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Research article

Key factors influencing sustainable population growth: A DEMATEL-ANP combined approach

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A R T I C L E I N F O

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A B S T R A C T

This study highlights the importance of sustainable social demographic growth. It uses a model that combines the Decision-making Trial and Evaluation Laboratory (DEMATEL) with the Analytic Network Process (ANP) to examine key factors affecting this growth and their interactions. The analysis focuses on six critical factors: economic development, education and gender equality, health services, environmental sustainability, immigration policies, and technological advancement. Experiments using government and international organization databases include comparative experiments with deep learning prediction models, ensemble learning models, Causal Inference Models, complex network analysis models, and agent-based models. Comparison metrics cover accuracy, precision, recall, and F1 score. The results indicate that, with a data volume of 4000, the optimized model achieves an accuracy of 0.973, precision of 0.981, recall of 0.969, and an F1 score of 0.89, demonstrating the model's superior performance. The DEMATEL method analyzes the direct relationships among the factors. The results show that economic development and technological advancement have impact scores of 3.91 and 3.43, respectively, indicating their strong influence on other factors and their role in promoting sustainable demographic growth. Education and gender equality, health services, and technological advancement each have impact scores of 3.39, meaning they are significantly affected by other factors and are sensitive in the growth process. Finally, the ANP method is used to calculate the weights of each factor, determining their relative importance in sustainable social demographic growth. The results highlight that economic development level and technological advancement and innovation are core factors influencing sustainable social demographic growth, with significant direct and indirect impacts on other factors and a crucial role in the overall system. These findings provide a scientific basis for formulating relevant policies and interventions, particularly in prioritizing and strengthening economic and technological development strategies. This study offers valuable insights for research in demography, sustainable development, and social policy formulation.

1. Introduction

With the ongoing global population growth, population sustainability has become a global challenge, especially against the

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backdrop of limited resources and environmental vulnerability [1–3]. Population growth is intricately linked to various aspects such as economic development, resource consumption, environmental protection, and social welfare, with complex and far-reaching interactions among these factors. To achieve sustainable population growth—meaning meeting the needs of the current population without compromising the ability of future generations to meet their needs—it is essential to thoroughly understand the key factors influencing population growth and their interaction mechanisms [4–6]. In the contemporary era, advancements in data science and computational technology have led traditional population research methods to evolve towards more complex and refined analytical models. Advanced data analysis tools and models, such as Decision-making Trial and Evaluation Laboratory (DEMATEL) and Analytic Network Process (ANP), help identify key factors affecting population sustainability. These methods offer precise assessments of these factors. This provides a scientific basis for policy-making and practice. This study is motivated by the pressing need to address the challenges posed by rapid global population growth on resources, environment, economy, and social welfare, and the urgent requirement for scientifically-based sustainable solutions [7]. Advanced analytical tools like DEMATEL and ANP present new approaches for analyzing and solving complex social science issues, particularly in examining factor relationships [8].

Based on this background and motivation, the aim of this study is to explore the key factors influencing social population sustainability by combining DEMATEL and ANP models. By analyzing the interactions and relative importance of these factors, the study seeks to provide new insights and methodological support for research and practice in relevant fields.

2. Literature review

In previous studies, Zhanbayev et al. (2023) highlighted a significant positive correlation between economic development and population growth. They noted that increased income from economic growth could improve healthcare and living conditions, thereby influencing birth and death rates [9]. This experiment helps understand the crucial role of economic development in promoting sustainable population growth. However, these experiments primarily rely on regression analysis of economic data and fail to explore the complex interactions between economic development and other social factors. Lin and Zhou (2022) proposed that long-term economic stability is crucial for sustainable population growth through comparative studies of multiple countries. They demonstrated how economic fluctuations and instability indirectly affect population growth by influencing employment opportunities and social safety nets [10]. While this experiment reveals the importance of economic stability, its methods are limited to descriptive analysis and do not fully dissect the multifactor interactions behind economic fluctuations. Fallah et al. (2022) discovered that economic globalization had a profound impact on population growth and migration patterns. Globalization not only fostered international economic cooperation but also accelerated talent mobility, thus affecting global population distribution [11]. This experiment provides valuable insights into migration under globalization but overlooks the influence of other critical factors such as environmental and social policies on population dynamics. Abid et al. (2022) proposed that improvements in educational levels, particularly for women, were closely related to declines in fertility rates and population aging. They emphasized that investment in education was key to achieving sustainable population growth [12]. However, this experiment focuses mainly on the direct link between education and fertility rates, lacking in-depth exploration of the interaction between education and other population growth factors. Henderson and Loreau (2023) identified that promoting gender equality contributes to healthy population growth. They pointed out that gender equality not only enhances the social and economic status of women but also significantly impacts family size and reproductive behavior [13]. This experiment provides empirical support for the relationship between gender equality and population growth but is based mainly on macro statistical analysis, lacking detailed examination of micro-level mechanisms. Luo et al. (2022) suggested that the design of social policies and welfare systems played a decisive role in promoting sustainable population growth. Policies supporting families, the elderly, and children were crucial for balancing fertility rates and improving population health [14]. Nevertheless, this experiment does not systematically evaluate the interactions between these policies and other factors such as economic and environmental influences. Lin et al. (2022) proposed a close relationship between environmental protection and sustainable population growth. Their experiment emphasized the importance of protecting and sustainably utilizing natural resources to ensure long-term population growth [15]. However, their methodological focus on environmental factors does not fully analyze the interaction between environmental and socioeconomic factors. Wang et al. (2022) showed that climate change significantly impacted population growth and migration, particularly in climate-sensitive regions, where environmental factors became major drivers of migration [16]. Although this experiment highlights the importance of climate change, its analytical methods do not effectively integrate the influence of other related factors.

