An Integrated IVHFS and DEMATEL-ANP Framework for Competitive Intelligence Evaluation in Smart Factories

Wei Lo[1], Mingyuan Li[2,3,*], Dingxuan Huang[4,*], Chun-Ming Yang[5], Wenting Deng[5,6] and Shiyao Li[5,6]

[1] College of Economics and Management, Fujian Agriculture and Forestry University, Fuzhou, 350002, China

[2] Institute for Six-Sector Economy, Fudan University, Shanghai, 20433, China

[3] School of Business Administration, Guangxi University of Finance and Economics, Nanning, 530007, China

[4] School of Management, Chongqing University of Technology, Chongqing, 400054, China

[5] School of Economics and Management, Dongguan University of Technology, Dongguan, 523808, China

[6] School of Management and Economics, Kunming University of Science and Technology, Kunming, 650093, China

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[1]College of Economics and Management, Fujian Agriculture and Forestry University, Fuzhou, 350002, China

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ABSTRACT

In the era of big data, the ability to evaluate high-quality and actionable competitive intelligence (CI) has become essential for smart factories to support data-driven decision-making and maintain technological and operational advantages. However, the highly dynamic and complex nature of the smart manufacturing environment introduces considerable uncertainty, hesitation, and interdependencies among evaluation indicators, posing significant challenges to traditional decision-making frameworks. To address these issues, this study proposes an integrated framework that combines interval-valued hesitant fuzzy sets (IVHFS) with the decision-making trial and evaluation laboratory-analytic network process (DEMATEL-ANP). IVHFS is employed to capture the ambiguity and hesitation inherent in expert judgments, enabling a more flexible and realistic representation of evaluation inputs. Subsequently, the DEMATEL-ANP approach is used to uncover the causal relationships among CI indicators and to construct a network-based weighting structure that reflects their interdependencies. A case study in a smart factory is conducted to validate the practicality and effectiveness of the proposed framework, and a sensitivity analysis confirmed its stability.

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1 Introduction

The rapid advancement of technologies such as the World Wide Web (WWW), the Internet of Things (IoT), and cloud computing has revolutionized value creation in the manufacturing sector [1]. Smart factories, as a key embodiment of Industry 4.0, increasingly rely on these digital innovations to enable real-time monitoring, intelligent coordination, and data-driven optimization of operations [2]. However, the convergence of accelerating technological change, globalization, and market volatility has introduced profound challenges for manufacturers seeking to sustain competitiveness. In this

*Correspondence: Mingyuan Li, Dingxuan Huang (2018210020@gxufe.edu.cn, huangdingxuan@cqut.edu.cn).

context, competitive intelligence (CI) has become a strategic necessity. Rather than merely collecting information, CI now plays a central role in linking external developments with internal decision-making by transforming multisource data into actionable insights through advanced analytical methods. For smart factories operating in highly automated, information-rich, and rapidly evolving industrial environments, building a robust, adaptive, and ethically grounded CI system is essential to drive continuous innovation, enhance operational excellence, and maintain long-term competitive advantage [3,4].

CI is a systematic process aimed at gaining a competitive advantage by transforming collected information about the external environment, competitors, and competitive strategies into actionable insights [5]. The importance of CI lies in its ability to enhance customer satisfaction, improve profitability, and strengthen a company's position in the face of international competition [6–8]. CI is generally seen as a tool that systematically scans the environment to help companies grasp key non-market factors, such as shifting social trends, environmental concerns, and changes in government policies. At the same time, it involves analyzing competitive dynamics, including updates about competitors, suppliers, customers, and their strategies, along with understanding their strengths and weaknesses. This comprehensive understanding allows companies to identify current and emerging opportunities and threats more accurately [9–13]. The application of appropriate Using the right CI tools helps support better decision-making, mitigates ethical and legal concerns tied to strategic choices, and encourages greater trust and openness with stake-holders [14]. Moreover, the systematic collection, analysis, and interpretation of CI assist companies to rapidly obtain valuable intelligence regarding products, technologies, and trends in competitive environments. This ability allows for better predictions of competitor moves and market trends, which can lead to improved performance for the organization [15,16]. Beyond monitoring competitors, CI helps companies in generating meaningful and actionable insights by identifying divergences in user needs and perceptions between their own offerings and those of competitors [12,17]. Therefore, the development of a comprehensive CI evaluation index system is essential not only for improving the quality and efficiency of intelligence processes but also for serving as a strategic foundation to guide a company's future direction.

