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Prioritization Decision-making Model for Sustainable Development Goals Based on Multi-factor Simulated Annealing Particle Swarm Algorithm

Binghui Liang[1], Junyong Cao[2,*], Jiancheng He[3], Shuyang Li[4], Xianliang Zhang[4], Jianhao Ou[5]

[1] Faculty of Mathematics and Computational Sciences, Wuyi University, Jiangmen 529000, China.

[2] School of General Education, Wuyi University, Jiangmen 529000, China.

[3] School of Economics and Management, Wuyi University, Jiangmen 529000, China.

[4] Faculty of Intelligent Manufacturing, Wuyi University, Jiangmen 529000, China.

[5] School of Foreign Languages, Wuyi University, Jiangmen 529000, China.

[*] The corresponding author:Junyong Cao; Correspondence: liangbinghui20@gmail.com.

Abstract: On September 25, 2015, the United Nations (UN) saw the adoption of 17 Sustainable Development Goals (SDGs) by 193 member states at the United Nations Sustainable Development Summit. The prioritization of the 17 Sustainable Growth Goals will contribute to the quick joint action by the UN to eradicate poverty, protect our planet, and improve the quality of life and futural prospects for all. In view of the challenges related to the 17 SDGs identified by the United Nations, our team has introduced a new model to quantify and assess their development potential. This model determines their priorities based on the established network of sustainable development relationships through a Post-Decision

Future Development forecasting approach to analyze the impact of major international movements on the SDGs. This article transforms the statistical data of the United Nations Sustainable Development Goals into a relationship network. It introduces the overall development speed and establishes the AHP-MLR model to determine the comprehensive influence of the SDGs. Additionally, the SA-PSO algorithm optimizes the ARIMA model to predict changes in 17 SDGs in the next decade. The predictive results indicate that SDG16 will boost the overall development speed by 23% in the next ten years, solidifying its status as the most promising direction for the next decade. We assume the successful realization of quality education, rebuild the relationship network and influence, and introduce three preliminary goals through AHP-MLR model analysis. As such, it is concluded that Internet access will be the focal point of the latest development. Finally, we convert the relationship network into a weighted undirected graph and, with SDG9 as the origin, generate a minimum spanning tree (MST). The results show that this assumption facilitates highly efficient development in SDGs (SDG 6, SDG 8, SDG 12) related to resource utilization. The research model presented in this article serves as an effective tool for the UN and other decision-makers to better understand and optimize the implementation of the SDGs, which, in turn, promotes the realization of global sustainable development.

Keywords: relational network; AHP-MLR model; multi-factor simulated annealing particle swarm algorithm; BFGS algorithm; MST model

Introduction

On September 25, 2015, the United Nations Sustainable Development Summit was held at the New York headquarters, where 193 member states formally adopted 17 SDGs at the summit. This historic moment marks a shared global commitment to social, economic and environmental sustainability. The formulation of the SDGs aims to comprehensively solve the three dimensions of sustainable development issues—social, economic and environmental—within the timeframe of 2015 to 2030 and guide the world towards a more sustainable development path. The creation of these goals reflects a well-thought-out process based on extensive international cooperation and participation to ensure the active involvement of countries in global sustainable development. These goals are not mere commitments on paper; rather, they serve as actionable guides to solve major global issues. For example, according to the Prototype Global Sustainable Development Report (2014), SDGs contribute guiding opinions to global sustainable development, with objectives ranging from poverty reduction and hunger alleviation, to protection of biodiversity, mitigation of land degradation, elimination of gender inequality, improvement of education quality, and promotion of productivity and technological achievement. These goals span multiple sectors and areas, providing a comprehensive perspective on global sustainable development.

However, an examination of the progress of the 17 goals in The Sustainable Development Goals Report 2023: Special Edition reveals a notable slowdown in the current progress across many fields. For example, SDG1 (without poverty) is developing in alignment with the current trend, but by 2030, an estimated 575 million people will still live in extreme poverty, and only one-third of countries will halve poverty scales; SDG7 (affordable clean energy) is considered insufficient, and at the current pace, about 660 million people will lack access to electricity by 2030, while nearly 2 billion will still rely on polluting fuels and cooking technologies. These situations pose obstacles to the fulfilment of the stated goal by 2030. Even in the context of the COVID-19 pandemic, geopolitical conflicts and serious threats to the global economy, several areas have even suffered regression. For instance, SDG12 (Responsible Consumption and Production) mentioned substantial deviation from the 2030 target of halving food waste and losses per capita. SDG16 (Peace, Controversy and Strong Institutions) also shows regressive data. As of the end of 2022, 108.4 million people worldwide found themselves forcibly displaced, an increase of 19 million compared to the end of 2021, a 2.5-fold increase over the past decade. Inequality and emerging human rights challenges make peaceful and inclusive societies further out of reach. Considering that we are already halfway through the timeline for the 17 Sustainable Development Goals, there is a growing apprehension that we will most likely be unable to fulfill our commitment to the goals.

Given the complex and ever-changing international situation and the actual conditions of different countries, it is challenging to fully cover SDGs. According to The Sustainable Development Goals Report 2023: Special Edition, the gap in progress assessment among SDGs goals has reached escalated to a global regional coordination crisis. In addition, more than 50 % of countries are unable to take into account all the SDGs at the same time. Although a few member countries, like China and Sweden, perform well, the capability of most others, especially less developed countries or those with heavily skewed industries, to address both SDGs is in question. Urgently, the focus should be on the priority development decision-making issue of the SDGs to ensure their realization on a more reasonable scale.

To better understand the priority decision-making issue of SDGs, this study analyzes officially provided cases by the UN to examine the potential of SDGs priority selection. The next section will explore existing theories and literature on previous evaluation and simulation studies related to SDGs to guide our research effectively. Subsequently, the paper propose a mathematical model for SDG indicator selection. Analytical hierarchy process (AHP-MLR), time series analysis (ARIMA model), particle swarm optimization algorithm (SA-PSO) and other methods are combined to establish a relationship network and predict SDG progress, which involves the transformation of the relationship network into a weighted undirected graph to study the interrelationships between SDGs, thereby aiding in the formulation of policies and strategies. In addition, international cooperation and knowledge sharing will also play an important role in SDG realization, given the cross-border nature of many issues.

In this study, we will continue to delve into the development and priority decisions of the SDGs to provide insights and support for achieving this global consensus. Our focus will center on the relationship between the SDGs and the maximization of goal achievement through optimization strategies. Through reasonable data support and mathematical modeling, we seek to provide stronger support for the realization of SDGs and ensure the fulfillment of this ambitious vision in 2030.

Research motivation

The motivation for this study comes from the recognition that sustainable development has become an important area of interdisciplinary research. In particular, it has become a global issue for policymakers, scholars, and the public. Although many countries and organizations have taken various measures to promote sustainable development, many challenges remain in terms of the achievement of sustainable development. This work, therefore, focuses on the priority evaluation of sustainable development and aims to provide policy recommendations for policymakers.

Research questions and objectives

To study the relevance of the 17 SDGs, our team used mathematical models to assist the UN in prioritizing SDGs. The inspiration for this research comes from the narrative of SDG big data modeling [15 , 16]. Strictly speaking, the research method in this article goes beyond mere big data modeling; it involves establishing relationship networks, applying mathematical models and utilizing prediction methods. This approach aims to study the priorities of the 17 SDGs and provides a precise method to effectively address the changing international situation and various challenges. The methodology is designed to answer the complexity of the appeal question through the pursuit of the following five objectives.

1. Establish a relationship network for the 17 sustainable development goals.

2. Use established relationships to assess priorities for the 17 Sustainable Development Goals.

3. Based on the order of the 17 sustainable development goals, select SDG16 as a development priority and predict what can reasonably be achieved in the next 10 years.

