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Research article

Unveiling dynamics of urbanization, rural logistics, and carbon emissions: A study based on China's empirical data

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Abstract: In an era where global focus intensifies on sustainable development, in this study, I investigate the interplay between rapid urbanization, rural logistics evolution, and carbon dynamics in China. We aim to bridge the gap in existing literature by examining the tripartite relationship between these areas and their collective impact on sustainable development. I explore the dynamic interaction mechanisms between urban construction, rural logistics development, and carbon emissions, assessing their joint influence on sustainable development. A detailed analysis of demand dynamics and market mechanisms supporting urbanization, rural logistics development, and carbon emissions has been initiated, leading to the establishment of a theoretical framework. This framework adeptly captures the interdependencies and constraints among these variables, offering a mathematical and bioscientific perspective to understand their complex interactions. Furthermore, a sophisticated nonlinear model based on key quantitative indicators like urbanization level, rural logistics development, and carbon emissions has been incorporated. Considering the multivariate nature, uncertainty, and dynamism presented by the nonlinear model, genetic algorithms have been employed for the estimation of model parameters. Through rigorous empirical testing using data from China spanning the years 1991–2021, I not only validate the effectiveness of the model but also accurately the interactions between urbanization processes, rural logistics progression, and carbon emissions. The findings demonstrate that urban construction significantly drives rural logistics development and uncover a pronounced nonlinear relationship among urbanization, rural logistics development (with a significant pull effect of 4.2), and carbon emissions growth. This research highlights the subtle balance between rural-urban development and environmental management, providing theoretical backing for the creation of sustainable policy frameworks in rural contexts and setting a foundation for future research in this domain.

Keywords: rural logistics; urbanization; carbon emissions; empirical data analysis; environmental impact; nonlinear modeling; theoretical framework

1. Introduction

In the current global scenario, characterized by an intricate interplay between environmental and economic challenges [1,2], the phenomenon of climate change stands at the forefront, marked by a discernible increase in the frequency of natural disasters and extreme meteorological events [3,4]. These phenomena, while exerting significant impacts on both ecological systems and human societies, also pose a palpable threat to the stability of the global economic infrastructure [5]. Concurrently, the fabric of international relations is increasingly complicated by the variable nature of local conflicts and geopolitical tensions [6,7]. This complexity is further compounded by the widespread propagation of economic instability, which serves to amplify the uncertainties inherent in the global economic system [8].

Responding to this complex scenario, the Chinese government has proactively engaged in strategic planning to address these dual challenges. Central to this approach is the implementation of the *Dual Circulation* development strategy, complemented by the *Dual Carbon* objectives, forming the cornerstone of China's pursuit of sustainable development [9,10]. The *Dual Circulation* strategy endeavors to establish a harmonious balance between domestic and international economic flows [11], while concurrently addressing pressing environmental concerns. The *Dual Carbon* goals, on the other hand, are aimed at achieving carbon neutrality, a critical objective in mitigating the adverse impacts of climate change [12]. These strategies collectively embody a holistic approach, seeking not only to address environmental issues but also to stimulate economic growth, thereby representing a comprehensive response to the multifaceted challenges posed in the modern global context.

In the context of the strategic framework delineated for addressing contemporary global challenges, urbanization emerges as a pivotal element [13–15]. This process plays a dual role: First, by refining consumption patterns and advancing the consumption structure, urbanization effectively translates the demographic dividend into an expansive domestic market [16]. This transformation is instrumental in bolstering the domestic circulation economy. Second, urbanization enhances the connectivity between urban centers and international markets [17]. This improvement fosters national trade and investment. It also augments the global competitiveness of urban areas [18]. Consequently, urbanization acts not merely as a catalyst for domestic economic circulation but also synergizes with international economic flows, thus contributing significantly to the integration and interconnectedness of the global economy. However, this trajectory of urbanization, particularly in the context of China, is accompanied by a spectrum of environmental challenges, with carbon emissions being a focal concern. As urbanization intensifies, there is a concomitant increase in both energy consumption and carbon emissions [19]. This trend presents a formidable challenge in the pursuit of the *Dual Carbon* objectives, which aim for carbon peak and carbon neutrality. The dynamic interplay between urbanization and its environmental impact necessitates a comprehensive understanding and innovative approaches to ensure sustainable urban development while aligning with the broader goals of environmental conservation and carbon neutrality.

In the intricate urban-rural economic cycle, rural logistics serve as an indispensable conduit, playing a pivotal role in bolstering rural development and bridging the gap between rural economies and urban marketplaces [20]. The advancement of rural logistics is key to enhancing the distribution of agricultural produce, which in turn augments the income of farmers and catalyzes economic growth within rural domains [21]. This process, integral to the overall socioeconomic framework, contributes to the stabilization and prosperity of rural areas. However, the expansion of rural logistics systems presents a multifaceted challenge, primarily due to its association with environmental concerns, notably carbon emissions. As rural logistics networks grow, there is an observable increase in carbon emissions, a phenomenon that directly contradicts the objectives of China's *Dual Carbon* goals, which encompass both carbon peaking and carbon neutrality [22,23]. This presents a significant challenge in balancing the growth and efficiency of rural logistics with the imperative of environmental sustainability.

Therefore, it becomes imperative to dissect and understand the complex and dynamic interplay between urbanization, the evolution of rural logistics, and their consequent impact on carbon emissions. This understanding is crucial for devising strategies that can harmonize the objectives of economic development and environmental sustainability, particularly in the context of achieving the *Dual Carbon* targets. Such an analysis requires an interdisciplinary approach, combining insights from mathematical modeling, economic theory, and environmental science to create comprehensive solutions that align with the overarching goal of sustainable development.

In the realm of sustainable development, the interplay between urbanization, the evolution of rural logistics, and carbon emissions presents a multidimensional and intricate challenge. Historically, research in this domain has predominantly concentrated on the binary interactions between these elements. Nonetheless, a holistic understanding of their interdependencies and wider implications necessitates a thorough examination of several critical aspects:

1) How does urbanization impact carbon emissions? As the process of urbanization advances, do energy consumption and carbon emissions show an increasing trend, thereby posing challenges to the achievement of the *Dual Carbon* goals?
2) What is the correlation between the development of rural logistics and carbon emissions? Does the expansion of rural logistics lead to an increase in carbon emissions, and how can carbon neutrality be achieved while developing rural logistics?

