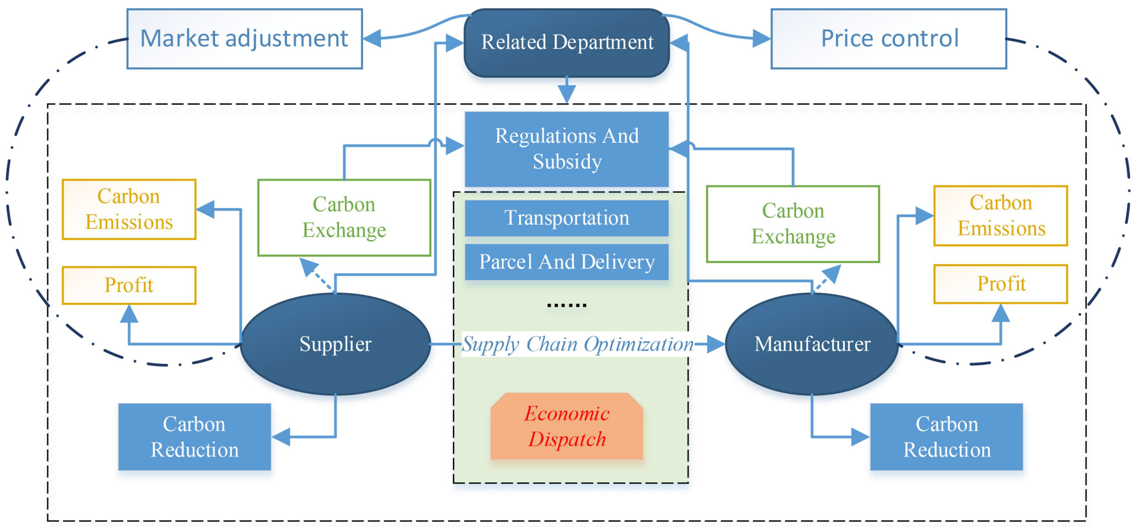

FIGURE 2
The dispatch in the low-carbon economy.

$$F_{EP}(t) = \min \sum_{i=1}^{r} \left(\sum_{k=1}^{M} C_k \left(\sum_{i=1}^{N} r_{ik} P_i(t) + ar_{grikl} Q_{buy}(t) \right) \right) \quad (2)$$

In the lowest cost objective function, there are four terms, which correspond to the transportation costs and production scheduling costs at the relevant suppliers and manufacturers in Figure 2, while the latter carbon emission function is a further refinement of the carbon emission-related coefficients, including factors such as fuel consumption in transportation and production carbon emissions. Taking F_2(t) in production scheduling as an example, it is calculated as shown in Eq. (3).

$$F_2(t) = \sum_{i=1}^{n} k_i P_i^t \quad (3)$$

where k indicates the specific link of the product in the supply chain, P indicates its corresponding equipment consumption parameters, and n is the total number of equipment links. Through intelligent scheduling, reducing carbon emissions and costs can be achieved, so the optimization of carbon emission function also considered the optimization of equipment consumption parameters. On this basis, the impact of environmental factors and policy-oriented factors on the model should be considered. It can be found that the established model has a large number of parameters and its own adjustment ability is not strong, so it is urgent to introduce intelligent optimization methods to complete the optimization of the model.

3.2. Model optimization using SA-ACPSO

Considering machine learning and deep learning, the model itself often falls into the problem of locally optimal solutions, which also occurs in multi-agent-based modeling. In the process of model building, if the initial values are not selected properly, the algorithm will converge to the local extremes, which greatly reduces the prediction performance of the model. The commonly used method for the model optimization is the meta-heuristic algorithm like the GA and PSO (Agushaka et al., 2022a). Some scientists proposed the new metaheuristic method based the classic ones (Agushaka et al., 2022b). The SA-ACPSO method is an improvement of the traditional PSO method, which is shown in algorithm 1 (Qian et al., 2009).

PSO algorithm
1. Coding and random particles generation
2. Fitness calculation of each particle
3. The particles replicate according to fitness
If the condition is met, it will be terminated. Otherwise, go back to step 2

The specific algorithm flow is shown below, first defining the number of particles in the particle swarm and their corresponding characteristic parameters.

$$P_j = \left[C_j \varepsilon_j \sigma_j \right] j = 1,2,..,Q \quad (4)$$

Performing random initialization of the particles after the definition is complete. Then let the particles be updated. Each particle in the kth iteration is defined by three characters (1) the position in the search space $P_j(k)$; (2) the best position during iterations 1 ~ k, $P_{jbest}(k)$; (3) the flight speed $V_j(k)$.

Furthermore, the global optimal position of the whole particle swarm is defined as $P_{jbest}(k)$, then each particle is iteratively updated during the flight as a function of the velocity V_j and the position P_j is defined. The process for the PSO update can be expressed as follows:

$$a(k) = (a_{\max} - a_{\min}) \left(\frac{k}{K} \right)^2 + a_{\min} \quad (5)$$

$$c_1(\mathrm{k}) = (C_{1\max} - C_{1\min})\left(\frac{k^2}{K}\right) + c_{1\min} \tag{6}$$

$$c_2(k) = (C_{2\min} - C_{2\max})\left(\frac{k^2}{K}\right) + c_{2\max} \tag{7}$$

$$v(k+1) = \alpha(k)v_j(k) + c_1(k)r_1\left[P_j(k) - P_{jbest}(k)\right] + c_2(k)r_2\left[P_j(k) - P_{gbest}(k)\right] \tag{8}$$

$$P_j(k+1) = P_j(k) + v_j(k+1) \tag{9}$$

where $\alpha(k)$ is the inertial variable, $c_1(k)$ and $c_2(k)$ are the acceleration factors representing the self-cognitive and social-cognitive parameters, respectively, r_1 and r_2 are the two random variables randomly distributed between 0 and 1, and K is the maximum iterations. It should be noticed that the speed and position of the particles are determined by the optimal position of the individual P_{jbest} and the global optimal position of the whole particle population P_{gbest}. To better increase the population diversity and improve the probability of the global solution can be achieved by introducing the simulated annealing operator SA, which can probabilistically avoid the local optimal solution and converge to the global optimal solution. In this paper, a chaos factor is added to the SA-ACPSO algorithm (Narayanan et al., 2020), which is calculated as shown in Eq. (10).