4. Explore potential changes to the network of relationships, priorities and the list of SDGs, assuming that one of the SDGs is achieved.

5. Assume that international changes occur and explore the impact on networks, priorities, and progress at the United Nations.

The method chosen

This essay adopts an integrated analytical framework based on multiple methodologies to provide an in-depth examination of the United Nations' SDGs and provide key insights into their development potential and priorities. Our analysis incorporates techniques such as correlation matrix, Minkowski distance, etc., to construct the relationship network among SDGs. Through linear fitting, we evaluate the independent influence of each SDG and apply the AHP-MLR model to comprehensively consider these factors for priority determination and also use the ARIMA model to predict future development and introduce the SA-PSO algorithm to improve model accuracy. By transforming the relationship network into a weighted undirected graph, the impact of international changes on the SDGs and study the paths of influence propagation are analyzed. This comprehensive methodological framework serves as a powerful tool for in-depth understanding and optimization of the implementation of the SDGs and provides crucial support for global sustainable development. This section outlines the analytical mechanics of the framework based on these considerations.

Data Sources

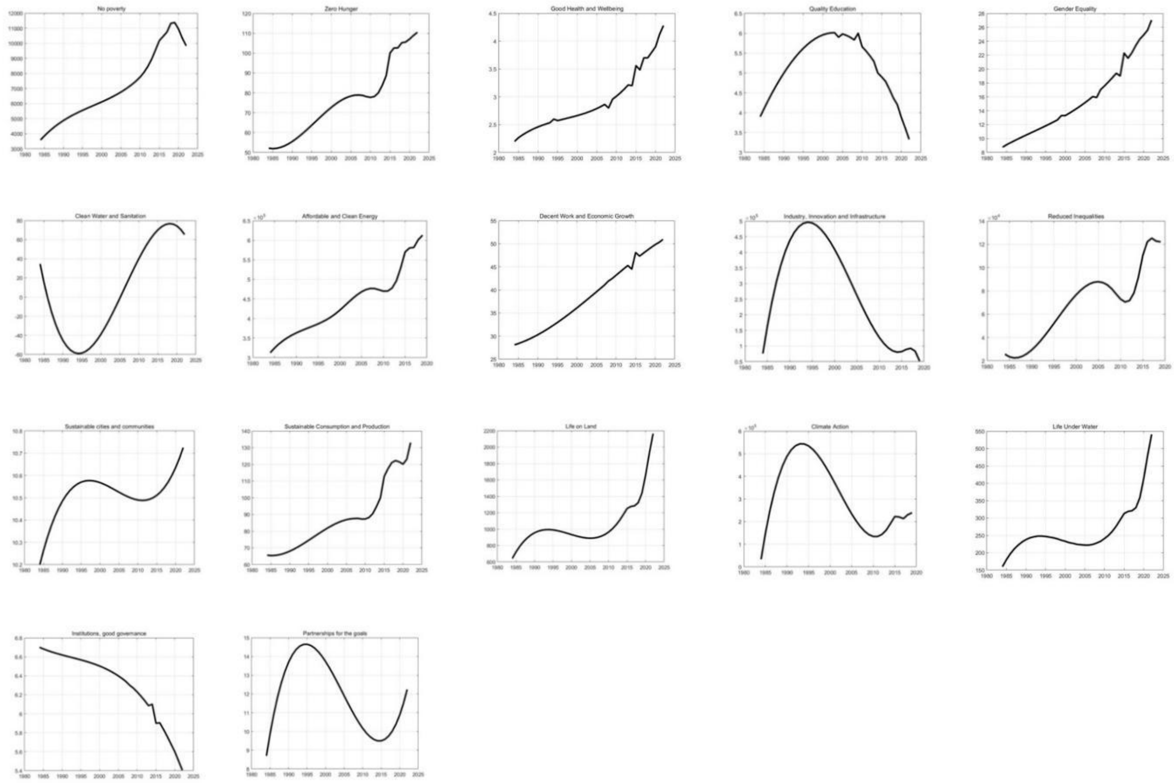


Figure 1: Global average SDGs index (before eliminating dimensions)

The data in Figure 1 is sourced from the sustainable development indicator data of global countries published by the UN official website database in 2022 (the global average is selected for each SDG).

Freeman[1] and Lankford[2] et al., drawing on knowledge from the field of economics, developed an analytical model to estimate and study the willingness to pay (WTP) for the transition to SDGS, taking into account the interaction of achieving other SDGs. We conducted a quantitative assessment of global progress towards the SDGs from 1984 to 2018, with representative indicators utilized for each goal [3]. This type of analysis aids decision-makers in prioritizing the achievement of specific goals or sets of goals and highlighting the net gains and losses from achieving one goal that affects others. The implications of this research are crucial for achieving sustainability through the pursuit of SDGs.

Fonseca, Dominguez and Ma Di used the indicator data source of the Sustainable Development Goals Index (SDG-I) to analyze the interrelationships between the 17 SDGs proposed by the UN. To test the normality of the data, the Kolmogorov-Smirnov test was applied, revealing that most of the data in this set did not conform to the normal distribution. Therefore, the Spearman rank correlation coefficient method, which does not require normally distributed data but can provide more robust results, was employed for research. Using this approach, the study identified a series of interactions between SDGs (co-benefits to be exploited) and the relevance of potential trade-offs between SDGs. For instance, there are synergies between “No Poverty” (SDG 1) and “Good Health and Well-being” (SDG 3) with most other goals, but a modest negative correlation exists between “Affordable Clean Energy” (SDG 7) and “Sustainable Consumption and Production” (SDG 12). This analysis supports the idea that there are more positive than negative interactions between the SDGs [4]. Courtney Vegelin and Joyeeta Gupta believe, from a sociological perspective, that sustainable development is a comprehensive development that considers social, economic and ecological aspects. It revolves around inclusivity and sustainability and making pro-growth trade-offs on social and ecological issues to live within ecological limits for the development of the entire society. However, the author also pointed out the lack of clear quantitative indicators and planning for some of these issues that remain to be solved [15].

Implementation Strategy

Our work follows the following workflow, as shown in Figure 1.

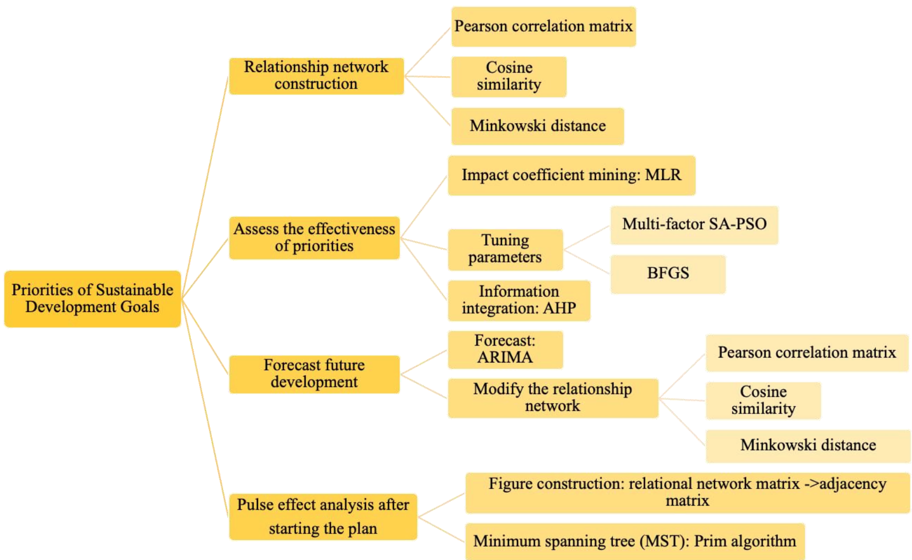


Figure 2: Mathematical model in Task

- For Goal 1: Statistical data on SDGs from 1984 to 2018 was extracted from the UN official website. The relationship matrix was constructed through the following three methods: cross-correlation matrix, cosine similarity and Minkowski distance. The relationship network was obtained by weighting the three relationship matrices.