This study points out that many existing research efforts focus only on single or a few factors. They neglect the complex interactions and feedback mechanisms among multidimensional factors such as economic, social, and environmental aspects. Moreover, traditional research methods like regression analysis and causal models have limitations in handling multifactor interdependencies and complex feedback relationships. Therefore, this study combines DEMATEL and ANP methods, covering factors across multiple dimensions, including economic, educational, health, and environmental aspects, and delves into the interactions and comprehensive effects among these factors. By using the DEMATEL method to analyze the influence relationships and mechanisms between factors, and the ANP method to calculate the weights and relative importance of each factor, it proposes a novel analytical framework. This framework provides a more accurate approach to handling and analyzing complex system dynamics and interdependencies among factors, thus offering new perspectives and methodological support for current research.

3. Factors of social population sustainable growth based on combination model

3.1. The impact of social population growth

Population growth denotes the increase in the number of individuals within a specific time period [17,18]. This phenomenon is influenced by various factors, including fertility rates, mortality rates, and immigration. The population growth rate is commonly used to quantify the speed of population increase, reflecting the dynamic changes occurring within a country or region [19–21]. Population growth has significant implications for social, economic, and environmental aspects, making it a critical subject in the fields of demography, sociology, economics, and policy-making. Since the Industrial Revolution, global population growth has entered an unprecedented phase of acceleration [22]. Over the past two centuries, advancements in medical care, agricultural productivity, and overall living standards have contributed to an increase in the global population from 1 billion to nearly 8 billion. This rapid growth has led to increased population density, accelerated urbanization, and considerable strain on natural resources and the environment. The effects of social population growth are summarized in Table 1.

Population growth represents a complex global challenge that necessitates collaborative efforts from governments, international organizations, and various sectors of society through comprehensive strategies and coordinated actions. To achieve sustainable population growth, it is essential not only to manage population quantity but also to focus on enhancing population quality and improving living conditions [23–25].

3.2. Mechanism and characteristics of DEMATEL and ANP

The DEMATEL method is designed to analyze and address the influence relationships among various factors within complex systems. The core objective of this method is to reveal both direct and indirect relationships between factors by constructing an impact matrix, thereby determining the influence and degree of impact of each factor. Specifically, DEMATEL involves constructing an initial impact matrix based on expert judgment and quantitative analysis, where each element in the matrix represents the extent of direct influence one factor has on others. Subsequently, through matrix operations, a total impact matrix is derived, which reflects not only direct influences but also indirect effects transmitted through other factors [26]. Its method uses the basic steps as shown in Fig. 1:

The final output of this process is a visual causal diagram, which clearly illustrates the causal relationships between various factors and categorizes them into "cause factors" and "effect factors." Cause factors are typically those that have a strong influence on other factors but are minimally affected by them, whereas effect factors are the opposite [27]. In a study on traffic management in a city, the DEMATEL method analyzes factors affecting traffic congestion. These factors include road infrastructure, public transportation efficiency, residents' travel habits, and policies. DEMATEL helps researchers identify key factors, such as public transportation efficiency, which significantly influences other factors like travel habits and road congestion. This makes it a focal point for addressing traffic issues. When using DEMATEL to analyze sustainable population growth, it shows that economic development and technological innovation directly impact other factors and hold a central position in the influence network.

ANP is designed to address the interdependencies among multiple factors in complex decision-making problems by establishing a network structure model to determine the relative importance of each factor. Unlike Analytic Hierarchy Process (AHP), which assumes independence among factors at different levels [28, 29], ANP allows for feedback and interdependencies between factors, making it more flexible and accurate in handling complex decision-making issues in real-world scenarios. Its characteristics are shown in Table 2:

The application process of the ANP involves several steps: Firstly, identify the key factors of the research problem and organize these factors into a network structure, where nodes represent different factors and links denote the dependencies between these factors. Next, evaluate the relative importance of each factor through pairwise comparisons and construct a judgment matrix. Then, use the eigenvalue method to calculate the weights of each factor. Finally, compute the overall priority weights through the supermatrix to determine the relative importance of each factor in the decision-making process. As a real-world application example, ANP is widely used in supply chain management. In the supply chain decision-making process of a multinational corporation, researchers use the ANP method to analyze key factors that affect supply chain performance. These factors include supplier reliability, transportation costs, market demand fluctuations, and supply chain resilience. Through ANP analysis, the company identifies "supplier reliability" as the most critical factor. It prioritizes resources for managing suppliers and developing long-term partnerships. This approach enhances

Table 1
The impact of social population growth.

Dimension	Impact
Social economy	Population growth has a dual impact on economic development. On the one hand, the increase in population means the expansion of the labor market and the increase in consumer demand, which is conducive to the expansion of the economic scale. On the other hand, if the population growth rate exceeds the economic growth rate, it may lead to an increase in employment pressure and a decrease in per capita resources and services, thus having a negative impact on social welfare.
Environmental resources	Population growth intensifies the demand for natural resources, including water resources, land and energy, which leads to over-exploitation of resources and environmental degradation. In addition, population growth has also increased waste and greenhouse gas emissions, which has had an impact on ecosystems and global climate change.
Social structure and services	The rapid population growth has put forward higher requirements for public services and infrastructure such as education, health care, housing and transportation. In the case of limited resources, this may lead to insufficient service supply and affect social well-being and quality of life.