$$z_{n+1} = \mu z_n(1 - z_n), n = 0,1,2\ldots \tag{10}$$

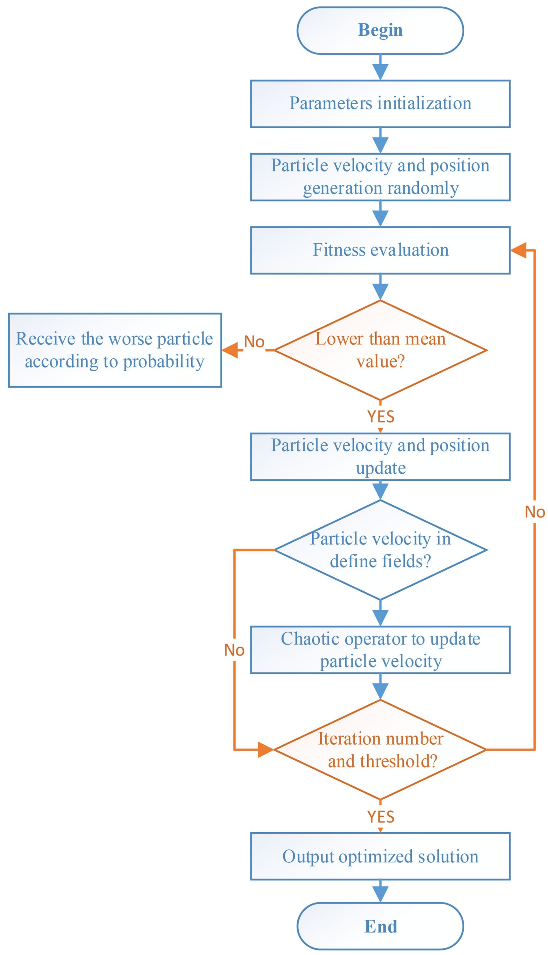

FIGURE 3
The flow chart of the model optimization using the SA-ACPSO.

The chaotic state regulation of the model is accomplished through the control variable μ. The chaotic algorithm is shown in the *Chaos Algorithm.*

Chaos algorithm
1. Select an initial value in the interval [0,1] and substitute it into the Eq. (10) for iteration
2. Generate chaotic random sequence $Z = a_1, a_2, a_3 \ldots$
3. Then, the optimization variable X is obtained by mapping $Z \to x : x = a + (b - a)$
4. $x \in [a,b]$

The overall process of model parameter optimization through the SA-ACPSO method is shown in Figure 3.

First, initialize the parameters, then randomly generate the particle velocity and position, and then evaluate the particle fitness. When the fitness is less than the average value of the objective function at the moment, update the particle position, otherwise record the individuals with poor fitness. After updating the particle speed and position, judge whether the particle is in the definition domain. If not, judge whether the maximum number of iterations is reached. If not, return to step 3. If the maximum number of iterations is reached, the output is the current optimal value.

4. Experiment and result analysis

4.1. The result of the economy dispatch and carbon reduction

According to the model described in section 3.1, the inputs and outputs are normalized according to the characteristics of the data at this stage when building the model in this paper. After completing the corresponding parameter optimization according to the existing low-carbon model, the effect of this paper is tested, and the results are shown in Figures 4, 5.

Figure 4 shows the economic cost effect before and after the optimization using the proposed optimization algorithm. The economic cost is reduced after the optimization of economic dispatch by this method, and the economic cost is reduced for each quarter. Similarly, for carbon emissions, after optimizing

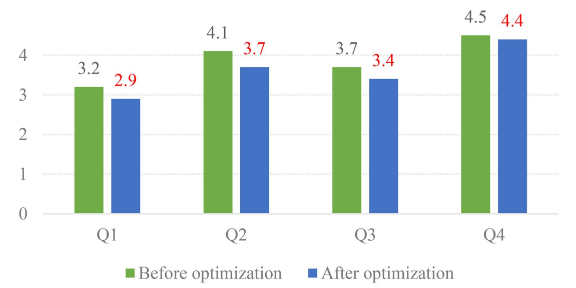

FIGURE 4
The economy cost effect before and after the model optimization.

TABLE 1 The economy cost and carbon reduction ratio.

Quarter	Economy cost reduction ratio	Carbon emissions reduction ratio
Q1	0.09	0.13
Q2	0.10	0.17
Q3	0.08	0.18
Q4	0.02	0.18

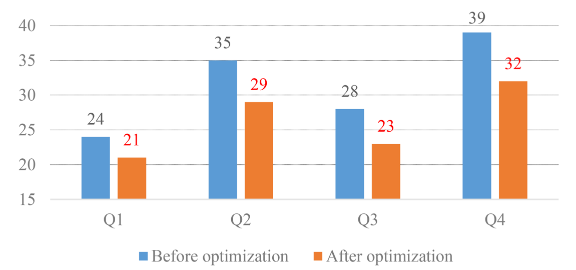

FIGURE 5
The carbon emissions before and after optimization.

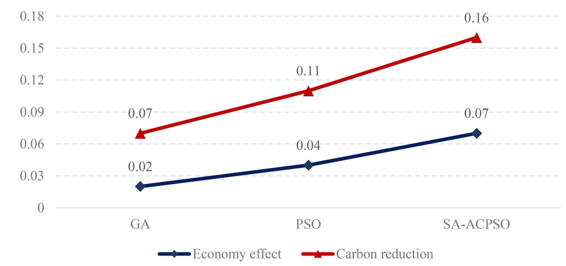

FIGURE 6
The economy effect and carbon reduction using different optimization methods.

the scheduling parameters, the results have achieved the expected effect and carbon emissions have been reduced to a certain extent.

As seen in Table 1, after the optimization of the model's scheduling, its carbon emissions and economic costs in each quarter show a trend of reduction. Amount of carbon emission reduction is more obvious, which provides a reference basis for the future green development of enterprises and their corresponding supply chain enterprises.

4.2. The comparison among different methods

To better illustrate the optimization effect, method comparison experiments were conducted in which a GA method of the same class as the PSO method was selected for comparison, the traditional PSO method without the addition of chaotic methods and annealing operators was tested, and the economic cost reduction rate and carbon emission reduction rate were compared, and the results are presented in Figure 6.

In this paper, the average reduction ratio is selected to illustrate the comparison process, i.e., the data from Q1-Q4 are averaged for comparison. The comparison results in Figure 6 show that the GA method performs an average in model optimization, while PSO is slightly better, but both are lower than the method proposed. It can also be seen that the optimization of carbon emissions is better than the optimization of economic costs for all types of methods. The problem of higher carbon emissions persists in the whole cycle of the supply chain, which needs to be further explored and illustrated in future research.

4.3. Model test and application

To test the effectiveness of the optimization model proposed, the test was conducted based on historical data of the relevant companies in the region and compared with their historical economic costs and carbon emissions, etc. The framework for the model test is shown in Figure 7.

