Environment, Development and Sustainability
https://doi.org/10.1007/s10668-024-04526-4

Systematic scenario modeling for priority assessment of sustainable development goals in China under interaction and uncertainty

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Received: 7 August 2023 / Accepted: 16 January 2024

Abstract

As an integrated and indivisible agenda encompassing the realms of economics, society, and the environment, the sustainable development goals (SDGs) manifest intricate interactions and uncertainties. These complexities pose numerous challenges for nations in their pursuit of the SDGs, including the need to harmonize SDGs (co-benefits or trade-offs), prioritize SDGs, and shape forward-thinking and coordinated development pathways. Consequently, this study introduces a systematic scenario modeling approach, founded upon the CIA-ISM framework, to assess SDG priority and analyze development pathways. The approach is a scalable and generic modeling approach that can effectively addresses the interactions between the SDGs while accounting for uncertainty. Modeling with the focus on the 17 SDGs, the implementation of the CIA-ISM framework initially engages the experts to estimate the occurrence likelihood and interaction degree of SDGs, thereby facilitating priority assessment, causal scenario generation, and sensitivity analysis. This study utilizes China as a demonstrative application for the proposed framework and validates the outcomes through expert feedback and pertinent literature. Based on the outcomes, three SDG implementation pathways of China are recommended with the most robust and foundational causal loops G1 and G5 as the starting point: G1 + G5 → G8 → G3 → G7; G1 + G5 → G2 → G13 → G15, and G1 + G5 → G2 → G6 + G12. Overall, the CIA-ISM-based scenario modeling approach proves adept at capturing the prioritized and hierarchically clear causal pathways of the SDGs, arising from their intricate interaction, while factoring in uncertainty.

Keywords Sustainable development goals · Priority assessment · Interaction · Uncertainty · Systematic scenario modeling · CIA-ISM

1 Introduction

The Sustainable Development Goals (SDGs) represent a global agenda adopted by the United Nations in 2015 to tackle the diverse social, economic, and environmental obstacles confronting the world (UN General Assembly, 2015). These objectives encompass 17 precise targets spanning a broad spectrum of areas, including poverty eradication, healthcare,

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education, gender equality, and sustainable energy. The goals possess universality and apply across nations and regions, irrespective of their size or developmental stage, as they encapsulate global concerns, offering a shared vision and reference framework for addressing global challenges (Allen et al., 2018). This common aspiration stimulates nations to foster collaboration, exchange experiences, implement best practices, and enhance global cooperation to address shared challenges. It is worth noting that due to differences among countries in terms of development levels, resource distribution, culture, and political backgrounds, the implementation of SDGs becomes complex and diverse, requiring customization based on each country's specific circumstances. The attainment of SDGs contributes to ensuring a harmonious and enduring well-being, encompassing economic, social, and environmental aspects, for both present and future generations.

However, nations encounter numerous hurdles in realizing the SDGs, such as harmonizing interaction (co-benefits or trade-offs) among the goals, prioritizing and integrating them with integrated objectives, and aligning national strategies with the actual internal and external circumstances of each country, thereby shaping a forward-thinking and cohesive development vision (Messerli et al., 2019; Plag & Jules-Plag, 2020). These challenges primarily stem from the integrated and indivisible nature of the SDG framework, with intricate interactions spanning economic, social, and environmental dimension (Nilsson et al., 2018; Swain, 2018). Specifically, there is potential for synergy and mutual reinforcement between different SDGs, commonly called "co-benefits." However, conflicting objectives or "trade-offs" may also arise. Furthermore, uncertainties arising from complex interactions between SDGs and their implementation across varying scales, encompassing diverse societies, cultures, and policies, pose significant challenges to achieving the SDGs (Crespo Cuaresma et al., 2018; Georgeson & Maslin, 2018). Consequently, policymakers must leverage decision-support techniques and methodologies to enhance analytical capabilities and bolster the credibility of decisions (Aly et al., 2022). In this context, ideal techniques and methodologies for SDG policy analysis and formulation necessitate the application of systems thinking to address the multifaceted interactions and contradictions among economic, ecological, and social components while accounting for the uncertainties inherent in SDG analysis, planning, and implementation (Moon, 2017; Scherer et al., 2018).

Currently, researchers are actively exploring modeling techniques and methodologies to capture the intricate interactions and interdependencies within the SDGs, represented by network modeling, Bayesian network modeling, and system dynamic modeling (Almannaei et al., 2020; Aly et al., 2022). Network modeling has emerged as a prevalent technique for studying these interactions, representing the SDGs as nodes and their interactions as linkages (Le Blanc, 2015; Mainali et al., 2018; Newman, 2006). However, the current focus of network modeling primarily revolves around capturing the complex interactions among SDGs while overlooking the causal relationships between the (Allen et al., 2021). This gap in research hampers the formulation of effective policies and strategies for achieving the SDGs. Additionally, most SDG network modeling approaches fail to adequately address uncertainty, which is crucial for assessing the likelihood of realizing the SDGs and associated risks (Aly et al., 2022). In addition, Bayesian networks and system dynamics are also common approaches for SDG association modeling (Aly et al., 2022). Bayesian network modeling focuses on capturing the causal logical relationships and uncertainties among SDGs (Kelly et al., 2013; Qazi & Al-Mhdawi, 2023). System dynamics modeling captures the dynamic behavior and feedback responses of the SDG system (Collste et al., 2017; Elsawah et al., 2017). However, they have limitations, such as the need for prior knowledge, data requirements, and assumptions that may not fully capture the complex interactions and feedback mechanisms among SDGs. Specifically, the assumptions made in BN modeling may result in an incomplete representation of interactions (Requejo-Castro et al., 2020), while SD models may struggle with the complexity of SDG interactions and parameter estimation (Pedercini et al., 2020). Therefore, it is promising to develop an integrated framework that effectively captures the interactions, uncertainties, and causal relationships within the SDGs.

In summary, this study focuses on modeling approaches that account for SDG interactions. The primary objectives of this research are as follows: (1) to propose an integrated framework that effectively captures the interactions and uncertainties inherent in the SDGs while simultaneously extracting the causal relationships within their intricate linkages; and (2) to examine various scenarios and causal logics pertaining to the attainment of the SDGs in China using the proposed methodology, thus providing recommendations for the developmental pathways necessary to achieve the SDGs in China. To accomplish the above objective, this study introduces a systematic scenario modeling approach based on CIA-ISM for assessing the priority of the SDGs. First, the study considers the 17 SDGs as the core event set and constructs the critical feature set of SDGs as the foundation for subsequent assessment. Subsequently, experts with diverse professional backgrounds in the field of SDG research are invited to estimate the probabilities of SDG occurrence and the degree of interaction among the SDGs, utilizing the Global Sustainable Development Report 2019 (GSDR 2019) and the aforementioned critical feature set as references. These estimates are input into the CIA-ISM model for SDG priority, causal scenario generation, and sensitivity analysis. These estimations are input into the CIA-ISM model to prioritize the SDGs, generate causal scenarios, and conduct sensitivity analysis. Finally, recommendations for the path to achieving the SDGs in China are provided based on the CIA-ISM results.

This study represents a pioneering effort to integrate the CIA-ISM method into SDG priority assessment. The key innovations and contributions of this paper are outlined below: Methodologically, this paper presents an integrated framework for assessing SDG priorities and formulating development policies, utilizing the CIA-ISM systematic modeling approach. The framework adeptly captures the interactions and uncertainties inherent in the SDGs while simultaneously extracting the intricate causal relationships among them. By utilizing a systematic scenario modeling approach, it offers a scientifically sound method for assessing SDG priorities. Practically, the proposed approach serves as a generic modeling technique for SDGs, enabling the integration of goal interactions, generation of causal derivations under diverse scenarios, and sensitivity analysis of outcomes. These findings serve to guide decision makers in their pursuit of SDGs by aiding the formulation of corresponding development pathways and offering decision support to achieve the SDGs.

The remaining parts of this paper are organized as follows: Sect. 2 conducts a literature review of modeling approaches concerning interactions among SDGs. In Sect. 3, the research process for assessing the priority of SDGs using the CIA-ISM modeling approach is presented. Section 4 outlines the process of modeling China's SDGs based on CIA-ISM, encompassing event definition, data collection, and CIA calculation. Section 5 analyzes the results derived from the CIA-ISM modeling of China's SDGs, focusing on SDG priority, scenario generation, and sensitivity analysis. Section 6 primarily validates the outcomes obtained through the CIA-ISM modeling of China's SDGs and offers policy recommendations for attaining China's SDGs based on these findings. Lastly, Sect. 7 presents the conclusions and outlines directions for future research endeavors.

2 Literature review

The SDGs represent an integrated and indivisible agenda of universal scope, covering economic, social, and environmental dimensions, with interactions that cannot be ignored (UN General Assembly, 2015). Within this framework, understanding and managing the interactions (including co-benefits and trade-offs) among the SDGs is crucial for assessing SDG priorities and formulating development policies that foster integration, coherence, and efficacy (Allen et al., 2018). Consequently, an increasing cohort of researchers is actively exploring and advancing modeling methodologies that capture the intricate interactions and interdependencies inherent within the SDGs (Almannaei et al., 2020). The most mainstream modeling approaches that currently consider the interactions between the SDGs include: network modeling, Bayesian network (BN) modeling, and system dynamics (SD) modeling (Aly et al., 2022).

Network modeling has emerged as a prevalent technique for studying the interactions between the SDGs (Bennich et al., 2020). The SDGs are depicted as nodes in network modeling, while the linkages represent interactions (Le Blanc, 2015; Newman, 2006). Notably, these linkages possess directions, weights, and signs that gauge the direction and intensity of associations between co-benefits (positive) and trade-offs (negative) among the SDGs (Mainali et al., 2018). The critical advantage of network modeling for the SDGs lies in its ability to efficiently process and integrate data from diverse sources into multiple types of systems (e.g., social, economic, and environmental systems) (Lim et al., 2018; Sebestyén et al., 2019). Moreover, network modeling enables the examination of SDG priority by analyzing node properties or network structures that emerge from complex interactions (Weitz et al., 2018). For instance, Swain and Ranganathan (2021) constructed an SDG network utilizing IAEG-SDG data, wherein they assessed the priority of SDGs based on eigenvector centrality, betweenness centrality, and closeness centrality, subsequently conducting community detection (Swain & Ranganathan, 2021). Similarly, Dawes (2022) devised a comprehensive network modeling approach encompassing all 17 SDGs as nodes (Dawes, 2022). This approach incorporates association strengths derived from ICSU reports, GSDR 2019 reports, and IAM surveys as network linkages, exemplifying its universal applicability in priority, robustness, and sensitivity analysis. However, network-based modeling of SDG primarily focuses on capturing the complex interactions among SDGs while overlooking the causal relationships between them. These causal relationships encompass both direct and indirect links between SDGs, elucidating how one SDG's attainment facilitates or impedes others' achievement. Analyzing these causal relationships assumes paramount importance in formulating effective policies and strategies (Aguilera et al., 2011). In addition, the majority of SDG network modeling fails to provide adequate treatment of uncertainty (Aly et al., 2022). Given the multitude of intricate factors and variables involved in SDGs, uncertainties often arise in their interactions. Effectively addressing and accounting for uncertainty constitutes a crucial aspect of the modeling process, as it furnishes valuable insights into the likelihood of realizing SDGs and associated risks (Allen et al., 2021). Overall, SDG network analysis falls short in exploring the causal paths toward achieving SDGs, while focusing on examining the interrelationships among SDGs. The CIA-ISM-based SDG prioritization scenario modeling framework presented in this study, however, adeptly captures the interactions among the probabilities of realizing the SDGs and subsequently illustrates their causal paths.