- For Goal 2: We introduced the overall development speed through linear fitting of the 17 SDGs and explored their independent effects under the independence assumption. The AHP-MLR model was devised to combine independent effects and representative dependent relationship network information to generate a comprehensive impact assessment of SDGs.

- For Goal 3: the ARIMA model was employed to predict changes in SDG 16 over the next decade after prioritization. To improve the accuracy of the ARIMA model, adaptive factors and asymmetric learning factors were introduced into the SA-PSO algorithm for the first time. These factors, together with the BFGS algorithm, were used to optimize the loss function in the fitting.

- For Goal 4: We assumed the successful implementation of SDG 4 (Quality Education). Based on the prediction information of the ARIMA model, the influence distribution of the relationship network and SDGs within ten years was reconstructed through the relationship matrix and the AHP-MLR model. Then, three preliminary goals (popularization of the Internet, tourism and cultural exchanges, and human longevity) were introduced into the network, and their impacts were analyzed.

- For Goal 5: The relationship network was converted into a weighted undirected graph. Assuming a major international technological advance, it was determined that it would ultimately impact SDG 9 (Industry, Innovation and Infrastructure). Therefore, the node represented by SDG 9 was designated as the origin and Prim's algorithm was employed to generate a minimum spanning tree. The minimum spanning tree was used as the influence propagation path for "major technological progress". The relationship network and SDGs influence distribution were then reconstructed based on the relationship matrix and AHP-MLR model.

Table 1 lists the key mathematical symbols used in this article.

Table 1: Mathematical symbols used in this article

Symbol	Description
x_i	Time vector series of the i-th SDG (1984 ~ 2018)

P_{ij}	The i-th SDG and the j-th SDG in the associated network
y_t	Overall development speed of SDGs at time t
ω	Influence coefficient vector/weight vector
$L(\omega)$	Loss function in linear fitting
CI	Consistency index
RI	Average random consistency index
CR	Consistency ratio

Relational network based on correlation matrix, cosine similarity and Minkowski

The primary objective of the relationship network is serve as a visual tool that enables researchers and policymakers to gain a deeper understanding of the interactions between SDGs, discover potential influencing factors, and identify possible priorities. By visualizing SDGs as networks, researchers can more easily identify which SDGs have a significant impact on other SDGs, thereby providing a strong basis for formulating policies and strategies. The construction of this relationship network marks a critical first step in the research and provides an important basis for subsequent analysis and decision-making.

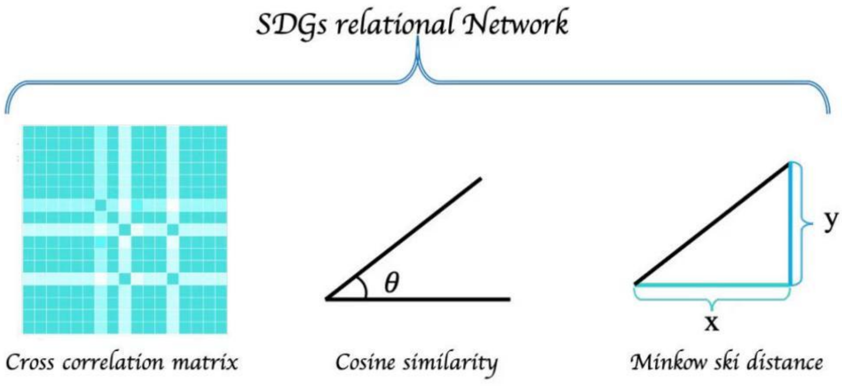


Figure 3: Schematic diagram of the method of building an association network

To facilitate the comparison of SDG time vector data, it is necessary to normalize the data. Assuming that the time series vector of the i-th SDG is $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]$, the transformation method is as follows:

$$x_{ij} = \frac{\bar{x}_{ij} - \min_k \bar{x}_{ik}}{\max_k \bar{x}_{ik} - \min_k \bar{x}_{ik}} \tag{1}$$

Here, $\bar{x}_{ij}$is the j-th time point data of the I-th time series vector before elimination.

Then, three methods are employed to determine the similarity between vectors:

1. Apply the Pearson correlation coefficient matrix [6] to calculate the correlation between the two sets of vectors, i.e., the correlation between SDGs, as follows:

$$\rho_{ij} = \frac{Cov(x_i, x_j)}{\sqrt{Var(x_i) \times Var(x_j)}} \tag{2}$$

Here, is the element in row I and column J of the Pearson correlation coefficient matrix, which reflects the degree of correlation between the two SDGs. is the covariance between the I-th SDG and the j-th SDG, is the variance between the I-th SDG vector elements, defined as follows:

$$Cov(x_i, x_j) = E(x_i \cdot x_j) - E(x_i) \cdot E(x_j) \tag{3}$$

and

$$Var(x_i) = \frac{\sum_{j=1}^{n} \left[x_{ij} - E(x_i)\right]^2}{n} \tag{4}$$

Here, $E(x_i)$is $x_i$the mathematical expectation (mean) of each element.

2. Apply cosine similarity [7] to measure the similarity between vectors:

$$cos\,(x_i, x_j) = \frac{x_i}{\|x_i\|_2} \cdot \frac{x_j}{\|x_j\|_2} \tag{5}$$

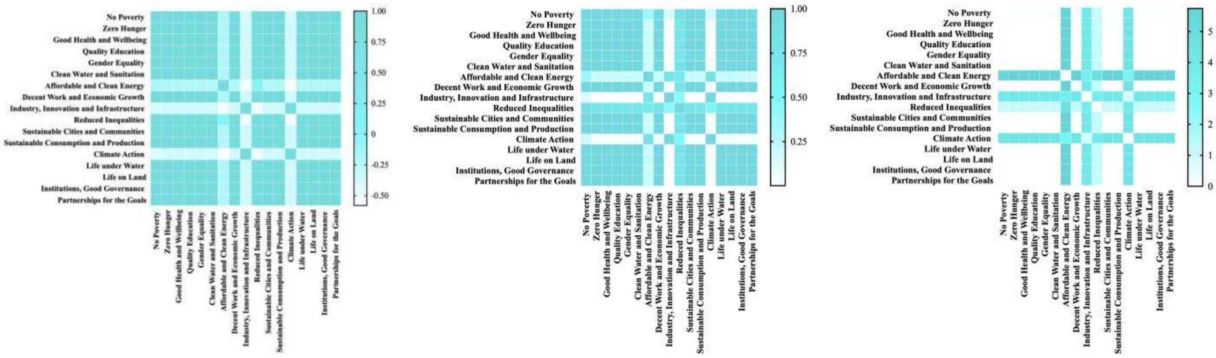
Here, $\|x_i\|_2$represents the L2 norm, which is the module of the vector.

3. Apply Minkowski distance [8] to calculate the distance d between vectors to reflect the correlation:

$$\mathrm{d}(x_i, x_j)_{\mathrm{p}} = \sqrt[\mathrm{p}]{(x_{i1} - x_{j1})^{\mathrm{p}} + (x_{i2} - x_{j2})^{\mathrm{p}} + \cdots + (x_{in} - x_{jn})^{\mathrm{p}}} \tag{6}$$

This article assumes $\mathrm{p} = 2$, that is, to solve the Euclidean distance.