The historical data are first inputted according to the model requirements, and the optimized model is used to optimize the economic dispatch and carbon emission reduction, and the obtained data are uploaded to the enterprise expert panel for evaluation, and the contemporaneous historical data are provided for reference. To illustrate the role of the proposed method more accurately in the joint emission reduction of enterprises, i.e., multi-objective cooperation and full-cycle optimization, we give the emission reduction effects of enterprises under different cooperation scenarios during the testing process as shown in Figure 8.

It can be found that the reduction effect is not obvious when they only reduce emissions individually, and although there is a certain reduction of carbon emissions in each quarter, it is not as good as the joint reduction effect. This is because after the optimization of model parameters, through the control and optimization of global variables, all industries form a unified whole in the whole cycle. The multi-directional scheduling of the upstream and downstream industrial supply chain has better fulfilled the

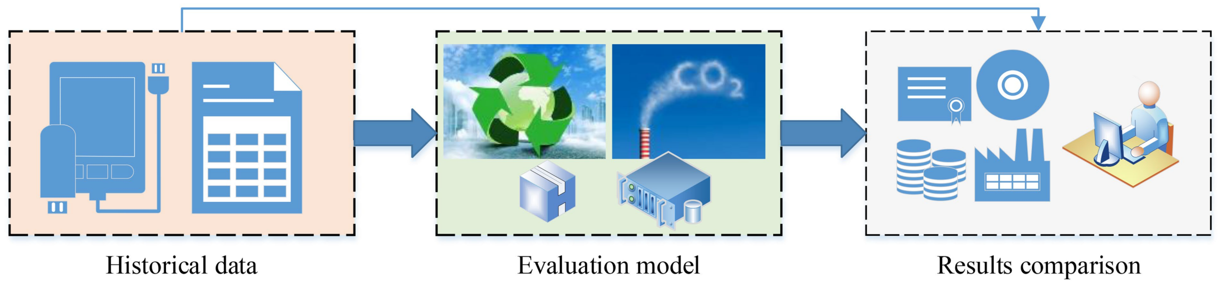

FIGURE 7
The framework for the economy dispatch application test.

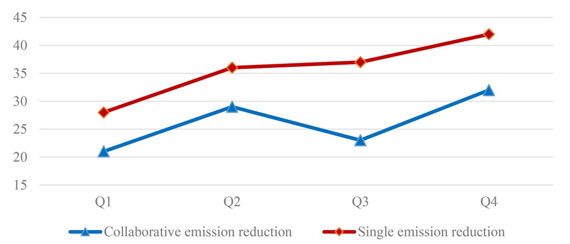

FIGURE 8
The carbon reduction in the different emission ways in the test data.

low-carbon emission target, providing a reference model for more enterprises' green development.

5. Discussion

5.1. Model performance analysis

At present, there are many factors involved in carbon emissions and enterprise supply chain scheduling. It is difficult to fully quantify them to achieve parameter optimization and complete strategy optimization through a neural network or machine learning. First of all, the influence factors of parameter selection on the enterprise are unknown (Dhiman and Kumar, 2017). On the other hand, because many parameters in the neural network are difficult to explain, it is difficult to apply them in practice. Therefore, this paper selects the multi-agent method, which is widely used in complex system modeling. To optimize the relationship between each link in the model promotion model, this paper uses the SA-ACPSO method to optimize accordingly. The SA-ACPSO algorithm mentioned in this paper combines the simulated annealing operator and the mixed pure perturbation based on PSO and makes particles increase their randomness and ergodicity through chaotic mapping, which can improve the ability of the algorithm itself to avoid local convergence, which is, improve the global convergence performance (Singamaneni et al., 2022). In order to better conform to and adapt to the characteristics of the multi-objective and multi-constraint of the economy scheduling problem, the inertia weight of particles will be adjusted before scheduling, which can enable the algorithm to expand the search scope at the initial stage. The optimization can also improve the accuracy of solution seeking at the later stage of solution seeking, optimize the solution seeking efficiency.

5.2. Inspiration from supply chain emission reduction

The industrialization has accelerated the pace of economic development, but it has also brought about an environmental crisis and resource shortage. To solve the "greenhouse effect" in the environmental crisis, a low-carbon economy is the best solution, in which the government plays an indispensable role and needs to actively guide enterprises to make energy-saving and sustainable development of the circular economy as the new development goal in the future (Chung et al., 2013). A low carbon economy can reduce carbon emissions to the lowest possible level or zero in production and life, and maximize ecological and economic benefits, which can be equated with the concept of Green (De Giovanni, 2014). The low-carbon supply chain advocates the concept of low or even zero emissions and promotes the green concept in the whole closed loop of raw material procurement-design-production-delivery-support of the company, to achieve the maximum sustainable development with the minimum environmental sacrifice (Ahmad et al., 2022). The internal and external influences of the supply chain jointly affect the emission reduction behavior of supply chain companies. For suppliers, regardless of the external environment, reducing the cost is a core, so it is necessary to make both or more parties reduce the cost of emission reduction through cooperation. For manufacturers, are more influenced by external factors (carbon regulation, market preferences for low carbon) and need to cooperate to reduce carbon abatement costs in addition to cooperating to better exploit carbon regulation and market preferences to avoid penalties. Under different scenarios, the choice of strategies will vary under different preferences of firms. When the market preference for low carbon is strong and government subsidies are strong, the abatement full cooperation strategy is optimal if firms focus more on low carbon, and the abatement technology and knowledge sharing strategy is optimal if firms focus more on profit. If the market's low carbon preference is general and the government's emission reduction subsidy is moderate, if the cooperation coefficient is found, the complete cooperation strategy for emission reduction is optimal. When the market is not low carbon biased and the government does not have low carbon subsidies, the emission reduction technology and knowledge-sharing strategy are optimal. Therefore, subsidies and policies of relevant government departments cannot fundamentally solve the problem of optimal scheduling and carbon emissions in all links of the supply chain, and enterprises need to be reformed from within by more intelligent means to achieve efficient operation.

6. Conclusion

As required by the low carbon economy development, we give an integrated method for the supply chain. This paper researches the problem of emission reduction optimization and efficient economic dispatch of enterprise supply chain in the context of low-carbon economy and proposes an SA-ACPSO method to optimize the model built based on multi-Agent method, which reduces carbon emissions by 0.16 and economic costs by 0.07, helping enterprises to reduce carbon emissions and corresponding operating costs. In the comparison of optimization methods, the SA-ACPSO method in this paper is significantly better than the GA method and single PSO method, which greatly improves the model performance. In the actual test, this paper analyzes the historical data of enterprises and finds that the joint emission reduction performance is significantly better after the integrated management of the supply chain. From the these results we can draw that the optimization for supply chain using the AI-based methods can greatly reduce the human work and improve the efficiency. The new ideas for the carbon-neutral can be got from the research,

However, the relationship considered in this study is relatively simple, and the competition relationship and environmental impact in supply chain enterprises is not considered, which often makes the model more complex and should be considered in the future. At the same time, it is the future research focus and direction to form corresponding model paradigms for specific industries to help them achieve win-win results in economic development and carbon emission reduction.