Bayesian networks (BN) and system dynamics (SD) are common SDG association modeling approaches (Aly et al., 2022). BN depicts the causal relationships among SDGs as a directed acyclic graph (Aguilera et al., 2011). Within this graph, the SDGs are represented as nodes connected by arrows, which denote the logical causal relationships between them (Kelly et al., 2013; Qazi & Al-Mhdawi, 2023). For instance, Requejo-Castro et al. (2020) proposed a data-driven BN modeling to discern the interconnections of SDG 6 (Clean Water and Sanitation) with other SDGs (Requejo-Castro et al., 2020). Using BN modeling in the context of SDGs allows for effectively capturing causal logical relationships while considering uncertainties (Benjamin-Fink & Reilly, 2017; Ekici & Önsel Ekici, 2021). However, the modeling process of BN necessitates prior knowledge and parameter estimation (Requejo-Castro et al., 2020). This typically involves analyzing historical data, leveraging expert insights, and calibrating model parameters (Hosseini & Sarder, 2019). Thus, constructing an accurate SDG BN model may impose a substantial workload and data requirements. Moreover, the intricate interdependencies and feedback loops among SDGs pose additional challenges to BN modeling (Cronk & Bartram, 2018). It is important to note that BN assumes conditional independence in their modeling process, implying that each variable is independent given its parent node. This assumption can result in an incomplete representation of the complex interactions and feedback mechanisms among SDGs, thereby limiting the credibility and reliability of the obtained BN modeling results. This assumption can result in an incomplete representation of the complex interactions and feedback mechanisms among SDGs, especially the causal loops within the SDGs, thereby limiting the credibility and reliability of the obtained BN modeling results. In contrast, the CIA-ISM-based framework proposed in this paper can explore the causal coupling relationships and development pathways between the SDGs without requiring prior knowledge of the causal directions between them, even in cases involving causal loops.

Regarding SD modeling of SDGs, it primarily focuses on capturing the dynamic behavior and feedback responses within the evolving SDG system (Elsawah et al., 2017). For example, using a system dynamics model, Collste et al. (2017) explored the impact of PV capacity investment in Tanzania on SDG 3 (Good Health and Well-being), SDG 4 (Quality Education), and SDG 7 (Affordable and Clean Energy) (Collste et al., 2017). However, SD models may face difficulties in handling the complexity of SDG interactions due to simplifications and assumptions that may not fully capture the existing system's diverse complexities and feedback mechanisms (Ding et al., 2018). Similar to BN modeling, SD models also require numerous parameter estimates to describe the behavior and interactions of the system (Pedercini et al., 2020). However, determining these parameters is often challenging as many may not be directly observable and need to be inferred or fitted to the model. Inaccuracies in parameter estimation can lead to biased predictions by the model. Instead, the CIA-ISM-based framework proposed in this paper can capture the prioritization and causal coupling between SDGs through heuristic estimation by experts in the absence of objective data.

To the best of our knowledge, this is still a brand-new research field to propose an integrated framework that effectively captures the interactions and uncertainties inherent in the SDGs while extracting the causal connections within their intricate linkages. Consequently, this study introduces a systematic scenario modeling approach for the priority assessment of SDGs based on CIA-ISM and applies it to assessing SDG priorities and development path in China.

3 Methodology

3.1 Cross-impact analysis (CIA)

Cross-impact analysis (CIA) is widely applied to analyze the impact of relationships between events on resultant events and to minimize future uncertainty (Bañuls et al., 2013).

CIA analyzes the coupling relationships between factors through a cross-impact matrix to provide forecasts on possible future trends, emphasizing the interactions and nonlinear effects between factors. Due to its effectiveness in analyzing complex scenarios with various interactions, the CIA model has become one of the most common methods for generating and analyzing scenarios (Ramirez de la Huerga et al., 2015; Turoff et al., 2016; Wang et al., 2022a, 2022b).

3.1.1 Event set creation and group estimation

The CIA model commences with identifying the event set, which serves as the fundamental building block of the CIA-ISM and forms the foundation for subsequent critical event detection, scenario generation, and causal logic analysis. Specifically, events in the CIA model can be defined as the smallest modeling units within the expected system analysis scale, as determined by decision-makers in accordance with their research objectives. Each event within the event set has a distinct probability of occurrence. The deterministic events in the event set can function as crucial initial conditions and scenario assumptions for the overall CIA model. The CIA model can simulate the effect of that event on other events in the event set, by indicating the occurrence or non-occurrence of a particular event at a given time. Each event within the set possesses three attributes: the likelihood of occurrence, the state of occurrence, and the degree of interaction with other events within the set (Turoff, 1971). It should be noted that (1) the events analyzed by the CIA only exist in two states: occurring or not occurring, and there is no intermediate state; (2) the selected events occur at most once during the period analyzed by the CIA model, and there are no repeated occurrences (Turoff, 1971). Apart from the event set, the concept of the external environment is also crucial to the CIA model (Wang et al., 2022a, 2022b). The external environment refers to the environmental conditions that are not chosen as part of the event set but have an impact on the event set. The impact of the external environment is a pivotal basis for assessing the soundness and validity of the constructed model in subsequent CIA model calculations. The aim of this study is to investigate the priority of SDGs and analyze their potential causal pathways. Therefore, this research will utilize SDGs as the “events” for CIA modeling.

Expert group estimation is necessary to determine the probability of each event occurring and the degree of interaction between events, once the event set has been established. The probability of an event occurring and the degree of interaction between events can be assessed through the analysis of relevant literature or by consulting experts in the pertinent field. The expert group estimation is a complex, multi-round feedback process, which typically comprises three rounds during the application of the CIA-ISM: individual expert opinion feedback, expert group opinion feedback, and opinion feedback based on the validation of the CIA-ISM model. The probability of an event occurring P_i of event i and the degree of interaction between events R_{ij} of event i on event j required by the CIA-ISM model can be judged by the semantic interpretations in Tables 1 and 2 (Zhang et al., 2018).

3.1.2 Cross-impact analysis process

Conducting a cross-impact analysis is necessary to quantitatively analyze and forecast interactions among various events after acquiring event estimates. Cross-impact calculations facilitate the identification of potential associations between factors, comprehension of their

Table 1 Semantic interpretation of the probability of occurrence of an event

Semantic interpretation	Possibility (%)	Semantic interpretation	Possibility (%)
Very unlikely	5	Possible	60
Highly unlikely	15	Likely	75
Unlikely	25	Highly likely	85
Possibly not	40	Almost certain	95
Uncertain	50		

Table 2 Semantic interpretation of the degree of interaction between events

Semantic interpretation	Degree value
j has a significant positive impact on *i*	0.99
j has an obvious positive impact on *i*	0.9
j has a great positive impact on *i*	0.8
j has a certain positive impact on *i*	0.7
j has a slight positive impact on *i*	0.6
j has no impact on *i*	0.5
j has a slight negative impact on *i*	0.4
j has a certain negative impact on *i*	0.3
j has a great negative impact on *i*	0.2
j has an obvious negative impact on *i*	0.1
j has a significant negative impact on *i*	0.01

interaction patterns, and prediction of the effects caused by alterations in specific factors on others (Bañuls & Turoff, 2011). The process of cross-impact analysis entails establishing a network of event coupling relationships. This is accomplished by effectively integrating event occurrence probabilities and interaction degrees to form a comprehensive internal cross-impact coefficient. Figure 1 depicts the implementation flowchart for this process.

The input data for CIA calculations will utilize the probability of occurrence and the degree of interaction of events, which have been obtained through literature analysis or expert estimates. The Fermi–Dirac distribution function is applied by drawing an analogy between event occurrence and atomic excited states to compute the internal cross-impact coefficient matrix C between these events, as presented in Eq. (1) (Turoff, 1971). This process essentially involves decomposing the causality of events via subjective estimations of their likelihood of occurrence. Specially, this process depends more on a subjective understanding of the problem or event, rather than probability distribution.

$$C_{ij} = \frac{1}{1 - P_j}\left[\ln\left(\frac{R_{ij}}{1 - R_{ij}}\right) - \ln\left(\frac{P_i}{1 - P_i}\right)\right] \tag{1}$$

where C_{ij} refers to the internal cross-impact coefficient of jth event on ith event. P_i and P_j represent the estimated probability of occurrence for ith event and jth event, respectively. Additionally, R_{ij} represents the estimated degree of interaction of ith event given jth event.

Subsequently, the external impact coefficient can then be further calculated to measure the impact caused by events not included in the critical event set, as in Eq. (2).