The bondage structure and interactions between urbanization, rural logistics, and carbon emissions require more refined analysis in this study to deepen the understanding of these issues, as shown in Figure 1. We first construct a binding model based on the developmental demands and market laws of urbanization, rural logistics, and carbon emissions; second, we use a nonlinear model to capture the dynamic interactions among them. Next, based on empirical data from China from 1991 to 2021, we estimate parameters using advanced mathematical tools like genetic algorithms, ensuring the methodological rigor of the research. Finally, the interaction mechanisms between urbanization, rural logistics, and carbon emissions are revealed based on the parameter estimation results. The following subsections provide more detailed descriptions of the process. This research endeavors to bridge existing knowledge gaps and shed new light on the dynamic interplay between urbanization, rural logistics, and carbon emissions. We anticipate that our findings will elucidate the underlying mechanisms driving these interactions, thereby providing valuable insights for policymakers.

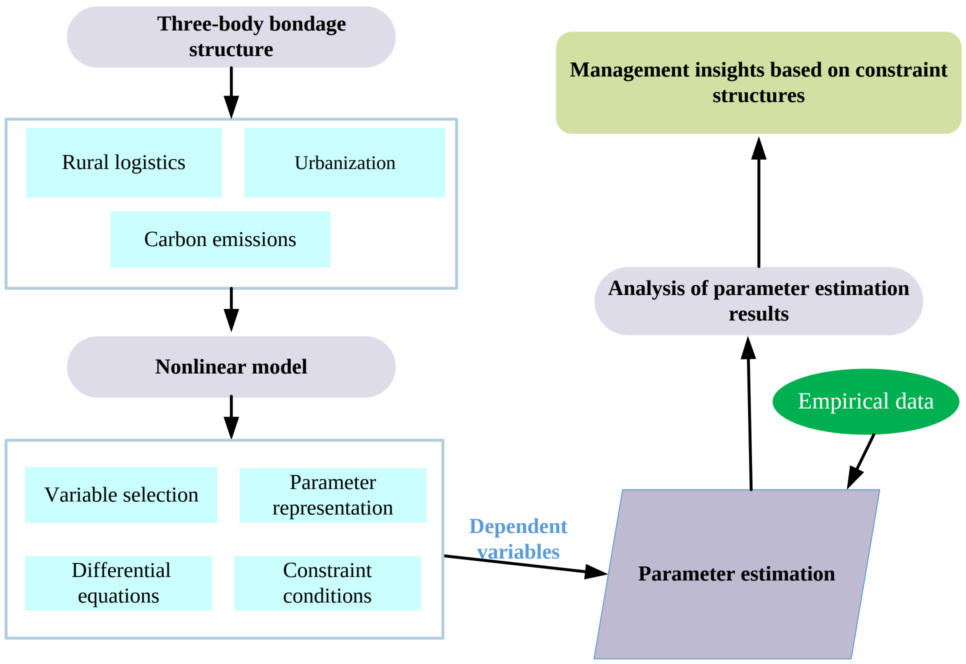

Figure 1. The research framework for analyzing the interaction mechanism.

The paper is structured as follows: Section 3 introduces the binding structure between rural logistics development, urbanization, and carbon emissions, and establishes a nonlinear mathematical model. Section 4 utilizes empirical data from China to estimate the parameters of the nonlinear mathematical model according to the genetic algorithm. Section 5 uses the model parameters to validate the theoretical reasoning of the proposed model and presents management implications based on the binding structure. Finally, the concluding remarks are presented in Section 6.

2. Literature review

The introduction of the concepts of *dual carbon* goals and the dual economic cycle has elevated the level of attention on urban construction, rural logistics, and carbon emissions to a new height. To systematically review the existing theoretical research in these three areas, based on the differences in the dimensions of the research elements, the content can be categorized into the following two types.

2.1. Advanced analysis of binary relationships

2.1.1. Urbanization and logistics development

The foundational work of Behrends [24], Liu and Su [25], and Pradhan et al. [26] posited logistics development as a catalyst for urbanization, a premise further reinforced by Chanieabate et al. [27] through their identification of a positive correlation between logistics infrastructure and urbanization. Tan et al. [28], however, introduced the concept of a nonlinear relationship, where logistics' impact on urbanization varies in accordance with local demographic factors. Liu et al. [29] leveraged panel threshold models to uncover substantial interval effects, underscoring the complexity of interactions over mere linear correlations, thus opening avenues for intricate mathematical modeling and analysis in this field.

2.1.2. Urbanization and carbon emissions

Pioneering research by Liu et al. [30], Lin et al. [31], and Tan et al. [32] positioned urbanization as a pivotal driver of carbon emissions, closely linked with environmental degradation [33,34]. Wang and Chen [35] illuminated a significant positive correlation between urbanization and carbon emissions, particularly in ASEAN countries, with land development playing a more crucial role than population growth [36]. The introduction of a U-shaped relationship between urbanization and carbon emissions by Shahbaz et al. [37], Wang et al. [38], and Peng et al. [39] suggests diverse patterns at different urbanization levels [40], indicating a complex system of variables that can be explored through advanced mathematical modeling in biosciences and engineering.

2.1.3. Rural logistics and carbon emissions

In exploring rural logistics, Lu and Liu [41] discerned a positive correlation with carbon emissions, marked by regional disparities. Zheng et al. [42] attributed high carbon emissions in Jiangsu to a larger scale of logistics output in employment, while Zhu et al. [43] emphasized the significant role of logistics' energy intensity in regional carbon emissions. The positive correlation between logistics performance and carbon emissions highlighted by Karaduman et al. [44], and the substantial contribution of road and air transport noted by Zhang et al. [45]. Zhang et al. [46] identified the expansion of logistics scale as a primary driver of emission growth, and Zhang and Li [47] revealed negative decoupling between logistics development and carbon emissions, all contribute to a nuanced understanding that can benefit from mathematical biosciences and engineering methodologies.