We used the above correlation coefficient, cosine similarity and Minkowski distance similarity to establish correlation networks of 17 SDGs, as shown in Figure 4 below:



(a) Cross-correlation matrix (b) Cosine similarity (c) Minkowski distance

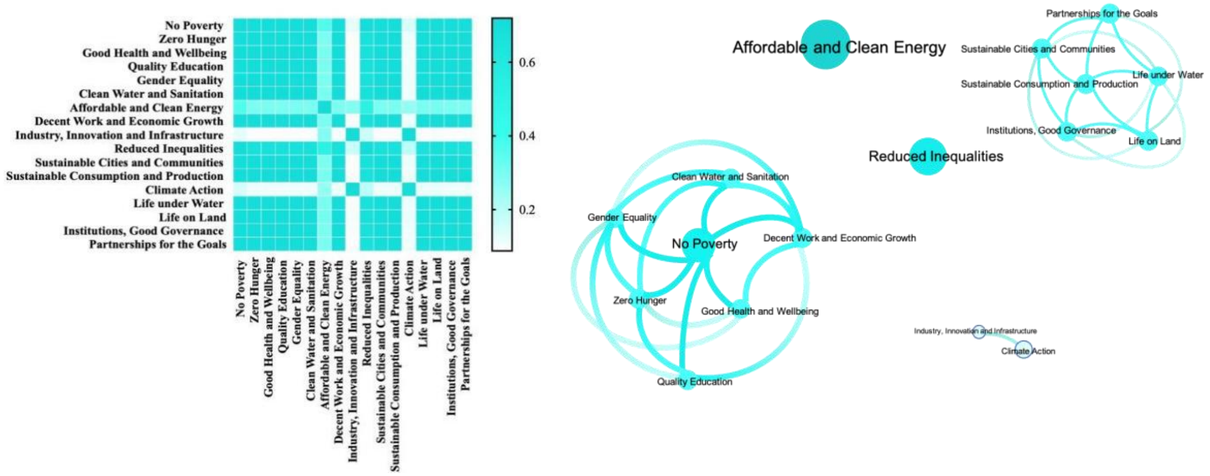
Figure 4: Three kinds of similarity generating network

Analyzing and discussing the established relationship network, we observed that the relationship network established by Minkowski distance similarity presents an opposite color block to the other two methods, although it shares a similar shape distribution, because the autocorrelation coefficient and cosine similarity tends to approach 1, indicating a better fitting effect and a positive correlation with numerical values. In contrast, when using distance, the closer the distance between vector points, the higher the similarity. Given the negative correlation of similarity with the numerical value, this phenomenon is considered normal and reliable. On the other hand, gender equality and sustainable cities and communities show minimal correlations with other SDGs, suggesting that they can be approximately treated as independent variables.

The final correlation network was designed as a weighted sum:

$$P_{ij} = \mu_1 \rho_{ij} + \mu_2 \cos\left(x_i, x_j\right) - \mu_3 \mathrm{d}\left(x_i, x_j\right)_{\mathrm{p}} \tag{7}$$

Here, μ_1, μ_2, μ_3 are positive weight coefficients, set to 0.35, 0.35 and 0.3, respectively. The subtraction of the third term is because $\mathrm{d}\left(x_i, x_j\right)_{\mathrm{p}}$ is negatively correlated with similarity. Finally, the final relationship network used later in this article is obtained.



(a) (b)

Figure 5: Associative network matrix (a) and Associative network diagram (b)

AHP-MLR evaluation model based on multi-factor SA-PSO and BFGS algorithm

The multi-factor SA-PSO algorithm uses the particle swarm optimization principle to simultaneously adjust multiple factors to seek the optimal weight and parameter configuration. This enhances the adaptability of the AHP-MLR model. At the same time, the BFGS algorithm, as a quasi-Newton method, effectively addresses nonlinear problems and contributes to the accuracy of the evaluation model. The main goal of this comprehensive approach is to reduce model complexity while maintaining a high degree of sensitivity and accuracy concerning SDGs data. This ensures a more comprehensive understanding of interactions and influencing factors between SDGs.

To identify priority SDGs for development, the impact of each SDG on the overall development speed is considered. The y_t calculation method for the overall development speed at time t is defined as follows:

$$y_t = \frac{\sum_{i=1}^{17} \alpha_{it}}{17} \tag{8}$$

Here, α_{it} is the relative change speed of the i-th SDG at time t, as follows:

$$\alpha_{it} = \frac{x_{i,t+1} - x_{it}}{x_{it}} \tag{9}$$

We call it the overall development speed time series of SDGs. Next, we use it in multiple linear regression to explore $y = [y_1, y_2, \cdots, y_n]$, representing the impact of each SDG on the overall development speed.

We establish $x_i (i = 1, \cdots, 17) y$ a multiple linear regression model with independent variables and dependent variables:

$$y = \sum_{i=1}^{17} \omega_i x_i \tag{10}$$

Here, $\omega_i$represents the influence coefficient of the i-th SDG on the overall development speed.

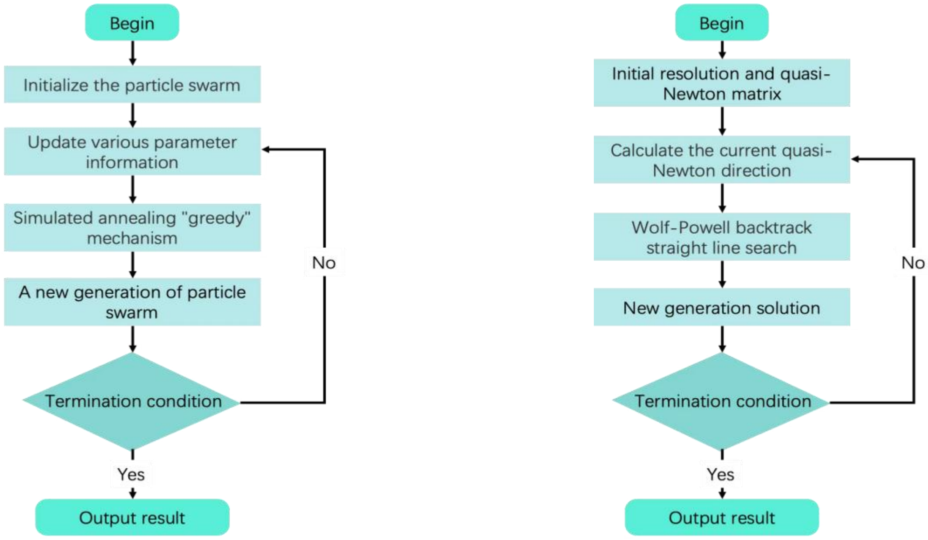
Using historical data to fit a multiple linear regression model [9] is to minimize its fitting loss. Therefore, an $\omega = [\omega_1, \omega_2, \cdots, \omega_{17}]$unconstrained optimization mathematical model about the decision vector is established:

$$min\ L(\omega) = \sum_{j=1}^{n} \left(y_j - \sum_{i=1}^{17} \omega_i x_{ij} \right)^2 \tag{11}$$

By fitting historical data, we can obtain the importance of each SDG to the overall development, aiding in the selection of priority SDGs for development.

For the influence coefficient vector obtained by fitting ω, we aim to screen the influence of white noise or perturbed data in the fitting. Therefore, after solving, the influence coefficient of each SDG undergoes further refinement through the AHP analytic hierarchy process [10].

Two optimization algorithms are designed: one is a swarm intelligence optimization algorithm, the SA-PSO algorithm [13] based on compression factor [11] and asymmetric learning factor [12]; the other is a gradient optimization algorithm with excellent results BFGS quasi-Newton method [14]. Then, the results are further discussed through the analytic hierarchy process, and solutions to the identified problems are given.