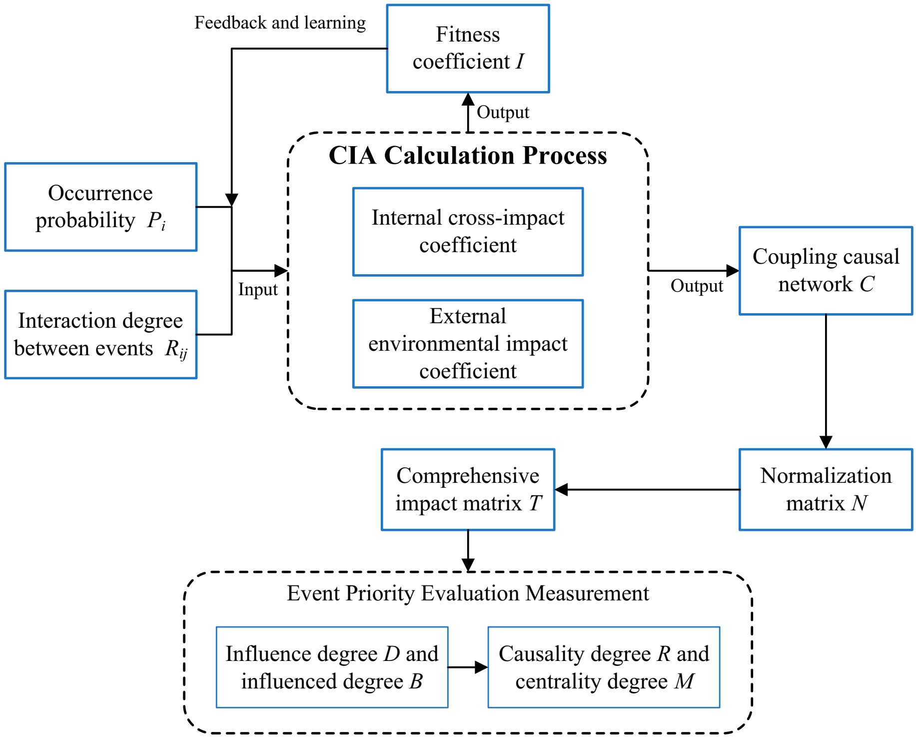

Fig. 1 Implementation flowchart for CIA process

$$G_i = \ln\left(\frac{P_i}{(1 - P_i)}\right) - \sum_{(k \neq i)}^{N} C_i k P_k \tag{2}$$

where G_i denotes the external impact coefficient of the ith event and N represents the total count of events.

In order to assess the model's fitness and its explanatory ability with respect to the event set, Eq. (3) is utilized to determine the fitness coefficient, denoted as I.

$$I = \frac{\sum \left| C_{ij} \right|}{\sum \left| C_{ij} \right| + \sum \left| G_i \right|} \tag{3}$$

where the fitness coefficient I represents the share of cross-impact effect among the event set, in relation to the overall impact of the events. The fitness coefficient I indicates the extent to which the probability of an event's occurrence can be attributed to the impact of the event included, which reflects the amount of information in the model. Finally, a coupling causal network C between CIA-based events can be then obtained.

Subsequently, this study proposes a measurement for critical event priority detection based on the CIA model. Event priority assessment measurement based on the coupling causal network C can be computed, namely centrality degree and causality degree. Prior to priority assessment measurement, the coupling causal network C must be normalized, as demonstrated in Eqs. (4–5) (Si et al., 2018).

$$s = \max\{\max \sum\nolimits_{i} |C_{ij}|, \max \sum\nolimits_{j} |C_{ij}| \tag{4}$$

$$N = \frac{C}{\mathrm{s}} \tag{5}$$

where C_{ij} denotes the element within the coupling causal network C, specifically the internal cross-impact coefficient.

The next step is to transform the normalization matrix N into a comprehensive impact matrix T, which is calculated as in Eq. (6), taking into account the transferability of impacts. This can be calculated using Eq. (6) (Singh & Bhanot, 2020). The comprehensive impact matrix T is important as it fully captures the extent of the impacts.

$$T = |N|(I - |N|)^{-1} \tag{6}$$

where I denotes the unit matrix.

The influence degree D and the influenced degree B for each event are computed using the formulas presented in Eq. (7), based on the comprehensive impact matrix T (Khan et al., 2021). The influence degree D quantifies the combined direct and indirect influence exerted by an event on all other events. Conversely, the influenced degree B measures the cumulative direct and indirect influences of all other events on the event.

$$\begin{aligned} D_i &= \sum_{j=1}^{n} t_{ij} \\ B_i &= \sum_{j=1}^{n} t_{ij} \end{aligned} \tag{7}$$

By calculating the overall impact level of each event, namely the centrality degree M, and the net impact level, known as the causality degree R, the extent of their influence on the system can be measured, as shown in Eq. (8). The centrality degree M encompasses both the event's influence on other events and the influence of other events on it. On the other hand, the causality degree R considers the remaining impact level of the event after accounting for its influence on other events. Events with a causality degree R greater than 0 are called causative events, and events with a causality degree R less than 0 are called resultant events. By assessing the centrality degree M and causality degree R, the significance of events within the coupling causal network can be assessed, aiding decision-makers in identifying the events that exert substantial influence on the system.

$$\begin{aligned} M_i &= D_i + B_i \\ R_i &= D_i + B_i \end{aligned} \tag{8}$$

Lastly, the priority of events can be quantified through the computation of event causality degree and centrality degree from the coupling causal network.

3.2 Interpretive structural modeling (ISM)

John Warfield developed interpretive structural modeling (ISM) in 1973 as a valuable tool for examining intricate socioeconomic system (Warfield, 1974). One of ISM's greatest strengths is its ability to scrutinize and expose intricate relational structures, breaking down the complicated elemental relationships in a system into a simple and methodical multi-level recursive network model (Chand et al., 2020). ISM offers potent tools to streamline the outcomes of CIA and pinpoint crucial events as the CIA model is compatible with other visual analysis techniques and easy to compute (Bañuls & Turoff, 2011). The process of utilizing ISM for structured generation of the coupling causal network generated by CIA is depicted in Fig. 2.

The coupling causal network serves as the initial reference point for ISM operations, which are subsequently employed to generate causal scenarios and conduct evolutionary analyses. As the coupling causal network incorporates both positive and negative effects (i.e., positive and negative values of link weights) among events, and since the ISM model necessitates input data in the form of a matrix comprised of non-negative elements, all internal cross-impact coefficients within the coupling causal network are initially transformed into positive values using the procedures specified in Eq. (9) (Wang et al., 2022a, 2022b).

$$\tilde{f}_{(2i)\times(2j)} = \begin{cases} \tilde{f}_{(-i),(+j)} = \left|C_{ij}\right| \text{ and } \tilde{f}_{(+i),(-j)} = \left|C_{ij}\right|, & \text{if } C_{ij} < 0 \\ \tilde{f}_{(-i),(-j)} = \left|C_{ij}\right| \text{ and } \tilde{f}_{(+i),(+j)} = \left|C_{ij}\right|, & \text{if } C_{ij} > 0 \end{cases} \tag{9}$$

Table 3 illustrates the ISM input matrix obtained from the aforementioned procedures as shown in Eq. (9). Positive event impacts can be denoted by $(+i, +j)$ and $(-i, -j)$, whereas negative impacts can be represented by $(+i, -j)$ and $(-i, +j)$.

The system employs different thresholds to establish a more succinct causal relationship to mitigate the impact of noise on causal relationships between events, as demonstrated in Eq. (10). Analyzing the ISM causal hierarchical network structure with varying thresholds enhances managers' comprehension of the cause-effect connections between events.

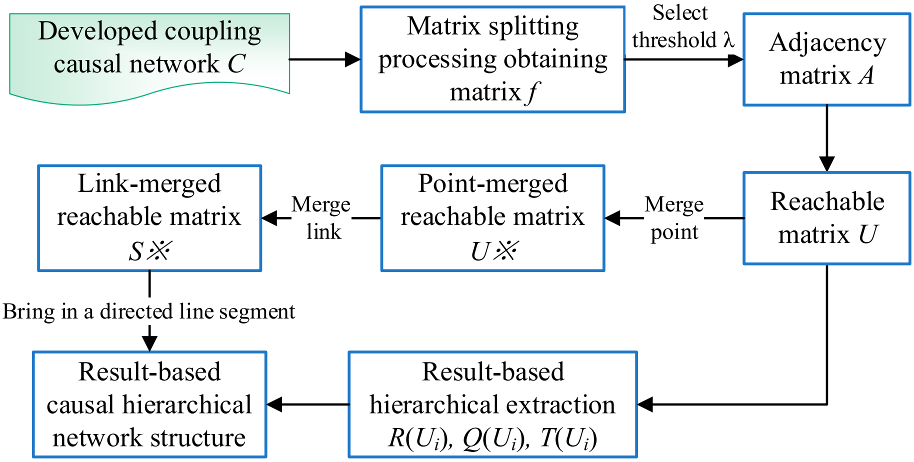

Fig. 2 Steps of ISM structured generation

Table 3 The transformed ISM input matrix

	Occurrence of events $(+j)$	Non-occurrence of events $(-j)$
Occurrence of events $(+i)$	$(+i, +j)$	$(+i, -j)$
Non-occurrence of events $(-i)$	$(-i, +j)$	$(-i, -j)$

$$A = [a_{ij}] = \begin{cases} 1 & \text{if } \tilde{f}_{ij} \geq \lambda \\ 0 & \text{else} \end{cases} \tag{10}$$

The adjacency matrix A is then used as the input to the ISM to calculate the reachable matrix U (Wang et al., 2022a, 2022b).

$$(\mathrm{A} + I)^{k-1} \neq (A + I)^{k} = (A + I)^{k+1} = U \tag{11}$$

In order to construct the causal hierarchical network structure diagram for the CIA-ISM scenario, a series of steps must be taken. Firstly, the reachable matrix U needs to be decomposed and a recursive hierarchy needs to be built. Then, a structure analysis of the reachable matrix is conducted to obtain the reachable set $R(U_i)$, prior set $Q(U_i)$, and common set $T(U_i)$ in sequence (Liu & Li, 2020). The reachable set $R(U_i)$ refers to the functional set of elements in the reachable matrix U that contain 1 in the corresponding rows of the elements U_i corresponding to the columns. The prior set $Q(U_i)$ represents the functional set of matrix elements in the reachable matrix U that contain 1 in the corresponding columns of the elements U_i corresponding to the rows. The common set $T(U_i)$ is the intersection of the reachable set $Q(U_i)$ and the prior set $Q(U_i)$. Finally, to obtain the causal hierarchical network structure diagram for the CIA-ISM scenario, the cascade extraction is repeated according to the condition $T\left(U_i\right) = R(U_i)$, which is named as result-based hierarchical extraction.

The ISM system structure can be simplified by merging redundant nodes and eliminating superfluous edges. The SCCs algorithm can be employed to merge the nodes within the reachable matrix R to obtain the point-merged reachable matrix $U\prime$ (Tarjan, 1972). Additionally, duplicate paths can be removed by implementing Eq. (12) to obtain the general skeleton S.

$$S = U\prime - (U\prime - I)^2 - I \tag{12}$$

where I is the unit matrix.

The integration of the general skeleton with the causal hierarchy extracted from the ISM leads to the formation of a network of event-coupled causal hierarchies. By utilizing the ISM algorithm, which involves selecting the CIA threshold, performing hierarchical extraction, and executing merging of redundant nodes and elimination of superfluous edges operations, the cluttered coupling causal network can be converted into a structure that possesses a clear hierarchy and significantly reduced complexity. The use of CIA-ISM allows for a more comprehensive and systematic analysis of the complex relational structures found within socio-economic systems.