2.2. Integrative tripartite relationship analysis

This comprehensive synthesis of existing binary relationships among urbanization, rural logistics, and carbon emissions delineates a complex and multifaceted interplay between these elements. Current research, however, indicates a notable gap in the theoretical exploration of their interconnectedness. Liang and Fang [48] scrutinized logistics development and urbanization as variables impacting logistics carbon emissions. Liu et al. [49] conducted an analysis from both national and regional perspectives, identifying logistics development as a benchmark for increased emissions on a national level, and land urbanization as a key regional factor. These studies, predominantly focusing on individual impacts, overlook the deeper interactive mechanisms between all three components. The mechanism of interplay between rural logistics, urbanization, and carbon emissions forms a complex and crucial area in environmental and economic sustainable development research. In the context of *Dual-Carbon* and *Dual-Circulation* strategies, understanding these interactions becomes increasingly crucial, presenting novel research perspectives and challenges for sustainable development. This scenario calls for a sophisticated approach in mathematical biosciences and engineering to model these complex relationships and contribute significantly to the field of sustainable development.

3. Research methodology

3.1. Theoretical analysis

The interaction between rural logistics, urbanization, and carbon emissions forms a complex socio-economic environmental system. At a micro level of analysis, urbanization construction, accompanied by the aggregation of population and industries, optimizes spatial structure, enhances regional production capacity, and also stimulates a rise in the demand for rural logistics services. This growth in demand promotes the expansion of the rural logistics network, but it may also lead to reduced transportation efficiency and increased transportation costs. Additionally, urbanization might cause seasonal or cyclical fluctuations in the demand for rural logistics, adding complexity to logistics management. Due to the highly dispersed nature of rural logistics demand, it plays a key role in connecting rural areas with cities during the urbanization process.

As rural logistics develop, they address the issue of uneven infrastructure, enhance the efficiency of resource distribution between urban and rural areas, reduce logistics costs, and accelerate the penetration speed of agricultural products into cities and industrial goods into rural areas. This promotes the economic integration of urban and rural areas, advances the market integration of rural and urban areas, strengthens the market involvement of rural products, fosters the market expansion of products and services in urbanized areas, and narrows the social development gap between urban and rural areas, thus driving rapid urbanization. However, if rural logistics are not effective, it will inevitably hinder the economic development and market expansion of urbanized areas, affect the adjustment of rural industrial structure, fail to achieve effective aggregation of resources, manpower, and financial power, and delay the process of urbanization. Additionally, insufficient effectiveness of rural logistics will also inevitably lead to a large amount of unnecessary carbon emissions, increasing environmental constraints, and thereby restricting the development of rural logistics and urbanization.

At the macro level, urbanization construction triggers the aggregation of industries and resources, increasing societal consumption demand. This increase in demand directly impacts the development of rural logistics. Rural logistics provide logistic services for the needs of rural areas, and carbon emissions are a negative externality resulting from urbanization construction and the development of rural logistics. Due to insufficient development of rural logistics, the regional adaptability of rural logistics is reduced, limiting infrastructure construction, delaying the application and innovation of new logistics technologies, and weakening the spillover effects on economic, social, and spatial aspects of urbanization construction.

Moreover, weakened levels of urbanization construction fail to provide sufficient spillover effects for rural logistics, indirectly slowing down the development process of rural logistics, affecting the perfection of the rural logistics market mechanism, and failing to realize the spillover effects of rural logistics on urbanization construction. Both urbanization construction and the development of rural logistics rely on energy, leading to a large amount of carbon emissions. Excessive carbon emissions inevitably trigger environmental constraints, directly affecting resource allocation and environmental constraints. The aforementioned analysis reveals the cyclical feedback among rural logistics, urbanization, and carbon emissions. Urbanization drives the development of rural logistics, while effective rural logistics can support a more efficient urbanization process. Furthermore, increased carbon emissions may lead to changes in environmental policies, which in turn can affect the development modes of urbanization and rural logistics. Therefore, utilizing pattern recognition modeling methods to fundamentally grasp the structure between these three aspects, focusing on spillover effects, logistics effectiveness, and environmental constraints is crucial.

Despite the intricate and nonlinear interdependence between urbanization construction, rural logistics development, and carbon emissions, an analysis can be conducted from a goal-oriented perspective by considering their respective overarching objectives: the sustainable development of rural logistics, the improvement of urbanization quality, and carbon emission reduction. Taking into account the characteristics exhibited by each entity, such as the spillover effects of urbanization construction, the logistics efficiency of rural logistics, and the environmental constraints posed by carbon emissions, a framework depicting their interconnections can be constructed through the application of pattern recognition modeling methods. The specific configuration of this interrelated framework is illustrated in Figure 2.

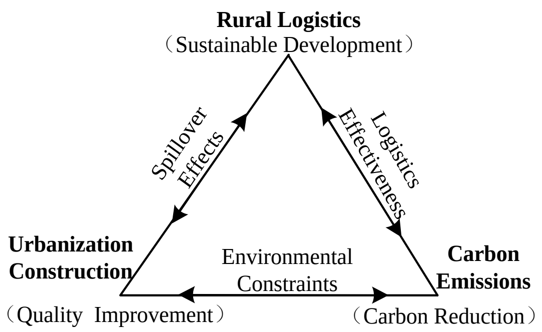

Figure 2. Three-body bondage structure of urbanization construction, rural logistics and carbon emission.

The entities involved in urbanization construction, rural logistics development, and carbon emissions are driven by their individual objectives, necessitating them to make decisions that are relatively independent but contextually dependent. However, as integral components of the rural system, these entities are subject to inevitable influences from other entities. This bottom-up influence engenders a dynamic interplay among urbanization construction, rural logistics development, and carbon emissions, leading to their mutual permeation, interdependence, and reciprocal constraints. In order to further explore the intricate relationship among urbanization construction, rural logistics development, and carbon emissions, this study draws upon the theoretical framework of the Ternary Paradox. It distills the three nonlinear relationships of urbanization construction, rural logistics development, and carbon emissions into a coordination relationship between overall objectives and entity characteristics. As depicted in Figure 2, there exists a bondage relationship among urbanization construction, rural logistics development, and carbon emissions. The realization of the overall objectives of any two factors necessitates the coordination of the entity characteristics of the remaining factor. Furthermore, the interaction between any two factors exerts an impact on the third factor.