Evaluating the performance of an CI evaluation system in smart factories is a challenging and complex process that involves many tasks, goals, and indicators [8,18]. Nevertheless, existing CI evaluation systems often lack clearly defined and effective evaluation indicators [19]. Moreover, the presence of subjective information, ambiguous data, and inaccurate judgments frequently undermines the reliability of the indicator selection process [20]. To identify the most valuable intelligence and improve the quality and efficiency of strategic decision-making, it is necessary to integrate multi-level evaluation indicators and assess CI using a systematic and structured approach. This task constitutes a typical multi-criteria decision-making (MCDM) problem [21]. Within the MCDM framework, evaluation indicators and their associated weights are two fundamental components, with particular emphasis placed on the determination of indicator weights as a critical factor in effectively solving such problems [22]. The rationality of weight assignment directly affects the accuracy and objectivity of CI evaluation results [23,24]. Currently, most weighting methods rely heavily depend on expert judgment, which, while enhancing the credibility of the results to some extent, also introduces several limitations. Relying solely on experts' subjective experience and domain knowledge often overlooks the interdependencies among indicators, leads to insufficient analysis of CI influencing factors under uncertain conditions, and lacks effective weighting methods that systematically account for uncertainty within the CI evaluation process [25].

This study proposes an integrated framework combining interval-valued hesitant fuzzy sets (IVHFS), decision-Making trial and evaluation laboratory (DEMATEL), and analytic network process (ANP). Initially, IVHFS are used to represent evaluation information for determining indicator weights. This method not only enhances the precision of expert judgment but also preserves the fuzzy information contributed by multiple expert groups [26]. A scoring function for IVHFS is then applied to the evaluations from expert groups. This approach preserves each expert's input without needing to combine their opinions, which also allows for the detection of relationships between different evaluation indicators [27]. Following this, the DEMATEL method is applied to analyze the causal relationships among CI evaluation indicators, providing insights into the degree of influence exerted by each indicator on the others [28]. Based on the results of DEMATEL, the ANP method is then used to construct a network structure for CI evaluation, through which the relative importance of each indicator is calculated. Indicators with higher importance values are exerting a stronger influence on CI evaluation outcomes [25,29]. By combining IVHFS with the DEMATEL-ANP approach, the proposed approach not only improves the ability to represent expert evaluations under conditions of uncertainty but also quantifies indicator weights based on their interrelationships. This provides a novel and systematic approach for weight determination in CI evaluation systems, thereby improving the rationality of the weighting process and ensuring the reliability of the evaluation results. Finally, a case study of a smart factory in the electronic assembly sector is conducted to validate the feasibility and effectiveness of the proposed approach, and its sensitivity is further examined.

2 Literature Review

2.1 CI Evaluation Index System for Smart Factories

CI plays a critical role in shaping how companies make decisions, directly impacting the development and choice of their strategic initiatives [30]. Managers can obtain CI from various sources, including user feedback, surveys, and business analysis [31]. However, traditional methods often fall short of delivering timely and accurate insights into a company's real competitive status [32]. First, user-generated content often includes a lot of irrelevant or repetitive in-formation, which means companies need to dedicate considerable time and resources to filtering, interpreting, and analyzing the data effectively [33]. Second, the vast volume, diverse origins, and heterogeneous nature of available data create substantial demands for highly efficient data processing and analytical methods [34]. Third, the ambiguity and uncertainty often found in how users express themselves make it even more challenging to extract insights that are both accurate and reliable [35]. Given these challenges, companies must adopt appropriate methods and technologies, along with a systematic CI evaluation index system, to effectively collect and process, and analyze intelligence, enabling firms to swiftly grasp user perceptions of their offerings and to gain valuable insights into competitors' market strategies. This finally leads to better analysis of CI and helps inform smarter strategic decisions.