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

This study was approved by the Faculty of Business, Monash University. The participants provided written informed consent to participate in this study.

Author contributions

JD contribution lies in the writing of the first draft, data analysis and sorting experimental ideas and method design.

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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.

Publisher's note

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The influence of regional tourism economy development on carbon neutrality for environmental protection using improved recurrent neural network

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Introduction: The escalation of the global economy has contributed to the emergence of several environmental challenges, such as global warming and the gradual depletion of the natural environment, which has adversely impacted people's lives. In response, nations across the globe have embraced the carbon neutrality concept as a means to safeguard the environment and foster a green economy.

Methods: This study assesses the environmental impact of the tourism economy concerning carbon neutrality. Firstly, the quantification of carbon emission-related data in the region is executed using a hierarchical analysis method to pre-process the data for model training. Secondly, this paper utilizes the LTC-RNN (liquid time constant-recurrent neural network) model for model training. The model training is based on expert evaluation labels and cross-validation to execute comparison experiments.

Results: The evaluation results of the model with different training features are compared with the expert results, and the optimal model with 10 features is identified, achieving an accuracy of more than 85%. Finally, practical testing is conducted, and the outcomes indicate that the proposed method can accomplish the task efficiently.

Discussion: The proposed method provides technical support for the environmental evaluation of the green tourism economy in the context of carbon neutrality. It also presents novel ideas for accelerating the carbon neutrality agenda and fostering a low-carbon economy.

KEYWORDS

carbon neutrality, travelling economy, environmental evaluation, RNN, green development

1. Introduction

As human society advances, the relationship between nature and humankind has undergone a gradual transformation from the original compliance with nature to the present exploitation of it. While this alteration has facilitated a swift enhancement in both life quality and the economy, it has also led to environmental degradation and global warming, resulting in a set of fresh challenges. To combat climate change and strike a balance between economic development and environmental protection, the United Nations has issued a clear-cut verdict on the global

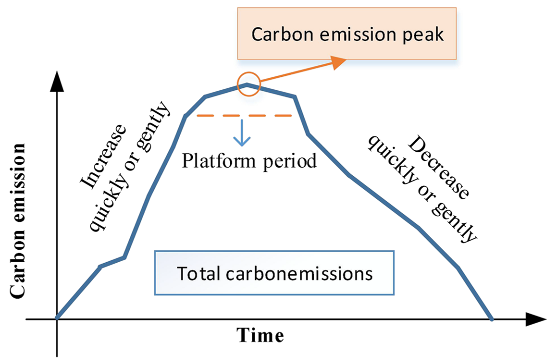

FIGURE 1
Process of the peak carbon dioxide emissions.

climate, urging each nation to actively promote energy conservation and emission reduction. Consequently, carbon peaking and carbon neutrality have emerged as the national strategies of most countries (Xiang et al., 2022). Carbon peaking and carbon neutrality are the two stages of carbon reduction targets, with the entire process outlined in Figure 1 (Becken et al., 2001). Carbon neutrality refers to the complete absorption and offsetting of carbon emissions. In most research studies related to carbon neutrality, the focus can be divided into the following three aspects: (1) exploring the carbon emission factors (Geidl et al., 2007; Basu et al., 2012); (2) identifying the path and methods to achieve carbon neutrality; (3) examining the challenges and opportunities for industry development in the future, including the power industry, transportation industry, construction industry, and coal industry (McKay et al., 1979; Chen et al., 2013).

The utilization of carbon peaking and carbon neutrality in diverse industries highlights the significance of green economic development, emphasizing the necessity of accomplishing sustainable development through technology and intelligent approaches, with energy conservation and emission reduction at the core (Ma et al., 2022). As the Covid-19 pandemic approaches a stable phase and draws to a close, the tourism industry is experiencing a resurgence, but this sector also contributes significantly to global carbon emissions. The objective of tourism development is to strive for low carbon and even carbon neutrality by minimizing carbon emissions and increasing carbon absorption. This objective serves as a fundamental principle for countries around the world that aim to develop their tourism economies and seek sustainable growth in the post-Covid19 era (Li et al., 2020). Figure 2 illustrates the carbon emission-related factors and relevant interventions associated with the tourism industry. The sole approach to enhance the carbon-neutral process of the tourism industry is to adopt intelligent means to assess pertinent factors, providing practical and objective data support for relevant measures. Thus, the most crucial task to achieve carbon neutrality and environmental protection in the tourism industry is to establish an intelligent regression model based on multiple factors.

As depicted in Figure 2, carbon emissions in the tourism industry are primarily categorized into four groups: transportation, accommodation, activities, and food. These categories entail several unknown factors that are difficult to assess by humans for environmental impact and carbon neutrality in the tourism economy process. Therefore, it is crucial to adopt more intelligent means to achieve assessments (Becken and Patterson, 2006). The carbon emission and environmental assessments illustrated in Figure 2 can be reduced to a multi-objective regression issue, which is an intelligent strategic decision. In the field of artificial intelligence, quantifying factors that belong to the multi-objective regression problem through environmental assessments and exploring intelligent evaluation and analysis based on multimodal and multidimensional data is gaining momentum with the continual development of machine learning and deep learning technologies (Perch-Nielsen et al., 2010). The employment of historical data to form supervised learning and complete artificial intelligence classification and assessments is vital to assess the tourism industry in the context of carbon neutrality.

The purpose of this paper is to investigate the importance of environmental assessment in achieving carbon neutrality in the regional tourism economy and to conduct regional environmental intelligent assessment based on multimodal data using deep learning technology. The goal is to provide detailed data for regional environmental monitoring and protection to accelerate carbon neutrality efficiency and offer new insights for carbon peaking and carbon neutrality demand. The paper's contributions are as follows:

1. Quantification of data according to carbon emission types from historical data of the tourism economy in the region, providing a data basis for subsequent model training and environmental assessment.
2. Optimization of the RNN model based on the LTC method to improve the accuracy of environmental assessment.
3. Completion of practical application tests using the established model, with results showing 85% accuracy when combining historical tourism data in the region for environmental assessment prediction, which is significantly better than the traditional RNN-based method.

The paper is organized as follows: Section 2 introduces related works in green travel economy research and environmental evaluation. Section 3 explains the establishment of the evaluation model, while Section 4 presents the experiment results and analysis, including the model application test. In Section 5, the results and implications for carbon neutralization are discussed. The paper concludes with a summary in the final section.