In a more nuanced perspective, urbanization construction exerts its influence on rural logistics development through the mechanism of spillover effects. However, it is important to note that the interplay between urbanization construction and rural logistics is not unilateral, as environmental constraints also exert their impact on both processes. Similarly, the development of rural logistics is contingent upon its ability to synchronize with urbanization construction by enhancing logistics efficiency. Nevertheless, this synergy is subject to the constraints imposed by the environment. Furthermore, the growth of carbon emissions plays a pivotal role in shaping the trajectory of urbanization construction and the sustainable development of rural logistics by means of environmental constraints. It is through the harmonization of logistics efficiency and environmental constraints that the level of urbanization construction can be elevated. The bondage relationship is manifested in the mutual constraints that exist among urbanization construction, rural logistics development, and carbon emissions, which impede the simultaneous attainment of their respective optimal objectives. It requires a process of negotiation and compromise among these three entities to find a balance and reconcile their divergent goals. Both urbanization construction and rural logistics development are constrained by environmental factors. The synergy between rural logistics development and carbon emissions growth is facilitated through spillover effects, while the mitigation of the impact of urbanization construction on carbon emissions growth necessitates the adjustment of logistics effectiveness. The relationship between urbanization construction, rural logistics development, and carbon emissions constitutes a complex network of constraints. This interplay can be comprehended by considering the spatial and temporal dimensions. From a spatial perspective, the effects between urbanization construction and rural logistics development can be examined within different spatial contexts but at the same point in time, encompassing various aspects such as positive or negative effects and causal relationships. Moreover, in the same spatial context but at different points in time, the non-linear and bifurcating relationship between the level of urbanization construction and carbon emissions can be explored. This nuanced understanding facilitates a deeper analysis of the intricate dynamics among these three components in the context of their spatial and temporal dimensions.

3.2. Research on nonlinear models based on the framework

Urbanization construction, rural logistics development, and carbon emissions serve as central components in the study and implementation of China's carbon peak. These factors are pivotal for analyzing the dynamics of rural low-carbon development. In light of the proposed structural framework, it is imperative to construct a clear nonlinear model to comprehensively investigate the intricate interdependencies among these variables. Genetic algorithms are employed to identify the binding parameters of the nonlinear model, aiming to depict the strength of the constraints between urbanization construction, rural logistics development, and carbon emissions.

3.2.1. Construction of a nonlinear model

To quantitatively depict the bondage structure among urbanization construction, rural logistics development, and carbon emissions, a unified mathematical formulation is employed to represent their interdependencies.

$$y = f(x_1, x_2, x_3, t) \tag{1}$$

In this context, x_1 denotes the magnitude of rural logistics development, x_2 represents the level of urbanization construction, x_3 signifies the quantity of carbon emissions, t denotes time, and f symbolizes the structural function that characterizes the interrelationships among these three variables.

From the analysis of the above structural constraints, it can be seen that the relationships between rural logistics, urbanization, and carbon emissions exhibit characteristics of cyclical feedback, dynamic changes, and complexity. Linear models are no longer sufficient to fully reveal the complex mechanisms of action. Nonlinear models, on the other hand, are a type of mathematical model that can more realistically reflect the complex relationships in the real world. This is particularly true in the analysis of the relationships among rural logistics, urbanization, and carbon emissions, where nonlinear models can reveal the complex and dynamic interactions among these factors. Therefore, this study utilizes the time-varying characteristics of differential equations to construct a data-driven nonlinear model based on differential formulas. As shown in Eq (2).

$$\begin{cases} \frac{dx_1}{dt} = \sum_{i=1}^{3} a_{1,i}x_i + \sum_{i=1}^{3}\sum_{j=1}^{3} b_{1,i,j}x_i x_j + c_1 \\ \frac{dx_2}{dt} = \sum_{i=1}^{3} a_{2,i}x_i + \sum_{i=1}^{3}\sum_{j=1}^{3} b_{2,i,j}x_i x_j + c_2 \\ \frac{dx_3}{dt} = \sum_{i=1}^{3} a_{3,i}x_i + \sum_{i=1}^{3}\sum_{j=1}^{3} b_{3,i,j}x_i x_j + c_3 \end{cases} \tag{2}$$

In the given context, the coefficients $a_{1,i}$, $a_{2,i}$, $a_{3,i}$, $b_{1,i,j}$, $b_{2,i,j}$, $b_{3,i,j}$, and c_i represent the influences and interactions between these variables. Specifically, coefficient $a_{1,i}$ quantifies the effects of rural logistics scale, urbanization construction level, and carbon emissions on the development of rural logistics. Coefficient $a_{2,i}$ characterizes the impacts of rural logistics development scale, urbanization construction level, and carbon emissions on urbanization construction. Coefficient $a_{3,i}$ captures the influence of rural logistics development scale, urbanization construction level, and carbon emissions growth on changes in carbon emissions. Coefficient $b_{1,i,j}$ describes the interaction among these variables and its impact on the scale of rural logistics development. Coefficient $b_{2,i,j}$ represents the interaction among these variables and its effect on the level of urbanization construction. Coefficient $b_{3,i,j}$ quantifies the interaction among these variables and its influence on carbon emissions. Last, coefficient c_i represents the constant term.

The representation of the nonlinear model, as outlined in your description and depicted in the image, integrates both linear and nonlinear relationships between urbanization, rural logistics, and carbon emissions. The model takes into account the direct linear relations of each variable as well as the nonlinear interactions and cumulative effects, which are critical for a comprehensive understanding of these complex dynamics.

3.2.2. Parameter estimation for the nonlinear model

Urbanization construction, rural logistics development, and carbon emissions serve as central components in the study and implementation of China's carbon peak. These factors are pivotal for analyzing the dynamics of rural low-carbon development. In light of the proposed structural framework, it is imperative to construct a clear nonlinear model to comprehensively investigate the intricate interdependencies among these variables. Genetic algorithms are employed to identify the binding parameters of the nonlinear model, aiming to depict the strength of the constraints between urbanization construction, rural logistics development, and carbon emissions.