Koronakos et al. [36] emphasized that constructing a comprehensive CI evaluation index system not only provides quantifiable data to supporct decision-making but also enables companies to monitor critical indicators, such as competitors' new product launches and shifts in market demand. This proactive approach allows for early identification of potential risks and supports the development of quick, effective response plans. Madureira et al. [31] pointed out that a strong and reliable CI index system provides managers with a dependable basis for making knowledgeable decisions. It helps to minimize risks and, through ongoing refinement, encourages innovation in management while boosting the organization's competitive edge. Similarly, Wang et al. [37] indicated that an CI evaluation index system helps companies in identifying key success factors, optimize resource allocation, and improve operational efficiency. Dishman and Calof [10] proposed several essential indicators for evaluating an CI system, including the comparability of intelligence, the effectiveness of intelligence outputs, and the analysis of market, industry, economic, and political trends. Fleisher and Wright [38] further argued that CI indicators should not only include leading indicators of current and future activities but should also be assessed in terms of their availability and reliability.

Based on a comprehensive review of existing literature [17,39–43], this study develops a set of 23 evaluation indicators for CI, categorized across three key dimensions: intelligence production capability, intelligence outcomes, and user experience effectiveness (Table 1). The indicators were generated through a structured, multi-stage process (Fig. 1). First, a broad pool of potential indicators was identified from prior CI studies. Second, overlapping or conceptually redundant indicators were consolidated to ensure clarity. Finally, the preliminary pool was reviewed by an expert panel of 5 individuals from academia, industry, and government agencies (mean experience: 10 years) in a two-round process. In each round, panelists rated the clarity, relevance, and importance of each indicator on a 5-point scale; a consensus threshold of ≥80% endorsement (ratings of 4 or 5) was applied, and percentage agreement across panel members was calculated to assess inter-rater agreement. Indicators failing to reach consensus were either reworded and re-evaluated in the second round or removed if consensus could not be achieved after two rounds.

Table 1: CI evaluation index system

First-level index	Second-level index	Definition	References
Intelligence production capability (D1)	Accuracy (C11)	Intelligence personnel can accurately understand and grasp users' intelligence needs, goals, and priorities	[17]
	Reliability (C12)	Intelligence sources are authoritative, credible, and highly verifiable	[17,41]
	Richness (C13)	Intelligence includes not only core content but also complete background information such as time, location, and subjects	[39,42]
	Discrimination (C14)	Intelligence personnel possess the ability to distinguish between true and false information and filter out misinformation	[39–41]
	Advancement (C15)	Advanced technologies and scientific tools are applied in intelligence collection and analysis	[17]
	Expertise (C16)	Personnel possess the necessary knowledge, skills, and analytical abilities to meet task requirements	[17,39]
	Compliance (C17)	Intelligence activities comply with relevant laws, industry standards, and professional ethics	[42,44]
	Standardization (C18)	Internal processes, systems, and quality control mechanisms are well-established and standardized	[40,44]
	Objectivity (C19)	Intelligence analysis results are neutral, impartial, and free from political or subjective bias	[42]
Intelligence outcomes (D2)	Relevance (C21)	Intelligence closely aligns with the strategic and decision-making needs of the company	[40]
	Comprehensiveness (C22)	Intelligence covers all critical elements with comprehensive and non-omissive information	[39,40]
	Timeliness (C23)	Intelligence is delivered promptly to support real-time decision-making	[17]
	Rationality (C24)	Intelligence insights and recommendations are logical, practical, and feasible	[17,41]
	Cost-effectiveness (C25)	Intelligence delivers benefits that outweigh costs, yielding positive strategic or economic returns	[39]
	Confidentiality (C26)	Intelligence maintains strong confidentiality during use and transmission to prevent leaks	[42]