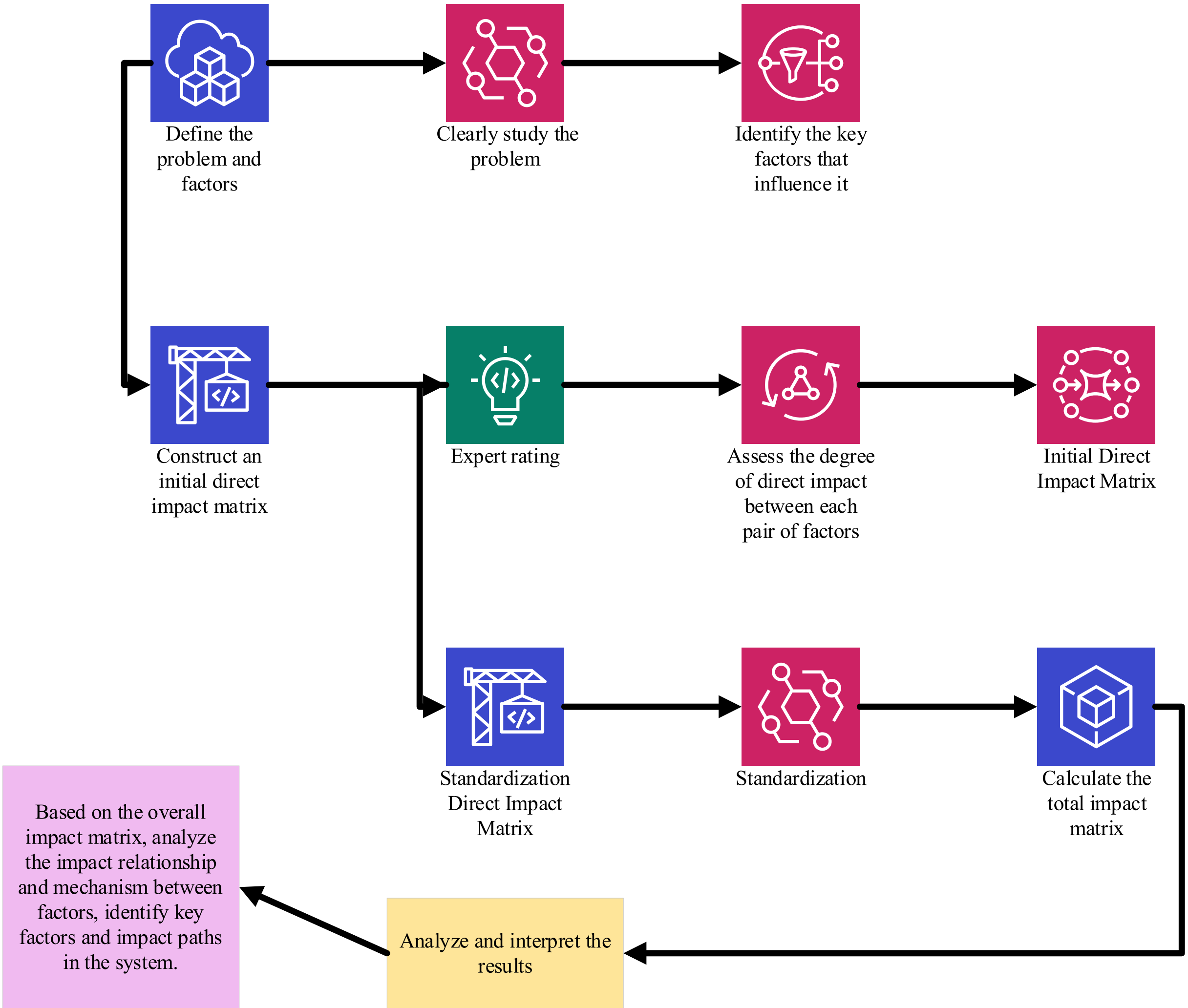

Fig. 1. Basic steps of DEMETAL analysis.

Table 2
Characteristics of ANP.

Characteristics	Analysis
Flexibility and adaptability	ANP provides a flexible framework, which can adapt to all kinds of decision-making problems, especially in the case of complex interdependence and feedback among factors.
Comprehensiveness	ANP can comprehensively consider all relevant factors and their interactions, providing a comprehensive method for analyzing and evaluating decision-making problems.
Combination of quantitative analysis and qualitative analysis	Through expert scoring and weight calculation, ANP combines quantitative analysis and qualitative analysis, making the decision-making process more scientific and reasonable.

the overall performance of the supply chain.

When addressing the issue of sustainable population growth, the combination of DEMATEL and ANP can provide a comprehensive and in-depth analytical perspective. DEMATEL can first identify and analyze the causal relationships between various influencing factors, helping researchers understand which factors are the primary drivers. Subsequently, ANP can further prioritize these factors to determine their relative importance, thereby providing a scientific basis for policy-making. For example, in the study of population policies in a certain country, the DEMATEL method might reveal that “economic development level” and “education quality” are two key factors influencing population growth. ANP can then determine the relative weights of these factors under different policy scenarios, providing decision support for resource allocation and policy formulation by the government.

The DEMATEL and ANP methods together enable detailed analysis of relationships between factors in complex systems and also determine the priority of each factor. This provides a strong theoretical foundation and empirical support for sustainable population growth. By using these tools, researchers can better understand the multidimensional factors affecting population dynamics and suggest more effective policy recommendations.

3.3. Construction of DEMATEL and ANP combined model

In the study of key factors influencing sustainable population growth and their interaction mechanisms, a research framework utilizing the combination of DEMATEL and ANP models offers a systematic and comprehensive approach. This integrated model not only identifies and analyzes the key factors and their interactions but also determines their relative importance. Consequently, it provides valuable decision support for formulating effective policies and strategies. The structure of this combined model is illustrated in Fig. 2.