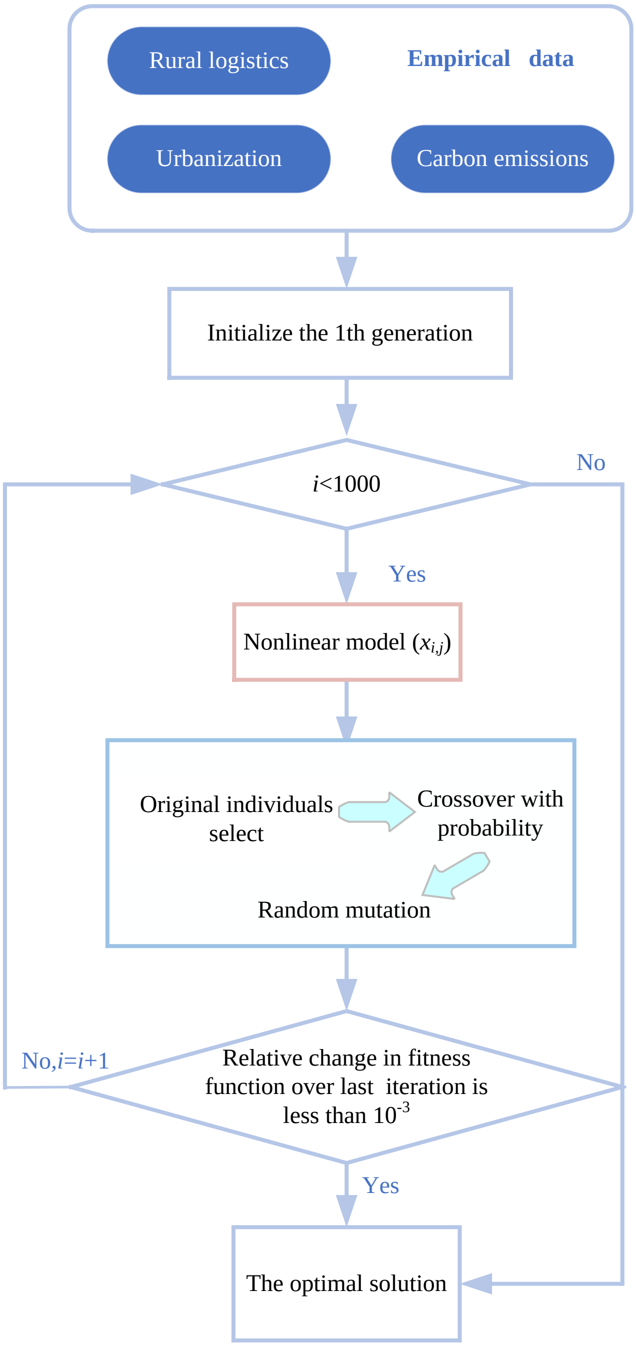

Figure 3. Flowchart of genetic algorithm.

All the procedures for the GA have been implemented following [50,51]. The genetic algorithm is embedded within the optimization session for nonlinear model parameter estimation introduced in Section 3.2.1. This session is fed by supported by empirical data on urbanization, rural logistics, and carbon emissions in China, covering the period from 1991 to 2021. The learning session finds the best fitting values for the coefficients of the nonlinear model by minimizing the error between the model's estimated outputs for urbanization, rural logistics, and carbon emissions and the actual data. Using these automated procedures for tuning the coefficients of the nonlinear model, shown in Figure 3, a significant improvement in the accuracy of the parameters a, estimated by the nonlinear model, is expected.

In the proposed genetic algorithm, a sample (or individual) $x_{i,j}$ of the population is a vector whose elements (or genes) are the unknown coefficients to be inserted into the coefficients of the nonlinear model. Where the index i represents the sample of the population (individual) in each j iteration (or generation). The proposed genetic algorithm selects the individual $x_{i,j}$ with the best combination of genes through the procedure that is described step by step below.

1) Initialization. In the initial function, the number n of individuals of the population to observe is defined. At the initial step, the set of genes for the m individuals x_i, within very wide predefined domains.

$$\begin{bmatrix} x_{1,1} \\ \vdots \\ x_{n,1} \end{bmatrix} = \begin{bmatrix} a_{1,1}^{1}, a_{1,1}^{2}, a_{1,1}^{3}, a_{1,1}^{11}, a_{1,1}^{12}, a_{1,1}^{13}, a_{1,1}^{22}, a_{1,1}^{23}, a_{1,1}^{33}, a_{1} \\ \vdots \\ a_{n,1}^{1}, a_{n,1}^{2}, a_{n,1}^{3}, a_{n,1}^{11}, a_{n,1}^{12}, a_{n,1}^{13}, a_{n,1}^{22}, a_{n,1}^{23}, a_{n,1}^{33}, a_{n} \end{bmatrix} \tag{3}$$

2) Fitness. For each individual $i: 1 \rightarrow n$, the corresponding set of genes, indicated in the rows of Eq (3), are used as coefficients of the nonlinear model presented in Section 3.2.1. For each set of genes, during the evolution of the corresponding nonlinear model parameter estimation algorithm, Eq (4) for $i = 1$ is continuously updated. The Eq (4) represents the error between the actual and estimated output values of rural logistics, urbanization, and carbon emissions from the nonlinear model at each computational step k.

$$fitness\left(\theta_i^k\right) = \frac{1}{\sqrt[2]{\frac{1}{n}\sum\left(x_{actual} - x_{estimated}\right)^{2}}} \tag{4}$$

This choice of Eq (4) is crucial for obtaining the correct results of the optimization process. After applying the nonlinear model to the available measured data, by using the n sets of genes as coefficients of the nonlinear model, an initial vector containing the results of the fitness function is obtained.

3) Selection. With the selection function, the process enters in an iterative cycle, where each j cycle represents a new generation of individuals. In this function, the two individuals having the lowest fitness value are selected from the current population x_j, i and defined as original individuals. To prevent premature convergence, the identifier is set to $i \neq j$.
4) Crossover & Mutation. Cross the selected individuals with a probability of 0.8 to generate sub-individuals. Mutation operations are performed with a probability of 0.005 in the newly generated sub-individuals to introduce new genetic variations. Once the new vector of sub-individuals is obtained, a sequence of the nonlinear model elaborations is performed. Each nonlinear model elaboration uses the new coefficients given by the sub-genes and by using the same reference measured cell quantities. During the evolution of each nonlinear model, the new fitness values for the children are calculated using the same fitness function introduced in Eq (4).
5) Population Update. The next generation of the population $k + 1$ consists of a combination of original individuals and sub-individuals, where worse original individuals are replaced by sub-individuals. In this way, the maximum amount is always n. The resulting fitness functions of the new population are simply obtained by merging the

corresponding fitness functions of selected original individuals and sub-individuals. The fitness vector is used at the next iteration $k + 1$ for the selection step, which selects the two parents of the new generation.