(Continued)

Table 1 (continued)

First-level index	Second-level index	Definition	References
	Diversity (C27)	Intelligence encompasses varied sources, formats, and content, supporting multi-perspective analysis	[40]
	Innovation (C28)	Intelligence captures the latest advancements in the industry, new trends, and innovative insights	[17]
User experience effectiveness (D3)	Consistency (C31)	Intelligence contributes synergistically to achieving corporate strategic goals	[41]
	Economic impact (C32)	Intelligence supports market expansion or resource optimization, enhancing economic performance	[41]
	Sustainability (C33)	Users tend to keep using and trusting the intelligence services over the long term	[42]
	Clarity (C34)	Intelligence is clearly expressed and well-structured for ease of understanding and application	[17,42]
	Satisfaction (C35)	Users are satisfied with the overall quality, timeliness, and relevance of the intelligence	[17]
	Importance (C36)	Intelligence plays a critical role in influencing actual decision-making processes	[39–41]

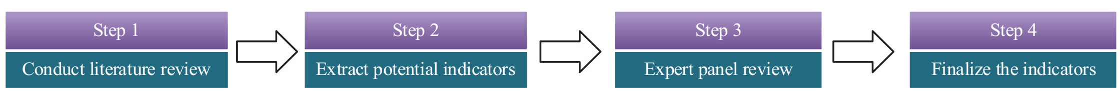

Figure 1: Development process of the CI evaluation indicators

2.2 *Evaluation Indicator Weighting*

Assigning appropriate weights to various CI indicators not only enhances their effectiveness in supporting decision-making but also contributes to the quality management of CI, thereby increasing its practical value for companies. The weights of evaluation indicators play a critical role in any assessment system, as it directly influences the accuracy and fairness of the evaluation results [44]. Weights reflect the relative importance of different indicators within the overall evaluation system and assist decision-makers in allocating resources and optimize strategies more scientifically [45]. Varying weight schemes can substantially influence management decisions. If weights are improperly assigned, critical factors may be overlooked, resulting in outcomes that deviate from reality and compromise the effectiveness of strategic decision-making [46]. Therefore, the rational determination of weights constitutes a key step in ensuring the practicality and robustness of the evaluation system. Typically, the process of determining weights should integrate expert opinions, data-driven analysis, and consideration of actual operational needs. This approach ensures that the assigned weights accurately reflect the significance of each indicator, which strengthens confidence in the decisions derived from this assessment [47].

Classical methods for assigning indicator weights include the grey method [48], the analytic hierarchy process (AHP) [49], fuzzy measures [50,51], the entropy method [52], and data envelopment analysis (DEA) [53]. While these weighting methods are generally effective, each possesses certain limitations. For example, AHP incorporates expert judgment but fails to account for the interrelationships among evaluation indicators and secondary-level indicators, which may compromise the comprehensiveness of the evaluation results. The grey method and fuzzy measures aim to reflect the inaccuracy of evaluation values; however, their limited precision can hinder the accurate reflection of the relative importance of indicators, potentially leading to imbalanced assessments. The entropy method works well for numerical analysis, but it does not account for the ambiguous or detailed language often found in expert opinions. This can lead to a gap between the numerical results and the deeper, qualitative understanding provided by experts. DEA, although useful for performance evaluation, requires a large volume of data to produce reliable results, inevitably increasing the complexity and cost of the evaluation process. In addition, having outliers or mismatched measurement units in the input and output data can seriously affect the reliability of the evaluation results. To address these challenges and to better explore the weighting process of CI evaluation indicators, this study aims to clarify the effects of expert preference expression, divergences in expert opinions during group decision-making, and the interrelationships among indicators on weight assignment.