4 Scenario-based SDGs priority assessment construction

4.1 Events definition

One of the objectives of this study is to employ the proposed CIA-ISM framework to assess the prioritization of SDGs and analyze potential developmental pathways. Therefore, according to the definition of the event in the CIA model mentioned in methodology section, the 17 SDGs are considered as events, but relying solely on expert estimates for their occurrence probabilities may result in unreliable reliability during the event definition. It is necessary to further quantitatively define the critical features of each goal for a more accurate estimation of the likelihood of achieving the SDGs. Then, the critical features can be used as the basis for measuring the probability of goal attainment. Comparability and practicality should serve as fundamental principles while selecting the critical features of the SDGs. Comparability requires that the selected critical features of the SDGs reflect the critical differences in implementing the goals across different regions or countries, enabling cross-regional or cross-national comparisons (Iyer et al., 2018). Practicality demands that the chosen critical features possess a broad statistical foundation and reliable data support, facilitating quantitative and comparative analysis (Jain et al., 2021). This paper presents 39 critical features for the achievement of the SDGs based on literature analysis and expert opinion, considering 232 SDGs indicators that (1) are applicable to cities; (2) are consistent with development indicators in national five-year plans or urban plans; and (3) have a broad statistical base, taking China as an illustration (Guo et al., 2021; Liu et al., 2015; Schmidt-Traub et al., 2017; Wang et al., 2020; Xu et al., 2020). The critical features of the SDGs are initially screened based on a literature analysis and then ultimately determined through collective expert discussions based on above principle. The core data is primarily sourced from the "Earth Big Data Support for Sustainable Development Goals Report (2022): China Chapter," officially published by the Chinese government. Table 4 gives the critical features of the SDGs. Experts can utilize this as a benchmark to assess the likelihood of China achieving its SDGs in 2030. Importantly, the achievement of the SDGs is influenced by various global crises (e.g., shifts in the global economy, political unrest, severe natural disasters, etc.), which often defy prediction, making it challenging to include them as part of critical events.

4.2 Data collection and cross-impact estimation

The data collection and cross-impact estimation process primarily involves estimating the numerical probability of achieving the SDGs by 2030 and determining the degree of interaction between the SDGs. This study invites five experts with diverse research and consulting backgrounds from the Chinese Academy of Social Sciences, China International Engineering Consulting Ltd., and the Development Research Center of Shandong Provincial People's Government to participate. Their expertise spans the domains requisite for estimating the probability of achieving SDGs. This helps to obtain a more precise estimation of the probability of achieving the SDGs. Specific information on the participating experts is shown in Table 5. Notably, this number of experts meets the number of estimators required by the CIA-ISM (Bañuls & Turoff, 2011).

The experts are provided with research reports concerning the SDGs in China from recent years as the foundation for their estimation (Guo et al., 2021). Moreover, the critical features of SDGs outlined in this paper serve as the basis for judgment guidelines for the

Table 4 Critical events of SDGs implementation for the CIA-ISM model

SDG ID	Short title of SDGs	Critical features of SDGs
G1	No poverty	The participation rate of urban employees' basic medical insurance has reached 100%
		The participation rate of urban employees' basic pension insurance has reached 100%
G2	Zero hunger	The per capita disposable income of urban residents has reached 55,000 RMB
G3	Good health and well-being	The number of hospital beds per 10,000 people has reached 75
		The number of practicing (assistant) doctors per 10,000 people has reached 45
G4	Quality education	The proportion of education expenditure has reached 4.5%
		The teacher-student ratio in primary schools has reached 13
		The teacher–student ratio in secondary schools has reached 9
G5	Gender equality	A legal framework has been established to promote, implement, and monitor gender equality and non-discrimination
G6	Clean water and sanitation	The coverage rate of water supply has reached 100%
		The water consumption per 10,000 yuan of GDP has reached 2.8 cubic meters
G7	Affordable and clean energy	The proportion of the population with access to electricity has reached 100%
		The energy consumption per 10,000 yuan of GDP has reached 0.3 tons of standard coal
G8	Decent work and economic growth	The per capita GDP has reached 165,000 yuan
		The added value of the tertiary industry as a percentage of GDP has reached 69%
		The urban registered unemployment rate has reached 1.7%
G9	Industry, innovation and infrastructure	The proportion of R&D expenditure to GDP has reached 4%
		The number of invention patents granted per 10,000 people has reached 8.8
G10	Reduced inequality	The proportion of actual foreign investment utilization in foreign direct investment has reached 5%
G11	Sustainable cities and communities	The number of books per person in public libraries has reached 2.2
		The proportion of direct economic losses caused by disasters to GDP has reached 0.09%
		The green coverage rate of built-up areas has reached 46.5%
		The annual average concentration of PM2.5 has reached 27 μg per cubic meter
		Emergency response plans for disasters have been developed

Table 4 (continued)

SDG ID	Short title of SDGs	Critical features of SDGs
G12	Responsible consumption and production	The harmless treatment rate of household waste has reached 100%
G13	Climate action	The contents of mitigation, adaptation, impact reduction, and early warning have been incorporated into primary, secondary, and tertiary education
		Relevant institutions for climate change adaptation have been established
G14	Life below water	The area of coastal and marine areas protected by returning farmland to forests or grasslands has reached 10%
G15	Life on land	The centralized treatment rate of sewage treatment plants has reached 100%
		The comprehensive utilization rate of general industrial solid waste has reached 99%
		The per capita green space area of parks has reached 19.5%
G16	Peace and justice strong institutions	The number of criminal cases filed per 10,000 people has reached 8%
		Birth registration has been achieved for all
		A legal framework has been established to promote, implement, and supervise ethnic equality
G17	Partnerships to achieve the goal	The proportion of mobile phone users to permanent residents
		The proportion of broadband Internet access users to total households
		Sustainable development coordination policies have been formulated
		At least one population and housing census has been conducted in the past decade

Table 5 Specific information on the participating experts

Expert	Working experience (years)	Title	Institution
1	5–10	Associate	Chinese Academy of Social Sciences
2	5–10	Senior	Chinese Academy of Social Sciences
3	> 10	Senior	China International Engineering Consulting Ltd
4	5–10	Associate	Development Research Center of Shandong Provincial People's Government
5	> 10	Senior	Development Research Center of Shandong Provincial People's Government

Table 6 Estimated probability of attaining SDGs in China by 2030

G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16	G17
0.85	0.7	0.6	0.7	0.85	0.55	0.6	0.75	0.6	0.4	0.6	0.55	0.7	0.65	0.55	0.75	0.6

experts to assess the probability of attaining SDGs in China by 2030. An online meeting is conducted among the experts to arrive at the probability estimation of China's SDGs achievement in 2030, using Table 1 as a probability estimation reference. Table 6 presents the resulting probability of achieving SDGs.

This study first determines the degree of interaction between SDGs through literature analysis, and then invite experts to assess its validity. To be specific, this study identifies semantic representations of specific linkages between SDGs based on GSDR 2019 and a comprehensive literature survey on studies exploring SDG interactions (Dawes, 2022; Pham-Truffert et al., 2020). The degree of SDGs interaction R_{ij} is derived in accordance with Table 2, and its rationality is assessed by experts. The final matrix of SDGs interaction degrees is presented in Table 7.

4.3 CIA calculation

Upon obtaining the probability of attaining China's SDGs in 2030 and the degree of interaction between SDGs, this study has constructed a cross-impact matrix of SDG estimations (refer to Table 8). The rows (i) and columns (j) in Table 8 represent the SDGs, and the values within the matrix indicate the internal cross-impact coefficients C_{ij}. A positive C_{ij} value suggests that the occurrence of the ith SDG has a positive influence on the jth SDG, whereas a negative value denotes a negative impact. G_i represents the external impact coefficient, denoting the likelihood of SDGs being influenced by factors beyond SDGs themselves. Based on the aforementioned parameters, the model fitness coefficient I can be calculated to assess the effectiveness of the SDG CIA-ISM model established in this study, as shown in Eqs. (13–16).

$$|\text{SDGs impact}| = \sum_{i=1}^{17}\sum_{j=1}^{17}|C_{ij}| = 200.79 \tag{13}$$

Table 7 Estimated interaction degree between SDGs

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16	G17
G1	0.88	0.90	0.88	0.85	0.90	0.73	0.85	0.88	0.85	0.85	0.85	0.85	0.85	0.85	0.75	0.88	0.85
G2	0.83	0.75	0.80	0.70	0.80	0.65	0.75	0.75	0.73	0.73	0.70	0.73	0.75	0.70	0.70	0.70	0.70
G3	0.63	0.63	0.70	0.60	0.60	0.60	0.60	0.80	0.60	0.60	0.60	0.60	0.60	0.60	0.63	0.60	0.60
G4	0.75	0.70	0.75	0.73	0.75	0.70	0.73	0.75	0.73	0.73	0.70	0.70	0.73	0.70	0.73	0.73	0.70
G5	0.90	0.90	0.90	0.88	0.85	0.85	0.85	0.88	0.85	0.88	0.85	0.85	0.85	0.85	0.85	0.88	0.85
G6	0.68	0.75	0.70	0.65	0.65	0.58	0.65	0.70	0.60	0.60	0.65	0.80	0.60	0.60	0.65	0.58	0.58
G7	0.78	0.65	0.80	0.70	0.65	0.78	0.65	0.75	0.65	0.65	0.73	0.70	0.73	0.65	0.55	0.60	0.60
G8	0.90	0.78	0.80	0.75	0.75	0.78	0.80	0.78	0.75	0.78	0.75	0.75	0.75	0.75	0.78	0.75	0.75
G9	0.65	0.65	0.63	0.60	0.63	0.70	0.73	0.70	0.60	0.60	0.65	0.63	0.65	0.60	0.60	0.60	0.60
G10	0.45	0.45	0.45	0.43	0.40	0.40	0.43	0.43	0.43	0.43	0.43	0.40	0.40	0.40	0.43	0.43	0.40
G11	0.70	0.63	0.78	0.63	0.63	0.65	0.60	0.63	0.60	0.65	0.63	0.60	0.65	0.60	0.55	0.60	0.60
G12	0.60	0.60	0.60	0.55	0.55	0.80	0.68	0.65	0.60	0.58	0.60	0.58	0.60	0.65	0.68	0.60	0.55
G13	0.80	0.85	0.75	0.70	0.70	0.75	0.80	0.75	0.73	0.75	0.75	0.73	0.75	0.58	0.80	0.73	0.70
G14	0.78	0.80	0.70	0.68	0.65	0.68	0.65	0.70	0.68	0.68	0.68	0.75	0.78	0.78	0.70	0.65	0.65
G15	0.70	0.78	0.65	0.55	0.58	0.65	0.45	0.73	0.55	0.55	0.60	0.58	0.75	0.58	0.73	0.60	0.55
G16	0.78	0.78	0.75	0.78	0.78	0.78	0.85	0.80	0.78	0.78	0.78	0.80	0.78	0.75	0.80	0.78	0.78
G17	0.65	0.70	0.63	0.60	0.60	0.65	0.65	0.65	0.65	0.63	0.65	0.65	0.65	0.63	0.70	0.63	0.65