2. Related works

2.1. Carbon neutral related research in the tourism

In the examination of carbon emissions in the tourism economy, the central emphasis lies on the current carbon source system, carbon emission estimation system, and estimation quandaries. In order to progress subsequent policy research, promote the carbon-neutral process, and establish the intelligent environmental assessment model outlined in this paper, it is essential to undertake a more meticulous appraisal of emissions. At present, carbon emission evaluation

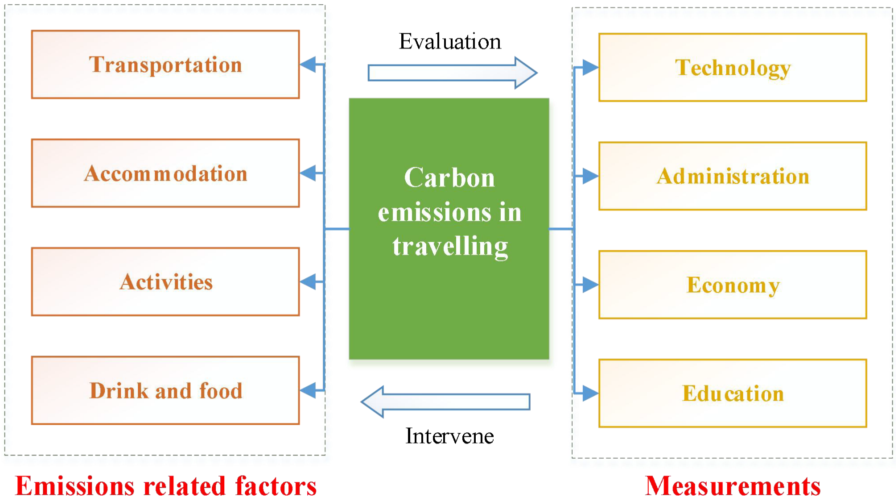

FIGURE 2
The carbon emissions in travelling.

TABLE 1 Index for the carbon emissions in different scales.

Scales	Index	Related research
Country	Traveling transportation, accommodation, and attraction. Drink and food, entertainment, museum, and sport	Becken and Patterson (2006) Perch-Nielsen et al. (2010) Dwyer et al. (2010)
Region	Transportation, warehousing and postal service, accommodation, and catering	Shi et al. (2010) Tao et al. (2014)
Tourist destination	Internal emissions of tourist destinations	Kelly and Williams (2007)

indicators are primarily separated into three levels, which are the national level and regional level. The exact emission indicators are illustrated in Table 1.

In the development of a nationwide carbon emission framework, Becken and Patterson (2006) categorized the tourism industry into three distinct domains: transportation, accommodation, and activities. Further subdivisions were made within each of the aforementioned sectors, culminating in the establishment of a comprehensive tourism energy carbon consumption system in New Zealand. Conversely, Perch-Nielsen et al. (2010) formulated a carbon emission standard for tourism in Switzerland by leveraging the country's tourism satellite accounts. In contrast, Dwyer et al. (2010) estimated carbon emissions and consumption by segregating the tourism industry into characteristic and related industries. Kelly and Williams (2007) investigated energy consumption systems in Canadian ski tourism regions and devised a framework to calculate carbon emissions in tourism destinations. Meanwhile, Shi et al. (2010) and Tao et al. (2014) scrutinized related industries within the tourism industry, such as catering and accommodation services, in their respective regions. Their detailed research on the construction of the carbon emission model of the tourism economy provides a theoretical basis for the creation of an intelligent evaluation model.

2.2. A multi-objective evaluation based on deep learning

The evaluation of the natural environment has traditionally been performed using GIS and other data. Remote sensing images are utilized to comprehensively analyze natural factors such as climate, land use, and cover (Quan and Bansal, 2021). Brezillon et al. (2006) contend that GIS visualization spatial information can be combined with other elements to evaluate natural resources and explicate ecological resource quality. However, in the context of a carbon-neutral tourism economy, it is challenging to employ GIS information directly for environmental assessment. Therefore, quantifying the carbon emissions related to the tourism industry based on the aforementioned sections to achieve multi-objective regression is the solution to this predicament. In recent years, with the proliferation of computer computing power, deep learning has gained widespread attention. Besides the conventional BP neural network, the radial basis function neural network, a widely used simple neural network, has been successfully applied in several research domains (Liu et al., 2019; Shi et al., 2022). Furthermore, when dataset dimensionality and breadth are sufficiently intricate, simple neural network models encounter various challenges, such as random initial weights resulting in the model falling into local solutions. Moreover, data sample size and dimensionality disparity lead to model overfitting. As a result, neural network optimization algorithms have emerged to address these issues, and they have become one of the research mainstreams (Huang and Lin, 2019; Li et al., 2019). In the study of multi-objective regression, RNN, LSTM, and related recurrent neural networks have been extensively investigated for power prediction (Kumar et al., 2022), traffic risk prediction (Guo et al., 2021), and financial investment risk assessment (Qu et al., 2019). Deep learning models, especially RNN network models, have demonstrated superior performance in prediction and evaluation problems after training with historical data. The diverse range of applications and data sources further highlight the generalization capability of deep neural network models.

Leveraging deep neural network models to process multi-objective and multi-source data, combined with numerical quantification methods, represents a crucial avenue toward achieving carbon neutrality. This approach facilitates the assessment of human carbon emissions in the tourism economy and enables the creation of a comprehensive index for environmental assessment. The RNN method, which possesses a certain degree of memory due to the weighting of previous output, is critical for environmental assessment of time-series data. Hence, in this paper, we select the RNN method and improve it for environmental assessment in the tourism economy.

3. Evaluation model establishment using improved RNN

3.1. RNN model

A simple RNN is shown in the left part of Figure 3. Compared with the traditional BP NN, the hidden layer has an extra recurrent part, and S in the hidden layer is determined by the input X and the last S. The W in the recurrent layer is the input weight, and by expanding it on the timeline, we can understand more clearly the input–output relationship at each time. The right part of Figure 3 shows that after the network receives the information xt at time *t*, the specific process for the information transmission can be abstracted as Eqs. (1) and (2).

$$O_t = g\left(V \cdot S_t\right) \quad (1)$$

$$S_t = f\left(U \cdot X_t + W \cdot S_{t-1}\right) \quad (2)$$

RNN and its enhanced models have the capacity for variable topology and full node weight sharing, and can effectively learn the intrinsic laws of nonlinear time series, thus enabling better prediction and regression analysis of future data. However, RNN exhibits slow convergence speed when dealing with large samples. To overcome this limitation, LSTM models have been proposed to enhance the memory capacity of RNN. However, LSTM has limited correction capability and may fall into the misconception of conditional extrema. To address these issues, Hasani et al. (2021) proposed an improved state equation for the hidden layer neurons in RNN, based on a numerical study of neural dynamics, and developed a liquid time constant neuron with a liquid time constant-recurrent neural network (LTC-RNN). The LTC-RNN has strong self-correction capability and the ability to find the global optimal solution.