(a) (b)

Figure 6: Multi-factor SA-PSO Algorithm Flow Chart (a) and BFGS algorithm Flow Chart (b)

Without loss of generality, the mathematical model (11) is equivalent to the solution

$$max \quad -L(\omega) = -\sum_{j=1}^{n}\left(y_j - \sum_{i=1}^{17}\omega_i x_{ij}\right)^2 \tag{12}$$

Multiple particles are randomly initialized by the computer $\omega_k^0(k = 1,\cdots,m)$, where k is the particle number. Each particle can be regarded as an individual in the flock of birds, and the particle's position changes with each iteration. PSO treats the particle group as the position of the bird flock, iterating in the form of simulating bird migration:

$$\omega_k^d = \omega_k^{d-1} + v_k^{d-1}t \tag{13}$$

where v_k^{d-1} is the moving speed from generation d-1 particles to generation d particles, referred to as the speed of generation d-1, $v_k^{d-1}\omega_k^{d-1}$and $\omega_k^d$are the results of particle number k iterating d-1 times and d times, respectively.

During the calculation, to reduce the calculation rate, the time period of one iteration is used as the unit of time t (with t=1) making the model run more efficiently. The direction of evolution during particle iteration is determined by three aspects: the inertial influence level, the personal subjective level and the social benefit level. The formulation is as follows:

$$v_k^d = wv_k^{d-1} + c_1r_1\left(pbest_k^d - x_k^d\right) + c_2r_2\left(gbest_k^d - x_k^d\right) \tag{14}$$

The inertia weight (w) is used to account for the inertia effect of the previous generation's movement speed. Individual learning factors (c_1) and social learning factors (c_2) consider the historical best positions of individual particles and particle groups. The $L(\omega)$ largest position is used as the best historical position to guide the particle group to move in the direction of the best position. r_1 and r_2 are random numbers between 0 and 1, which expedites particle convergence. In case the result of $L(\omega)$ is 0 during iteration, r_1、r_2 can also be used to adaptively correct the particles.

We improved the original PSO model by introducing the compression factor, asymmetric learning factor and the greedy mechanism in the SA algorithm for improvement:

$$\begin{cases} \omega_k^d = \omega_k^{d-1} + \omega_k^{d-1} t \\ v_k^d = \varphi\left[w v_k^{d-1} + c_1 r_1\left(pbest_k^d - x_k^d\right) + c_2 r_2\left(gbest_k^d - x_k^d\right)\right] \\ C = c_1^d + c_2^d \\ \varphi = \dfrac{2}{\left|2 - C - \sqrt{C^2 - 4C}\right|} \\ c_1^d = c_1^{ini} + \left(c_1^{fin} - c_1^{ini}\right) \times \dfrac{d}{K} \\ c_2^d = c_2^{ini} + \left(c_2^{fin} - c_2^{ini}\right) \times \dfrac{d}{K} \end{cases} \tag{15}$$

where φ is c_2 the c_1^{ini}, c_2^{ini} compression factor, c_1 which $c_2^d \epsilon \left[c_2^{ini}, c_2^{fin}\right]$ is c_1^{fin}, c_2^{fin} jointly $c_2$determined $c_1$by $c_1^d \epsilon \left[c_1^{fin}, c_1^{ini}\right]$It is the last generation individual learning factor and the last generation social learning factor.

In each generation of iterations, a greedy mechanism selects the better next-generation particle swarm based on the following principles:

1) If $L(\omega_k^d) \geq L(\omega_k^{d+1})$, then $x_k^{d+1}$the d+1th generation particle with number k is accepted.

2) If $L\left(\omega_k^d\right) < L\left(\omega_k^{d+1}\right)$, we calculate the acceptance probability $p = e^{-\frac{\left|L(\omega_k^d) - L(\omega_k^{d+1})\right|}{100 \times 0.95t}} \in (0,1)$, and then generate it through the random process attached to the computer r $\in (0,1)$. If r $\geq$ p, we accept $x_k^{d+1}$the d+1th generation particle with number k. If $r < p$, we do not accept the x_k^{d+1} d+1th generation particle with number k. Instead, we directly treat it as x_k^d the d+1th generation particle with number k for the next step of round particle swarm iteration.

Through such a screening mechanism, the accuracy of particle swarm iteration is improved, and the possibility of the particle swarm algorithm mistakenly converging to a local optimal solution is greatly reduced. The model setting parameters are as follows:

Table 2: Parameter settings of the simulated annealing particle swarm algorithm model

Parameter	Description	Number/Size
m	Number of particles	50
K	Maximum number of iterations	30
w	Inertial weight	9.5
c_1^{fin}	Maximum personal learning factor	2.5
c_1^{ini}	Minimal personal learning factor	one
c_2^{ini}	Minimum social learning factor	0.5
c_2^{fin}	Maximum social learning factor	2.25

The obtained influence coefficient series will be further refined during model revision.

The basic idea of BFGS to solve this optimization model is to approximate the function L with the second-order Taylor expansion f near the current solution. It then uses the existing information of the current solution (such as gradient, Hessian matrix, etc.) to construct a feasible descent direction or quasi-Newton direction. After that, a backtracking straight line search is performed along this direction according to the Wolf-Powell criterion to obtain a better next iteration point.

Random process generation x^0, setting error range $\varepsilon_0 > 0$, backtracking one-dimensional search parameters$\alpha = 0.4, \beta = 0.7$

For the convenience of description, record the next iteration point as ω^+, and obtain ω the feasible descent direction d of the current iteration point.

$$d = -\left[\nabla^2 f(\omega)\right]^{-1} \nabla f(\omega) \tag{16}$$

Where $\nabla^2 f(\omega)$ is the Hessian matrix at f ω, $\nabla f(\omega)$ is the gradient at f.

Starting from ωt the starting point, use Wolf-Powell backtracking straight line search along the direction to obtain the step factor t

Update the iterative solution by $\omega^+ = \omega + \alpha t$d updating and then test the stopping condition:

$$|f(\omega)| \le \varepsilon_0 \tag{17}$$

If the stop condition is met, the result will be output; otherwise, set $\omega := \omega^+$, and the above cycle will be repeated.

The results obtained through the BFGS method will be further refined in the model revision.

The comparison of the two algorithms for solving this problem is presented in Section 7 below:

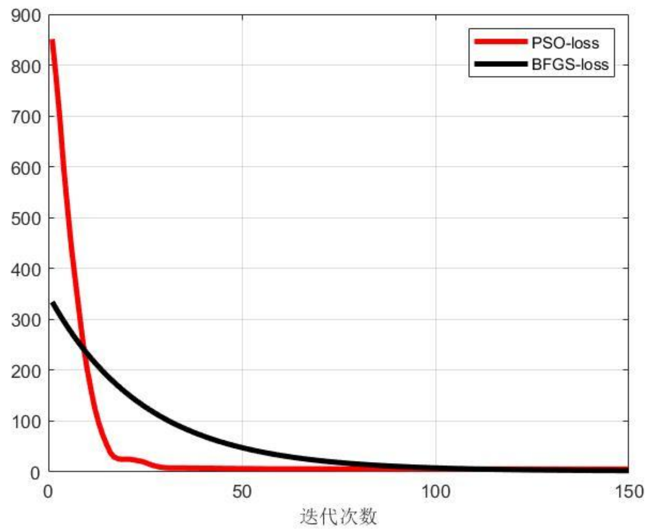


Figure 7: Innovative algorithm multi-factor SA-PSO algorithm and BFGS effect comparison

Upon comparing the two optimization algorithms, it becomes evident that our independently improved and innovative SA-PSO algorithm has greatly improved its performance and achieved convergence to the same accuracy with fewer iterations.