In the calculations, the relative weights of each factor are obtained through normalization and limit processing of the supermatrix. Pairwise comparisons are conducted for each factor in the network to assess its importance relative to other factors. This step results in a pairwise comparison matrix, where the elements reflect the relative importance of each factor. Subsequently, mathematical methods are used to calculate the maximum eigenvalue of this matrix and its corresponding eigenvector. Each component of the eigenvector represents the preliminary weight of a factor. Finally, the computed weight vector is normalized to ensure that the sum of all weights equals 1. This approach allows researchers to determine the relative importance of each factor within the system, providing a scientific basis for complex decision-making.

The optimization model integrates DEMATEL's capability to analyze the mechanisms of factor interactions with ANP's advantage in decision-making support. This integration allows the study to not only investigate the complex relationships between factors in depth but also to quantitatively assess the importance of each factor. Consequently, it provides robust methodological support for developing more scientific and rational population growth policies. Through this framework, the study can achieve a more comprehensive and nuanced understanding of the dynamic processes of sustainable social population growth and its influencing factors, which is highly significant for guiding research and practice in related fields.

3.4. Experimental design

The dataset utilized in this study is the World Development Indicators, which is available in the database of governments and international organizations. This comprehensive database, maintained by the World Bank, encompasses over 1500 indicators and covers various dimensions of global economic development, including demography, education, health, poverty, and the environment, with a historical span exceeding 50 years. The data, which is in time series format, extends from 1960 to the present and is instrumental

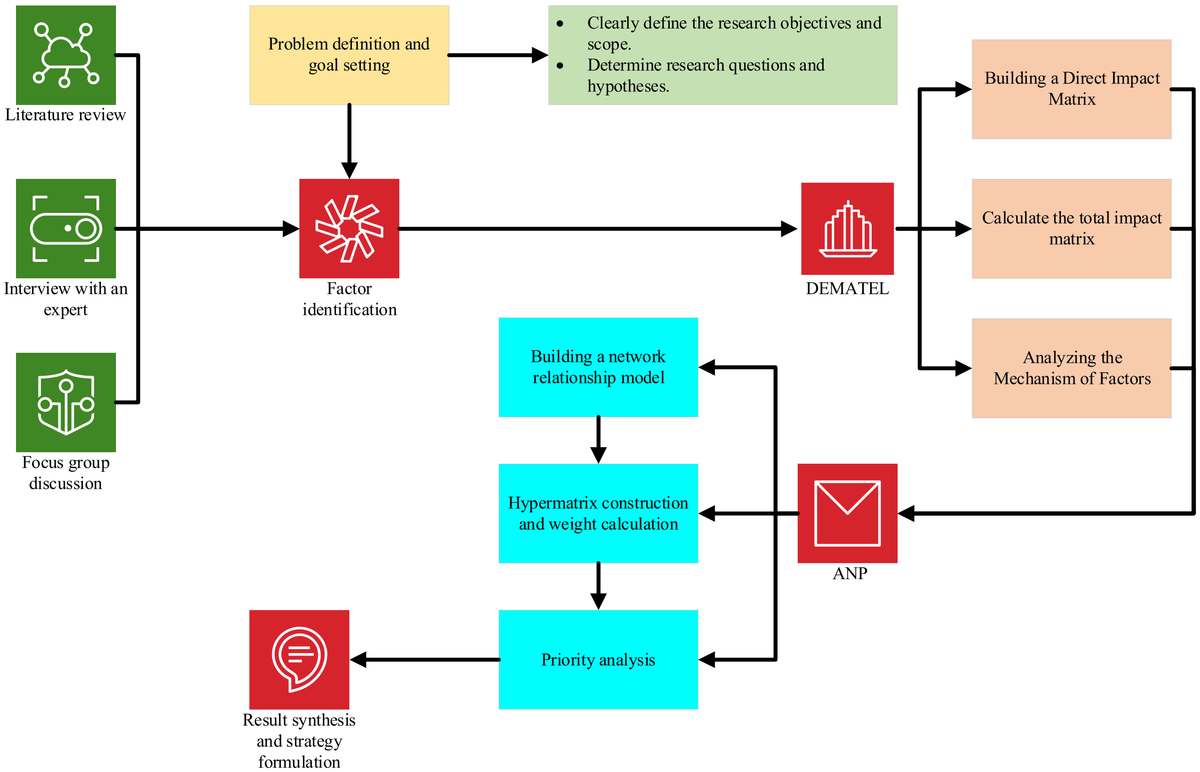

Fig. 2. Combined model architecture of DEMATEL and ANP.

for analyzing and forecasting population growth trends and their implications for sustainable development. The database is accessible for direct download from the World Bank's open data platform (download website: https://data.worldbank.org/indicator), with data typically available in CSV or Excel formats, and API access also provided. The hardware and software configuration parameters required for this experiment are detailed in Table 3.

Some related codes in this calculation are as follows:

```
Import pandas as PD.
Import numpy as np.
#Sample data loading.
Data = pd.DataFrame ({
    'Factor_1': np. random. rand (10),
    'Factor-B': np. random. rand (10),
    'Factor-C': np. random. rand (10),
    #Assuming multiple factors
})
#Data standardization processing.
Normalized_data=(data - data. min(.))/(data. max(.) - data. min(.))
Print (normalized data. head(.))
```