3.2. LTC-RNN model

The neuronal membrane integrator is an important model for describing the membrane potential of neurons in the nervous system. The state of a postsynaptic neuron can be described by Eq.(3):

$$C_{\mathrm{m},i}\dot{x}_i = g_{\mathrm{leak},i}\left[x_{\mathrm{leak},i} - x_i\left(t\right)\right] + \sum_{j=1}^{n} I_{\mathrm{in}}^{(i,j)} \quad (3)$$

Where: $C_{\mathrm{m,i}}$, is the cell membrane capacitance i is the cell membrane capacitance; described by the sigmoid nonlinear function, i.e.

$$I_{\mathrm{in}}^{(i,j)} = w_{ij}\left[E_{ij} - x_i\left(t\right)\right] / \left\{1 + \mathrm{e}^{-\gamma_i\left[x_j(t)+\mu_i\right]}\right\} \quad (4)$$

In Eq. (4): γ_{ij} and $\propto_{\mathrm{ij}}$ are the parameters of the sigmoid function; $\mathrm{x_j}\left(\mathrm{t}\right)$ is the state of the presynaptic neuron; $\mathrm{x_i}\left(\mathrm{t}\right)$ represents the state of the postsynaptic neuron; $\mathrm{w_{ij}}$ denotes the state of the connecting neuron i and neuron j of the connected neuron and the neuron's weight.$\mathrm{E_{ij}}$. This determines the sign of the synapse $\mathrm{I_{in}^{(i,f)}}$is used to indicate whether the synapse is an excitatory or an inhibitory synapse. Substituting Eq. (4) into Eq. (3) yields the neuron i. The equation of state of the neuron is

$$\begin{aligned}\dot{x}_i = g_{\mathrm{leak},i}\left[x_{\mathrm{leak},i} - x_i\left(t\right)\right] / C_{\mathrm{m},i} + \\ w_{ij}\sigma_i\left(x_j\left(t\right)\right)\left[E_{ij} - x_i\left(t\right)\right] / C_{\mathrm{m},i}\end{aligned} \quad (5)$$

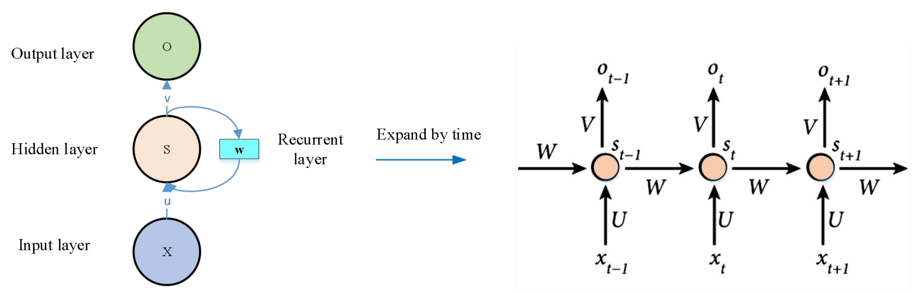

FIGURE 3
The structure of RNN.

where $\sigma(x_j(t))$, is the sigmoid function on $x_j(t)$ the sigmoid function, i.e.

$$\sigma(x_j(t)) = 1 / \left\{1 + e^{-\gamma_j [x_j(t) + \mu_\ell]}\right\} \tag{6}$$

On this basis, the state equation of the hidden layer neurons can be obtained as shown in Eq. (7).

$$\begin{aligned}\dot{x}_i = -\left[1/\tau_i + w_{ij}\sigma_i(x_j)/C_{m,i}\right]x_i + \\ x_{\text{leak},i}/\tau_i + w_{ij}\sigma_i(x_j)E_{ij}/C_{m,i}\end{aligned} \tag{7}$$

3.3. Training for LTC-RNN

The information necessitates quantification prior to training the LTC-RNN network. This paper achieves data quantification in accordance with the four constituent types featured in Figure 1, and the AHP method, combined with expert scoring, is employed in the quantification process. This method thoroughly considers the quantification and analysis process of the pertinent database.[1] To refine the training performance post-quantification and scoring, the data normalization method is utilized in this paper to execute the model training, and the normalization process is explicated in Equation (8).

$$X_{norm} = \frac{x - \bar{x}}{x_{\max} - x_{\min}} \tag{8}$$

Where x all denote the quantized values, and the markers therein denote the mean, the maximum and minimum value. After completing the data processing for model training, the specific process is shown in Figure 4.

To evaluate the accuracy, this paper forms model accuracy evaluation indexes based on the expert scoring prediction assessment results and the actual results whose calculation process is shown in Eq. (9)

$$M_{\text{acc}} = \left(1 - \sum_{m=1}^{M} \left|y - y_{\text{pre}}\right| / M\right) \tag{9}$$

4. Experiment result and analysis

4.1. The result for the environment evaluation

This paper emulates the data quantification and management methods utilized in the existing relevant environmental assessment (see Footnote 1) and risk assessment[2] studies, along with their respective databases, to finalize the data pre-processing. By quantifying four factors in the carbon emission process, a total of 15-dimensional quantitative data was acquired based on the recommendations of local experts. The model was then trained using ten-fold cross-validation, and the resulting credential recognition rate is depicted in Figure 5.

In Figure 5, the solid line is the accuracy distribution and dashed line represents the trend. It has been observed that the performance of the LTC-RNN model employed in this study is subject to significant variability when utilizing different features. Furthermore, the recognition accuracy of the model, which is indicative of its evaluative capability, displays an upward trend with increasing dimensionality of the data features, and reaches an optimal evaluation effect when the feature dimension is set to 10. To assess the performance of the LTC-RNN model, a 10-fold cross-validation model was chosen as the final model and subsequently compared to alternative models.

4.2. The comparison results of different methods

To assess the performance and underscore the superiority of the model, various relevant techniques have been compared in this study, including traditional RNN, LSTM, and PSO-RNN. Among the RNN category methods, the more popular LSTM approach was selected for comparison, which possesses a certain degree of memory but exhibits limited self-regulation capabilities. This issue is elaborated upon in the corresponding research section, specifically Section 2.2. PSO was employed to optimize the RNN, as it is advantageous and widely used in preventing the model from becoming trapped in initial extremes. Therefore, the model was chosen for comparison purposes to ensure its validation.