Table 8 Cross-impact matrix of SDG

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16	G17
G1	0.00	1.54	0.53	0.00	3.08	− 1.70	0.00	0.85	0.00	0.00	0.00	0.00	0.00	0.00	− 1.41	0.85	0.00
G2	4.69	0.00	1.35	0.00	3.59	− 0.51	0.63	1.01	0.31	0.20	0.00	0.27	0.84	0.00	0.00	0.00	0.00
G3	0.70	0.35	0.00	0.00	0.00	0.00	0.00	3.92	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.00	0.00
G4	1.68	0.00	0.63	0.00	1.68	0.00	0.31	1.01	0.31	0.20	0.00	0.00	0.41	0.00	0.27	0.49	0.00
G5	3.08	1.54	1.16	0.70	0.00	0.00	0.00	0.85	0.00	0.35	0.00	0.00	0.00	0.00	0.00	0.85	0.00
G6	3.53	2.99	1.62	1.39	2.79	0.00	1.05	2.59	0.51	0.34	1.05	2.57	0.68	0.59	0.93	0.41	0.25
G7	5.54	0.71	2.45	1.47	1.42	1.85	0.00	2.77	0.53	0.36	1.41	0.98	1.88	0.61	− 0.46	0.00	0.00
G8	7.32	0.46	0.72	0.00	0.00	0.31	0.72	0.00	0.00	0.23	0.00	0.00	0.00	0.00	0.31	0.00	0.00
G9	1.42	0.71	0.26	0.00	0.70	0.98	1.41	1.77	0.00	0.00	0.53	0.23	0.71	0.00	0.00	0.00	0.00
G10	1.37	0.68	0.51	0.34	0.00	0.00	0.26	0.41	0.26	0.00	0.26	0.00	0.00	0.00	0.23	0.41	0.00
G11	2.95	0.35	2.08	0.35	0.70	0.47	0.00	0.42	0.00	0.36	0.00	0.00	0.71	0.00	− 0.46	0.00	0.00
G12	1.37	0.68	0.51	0.00	0.00	2.57	1.33	1.67	0.51	0.17	0.51	0.00	0.68	1.20	1.18	0.82	0.00
G13	3.59	2.96	0.63	0.00	0.00	0.56	1.35	1.01	0.31	0.42	0.63	0.27	0.00	− 1.56	1.20	0.49	0.00
G14	4.12	2.56	0.57	0.37	0.00	0.25	0.00	0.91	0.28	0.19	0.28	1.07	2.06	0.00	0.51	0.00	0.00
G15	4.31	3.45	1.05	0.00	0.68	0.93	− 1.00	3.07	0.00	0.00	0.51	0.23	2.99	0.29	0.00	0.82	0.00
G16	0.92	0.46	0.00	0.46	0.92	0.31	1.59	1.15	0.35	0.23	0.35	0.64	0.46	0.00	0.64	0.00	0.35
G17	1.42	1.47	0.26	0.00	0.00	0.47	0.53	0.85	0.53	0.18	0.53	0.47	0.71	0.30	0.98	0.42	0.00
G_i	− 1.84	− 8.85	− 3.51	4.38	− 4.56	− 16.09	− 14.92	− 6.74	− 5.72	− 3.80	− 5.40	− 8.41	− 7.41	− 8.81	− 12.63	− 4.84	− 5.74

$$|\text{External environmental impact}| = \sum_{i=1}^{17} |G_i| = 123.66 \tag{14}$$

$$|\text{Total impact}| = \sum_{i=1}^{17} \sum_{j=1}^{17} |C_{ij}| + \sum_{i=1}^{17} |G_i| = 324.45 \tag{15}$$

$$\frac{|\text{SDGs impact}|}{|\text{Total impact}|} = 61.89\% \tag{16}$$

The fitness coefficient I for the SDGs CIA-ISM model developed in this study has achieved a level of 61.89%. This signifies that the data collected via literature analysis and expert interviews are robust. The SDGs and their internal cross-impact coefficients have been encapsulated into an SDG coupling causal network, illustrated in Fig. 3. The solid lines connecting the SDGs represent a positive relationship, while the dotted lines indicate a negative relationship. Furthermore, subsequent priority measurements and causal hierarchy generation for SDGs will be conducted based on the SDG coupled causal network.

5 Result

5.1 SDGs priority analysis

To quantitatively analyze the priority of SDGs, it is necessary to calculate the results of the comprehensive impact matrix T of the SDG coupling causal network based on Eqs. (4–6), as shown in Appendix 1.

The influence degree D, influenced degree B, centrality degree M, and causality degree R of each SDG are then calculated, as shown in Table 9.

Furthermore, a scatter plot illustrating the analysis of SDG priority is generated by plotting the centrality degree M on the x-axis and the causality degree R on the y-axis, as shown in Fig. 4.

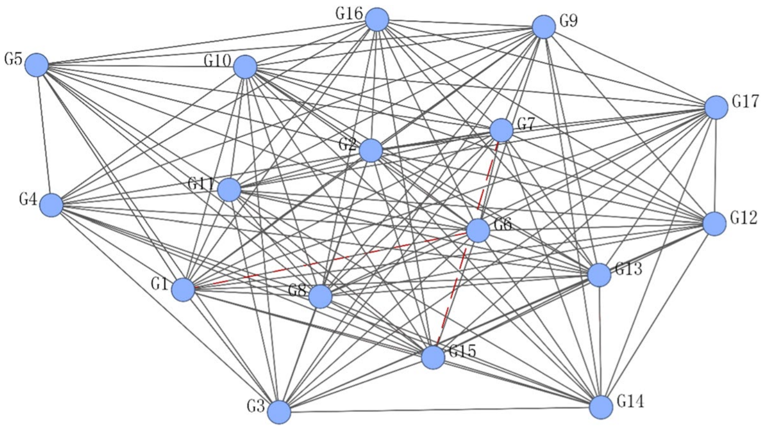

Fig. 3 SDG coupling causal network

Table 9 SDG priority measurement calculation results

	D	*B*	*R*	*M*	Ranking of *M*	Event type
G1	1.33	0.28	1.05	1.62	1	Causative event
G2	0.58	0.36	0.22	0.94	3	Causative event
G3	0.40	0.14	0.26	0.54	10	Causative event
G4	0.14	0.19	− 0.05	0.32	15	Resultant event
G5	0.49	0.22	0.27	0.72	8	Causative event
G6	0.32	0.63	− 0.32	0.95	2	Resultant event
G7	0.26	0.61	− 0.35	0.87	5	Resultant event
G8	0.66	0.28	0.38	0.93	4	Causative event
G9	0.10	0.25	− 0.15	0.35	14	Resultant event
G10	0.09	0.13	− 0.04	0.21	17	Resultant event
G11	0.15	0.24	− 0.08	0.39	13	Resultant event
G12	0.17	0.39	− 0.21	0.56	9	Resultant event
G13	0.31	0.42	− 0.11	0.73	7	Resultant event
G14	0.12	0.36	− 0.25	0.48	11	Resultant event
G15	0.26	0.54	− 0.28	0.80	6	Resultant event
G16	0.16	0.25	− 0.09	0.41	12	Resultant event
G17	0.02	0.26	− 0.24	0.28	16	Resultant event

The centrality degree of SDGs ranges from 0.21 to 1.62. G1 (1.62), G6 (0.95), and G2 (0.94) rank as the top three SDGs, playing a crucial role in accomplishing the entire sustainable development agenda. Conversely, G4, G10, and G17 possess relatively low centrality degrees, falling below one standard deviation from the mean and occupying

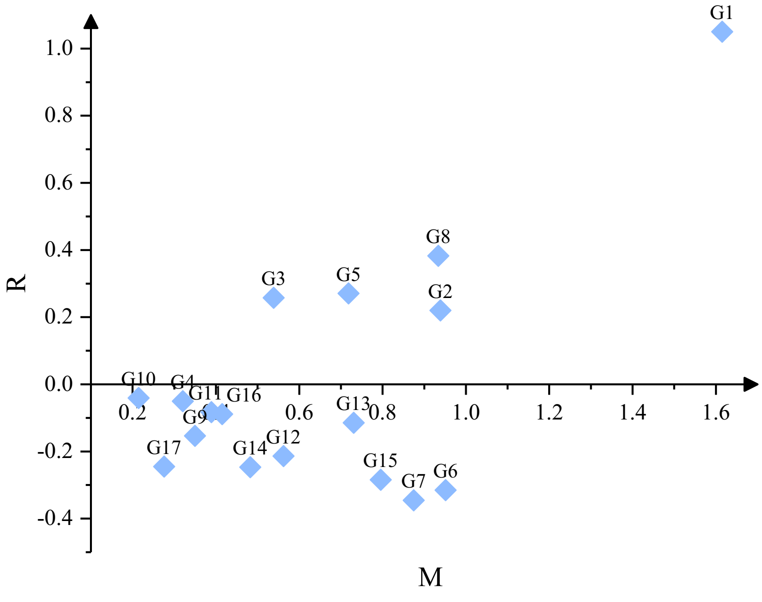

Fig. 4 The scatter plot of SDG priority quantitatively analysis

marginal positions within the overall SDG coupling causal network. Based on the causality degree results, most SDGs are resultant events, with only 5 identified as causative events: G1, G2, G3, G5, and G8. This implies that these 5 SDGs exert a significant impact on the entire SDG system and can directly contribute to the attainment of other goals. G6 and G7 exhibit the lowest causality degree, indicating a strong dependence on other SDGs for their achievement. Notably, G1 demonstrates both a high causality degree and centrality degree within the SDG coupling causal network, signifying its substantial influence on the entire SDG system, which deserves focused attention. In summary, analyzing the causality degree and centrality degree of SDGs provides a quantitative understanding of priorities for SDG achievement. However, these quantitative measures fail to depict the logic relationship and causal path of SDG accomplishment, hindering the promotion of specific SDGs in a comprehensive and targeted manner. Therefore, it is necessary to further analyze the causal relationships evidenced by the SDG coupling causal network, which will be presented in Sects. 5.2 and 5.3.