The experimental comparison models include Deep Learning Predictive Models (DLPM), Ensemble Learning Models (ELM), Causal Inference Models (CIM), Complex Network Analysis Models (CNAM) and Agent-Based Models (ABM). DLPM excel in handling large-scale data and complex nonlinear relationships. Through automatic feature extraction and learning across multiple neural network layers, these models can capture intricate patterns and relationships within the data. Consequently, DLPM offer significant advantages in predicting complex issues such as population dynamics, economic development, and environmental changes. DLPM is selected as a comparative model to evaluate the performance of the optimization model in handling complex forecasting tasks. ELM enhance overall performance by combining multiple weak learners. Common ensemble methods, such as Random Forests and Gradient Boosting Decision Trees, demonstrate strong generalization capabilities when dealing with multidimensional data and high-dimensional feature spaces. ELM is typically used to improve model stability and accuracy, particularly in addressing diverse influencing factors. Comparing the optimization model with ELM validates its advantages in terms of comprehensive performance and robustness. CIM focus on identifying and analyzing causal relationships between variables, revealing how certain factors directly or indirectly impact population growth. Causal inference has broad applications in policy evaluation and intervention effectiveness analysis. The choice of CIM as a comparative model aims to assess the effectiveness and accuracy of the optimization model in uncovering causal relationships and analyzing factor interactions. CNAM study complex associations between factors within social systems by constructing and analyzing network structures. CNAM excels in examining areas such as population migration, social interaction patterns, and information dissemination. Comparing the optimization model with CNAM allows for the evaluation of its performance in analyzing multi-layered, multidimensional systems, particularly in handling the interdependencies among multiple factors. ABM simulate the behavior and interactions of individual agents to study their impact on the overall system. ABM is commonly used to explore individual decision-making and social dynamics within complex systems. The selection of ABM as a comparative model is intended to examine the optimization model's performance in reflecting the impact of individual behaviors on the overall system, especially in accurately simulating population changes and social policy effects. The selection of these five models for comparison is based on their representativeness and broad applicability in the study of social population growth. By comparing the optimization model with these models, the study not only demonstrates its superior performance in handling complex, multi-factor systems but also validates its applicability and advantages across different scenarios. To ensure data accuracy, the parameters are consistently set throughout the experiment. The defined impact degree is measured on a scale from 0 to 4, with 0 indicating no impact and 4 representing a strong impact. To guarantee that the weight calculation of the hypermatrix converges to a stable state, convergence is deemed achieved when the weight change is less than 0.001. A consistency ratio below 0.1 is considered acceptable. For the DLPM, the learning rate is set to 0.01 and the batch size to 32 to balance convergence speed and training stability. The network consists of 5 layers, each with 128 hidden units, and uses the ReLU activation function. The ELM constructs 300 decision trees with a maximum depth of 10 to capture nonlinear relationships between features. The minimum sample split and minimum leaf node sample sizes are set to 5 and 2, respectively, to prevent overfitting while ensuring sufficient generalization capability. The subsampling rate is 0.8, and the learning rate is set to 0.05. For the CIM, the matching radius is set to 0.05, and the number of nearest neighbors for matching is 3. In the CNAM,

Table 3
Configuration of experimental hardware and software.

Device type	Parameter configuration
Processor	Inter(R) Xeon(R) CPU E5-2620 v4 @ 2.10 GHz
Graphics processing unit (GPU)	NVIDIA Titan Xp 12 GB
Internal storage	64 GB
Programming language	Python 3.6
Technical framework	Py Torch 1.7.0 deep learning framework

the network has 5000 nodes, with a modularity coefficient of 0.5 and a clustering coefficient of 0.3. The ABM includes 500 agents whose decision rules are based on utility maximization. The interaction range is set to 5 to simulate the impact of individual behavior on the entire system. The behavior update strategy employs synchronous updates with a time step interval of 5 units to ensure accurate simulation of dynamic changes in the real world.

4. Performance comparison of social demographic analysis models based on DEMATEL and ANP

4.1. Comparative experiment on the performance of social demographic analysis model

The performance indicators of experimental comparison include accuracy, precision, recall and F1 score. Accuracy is a fundamental metric for assessing the overall correctness of a model's predictions, representing the proportion of correctly predicted samples out of the total samples. In the context of population growth and social dynamics analysis, accuracy provides a direct reflection of the model's overall performance in handling all factors and variables. Precision measures the proportion of true positive samples among all