The genetic algorithm iterates generation after generation, continuously evolving until it reaches the predefined maximum number of iterations ($k \leq 1000$) or the fitness level meets a set threshold ($\varepsilon < 10^{-3}$). The iteration process stops upon satisfying one of these termination criteria, and specific results are then outputted. The algorithm selects the best-performing individual from the final generation as the optimal solution.

4. Empirical testing and result analysis

In this section, the time series data from 1991 to 2021 is utilized as the sample data to estimate the bondage parameters between urbanization, rural logistics development, and carbon emissions. The genetic algorithm is employed for this purpose in order to verify the rationality of the binding framework and the correctness of the nonlinear model.

4.1. Indicator selection and data sources

4.1.1. Indicator selection

The quantification of qualitative indicators in a scientific and rational manner is crucial for the validation of the structure and models of rural logistics development, urbanization, and carbon emissions. The principles of completeness and high frequency of usage were followed in the selection of indicators to maximize the reflection of the integrity and accuracy of the chosen quantitative indicators, as well as the representativeness and availability of the sample data [52,53]. x_1 adopts the quantified indicator of rural logistics scale value, which reflects the overall development scale of rural logistics, as well as the ability to reduce logistics costs and promote the sustainable development of logistics [54]. x_2 uses the quantified indicators of urbanization level, which are important measures for assessing China's economic development and industrialization [55]. It is a comprehensive reflection of regional social productivity development, technological progress, and industrial structure adjustment. It reflects the scale and achievements of urban construction over a certain period. This indicator is a composite index that can be measured by both urbanization rate and per capita gross domestic product. x_3 adopts the quantified indicator of carbon emissions from rural logistics as a measure [56]. This indicator represents the absolute amount of carbon emissions generated by rural logistics over a certain period, providing an overall reflection of carbon reduction levels in rural logistics.

4.1.2. Data sources

The data for rural logistics scale output, urbanization level, and rural logistics carbon emissions are sourced from the website of the National Bureau of Statistics of China, the *China Urbanization Rate Survey Report*, the *China Energy Statistical Yearbook*, and the *China Rural Yearbook*. The sample period is set from 1991 to 2021 in ordered to ensure data completeness.

4.2. Parameter estimation results

By employing a randomness test method, 80% of the sample data was randomly selected for estimating the model parameters, while the remaining 20% of the sample data was used for validating the estimated parameter values. This approach ensures the robustness and reliability of the parameter estimation process using a representative portion of the data for estimation and an independent portion for testing the estimated values. Based on the genetic algorithm flowchart in Figure 3, the algorithm code was implemented using Matlab R2017b.

The genetic algorithm in this study was configured with a population size of 200 and a total of 1500 iterations. To enhance the clarity of the model structure and concentrate the parameters, a reduction was made in the number of components from 13 to 10 in the nonlinear model. This reduction aimed at eliminating redundant pairwise interactions that could potentially introduce duplicated influences. The estimated values of the nonlinear model parameters for the three groups were obtained through calculations, and the specific values are shown in Table 1.

Table 1. Estimated values of model parameters.

Param		a_{11}	a_{12}	a_{13}	b_{111}	b_{112}	b_{113}	b_{122}	b_{123}	b_{133}	c_1
x_1	Set1	–0.2629	0.854	–0.259	–0.912	5.052	–2.631	–3.06	0.63	0	–0.008
	Set2	3.517	1.078	–4.36	–7.406	–4.220	4.433	0.785	2.938	–2.609	–0.034
	Set3	0.070	0.236	–0.179	–2.583	1.681	1.257	–0.540	1.224	–0.810	0.054
Param		a_{21}	a_{22}	a_{23}	b_{211}	b_{212}	b_{213}	b_{222}	b_{223}	b_{233}	c_2
x_2	Set1	0.1564	0.344	–0.340	–0.562	4.317	–3.613	–2.511	1.124	0	0.001
	Set2	–0.062	–1.284	1.327	0.075	0.000	0.000	9.077	–16.495	7.353	0.042
	Set3	–0.185	–1.020	1.355	0.676	0.000	0.000	6.050	–11.615	4.757	0.031
Param		a_{31}	a_{32}	a_{33}	b_{311}	b_{312}	b_{313}	b_{322}	b_{323}	b_{333}	c_3
x_3	Set1	–0.107	0.276	0.145	0.603	0.743	–1.206	–1.241	0.421	0	–0.006
	Set2	0.136	–0.640	0.617	–0.124	0.000	3.175	4.739	–7.895	0.000	0.020
	Set3	0.145	–0.634	0.606	–0.134	0.000	0.000	4.653	–7.624	2.995	0.019

4.2.1. Validity test of parameters

To validate the effectiveness of the model parameter values, a sample analysis of the mathematical model is performed. The three sets of parameters are individually applied to the model to obtain calculated values, which are then compared with the actual values of the sample data.

Figure 4 represents a comparison between the sample values and calculated values of model parameter x_1. In the Figure 4, curve 1 represents the sample curve of parameter x_1, curve 2 represents the calculated curve of parameter x_1 for the first set, curve 3 represents the calculated curve of parameter x_1 for the second set, and curve 4 represents the calculated curve of parameter x_1 for the third set. Based on the analysis of Figure 4, it can be observed that curve 2 and curve 4 have a similar magnitude of fluctuations, and both curves show a consistent overall trend without major variations. Curve 2 and curve 4 deviate significantly from the sample curve, and they do not align well with the observed trend of rural logistics development. This indicates that the first and third sets do not meet the requirements of parameter validity testing. Curve 3 and the sample curve exhibit a similar development trend, both experiencing significant fluctuations in the later stages of the sample period. This aligns well with the actual trend of rural logistics development, indicating that curve 3 satisfies the requirement of parameter validity testing. Therefore, the data from the second set can be considered as an alternative option for the model parameter x_1.

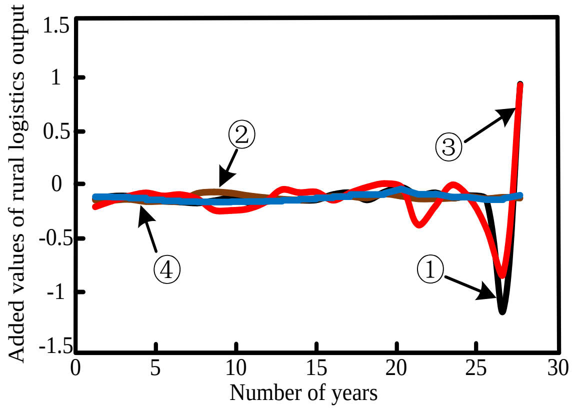

Figure 4. A comparison between the sample values and calculated values of rural logistics.