5.2 Scenario generation

After obtaining the SDG coupling causal network, the SDG coupling causal network is processed by splitting, selecting the threshold, hierarchical extraction, general skeleton calculation, and finally generating the SDG causal hierarchical network structure. The CIA-ISM generated SDG causal scenario directed graphs can show the direction and degree of impact among the SDGs. By choosing different thresholds of the CIA-ISM internal cross-impact coefficients to observe the changes in logic occurring among the SDGs, managers can deepen their understanding of the degree of interaction between the SDGs and the causal connections between the SDGs. In contrast to the static assessment of SDG priority measurement, this process focuses on the transmission of the causal logic of SDG occurrence which is a developmental perspective on SDG priorities. In order to select the appropriate $|C_{ij}|$ value as the threshold for generating the SDG achievement scenarios, this paper first counted the distribution of $|C_{ij}|$ (without zero value), as shown in Fig. 5. When counting the quantile distribution of impacts, repeated impact values are recorded only once.

Subsequently, the SDG causal hierarchical network structures corresponding to different thresholds are generated, and the features corresponding to different structures are shown in Appendix 2. Referring to the Pareto two-eight principle, the 20% with the highest impact strength in the SDGs coupling causal network is selected as the threshold (i.e., $\left|C_{ij}\right| = 2.06$), as an example of scenario generation in this study, as shown in Fig. 6.

As depicted in Fig. 6, G1 and G5 emerge as the foundational SDGs pivotal to attaining China's SDGs. By virtue of their causal connections with SDGs at each tier, the entire SDG framework assumes a profound role in regulating their realization. G6, G7, G11, G12, and G15 represent the outermost stratum of SDGs within the SDG framework, with their accomplishment being impacted by the attainment of other SDGs. Positioned in the intermediate layer of the SDG causal hierarchy, G2, G3, G8, and G13 are subject to the impact of the fundamental SDGs while simultaneously exerting impact on the achievement of surface-level SDGs. The causal hierarchy illustrated in Fig. 4 aligns, to a large extent, with the outcomes of SDG priority measurement, establishing (G1, G5) in L4, (G2, G8) in L3, and (G3, G13) in L2 as causal relationships among the events. The SDGs that do not appear in the figure are isolated due to their weak causal associations with other SDGs in the ISM selection threshold when generating the causal structure.

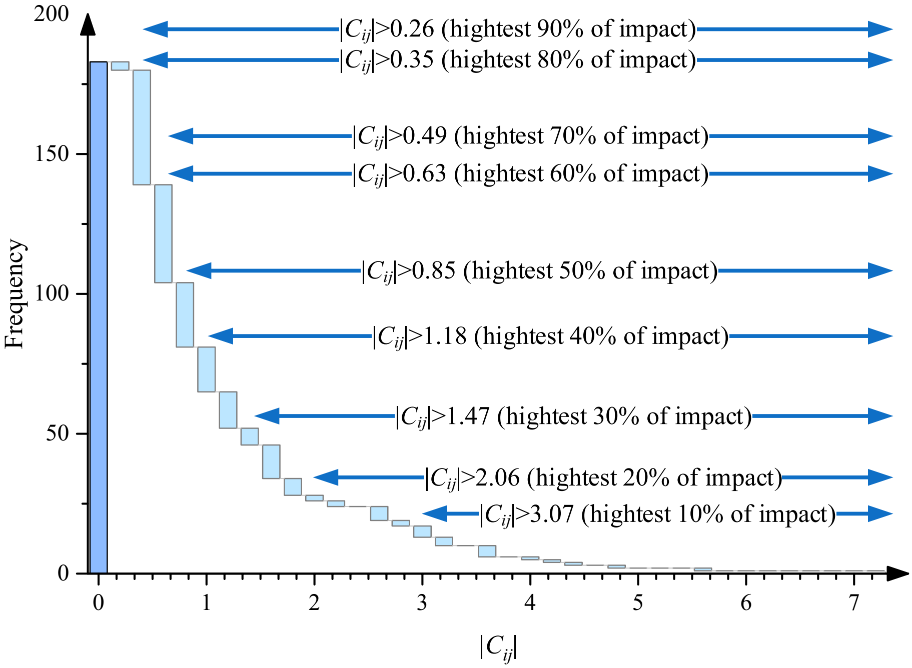

Fig. 5 Waterfall chart of the $|C_{ij}|$ distribution of the SDG CIA-ISM model

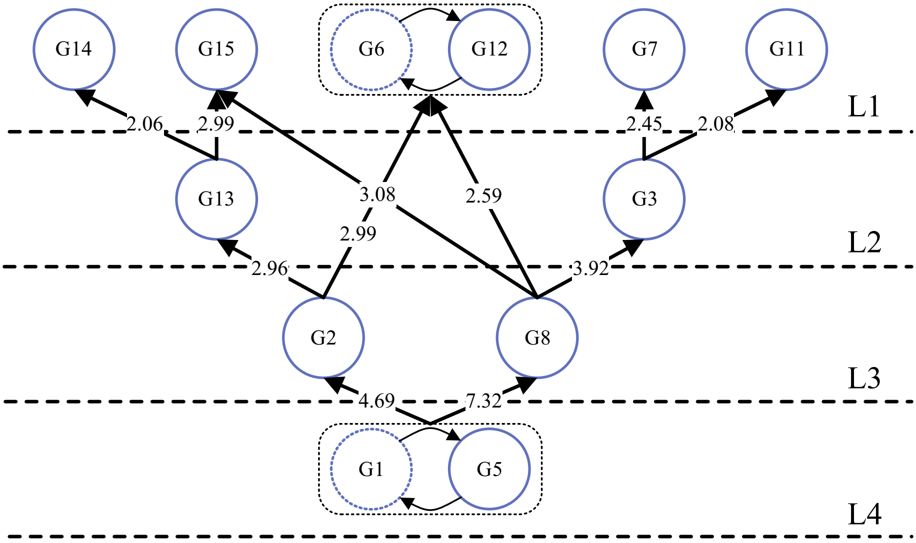

Fig. 6 Digraph for the threshold $\left|C_{ij}\right| = 2.06$

The causal transmission of the SDGs is subsequently analyzed, drawing upon the overarching causal hierarchy delineated above. An interactive and mutually reinforcing relationship between G1 and G5 emerges within China's pursuit of the SDGs, playing a pivotal role in supporting the accomplishment of other SDGs. The direct implementation of G1 and G5 contributes significantly to the attainment of G2 and G8. G2 and G8, in turn, serve as direct enablers for realizing G6 and G12. Simultaneously, the fulfillment of G6 and G12 exhibits interdependence and mutual reinforcement. Furthermore, G8 facilitates the realization of G3 and subsequently bolsters the achievement of G7 and G11. Similarly, G2 manifests a comparable causal transmission effect, encompassing G13, G14, and G15.

The most noteworthy finding is the robust causal relationship between G1 (eradicating poverty) and G5 (attaining gender equality), which forms the most robust causal loop within the entire SDG framework. It has emerged as the fundamental driver behind China's SDG accomplishments. The eradication of poverty assumes paramount importance in the pursuit of gender equality (Patel, 2019). Poverty disproportionately impacts women and girls, impeding their access to education, healthcare, and economic opportunities. Gender parity can be achieved by eliminating poverty, specifically by addressing gender disparities and ensuring equitable allocation of resources and opportunities for women and girls. Additionally, empowering their involvement in decision-making and development processes is crucial. Simultaneously, advancing gender equality contributes to poverty reduction objectives. Providing women and girls with equal access to economic opportunities and resources and elevating their income levels and financial autonomy helps mitigate the multi-generational effects of poverty. Enhancing the economic status of women uplifts family and community income levels, reduces the risk of poverty, and fosters better prospects for overall development, thereby driving the realization of the SDGs.

5.3 Sensitivity analysis

In order to deepen comprehension of the causal interdependencies among the SDGs, this study undertook an analysis of the causal framework of SDGs employing various impact thresholds as part of a sensitivity analysis. In addition to using $\left|C_{ij}\right| = 2.06$ for scenario generation, this study selects $\left|C_{ij}\right| = 2.59$ (top 85% highest impact), $\left|C_{ij}\right| = 3.07$ (top 90% highest impact), and $\left|C_{ij}\right| = 3.92$ (top 95% highest impact) as threshold values for conducting the sensitivity analysis.

Figure 7 portrays the causal scenario aligned with the SDG impact threshold of the top 85% highest impact. When comparing Fig. 7 with Fig. 6, it becomes apparent that Fig. 7 exclusively exhibits a causal loop between G1 and G5, whereas the causal loop involving G6 and G12 is disassembled. This underscores the paramount significance of the interplay between (causal loop "G1 and G5") in the overall process of SDG accomplishment, warranting concentrated attention. Additionally, G12 assumes an isolated position within the causal hierarchical network structure. Furthermore, contrary to Fig. 6 where G8 directly impacts G3, G6, G7, and G15, Fig. 7 demonstrates that G8 directly impacts G3, (G6, G12), and G15, while indirectly influencing G7 and G11 through G3. This discrepancy arises primarily due to the diminished degree of cross-impact from G3 to G7 and G11, falling below the threshold in this causal scenario. As a result, this causal relationship is disentangled, leading to the formation of an adjacent causal structure comprising G3, G7, and G11, thereby causing an upward shift in the causal hierarchy of G8. Additionally, the causal

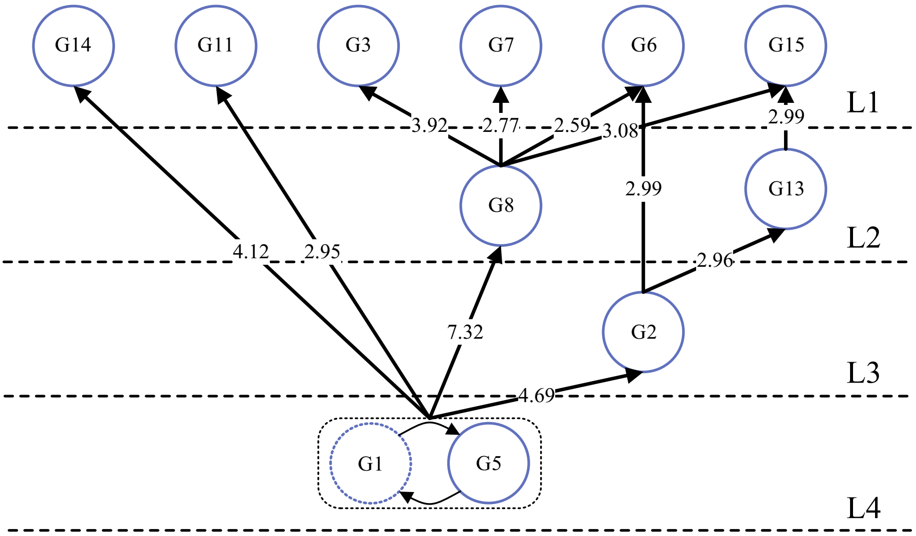

Fig. 7 Digraph for the threshold $\left|C_{ij}\right| = 2.59$

relationship between G14 and G13 is disentangled in Fig. 7 and is directly influenced by (G1 and G5).