The evaluation results obtained through various methods are depicted in Figure 6, from which we observe that the traditional RNN method exhibits subpar evaluation outcomes. Although there is some improvement achieved via optimization through the PSO method, the improvement is not substantial. In contrast, LSTM evaluation yields better results, which may be attributed to the higher historical correlation of the data involved in this study, ultimately leading to enhanced performance. In contrast, the LTC-RNN method delivers the most optimal evaluation results, thanks to its superior adaptability. Subsequent to the evaluation, we conducted an in-depth data analysis and computed the contribution rates of different types of features, as illustrated in Figure 7.

The aforementioned chart highlights that, among numerous carbon emission factors, the most impactful is the transportation factor, followed by various activities during the travel process, which can be attributed to the noticeable carbon emissions produced during transportation. These associated activities are often instrumental in attracting tourists and demand considerable material and human resources. The high energy consumption required to host events in a brief time frame leads to elevated carbon emissions, resulting in its top-ranked status in the characteristic ranking. This information represents a crucial reference for future carbon-neutral research,

1 https://github.com/18177-RHS/TED21-Assessment

2 https://github.com/pharmaR/risk_assessment

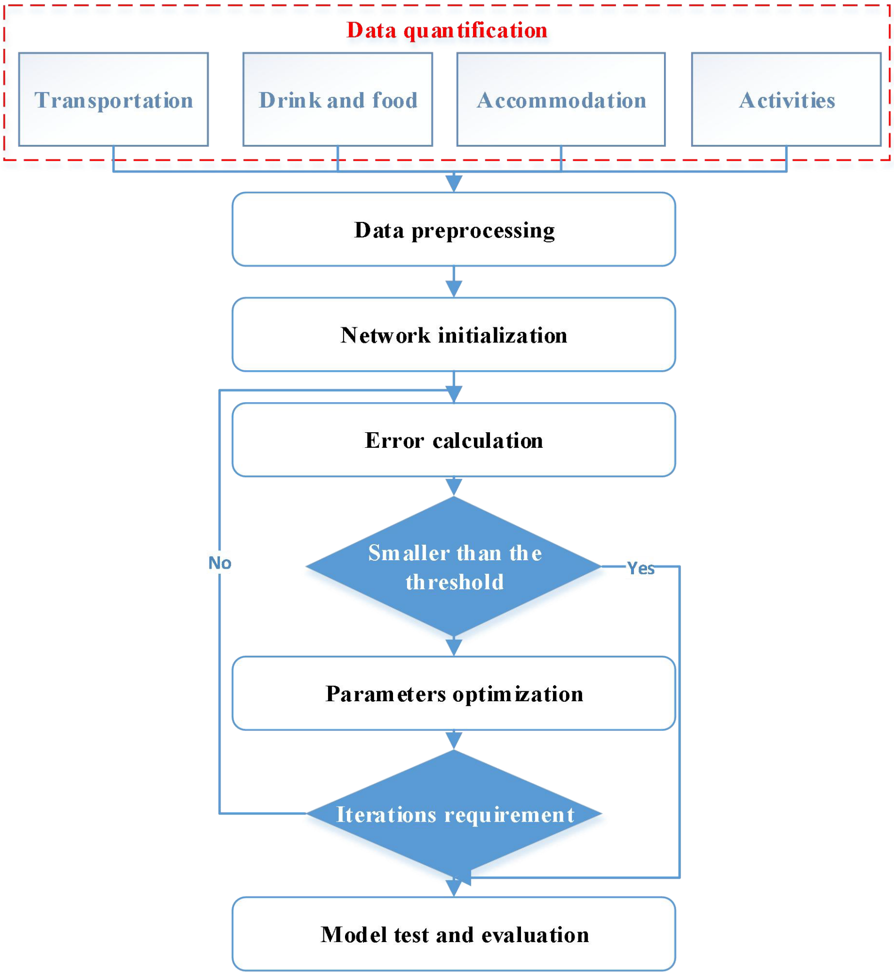

FIGURE 4
The framework for the LTC-RNN in the environment model training.

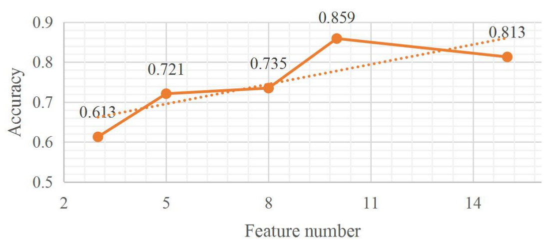

FIGURE 5
The result of the environment evaluation model using different features.

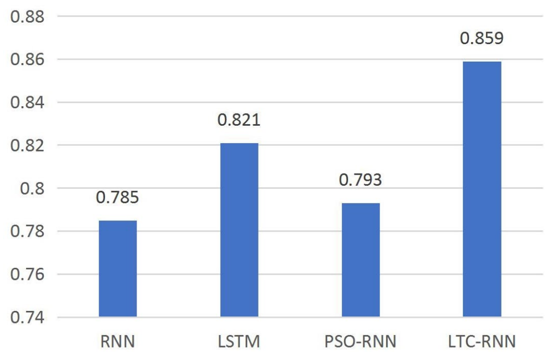

FIGURE 6
The accuracy result among different evaluation methods.

emphasizing the need to prioritize strategies for holding events that ensure their low-carbon nature.

4.3. The model application in practice

To test the effectiveness of the framework proposed, practical tests were conducted to actually validate quantified data, and the specific validation is shown in Figure 8.

During the validation process, we utilized cloud technology to transmit pertinent data to the server for calculations. Simultaneously, for the project itself, the content was disseminated to relevant experts for anonymous review, enabling them to perform the requisite evaluation and comparison work. Following the comparison and validation of the model's accuracy, the remaining experts conducted additional analyses and comparisons. The accuracy of models employing distinct methods with differing characteristics is depicted in Figure 9.

According to Figure 9, it can be found that under the low-dimensional features, each method does not perform well in the actual test, while with the increase of the feature dimension, its assessment accuracy shows an increasing trend. When the feature exceeds 10, there is a little decrease for the model. It can also be found that the model proposed has a high accuracy, which can best meet the environmental assessment in the context of carbon neutrality in the tourism field.