Figure 5 is a comparison analysis between the sample values and calculated values of the model parameter x_2. In the Figure 5, curve 1 represents the sample curve of parameter x_2, curve 2 represents the calculated curve of parameter x_2 for the first set, curve 3 represents the calculated curve of parameter x_2 for the second set, and curve 4 represents the actual curve of parameter x_2 for the third set. From Figure 5, it can be observed that curve 1 exhibits a similar development trend to curve 3 and curve 4. Throughout the entire sample period from 1991 to 2022, there are two peaks in urbanization development, indicating a significant non-linearity. This pattern aligns well with the trend of urbanization in China. Curve 2 exhibits relatively stable fluctuations and shows significant differences compared to the sample curve. This indicates that the first set of data does not meet the requirement of parameter validity testing. Therefore, the second and the third sets of data can be considered as alternative options for the model parameter x_2.

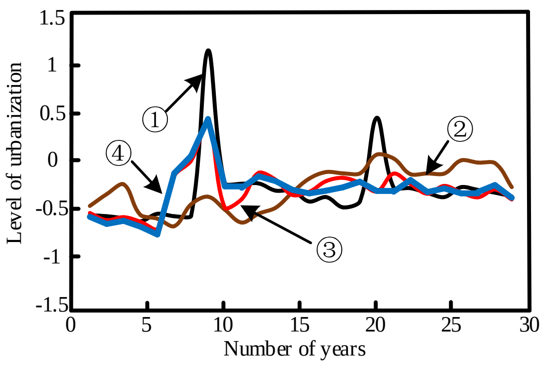

Figure 5. A comparison between the sample values and calculated values of urbanization construction.

Figure 6 is a comparison analysis between the sample values and calculated values of the model parameter x_3. In the Figure 6, curve 1 represents the sample curve of parameter x_3, curve 2 represents the calculated curve of parameter x_3 for the first set, curve 3 represents the calculated curve of parameter x_3 for the second set, and curve 4 represents the actual curve of parameter x_3 for the third set. From Figure 6, it can be observed that all four curves exhibit significant non-linearity in their fluctuations. However, curve 2 and curve 4 share a similar fluctuation pattern with minor variations. Interestingly, they display opposite trends compared to the sample curve. This deviation from the sample curve indicates that curve 2 does not meet the requirement of parameter validity testing for the model parameter x_3. Curve 1 and curve 3 exhibit a similar development trend, indicating that the second set of the calculated values can be considered as an alternative option for the model parameter x_3.

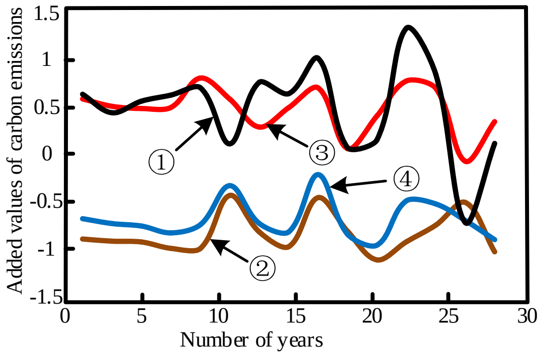

Figure 6. A comparison between the sample values and calculated values of carbon emissions.

4.2.2. Determination of optimal parameters

To enhance the goodness of fit in parameter estimation, an analysis of the errors between the calculated values and the sample values is conducted for further optimization. Initially, the mean square errors (MSE) of the calculated values are compared with the MSE of the sample values for each of the three groups. The group with a higher MSE for the sample values compared to the calculated values is excluded. Next, the remaining two groups of calculated values are compared, and the group with the lower MSE is chosen as the optimal solution for parameter estimation.

Table 2. Error results for model parameters.

Parameters	First set (MSE)		Second set(MSE)		Third set(MSE)	
	Calculated values	Sample values	Calculated values	Sample values	Calculated values	Sample values
x_1	0.244	0.235	0.189	0.209	0.080	0.070
x_2	0.251	0.102	0.214	0.245	0.036	–0.06
x_3	0.178	0.103	0.289	0.378	0.154	0.102

Table 2 presents the three sets of error results for the parameters of the nonlinear model. From Table 2, it is observed that the mean square errors (MSE) of the first set of calculated values in the nonlinear model are greater than the MSE of the sample values. The MSE of the second set of calculated values in the nonlinear model is smaller than the MSE of the sample values. The MSE of the third set of calculated values in the nonlinear model shows both positive and negative deviations from the MSE of the sample values.

Therefore, the second set of calculated values in the nonlinear model is selected as the optimal solution for parameter estimation. The results of the parameter estimation for the nonlinear model are presented in Table 3.

Table 3. The parameter estimates for the nonlinear model.

a_{11}	a_{12}	a_{13}	b_{111}	b_{112}	b_{113}	b_{122}	b_{123}	b_{133}	c_1
3.517	1.078	–4.36	–0.741	4.220	–4.433	0.785	2.938	–2.609	–0.034
a_{21}	a_{22}	a_{23}	b_{211}	b_{212}	b_{213}	b_{222}	b_{223}	b_{233}	c_2
0.063	–1.284	–1.327	0.075	0.001	–0.001	9.077	–1.645	7.353	0.042
a_{31}	a_{32}	a_{33}	b_{311}	b_{312}	b_{313}	b_{322}	b_{323}	b_{333}	c_3
0.136	0.640	–0.617	0.124	1.25	3.175	4.739	–7.895	0.618	0.20

5. Discussion

5.1. The analysis of the model parameters

From Table 3, it can be observed that the numerical values of parameters a_{12} is 1.078 and the numerical values of parameters a_{21} is 0.063. The values indicate that rural logistics development and urbanization are interdependent, exhibiting a significant positive correlation. Moreover, the value of parameter of a_{12} further directly indicates that urbanization has a greater driving effect on rural logistics development. The numerical values of parameters a_{13} is –4.36, and the numerical values of parameters a_{23} is –1.327. These numerical values indicate that carbon emissions have constraint effects on rural logistics development and urbanization, but there are differences in the constraint effects between the two. It can be inferred that during the process of evolutionary development, rural logistics development, urbanization, and carbon emissions all exhibit accumulated cyclic effects from Table 3.