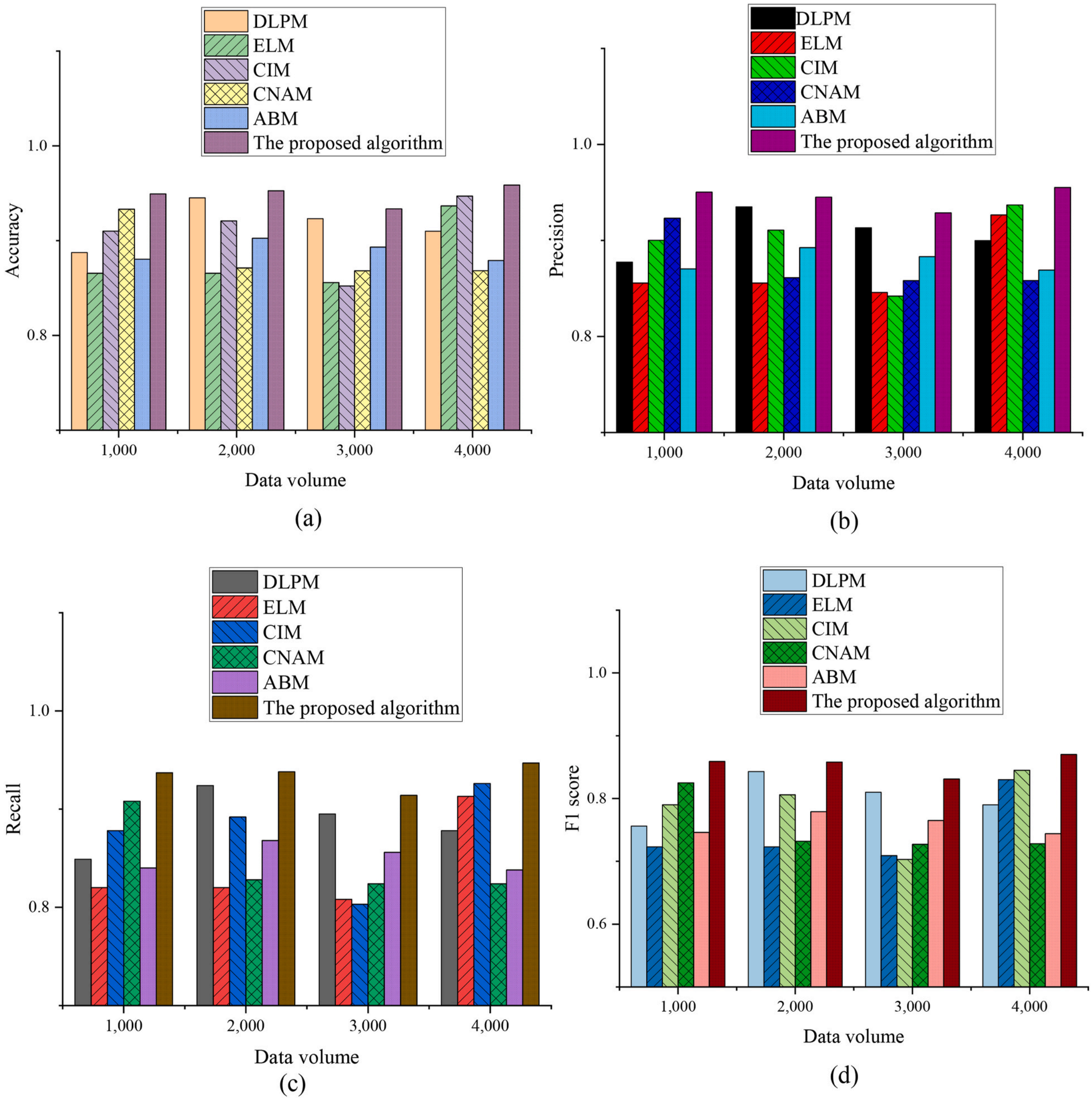

Fig. 3. Performance comparison results of combined model (a) accuracy; (b) precision; (c) recall rate; (d) F1 score.

samples predicted as positive. For identifying key factors in population growth and predicting policy effects, precision is crucial as it focuses on the model's accuracy in predicting positive cases (e.g., actual policy effects or population changes). Recall indicates the proportion of true positive samples among all actual positive samples. In research, recall is important for evaluating the model's ability to capture minority groups or marginal factors. The F1 score, which is the harmonic mean of precision and recall, provides a comprehensive performance evaluation metric by combining both precision and recall. Data preprocessing is performed before using the data, including handling missing values, addressing outliers, and removing duplicate data. Normalization is applied to ensure that each variable contributes equally to the model during training. This prevents any variable from disproportionately influencing the results due to differences in scale. Missing values are managed by either deleting samples with a high proportion of missing data or imputing missing values. Outliers are identified using the standard deviation method and are either removed or adjusted based on the situation. Normalization aims to bring data to the same scale, commonly achieved through min-max normalization. This ensures equal contribution of each variable to the model, avoiding any disproportionate impact due to differing scales. The experimental results are shown in Fig. 3:

The experimental results in Fig. 3(a) show that with 1000 variables, the optimized model's accuracy is 0.9493. In contrast, other models have accuracies ranging from 0.8656 to 0.9332. As the number of variables increases to 2000 and 3000, the optimized model's accuracy rises to 0.9526 and 0.9335, respectively, remaining the top performer. Other models fluctuate between 0.8558 and 0.9451. When the number of variables reaches 4000, the optimized model's accuracy further increases to 0.973, significantly surpassing other models. The closest competitor, CIM, achieves an accuracy of 0.947. In terms of Fig. 3(b), the optimized model achieves a precision of 0.9503 with 1000 variables. As the number of variables increases to 4000, the precision of the optimized model improves to 0.981, markedly exceeding the highest precision value of 0.937 achieved by other models. Regarding recall, the optimized model outperforms other models across all tested variable counts, particularly achieving a recall of 0.969 with 4000 variables. In Fig. 3(c), the recall of other models ranges between 0.8 and 0.93, with the CIM model showing the highest recall of 0.926 at 4000 variables among the five comparison models. For Fig. 3(d), the optimized model consistently performs better across all tested variable counts. Notably, with 4000 variables, the optimized model achieves an F1 score of 0.89. In comparison, other models' F1 scores range between 0.7 and 0.845, with the CIM model reaching an F1 score of 0.845 at 4000 variables, representing the best performance among the compared models.

In summary, the optimized model demonstrates significant superiority over other comparison models across the four key metrics of accuracy, precision, recall, and F1 score, particularly under large-scale variable conditions. This indicates that the optimized model has a stronger performance advantage in handling complex multivariable problems, providing a more reliable analytical tool for studying sustainable population growth.

4.2. Analysis of simulation experiment results

To further verify the effectiveness of the optimization system developed in this study, simulation experiments are conducted, and key factors for the sustainable growth of the social population are identified through expert interviews. The selected indicators are listed in Table 4.

The related scores directly influenced by experts are obtained, as shown in Fig. 4:

The influence degree, affected degree and centrality of each factor are calculated by scoring, and the result is shown in Fig. 5:

In Fig. 5, the levels of economic development and technological advancement and innovation achieve scores of 3.91 and 3.43, respectively, indicating their significant influence on other factors and their crucial role as key drivers of sustainable population growth. In terms of susceptibility to influence, education and gender equality, health and medical services, and technological advancement and innovation all score 3.39, suggesting that these factors are highly impacted by other elements and are sensitive components within the system. Further analysis of centrality metrics reveals that economic development and technological advancement and innovation have centrality scores of 7.28 and 6.82, respectively, highlighting their core positions within the system. This indicates that these factors are not only important sources of influence but also key elements that are influenced by other factors in the system. In other words, these two factors both drive the development of other elements and are significantly impacted by them.