5. Discussion

The LTC-RNN used in this paper improves the state equation of RNN neurons with the membrane integrator as a reference and uses the historical state of neurons to calculate hidden states, which enhances the self-correction capability of the model. The analysis of practical cases in this paper confirms that LTC-RNN can reach the optimal parameters quickly and stably with high computational efficiency. Also, LTC-RNN methods usually utilize a semi-implicit Euler solver to compute the hidden neuron states, which allows the global optimal solution to be sought directly without relying on other optimization methods (Shahparasti et al., 2017). Meanwhile, in this paper, the model fully considers multiple factors in travel to analyze and explore the internal link between each component to achieve a more accurate environmental assessment. Compared with traditional regression-based and machine learning methods, deep learning methods have become a hot research topic in multi-objective regression analysis due to their advantages in processing nonlinear data (Dong et al., 2019). RNN methods, on the other hand, have advantages in time-related data processing due to their excellent temporal memory, so this paper uses LTC-RNN to improve its own limitations to achieve better results in practical tests.

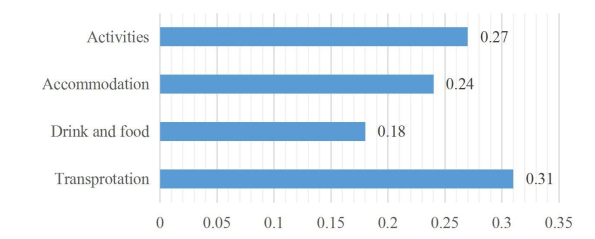

FIGURE 7
The contribution distribution of emission related factors.

Global warming is a very serious environmental problem facing human society, and the large amount of carbon dioxide produced by the economic activities of human society since the industrial revolution is considered to be the most important cause of climate warming. Climate change has already brought many negative impacts to the production and life of human society, so people must respond positively to reduce carbon emissions from human activities and slow down the warming trend. The path to achieve the goal of carbon neutrality can be summarized in four aspects: first, we should promote and strengthen the strength and depth of energy transformation and promote the digital transformation; second, we should develop a circular economy and promote resource use efficiency; third, we should improve the comprehensive carbon dioxide absorption system and seek carbon-neutral solutions based on natural ecology; fourth, we should accelerate the replacement of traditional fossil energy with renewable energy. Fourth, accelerating the replacement of traditional fossil energy by renewable energy (Masanet et al., 2020). The tourism economy, as a cleaner type of economy in the economic cycle, urgently needs to restore economic order by reviving such an economy in the post-Covid19 era to promote the process of carbon neutrality while developing the economy. To achieve low-carbon or even zero-carbon development of the tourism industry., we use the environmental intelligence evaluation model to assess carbon emissions, so that the tourism economic development strategy can be formulated to achieve a win-win situation for both economic and carbon neutral goals.

6. Conclusion

This paper investigates the environmental impact assessment of the regional tourism economy in the context of carbon neutrality and proposes an environment assessment framework based on LTC-RNN model. The model is firstly based on the historical tourism carbon emission data of the region for model training and expert assessment results, and its assessment accuracy is 85.9%, which is higher than the traditional RNN as

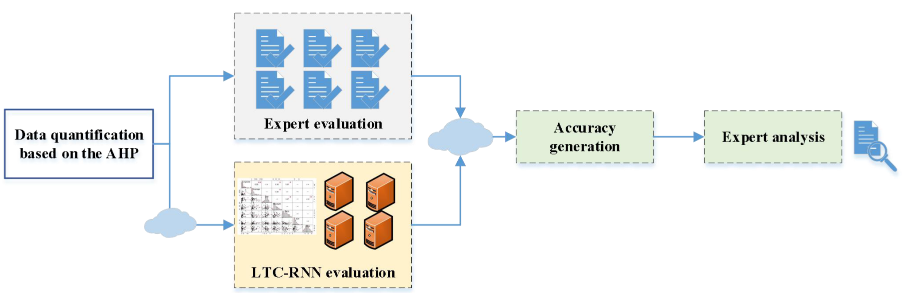

FIGURE 8
The framework for the test in practice.

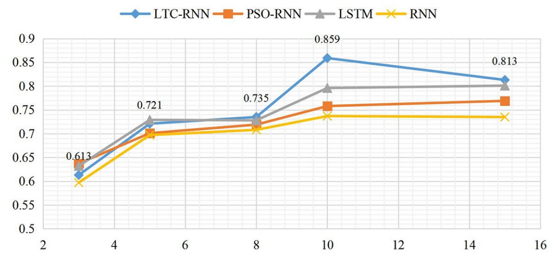

FIGURE 9
Model test using different methods.

well as LSTM and PSO-RNN methods. In the process of model optimization, it was found that the highest accuracy of the model evaluation was achieved when ten-dimensional features were used, and the model was tested in practical applications. The framework proposed also outperforms the traditional assessment methods in the practice test, which provides new ideas for future environmental impact assessment of tourism economic development in various regions. The intelligent assessment of the environment to achieve timely adjustment of tourism economic strategies and enhance the development wisdom to accelerate the process of carbon neutrality is a necessary way for economic development in the new era. In future research, improving the type of numerical quantitative indicators, enhancing the accuracy of model assessment, and testing in more regions and fields are the focus of future research. Meanwhile, completing relevant policy formulation and forming a paradigm of environmental assessment of tourism in the context of carbon neutrality are also future research directions.

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

This study was reviewed and approved by Shandong University of Finance and Economics. The participants provided their written informed consent to participate in the study.

Author contributions

The author confirms being the sole contributor of this work and has approved it for publication.

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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.

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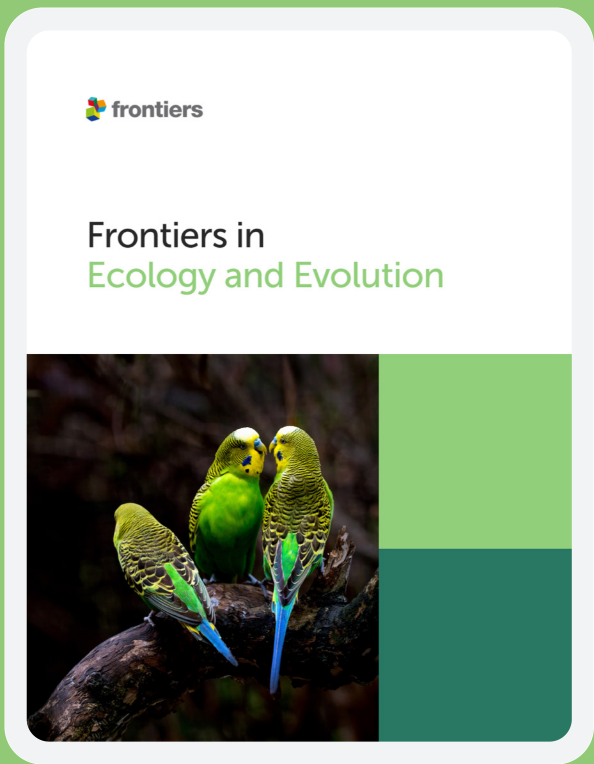

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