In comparison with Fig. 7, the causal hierarchical network structure representing the top 85% highest impact (Fig. 8) showcases a reduction in the number of layers from the original 4 to 3. This phenomenon primarily stems from the impact degree of G2 → G13 → G15 in Fig. 7 falling below the designated impact threshold, leading to the dissolution of this particular causal path. Within this causal scenario, only two causal paths persist: (causal loop "G1 and G5") → (G8) → (G3 and G15) and (causal loop "G1 and G5") → (G2) → (G15). The remaining SDGs (i.e., G6, G7, G13, and G14) directly experience the influence attributed to the causal loop "G1 and G5". Furthermore, G11 assumes an isolated position.

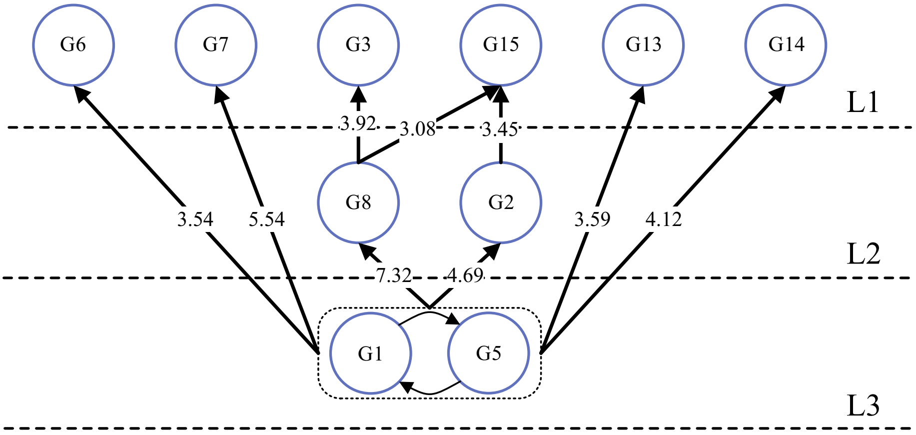

Fig. 8 Digraph for the threshold $\left|C_{ij}\right| = 3.07$

Figure 9 depicts the causal hierarchical network structure of the SDGs at a specific impact threshold ($\left|C_{ij}\right| = 3.92$). The structure displayed, focusing on the top 95% highest impact, exhibits enhanced conciseness and clarity compared to the aforementioned structure. Within this causal scenario, only one causal path, namely G1 → G8 → G3, persists, demanding concentrated attention in the pursuit of SDG accomplishment. Moreover, G2, G3, G7, G14, and G15 directly experience the beneficial influence of G1's promotion effect.

Scenario generation and sensitivity analysis convert the intricate and disorganized coupling causal network of the SDGs into a well-defined causal hierarchical network structure, showcasing distinct causal relationships across various impact thresholds. The measurement of SDG priority offers comprehensive macro-quantitative indicators to assess the attainment of the SDGs. By integrating the SDG priority measurement with the SDG causal hierarchical network structure, managers can elucidate the causal significance of the SDGs, as well as the underlying causal pathways linking the achievement of these goals within the intricate SDG landscape.

6 Discussion

6.1 Model validation

The validation process for the CIA-ISM model proposed in this study, which assesses SDG priority assessment in China, consists primarily of two components: initial expert validation and literature validation. The initial expert validation entails inviting experts who were involved in the initial data research to complete a questionnaire gauging their satisfaction with the model's outcomes. The questionnaire employs a Likert scale ranging from 1 (indicating complete disagreement) to 5 (indicating complete agreement). Table 10 presents the questionnaire items and the arithmetic mean of the expert responses. Notably, all

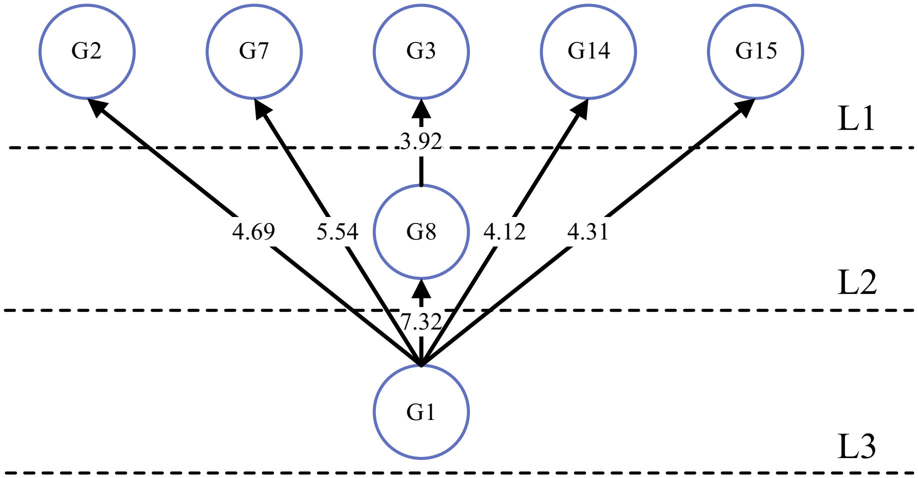

Fig. 9 Digraph for the threshold $\left|C_{ij}\right| = 3.92$

Table 10 Expert satisfaction questionnaire and feedback results

Question	Feedback
The CIA-ISM method is a suitable tool to generate a causal structure for the SDGs	5
The SDG priority measurement identifies the importance of the SDGs and their degree of impact on other SDGs	4.8
The SDG causal structure demonstrates a structure that is consistent with my opinion	4.8
The SDG priority assessment based on CIA-ISM can provide insight for developing pathways to achieve the SDGs	5

participating experts unanimously affirmed the validity of the CIA-ISM approach employed in this research, both in elucidating complex cause-effect relationships among the SDGs and in formulating pathways towards attaining sustainable development.

The literature validation primarily involves examining the correlation between the findings presented in this paper and those derived from other scholarly sources. To assess the ranking of SDG causality degree in the CIA-ISM model proposed herein, a comparison is made with the ranking of SDGs in the GSDR 2019 network as reported by Dawes (2022). The Spearman correlation coefficient is employed as the foundation for this comparative analysis, owing to its nonparametric nature, ability to account for diverse variable relationships, and limited susceptibility to outliers. Based on the computations, the Spearman correlation coefficient between the outcomes of this research and the relevant literature stand at 0.815, thereby confirming the soundness of utilizing the CIA-ISM approach for SDG priority assessment in this study.

6.2 Policy recommendations

Utilizing the causal loop "G1 and G5" as a foundation, this study integrates the measurement of SDG priorities with the hierarchical network structure of SDG causality, yielding three distinct paths for SDG priority development. These paths are as follows: (causal loop "G1 and G5") → G8 → G3 → G7; (causal loop "G1 and G5") → G2 → G13 → G15; and (causal loop "G1 and G5") → G2 → (causal loop "G6 and G12").

In the first development path, eradicating poverty and attaining gender equality play a vital role in fostering economic growth and promoting inclusivity (G8). They contribute to a more significant labor force and expanded markets while fostering a more equitable and inclusive environment, facilitating sustainable economic development. G8 facilitates enhanced access to healthcare coverage and essential services by generating employment opportunities, raising income, and improving living conditions (G3) (Pan et al., 2023; van Zanten & van Tulder, 2021). Economic growth, in turn, provides financial resources and support to enhance the quality and availability of healthcare facilities and infrastructure, thereby promoting healthy lifestyles and well-being (G3). Furthermore, G3 contributes to realizing G7 (affordable and clean energy) by improving environmental well-being, reducing pollution-related diseases, ensuring a reliable energy supply for healthcare services, enhancing the quality and accessibility of healthcare services, and creating sustainable employment opportunities in the energy sector (Shaheen et al., 2022; Wang et al., 2022a, 2022b). This developmental trajectory commences with poverty eradication and the achievement of gender equality and ultimately leads to the promotion of sustainable energy through the facilitation of economic growth and the establishment of inclusive and healthy lifestyles that prioritize well-being.

For the second development path, the development trajectory encompasses reducing poverty, eradicating hunger, implementing climate action, and preserving terrestrial ecosystems. Poverty elimination stands as the primary objective in attaining zero hunger. Through providing economic opportunities and enhancing living conditions, G1 establishes the fundamental basis for individuals to escape the poverty cycle and achieve a sustainable food supply. Simultaneously, gender equality serves as a pivotal determinant. By empowering women with equal rights and opportunities, G5 enhances their participation in agriculture and food production, thereby increasing food production capacity and promoting rural community development. The collective efforts of G1 and G5 create an equitable, inclusive, and sustainable environment that supports the achievement of zero hunger (G2) (Pakkan et al., 2023). G2 significantly contributes to Climate Action (G13) by promoting sustainable agricultural practices, addressing the linkages between hunger and climate change, and ensuring the harmony between environmental sustainability and food production (Khanal et al., 2021). Simultaneously, G13 contributes to G15 (life on land) by reducing carbon emissions, advancing sustainable energy and urban development, and adapting to climate change and disaster risk management (Coenen et al., 2022). The second developmental trajectory synergistically combines poverty eradication, food security assurance, climate change mitigation, and preservation of terrestrial ecosystems, thereby playing a crucial role in fostering sustainable development, achieving global food security, and preserving biodiversity.

The third path shares similarities with the second path as it is built upon the causal loops of “G1 and G5”, and G2. Attaining G2, which represents zero hunger, becomes a prerequisite for realizing G6, ensuring sustainable water resource management and sanitation. By guaranteeing adequate access to food and water, improving agricultural production and irrigation techniques, and providing safe drinking water and sanitation facilities, we can establish sustainable systems for water resource management and sanitation, thus significantly contributing to achieving the SDGs (Banerjee et al., 2019). Furthermore, hunger is often linked to overconsumption and wastage of resources (Hasegawa et al., 2019). Insufficient and unstable food supplies in impoverished areas challenge meeting basic needs. However, when resources are excessively consumed and wasted, this imbalance exacerbates the issue of hunger. By achieving zero hunger, we can reduce food waste, enhance agricultural productivity, and promote sustainable land utilization, laying the foundation for sustainable consumption and production patterns (G12) (Fonseca et al., 2020). Notably, G6 and G12 are mutually reinforcing and interconnected (Pradhan et al., 2017). Promoting sustainable water resource management and sanitation helps mitigate excessive utilization and pollution of water resources, thus facilitating the conditions required to achieve sustainable consumption and production patterns. Additionally, fostering sustainable consumption and production patterns minimizes resource wastage, reduces environmental pollution, and enhances resource efficiency, thereby contributing to water resource management and sanitation sustainability. This developmental approach highlights the interdependence of poverty eradication, gender equality, economic growth, urban and community development, and responsible consumption and production.