Table 4
Key factors of sustainable growth of social population.

Factor	Analysis
Level of economic development	A higher level of economic development is usually related to better health conditions, education level and living standards, which directly affect fertility and mortality.
Education and gender equality	The improvement of education level, especially that of women, is closely related to the decrease of fertility rate and the improvement of population quality. Gender equality plays a key role in improving women's position in education, work and decision-making, which in turn affects family size and reproductive behavior.
Health and medical services	Good medical and health services can reduce infant and maternal mortality and prolong life expectancy, thus affecting population structure and growth rate.
Environmental sustainability	The sustainable utilization of resources and environmental protection can guarantee the natural basis for long-term stable population growth and prevent population reduction caused by resource depletion or environmental degradation.
Immigration policy and mobility	The openness of policies can promote natural population growth and structural optimization, while strict restrictions may lead to brain drain and population aging.
Technological progress and innovation	Technological development plays a vital role in improving productivity, improving medical and health conditions and promoting the popularization of education, which indirectly affects population growth and sustainability.

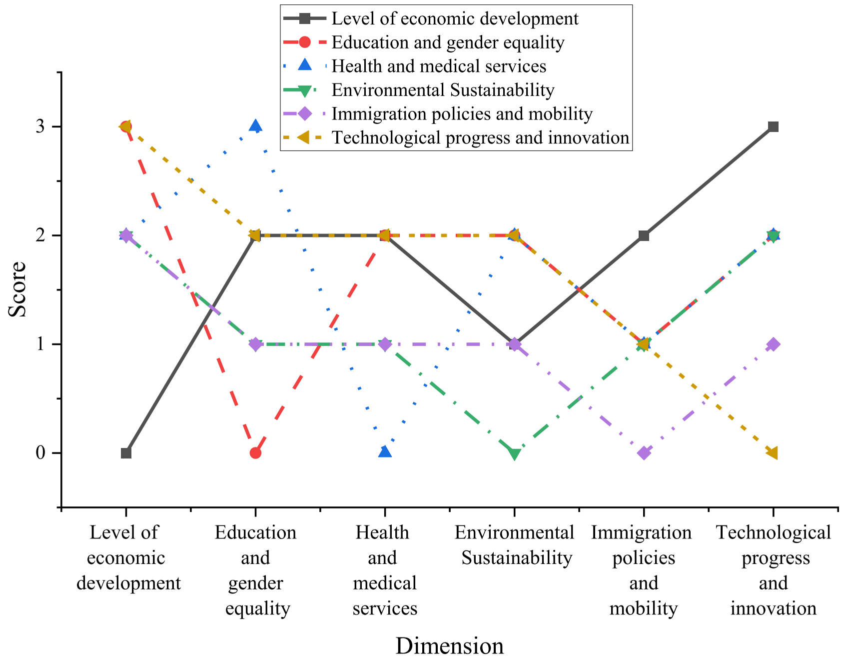

Fig. 4. Direct influence score.

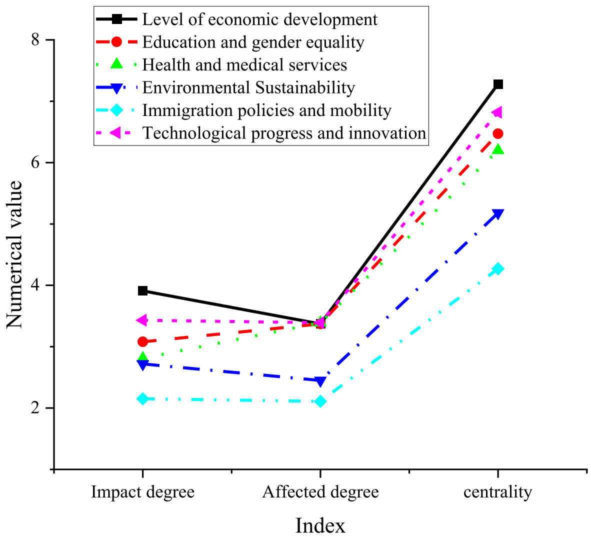

Fig. 5. Calculation result of influence degree.

Therefore, economic development and technological advancement and innovation play dual roles in sustainable population growth, serving as core elements that maintain system stability and drive development. This analysis underscores the importance of economic development and technological innovation in the study of sustainable population growth. They function not only as independent driving factors but also influence other key factors through complex interactions. The study suggests that when formulating related policies, priority should be given to enhancing economic and technological levels to achieve sustainable population growth goals. After that, the normalized hypermatrix is constructed through expert scoring and analysis results, as shown in Table 5:

The final weight of each factor calculated by the model is the same, which is 0.1667. This means that under this specific model, all factors have the same relative importance to the sustainable growth of social population.

4.3. Discussion

In the performance comparison experiments presented in this study, the optimized model consistently demonstrates superior

Table 5
Normalized hypermatrix.