When establishing the relationship network, we obtained the Pearson correlation coefficient matrix. By multiplying it with the optimized sequence ω, a more objective SDGs weight sequence $\breve{\omega}$ is derived. The 17-dimensional weight sequence is then subjected to the AHP model for enhanced effectiveness. A consistency test is employed to verify its accuracy. The specific steps are as follows:

1. Calculation of weight-weight matrix

$$W = \breve{\omega}^T \breve{\omega} \tag{18}$$

Here, $\breve{\omega}$is the SDGs weight sequence in the form of a row vector.

2. **Extraction of** W maximum eigenvalue $\lambda_{max}$and corresponding eigenvectorϖ

3. Consistency test

Calculate the consistency index CI

$$CI = \frac{\lambda_{max} - 17}{17 - 1} \quad (19)$$

Find the corresponding average random consistency index RI (this study is 17th order)

Table 3: Average random consistency index RI [16]

Order	**RI**	**Order**	**RI**	**Order**	**RI**
1	0	11	1.52	twenty one	1.6358
2	0	12	1.54	twenty two	1.6403
3	0.52	13	1.56	twenty three	1.6462
4	0.89	14	1.58	twenty four	1.6497
5	1.12	15	1.59	25	1.6556
6	1.26	16	1.5943	26	1.6587
7	1.36	**17**	**1.6064**	27	1.6631
8	1.41	18	1.6133	28	1.6670
9	1.46	19	1.6207	29	1.6693
10	1.49	20	1.6292	30	1.6724

Calculate the consistency ratio CR

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \quad (20)$$

If $\mathrm{CR} < 0.1$, the consistency of the matrix is acceptable.

Two sets of test results are calculated with CR=0.03. The weight sequences calculated by the two algorithms are superimposed after eliminating dimensions. The final weight distribution for each SDG is presented in Table 4:

Table 4: Final weight distribution of SDGs

SDGs	Final weight	SDGs	Final weight	SDGs	Final weight
SDG 1	0.10480	SDG 7	0.00050	SDG 13	0.00260

SDG 2	0.11051	SDG 8	0.11051	SDG 14	0.11056
SDG 3	0.11052	SDG 9	0.00261	SDG 15	0.11052
SDG 4	0.11052	SDG 10	0.09814	SDG 16	0.11069
SDG 5	0.11051	SDG 11	0.11052	SDG 17	0.11054
SDG 6	0.11012	SDG 12	0.11050		

In Table 4, SDG 16 has the highest weight, with strong institutions for peace and justice seen as the most effective priority. Therefore, the significance and possible impacts of SDG16 priority development are discussed as follows:

- The establishment of strong peace and justice institutions protects residents' legal rights from infringement, safeguards social justice and promotes the improvement of legal frameworks. In other words, a strong institution of peace and justice and a society ruled by law co-generate a positive feedback relationship that they reinforce each other and are inseparable.

- Strong peace and justice institutions can effectively curb violence, corruption and other unjust incidents. Measures such as riot prevention, implemented by strong government institutions, eliminate violent and dark societal forces. The establishment of effective, transparent and impartial law enforcement agencies effectively avoids unfair corruption. The development of strong peace and justice institutions promotes equality in the administration of justice. According to the official website of the Shenzhen Municipal People's Court of China, Shenzhen is actively promoting the rule of law and strengthening citizens' judicial recognition and participation in the construction of a rule-of-law society.

ARIMA model based on multi-factor simulated annealing particle swarm algorithm

The education, among the 17 SDGs, in many countries has even shown a downward trend due to the COVID-10 pandemic and wars. Therefore, it is of great significance to study the changes that will occur after achieving the goals of high-quality education. Next, the study prioritize the development of SDG 16, accelerating its development by 20% to predict the development of all SDGs over the next ten years.

Assuming historical data of SDG 16, we employ the ARIMA (p, d, q) model [17] to predict data for the next decade through the sequence $\{Y_n\}$:

The white noise sequence is extracted to $\{\varepsilon_n\}$:

$$\varepsilon_t = Y_t - \gamma_0 - \sum_{i=1}^{p} \gamma_i Y_{t-i} \tag{21}$$

Final integration:

$$\left(1 - \sum_{i=1}^{p} \gamma_i L^i\right)(1-L)^d Y_t = \alpha_0 + \left(1 + \sum_{i=1}^{q} \delta_i L^i\right)\varepsilon_t \tag{22}$$

L is the first item of the first-order difference sequence, and parameters p, d, and q are manually adjusted based on the approximate period of the actual war conflicts. The autoregressive coefficient is denoted as p, the order of the stationary sequence difference as d , and the movement as q. The average coefficients γ_i and δ_i are all parameters that require optimization, so the accuracy of parameter optimization is directly proportional to the accuracy of prediction. We use the improved SA-PSO model introduced in 5.2 for parameter optimization.

After obtaining the forecast for SDG 16 for the next 10 years, we increase its value by 20%, designating it as a priority development project. The impact on other SDGs is divided into direct impact E_1, indirect impact $E_2$and overall stability impact E_3. The calculation method is as follows (taking SDG j at time t as an example):

$$E_1 = 0.2 P_{16,j} Y_t \tag{23}$$

$$E_2 = 0.2 P_{16,i} P_{ij} Y_t \tag{24}$$

$$E_3 = 0.2 \frac{\overline{\omega}_j}{\overline{\omega}_{16}} Y_t \tag{25}$$

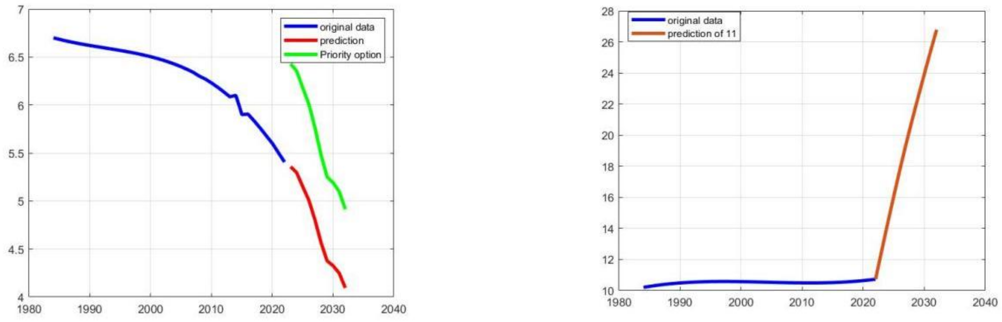
Here, $P_{16,j}$ is the correlation degree in the relationship network obtained for 4.3. $\overline{\omega}_j$is the final impact coefficient of SDG j in Table 5 (based on the combination of the two research methods).

For the index value of SDG j at time t $Z_{SDG\,j}$, we calculate it according to the following formula:

$$Z_{SDG\,j} = x_{jn} + E_1 + E_2 + E_3 \tag{26}$$

Here, $x_{jn}$is the exponential value of time n defined in section 4.2 (the last data in the training set).