Coefficient b_{111} indicates the presence of an accumulated cyclic negative effect on rural logistics development, with its effect being –0.741. Therefore, rural logistics development should be adapted to local conditions. On the other hand, coefficients b_{222} and b_{333} suggest that both urbanization and carbon emissions show accumulated cyclic positive effects, with effects of 9.077 and 0.618, respectively. Thus, under the context of a dual carbon strategy, it is crucial to properly coordinate urbanization and carbon emissions.

Based on parameters derived from the nonlinear model, the evolutionary process of rural logistics development is analyzed. The numerical value of parameter b_{112} is 4.22, and the coefficient indicates that the interaction between rural logistics development and urbanization effectively promotes rural logistics development. The numerical value of parameter b_{113} is –4.433, and it demonstrates that the interaction between rural logistics development and carbon emissions constrains rural logistics development. The numerical value of parameter b_{123} is 2.938, indicating that the current interaction between urbanization and carbon emissions effectively drives rural logistics development, consistent with the rapid development of rural logistics in reality. Based on parameters derived from the nonlinear model, the evolutionary process of urbanization construction is analyzed. The numerical value of parameter b_{213} is -0.001, it demonstrates that the interaction between rural logistics and carbon emissions has a negative effect on urbanization. The numerical value of parameter b_{212} is 0.001, and the coefficient suggests that the interaction between urbanization and rural logistics development has a positive effect on urbanization. The numerical value of parameter b_{223} is 1.645, and the parameter illustrates that the interaction between urbanization and carbon emissions hinders the progress of urbanization, with a bondage effect of 1.645.

Based on parameters derived from the nonlinear model, the evolutionary process of carbon emissions is analyzed. The numerical value of parameter b_{312} is 1.25, the coefficient indicates that the interaction between urbanization and rural logistics promotes an increase in carbon emissions. The numerical value of parameter b_{313} is 3.175, and the coefficient indicates that the interaction between rural logistics development and carbon emissions promotes carbon emission growth. Parameter b_{323} shows that the interaction between urbanization and carbon emissions has a negative effect on carbon emissions, with an effect of –7.895. From the perspective of pairwise interactions, urbanization and carbon emissions have a more significant driving effect compared to rural logistics development, which is generally consistent with the actual situation. The nonlinear effects of the interaction between urbanization and rural logistics development have a more pronounced impact on promoting rural logistics development. The nonlinear effects of the interaction between urbanization and carbon emissions exert a significant inhibitory effect on carbon emission growth.

In conclusion, rural logistics development, urbanization, and carbon emission growth are all subject to both linear and nonlinear influences, validating the deductive logic within the bondage structure among the three factors as outlined in Section 3.1. The constructed nonlinear model has been used to verify the rationality of the bondage structure between rural logistics development, urbanization, and carbon emissions.

5.2. Managerial implications

Based on the above research findings, we offer the following management policy recommendations for the implementation of the two major strategies and sustainable rural development.

Promoting the Green Logistics System in Rural Areas: Due to the constraining effect of carbon emissions on rural logistics and urbanization, it's crucial to advance sustainable development in rural logistics comprehensively. This involves re-planning and optimizing the rural logistics network to reduce transportation distances and times, thereby lowering energy use and carbon emissions. Introducing smart logistics systems can enhance efficiency and minimize unnecessary transport. Utilizing efficient logistics management software to optimize cargo loading and delivery routes is also key. Additionally, formulating policies that encourage the development of green logistics is essential, as it guides and promotes the widespread adoption of green logistics practices.

***Implement Sustainable Urbanization Strategies*:** The dynamic nature of the relationship between rural logistics, urbanization, and carbon emissions necessitates continuous monitoring. Developing a circular economy model, promoting green building standards, and the use of energy-efficient building materials, as well as vigorously advancing the digital transformation of urbanization management, are key steps. Governments and organizations should adopt adaptive management strategies that integrate new data and insights in real time, allowing for the ongoing optimization of policies and practices.

Foster International Cooperation and Technological Exchange: Promote transnational carbon trading and the development of carbon markets, encourage international collaboration in low-carbon technology research and development, and share resources and outcomes. Strengthen the coordination and cooperation of international environmental protection policies, provide technical support and financial aid, and assist underdeveloped regions in building low-carbon infrastructure.

6. Conclusions

In this article, I delve into the intricate dynamics among urban development, advancement of rural logistics, and carbon emissions, forming an integrated structural framework to encapsulate these elements and employing a nonlinear model for analysis. This framework is substantiated with empirical data spanning from 1991 to 2019 in China. Key observations reveal a mutual dependency between rural logistics and urban development, both exhibiting a direct and positive correlation with the escalation of carbon emissions. Notably, urban development exerts a more pronounced impetus on rural logistics, whereas carbon emissions impose a regulatory effect on both domains. Furthermore, the interplay between urban development and carbon emissions significantly mitigates the increase of carbon emissions, while the interaction between the progression of rural logistics and carbon emissions curtails the expansion of rural logistics.

Therefore, two main research contributions are provided by this study. First, a bondage structure framework of urbanization, rural logistics and carbon emissions is established, which provides an analysis framework for the internal correlation analysis of urbanization, rural logistics and carbon emissions. Second, a new bondage model of low-carbon rural logistics, rural economy and carbon emissions is proposed, which effectively corrects the one-sided cognition of the “economy-social-ecological” synergy of the existing models, breaks the black box of the interaction between rural logistics, urbanization and carbon emissions, and provides theoretical support for the “dilemma” paradox of decoupling rural economic development and environmental protection.

Although the investigation yields valuable insights into the nexus of rural economics and ecological sustainability, it is not without its limitations. A primary constraint is the exclusive reliance on Chinese data from 1991 to 2019. Future studies should aim to incorporate a more expansive and diverse collection of international data, thereby broadening the research's scope and relevance. Additionally, forthcoming in-depth analyses should integrate a broader spectrum of potential determinants, including policy frameworks and technological advancements. Such an approach would pave the way for a more holistic examination, significantly elevating both the scientific rigor and practical applicability of the findings.

Use of AI tools declaration

The author declares that they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The author declares that there are no conflicts of interest.

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