	Level of economic development	Education and gender equality	Health and medical services	Environmental sustainability	Immigration policy and mobility	Technological progress and innovation
Level of economic development	0.20	0.10	0.15	0.20	0.15	0.20
Education and gender equality	0.15	0.20	0.20	0.15	0.10	0.20
Health and medical services	0.20	0.15	0.20	0.10	0.15	0.15
Environmental sustainability	0.15	0.20	0.15	0.20	0.10	0.20
Immigration policy and mobility	0.10	0.15	0.15	0.20	0.20	0.20
Technological progress and innovation	0.20	0.20	0.20	0.10	0.15	0.15

performance across various variable orders. This achievement is primarily due to its thorough consideration of the complex interactions between factors during its design process and its use of advanced algorithms to precisely capture and analyze these relationships. Additionally, the construction of the optimized model effectively leverages the strengths of both DEMATEL and ANP methods, leading to the successful identification of key influencing factors and their mechanisms, which significantly enhances prediction accuracy. The broad implications of these research findings highlight that the insights obtained from the DEMATEL-ANP model offer new perspectives for population analysis and policy formulation. These insights are not only valuable for theoretical research but can also be translated into actionable policies and interventions. The study identifies economic development and technological advancement and innovation as core drivers of sustainable population growth. This finding is crucial for policymakers as it emphasizes the need to prioritize strategies for economic and technological development as primary means to promote sustainable population growth. Translating these research findings into actionable policies may involve several steps. First, increase investment in technological innovation to boost economic growth and improve quality of life. Second, develop and implement policies that support education and gender equality, which can promote sustainable population growth. Third, enhance health and medical services to prevent health issues from limiting population growth. The successful implementation of these policies relies on a clear understanding of the core drivers. The DEMATEL-ANP model helps policymakers identify the relative importance of these factors and their roles in the overall system.

Although deep learning prediction models excel in handling large-scale data and complex nonlinear relationships, they are highly dependent on data quality and quantity and are prone to overfitting. In contrast, the optimized model, which integrates DEMATEL and ANP methods, mitigates these issues and provides a more comprehensive analysis of the interactions among multidimensional factors. ELM offer advantages in improving model stability and robustness but fall short when dealing with systems characterized by high dependency and complex feedback mechanisms. The optimized model, by identifying key driving factors through DEMATEL and evaluating their weights using ANP, better handles interactions within complex systems. CIM excels in analyzing causal relationships between variables but faces limitations in managing complex multi-factor feedback. The optimized model performs better in such scenarios by revealing these intricate relationships and providing more precise analysis results. CNAM is proficient at examining network relationships within social systems but lack in quantifying factor importance and impact. The optimized model enhances practical applicability by integrating ANP, which provides quantitative assessments based on network analysis. ABM simulates the impact of individual behaviors on systems but experience increased computational complexity and resource demands as system scale grows. The optimized model demonstrates better adaptability to large-scale data and, through refined analytical methods, improves result reliability without adding computational burden. These detailed comparative analyses further highlight the significant advantages of the optimized model in handling complex factor interactions. This not only enhances the model's practical utility and applicability but also provides a more scientific basis for future policy development.

Finally, the study underscores the importance of economic development and technological advancement as key drivers of sustainable social population growth. This finding has substantial policy implications, particularly emphasizing the need to prioritize and strengthen economic and technological development strategies when formulating population policies. Through these insights, policymakers can obtain more comprehensive and scientific evidence to implement population policies and interventions that align with social, economic, and environmental sustainability goals.

5. Conclusion

This study, by constructing a research framework based on the DEMATEL and ANP combination model, provides an in-depth analysis of the key influencing factors and their interaction mechanisms for sustainable social population growth. It comprehensively considers multiple key factors affecting social population sustainability and uses the DEMATEL method to analyze both direct and indirect relationships between these factors, offering a new perspective on the complexity of population growth. By integrating DEMATEL and ANP methods, this study develops a novel combined model that effectively identifies the core factors impacting sustainable social population growth and assesses their weights, thereby enhancing the accuracy and reliability of decision analysis.

Ultimately, it also validated the optimized model's significant advantages in accuracy, recall rate, and F1 score compared to other existing models, demonstrating its potential application in complex system analysis. However, there are certain limitations in this study. First, the analysis primarily relies on existing data and literature reviews, which may not fully capture all factors affecting sustainable social population growth, particularly emerging or less-researched factors. Additionally, although the proposed optimized model performs well on many performance metrics, its computational complexity requires specialized knowledge and software support, which may limit its widespread application. The study mainly focuses on factors affecting sustainable social population growth, and the model's generalizability and applicability in other fields still require further validation. To address these limitations, future research could enrich and update the dataset of influencing factors using big data technologies and broader data sources, enhancing the comprehensiveness and accuracy of the research. Moreover, exploring methods to simplify the optimized model to reduce computational complexity, while maintaining or improving its performance, could make the model more understandable and accessible. Future work should also include more empirical studies, particularly case analyses in specific countries or regions, to assess and refine policy recommendations and provide more concrete guidance for actual policy-making. The main findings of this study offer concrete recommendations for policymakers and researchers. First, identifying economic development and technological advancement as core drivers of sustainable social population growth is crucial, implying that policymakers should prioritize and strengthen development strategies in these areas. Additionally, broader empirical research can validate the model's applicability in different contexts and explore its potential applications in other areas, providing clearer research insights for decision-makers and practitioners in the field of sustainable population growth. To simplify the optimized model and enhance its applicability, future research might consider incorporating more intuitive analytical methods or developing user-friendly tools to facilitate wider application of the model. Furthermore, verifying the model's generalizability and strategies for its broad application in various contexts will further enhance its practical value and impact. Through these efforts, this study will provide stronger support for the field of sustainable social population growth and offer scientific foundations for policymakers to develop effective intervention measures.

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CRediT authorship contribution statement

Fei Pang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Guo Miao:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Yingxu Li:** Writing – original draft, Supervision, Software, Resources, Project administration, Methodology, Investigation. **Yun Shi:** Writing – original draft, Software, Resources, Project administration, Funding acquisition.

Data statements

All data used or generated are included in this manuscript and the supplementary files.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e39404.

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