The described sustainable development pathway exemplifies an amalgamation of integrated goals and priorities, offering a comprehensive solution to advance sustainable development by converging multiple sustainable development goals. This pathway harmonizes objectives and policies across various domains, fostering a cohesive advancement and multifaceted transformation. Simultaneously, it embodies a forward-looking developmental perspective, interlinking the goals and underscoring the sequential nature of their attainment. Thus, sustainable development is an incremental journey necessitating the progressive realization of objectives across diverse realms. Consequently, the trajectory posited within this paper inherently manifests logical coherence and interconnectedness, epitomizing the integration of goals, policy coordination, and the pursuit of a long-term developmental horizon.

7 Conclusion

This study demonstrates a groundbreaking attempt to incorporate the CIA-ISM approach into the evaluation of SDG priorities. The core objective is to unravel the intricate correlations and causal logic underlying the assessment process. Embracing a comprehensive approach, this study employs seventeen SDGs as pivotal events within the CIA-ISM framework while constructing critical features of SDGs to serve as the foundation for expert estimation. Consequently, experts specializing in sustainable development and possessing diverse backgrounds are invited to assess the probability of each SDG's occurrence in China by 2030. Their estimations further verify the degree of interaction among the SDGs obtained from GSDR 2019. Through the application of CIA-ISM, expert estimates are processed to yield SDG priority measurements, generate causal scenarios, and conduct sensitivity analysis of the causal structure under various impact thresholds.

This study incorporates an initial expert questionnaire and a comparative analysis of existing literature to ascertain the feasibility and applicability of the proposed CIA-ISM-based SDG priority assessment. The initial expert validation results, derived from the questionnaire, demonstrate a high level of agreement, with all model validation questions scoring 4.8 or above on a scale 5. Moreover, the Spearman correlation coefficient between the ranking of reasons in the SDG priority measurement of this study and the ranking of SDG importance in related literature reaches 0.815. Hence, CIA-ISM emerges as a robust tool for SDG priority assessment and causal scenario analysis, exhibiting the potential to drive sustainable development initiatives forward.

Based on the results of this study, it can be inferred that in the context of China, the attainment of the SDGs heavily relies on the synergistic impact of G1 (no poverty) and G5 (gender equality), with G1 playing a more predominant role. By combining G1 and G5 with the causal hierarchical network structure of the SDGs, this research puts forward three paths for achieving the SDGs: G1 (no poverty) and G5 (gender equality) → G8 (decent work and economic growth) → G3 (good health and well-being) → G7 (affordable and clean energy); G1 (no poverty) and G5 (gender equality) → G2 (zero hunger) → G13 (climate action) → G15 (life on land); and G1 (no poverty) and G5 (gender equality) → G2 (zero hunger) → G6 (clean water and sanitation) and G12 (responsible consumption and production). These sustainable development pathways' internal coherence and interconnectedness signify an amalgamation of objectives and priorities, offering a comprehensive solution to propel sustainable development by harmonizing goals, aligning policies, and pursuing a long-term vision of progress.

This study represents a pioneering effort to integrate the CIA-ISM method into SDG priority assessment. The key innovations and contributions of this paper are outlined below: Methodologically, this paper presents an integrated framework for assessing SDG priorities and formulating development policies, utilizing the CIA-ISM systematic modeling approach. The framework adeptly captures the interactions and uncertainties inherent in the SDGs while simultaneously extracting the intricate causal relationships among them. By utilizing a systematic scenario modeling approach, it offers a scientifically sound method for assessing SDG priorities. Practically, the proposed approach serves as a generic modeling technique for SDGs, enabling the integration of goal interactions, generation of causal derivations under diverse scenarios, and sensitivity analysis of outcomes. These findings serve to guide decision makers in their pursuit of SDGs by aiding the formulation of corresponding development pathways and offering decision support to achieve the SDGs.

Future research can expand the application scenarios of the CIA-ISM method, considering external environmental impacts and broadening the scope and expertise of expert groups. This will facilitate a more thorough, accurate, and beneficial assessment of the SDG priorities. Subsequent studies should concentrate on extending the application scenarios of CIA-ISM-based SDG priority assessment to encompass a wider array of nations and regions. This will enable an understanding of the performance and priorities of diverse regions regarding sustainable development, providing guidance for policy formulation and action plans. Simultaneously, incorporating external environmental influences, such as scientific and technological advancements, climate-related disasters, and local conflicts, will permit more extensive research and a comprehensive assessment of SDG achievements. Furthermore, enlarging the size of interview panels and expanding the coverage of areas of expertise can yield more comprehensive and valuable insights. These insights will support decision-makers in making well-informed choices regarding sustainable development.

Appendix 1

See Table 11.

Table 11 The comprehensive impact matrix *T* of the SDG coupling causal network

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16	G17
G1	0.02	0.04	0.02	0.00	0.07	0.04	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.02	0.00
G2	0.12	0.01	0.03	0.00	0.08	0.02	0.02	0.03	0.01	0.01	0.00	0.01	0.02	0.00	0.00	0.00	0.00
G3	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
G4	0.05	0.00	0.02	0.00	0.04	0.00	0.01	0.03	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.00
G5	0.07	0.04	0.03	0.02	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.00
G6	0.11	0.08	0.04	0.03	0.07	0.01	0.03	0.07	0.01	0.01	0.02	0.06	0.02	0.01	0.03	0.01	0.01
G7	0.15	0.03	0.06	0.03	0.05	0.05	0.01	0.07	0.01	0.01	0.03	0.02	0.04	0.02	0.02	0.01	0.00
G8	0.16	0.02	0.02	0.00	0.01	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
G9	0.05	0.02	0.01	0.00	0.02	0.02	0.03	0.04	0.00	0.00	0.01	0.01	0.02	0.00	0.00	0.00	0.00
G10	0.04	0.02	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.00
G11	0.07	0.01	0.05	0.01	0.02	0.01	0.00	0.02	0.00	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.00
G12	0.06	0.03	0.02	0.00	0.01	0.06	0.03	0.05	0.01	0.01	0.01	0.01	0.02	0.03	0.03	0.02	0.00
G13	0.10	0.07	0.02	0.00	0.02	0.02	0.03	0.03	0.01	0.01	0.02	0.01	0.01	0.03	0.03	0.01	0.00
G14	0.11	0.06	0.02	0.01	0.01	0.01	0.00	0.03	0.01	0.01	0.01	0.02	0.05	0.00	0.02	0.00	0.00
G15	0.13	0.09	0.03	0.00	0.03	0.03	0.03	0.08	0.00	0.00	0.01	0.01	0.07	0.01	0.01	0.02	0.00
G16	0.04	0.02	0.01	0.01	0.03	0.01	0.04	0.03	0.01	0.01	0.01	0.02	0.01	0.00	0.02	0.00	0.01
G17	0.05	0.04	0.01	0.00	0.01	0.01	0.01	0.03	0.01	0.00	0.01	0.01	0.02	0.01	0.02	0.01	0.00

Appendix 2

See Table 12.

Table 12 Characteristics of CIA-ISM causal hierarchical network structure for SDG coupling causal network

Structure serial number	Feature threshold	Threshold range	Layer	Isolated SDGs	Causal loops	SDG contained in the causal loop (maximum)	Thresholds included
1	0.35	(0, 0.35)	1	0	1	17	16
2	0.42	(0.35, 0.42)	2	0	1	16	16
3	0.53	(0.42, 0.53)	2	0	1	15	16
4	0.85	(0.53, 0.85)	2	0	1	14	16
5	1.35	(0.85, 1.35)	2	0	1	13	27
6	1.37	(1.35, 1.37)	4	0	1	11	11
7	1.39	(1.37, 1.39)	4	1	1	11	12
8	1.41	(1.39, 1.41)	4	1	1	10	5
9	1.41	(1.41, 1.41)	4	1	1	10	37
10	1.47	(1.41, 1.47)	4	1	2	7	9
11	1.56	(1.47, 1.56)	4	2	2	7	4
12	1.59	(1.56, 1.59)	4	2	1	7	9
13	1.62	(1.59, 1.62)	3	3	1	7	11
14	1.68	(1.62, 1.68)	3	3	1	6	6
15	1.70	(1.68, 1.7)	3	4	1	6	31
16	1.77	(1.7, 1.77)	4	4	2	2	3
17	1.85	(1.77, 1.85)	4	5	2	2	2
18	1.88	(1.85, 1.88)	4	5	2	2	2
19	2.06	(1.88, 2.06)	4	5	2	2	1
20	2.08	(2.06, 2.08)	4	5	2	2	2
21	2.45	(2.08, 2.45)	4	5	2	2	1

Table 12 (continued)

Structure serial number	Feature threshold	Threshold range	Layer	Isolated SDGs	Causal loops	SDG contained in the causal loop (maximum)	Thresholds included
22	2.56	(2.45, 2.56)	4	5	2	2	1
23	2.57	(2.56, 2.57)	4	5	2	2	6
24	2.59	(2.57, 2.59)	4	6	1	2	1
25	2.77	(2.59, 2.77)	4	6	1	2	1
26	2.95	(2.77, 2.95)	4	6	1	2	2
27	2.96	(2.95, 2.96)	4	7	1	2	1
28	2.99	(2.96, 2.99)	3	7	1	2	2
29	3.07	(2.99, 3.07)	3	7	1	2	1
30	3.08	(3.07, 3.08)	3	7	1	2	8
31	3.45	(3.08, 3.45)	3	7	0	1	2
32	3.53	(3.45, 3.53)	3	7	0	1	1
33	3.59	(3.53, 3.59)	3	8	0	1	2
34	3.92	(3.59, 3.92)	3	10	0	1	2
35	4.12	(3.92, 4.12)	2	11	0	1	1
36	4.31	(4.12, 4.31)	2	12	0	1	1
37	4.69	(4.31, 4.69)	2	13	0	1	1
38	5.54	(4.69, 5.54)	2	14	0	1	1
39	7.32	(5.54, 7.32)	2	15	0	1	18

The values in columns 4 to 8 of the table are the quantities corresponding to the table headers

Acknowledgements We wish to acknowledge Engineer Wei Huang for his helpful computing method and comments.

Author contributions Renlong Wang was involved in writing—original draft, conceptualization, methodology, investigation, software, and visualization. Shutian Cui contributed to the formal analysis, validation, data acquisition, investigation. Mingang Gao contributed to writing—review and editing, supervision, and funding acquisition.

Funding This research was funded by the National Natural Science Foundation of China (Grant Number: 72134004).

Data availability statement The datasets generated and analyzed for this study can be requested from the first author at 13127073530@163.com.

Declarations

Conflict of interest The authors declare no conflict of interest.

Institutional review board statement Not applicable.

Informed consent statement Not applicable.

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