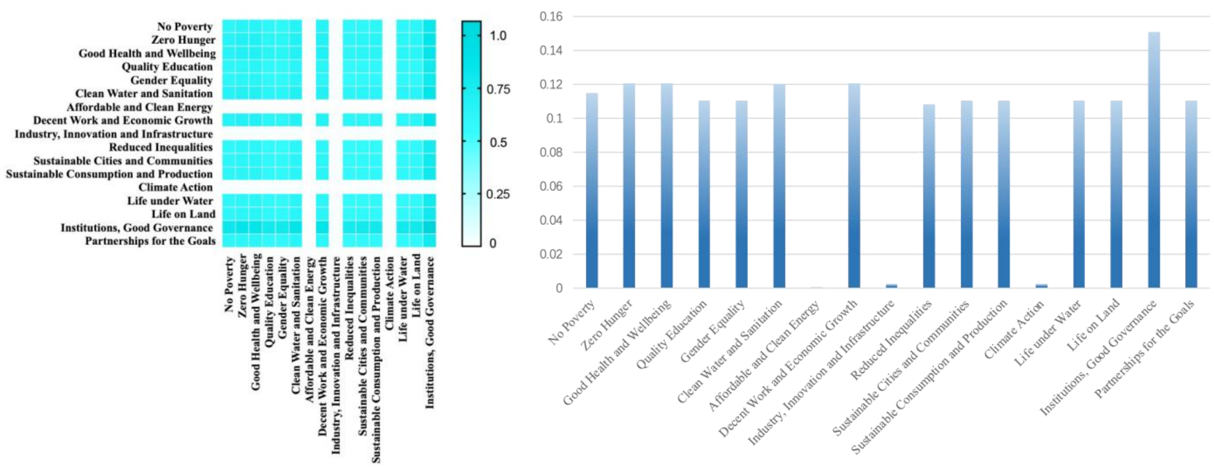
As a consequence of the SDG16 forecast based on the ARIMA model, the most prominent changes are observed in SDG 11, as shown in Figure 8:



(a) (b)

Figure 8: SDG 16 Forecast for the next Decade (a) and SDG 11 After the Impact (b)

The newly formed relationship network and the re-evaluated SDGs development effectiveness (weight ratio) are shown in Figure 9:



(a) (b)

Figure 9: Priority development of post-SDG 16 relationship network (a) and development effectiveness ratio (b)

It can be seen that making SDG 16 a priority results in a rapid development of SDG 11 (Sustainable Cities and Communities) over the next decade due to the increased focus on peace and justice organizations. The overall development speed of SDG is projected to increase by 23%. However, despite efforts to develop peace organizations, the projections indicate a potential decline, albeit mitigated. Therefore, even in the next decade, SDG 16 will continue to be a priority development. Building a peaceful and just environment remains crucial for the development of the SDGs.

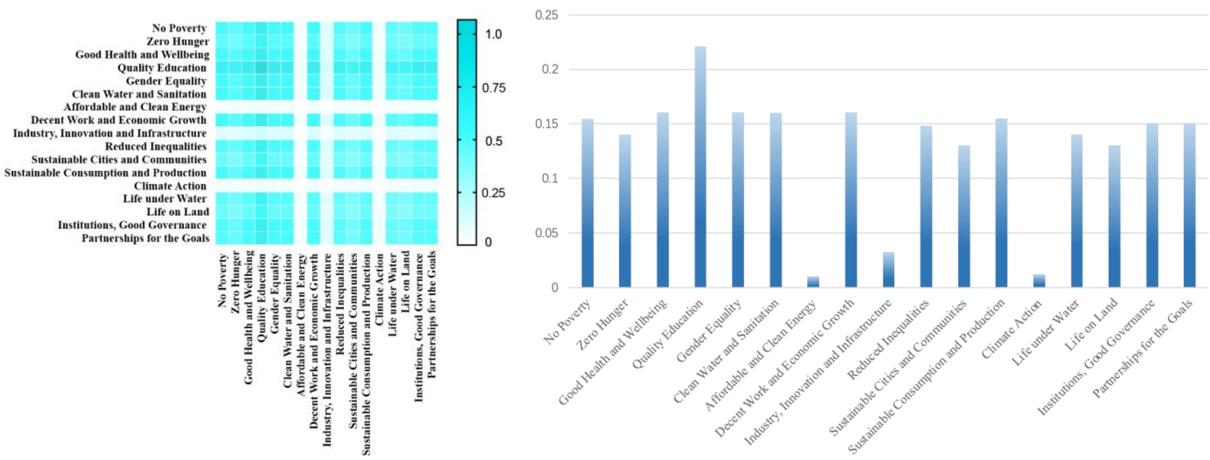
Analysis of the importance of sustainable development goals based on ARIMA model and AHP-MLR evaluation model

Among the 17 SDGs, education development in many countries is even on a downward trend due to the impact of the COVID-19 pandemic and wars. Therefore, it is of great significance to study the changes that will occur after the goals of quality education are achieved. We assume that when high-quality education is achieved, global public education spending will rise to 200% of current levels. According to the ARIMA model based on the SA-PSO algorithm in Section 6.2, the changes in the values of the remaining 16 SDGs can be calculated.

By intercepting time nodes in a year, a new SDG time series vector group is generated. Then, the correlation network is reconstructed through the cross-correlation matrix (2) and cosine similarity (5) Section in 4.3.$x_i^{New}(i = 1, \cdots, 16)$

The modified AHP-MLR model is then used to reconstruct the distribution of influence coefficients. This aids in the analysis of whether there have been changes in the priority startup items. In addition, to explore whether the SDGs encompass new goals worthy of inclusion by the UN, three aspects were selected as references: Internet penetration, tourism and cultural exchanges, and human lifespan. The impact coefficient for each aspect is obtained through the AHP-MLR model to determine whether it is worthy of inclusion.

A new relationship network and a new evaluation weight ratio are generated as follows:



(a) (b)

Figure 10: Relationship network after SDG 4 implementation (a) and development effectiveness ratio (b)

Based on the relationship network after the implementation of SDG 4, there is a significant increase in its correlation with other SDGs. The progress of each SDG exhibits remarkable acceleration, which shows that education indeed drives the progress of the world. Moreover, the overall development speed of SDG has surged by 56%, among which SDG 1, SDG 3, SDG 5, and SDG 7 have all seen significant increases. This indicates that the quality of education is of great help to the enhancement of capabilities and moral values of social members as well as the improvement of traditional concepts. At this point, our analysis indicates that two of our three preliminary SDGs are worthy of inclusion in the official SDGs by the UN (access and tourism and cultural exchanges), and Internet access will be the latest focal point for development.

Pulse effect analysis based on MST

Combined with the current era of information technology, the holistic study discusses the huge impact that technological progress can have on the United Nations' SDGs. Obviously, this subject is full of significance and challenges. Taking the development of artificial intelligence (AI) as an example, the research conducted by Margaret A. Goralski [18] outlines the main impact of AI on SDGs as follows:

While the AI revolution is widespread, with huge short-term gains across many industries or social aspects, its initial momentum is expected to wane, and the ultimate benefits are often addressed in SDG 9 by promoting industry, innovation and infrastructure. According to statistics, major technological innovation can increase the development speed of SDG 9 by 25% to 138%, with an average increase of 34%.

Therefore, we consider the final matrix based on the correlation matrix, cosine similarity and the relationship network established by Minkowski as an adjacency matrix. This approach considers the correlation between two SDGs as the weight between nodes and treats the relevant network as a graph, where SDG i is the I-th node. This yields a weighted undirected graph. Starting from the node corresponding to SDG 9, we seek the minimum spanning tree (MST) of the relevant network and use it as a model to assess the impact of AI.

Prim's algorithm, based on "greedy thinking" is characterized by has low computational complexity. Its operation steps are shown in flow chart 11:

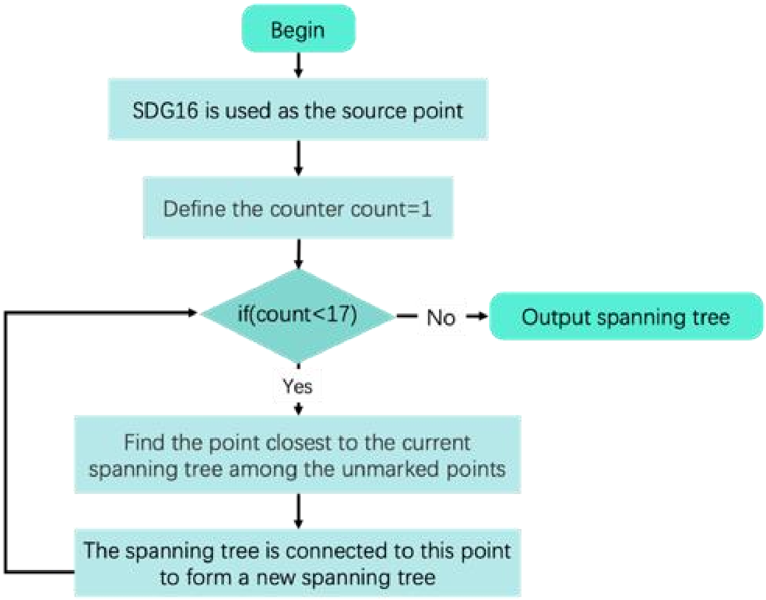


Figure 11: Minimum spanning tree flow chart

According to the primary and secondary relationship between SDGs and SDG 9 in the minimum spanning tree, the numerical changes after receiving the pulse effect of technological progress can be explored. By calculating the algorithm in 4.2, a new correlation network is constructed as follows:

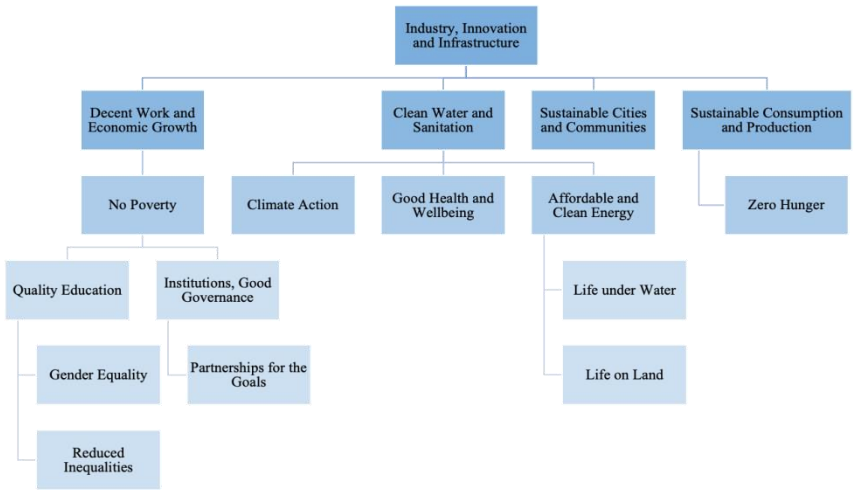


Figure 12: Minimum spanning tree diagram with SDG 9 as the source point

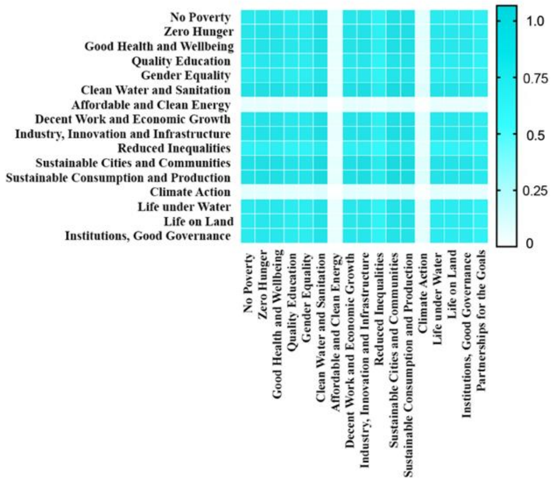


Figure 13: Correlation matrix with SDG 9 as the source point

The AHP-MLR model in Part 5 is applied to process the new association network and re-evaluate the priority selection. The resulting effectiveness of each SDG is illustrated in Figures 14.

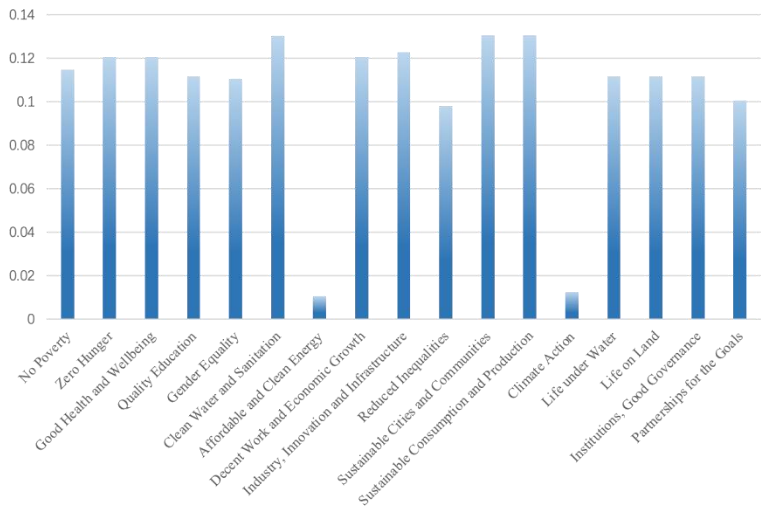


Figure 14: The development effectiveness of SDGs after technological progress

Based on the priority matrix diagram evaluation for the new MST analysis, it is concluded that revolutionary advances in technology first promote the rapid development of SDG 9 (industry, innovation and infrastructure) and then produce a pulse effect, causing huge changes in SDG. In particular, this impact is most significant on environmental goals (SDG 6, SDG 11, SDG 12) and brings significant improvements. This technological progress not only strengthens the interconnection between SDGs but also establishes close relationships among SDG 6, SDG 8, SDG 12 and other SDGs. Additionally, it enhances the recycling rate and resource utilization, increasing the overall development speed of global SDGs and presenting a potential 24% boost. However, it serves as a reminder that scientific and technological progress must be accompanied by the responsible use of resources to ensure the achievement of SDGs.

Conclusion

(1) We have established an SDGs priority decision-making model, which includes prioritization, simulation testing, energy efficiency prediction and impact effect analysis.

We firstly cite the time series of the 17 SDGs officially announced by the UA, secondly measure the prioritization of the SDGs by techniques such as the analytic hierarchy process, polynomial fitting, and feature extraction, thirdly perform three simulation experiments based on multi-factor simulated annealing particle swarm algorithm and L-BFGS algorithm in ARIMA model to predict the development of SDGs after the shock and finally apply MST algorithm to get minimal spanning tree to analyze pulse effect. The mathematical model constructed by our study on the 17 SDGs provides abundant and reliable development proposals for subsequent research on contemporary organizational decision-making regarding SDGs.

(2) This article uses the correlation method and the regression method under the independent assumption to rank the priority of the SDGs from a new perspective. We propose an advanced time series prediction model for simulation testing and train it on the officially released data set of the UN. The results highlight SDG16 as the most effective priority. Once launched as a priority, it catalyzes the development of SDG11 over the next decade, increases the overall development speed of SDG by 23% and mitigates the decline in the number of peace organizations; in addition, the rapid growth of SDG9 further results in significant improvements for SDG6, SDG11, and SDG12 through a pulse effect， strengthening the interconnections among SDG6, SDG8, SDG12 and other SDGs, providing a potential 24% opportunity for the increase in the overall development speed of the global SDGs.

(3) To solve the problem of how to discover new valuable SDGs, our study apply AHP model intergrating relationship network and independent weight to address objective effective assessment to make AHP-MLR model established by us have more solid consideration and a accurate result. Next, we propose a network framework that includes three aspects: direct impact, indirect impact, and overall impact. This network is utilized for simulation testing research on subsequent SDGs. Using the network to operate simulation testing on SDGs and

additionally comparing it with several main models, we figure out that the rate of convergence has 77.78 percent increase. What's more, In terms of exploiting the potential SDGs, the SDG mining model proposed in this article exhibits superior performance, with an average retrieval accuracy rate of 76.6% and a recall rate of 19.7%, showing higher precision and a repetition-free rate.

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