2.3 IVHFS

Due to the rapidly changs in the smart factory environments and the growing complexity of competitive intelligence sources, determining appropriate weights for CI evaluation indicators has become increasingly challenging. These difficulties are primarily reflected in the following aspects:

(1) Evaluators exhibit a certain degree of fuzziness and subjectivity in their understanding of CI indicators;

(2) Weight assignments are usually based on the insights of experts or decision-makers, but their opinions can vary quite a bit;

(3) The CI evaluation system is hierarchical, and as the number of indicators increases, the interrelationships among them become more complex;

(4) CI analysis requires the integration of both qualitative and quantitative methods, further complicating the weighting process;

(5) Limited individual cognitive capacity may introduce bias into the weight assignment process, particularly when evaluations depend on a single expert or a small group.

To address these issues, the concept of the IVHFS as an extension of traditional fuzzy sets is introduced [54]. Its most distinctive feature lies in allowing an attribute to be represented by multiple possible interval values. This approach not only captures the subtle ways decision-makers express their preferences and better reflects uncertainty in the decision-making process, but also tackles the difficulty of reaching consensus when opinions differ. Therefore, IVHFS offers a flexible and user-friendly approach to managing uncertain information, allowing for effective utilization of all available decision data. Numerous studies have successfully applied IVHFS to a range of decision-making contexts, including medicine company [55], supplier selection [56], personnel-machine position matching [57], warehouse processes management [58], and rescue route planning [59]. In this study, IVHFS is applied to represent expert opinions regarding the interrelationships among indicators. The weights of the evaluation indicators are then calculated using interval-valued hesitant fuzzy numbers (IVHFNs) [27].

2.4 DEMATEL-ANP Approach

The analytic network process (ANP), first proposed by Saaty in 1996, is a generalized form of the AHP. AHP is a widely used in MCDM for weight determination, as it effectively integrates expert judgment through a structured approach that combines qualitative and quantitative analysis [60]. However, AHP assumes that all indicators within the system are mutually independent, an assumption that does not align with the complexities encountered in real-world decision-making environments

[61]. To address this limitation, ANP introduces a network-based structure that captures the feedback and interdependencies among indicators, thereby providing a more realistic representation of complex systems. By overcoming the independence assumption inherent in AHP, ANP offers a more effective framework for weight calculation [62].

Despite its advantages, ANP still presents some shortcomings:

(1) In constructing internal relationships, ANP considers only the direct influences among indicators, neglecting the potential indirect effects arising from transitive relationships. Consequently, its treatment of inter-indicator relationships may remain incomplete;

(2) In traditional ANP approach, the weighted supermatrix is derived using the geometric mean method, which assigns equal weights to all clusters of indicators. This uniform weighting may fail to accurately reflect the relative importance of different clusters in practical contexts.

The DEMATEL method examines how different indicators within a system influence each other across multiple levels, using concepts from graph theory and matrix calculations to discover the underlying causal relationships. It is particularly effective in addressing complex interdependencies and identifying cause-and-effect relationships among indicators [63,64]. Many researchers have combined DEMATEL with ANP to address the limitations of the traditional ANP method, resulting in the DEMATEL-ANP approach. This integrated approach employs DEMATEL to construct the network structure required by ANP, thereby modeling internal dependencies, external influences, and cluster weights with greater accuracy [65]. The DEMATEL-ANP approach not only effectively reveals the network of interdependencies among indicators within and across clusters but also addresses the problem of equal cluster weighting caused associated with utilizing the geometric mean in traditional ANP [66]. Moreover, using a total-relation matrix in DEMATEL can help simplify the often complex process of making pairwise comparisons in ANP [67]. Consequently, the DEMATEL-ANP approach helps analyze how different indicators influence each other across various dimensions, while also providing a more objective and reliable way to assign their importance. To date, the DEMATEL-ANP approach has been successfully applied in various fields, such as financial service performance evaluation [68], intermodal freight transport systems [69], supplier selection [70], megaproject risk assessment [71], smart product-service systems [72], international distribution center location selection [28], and delivery platform assessment [73].

3 Methods

In this section, an approach combining IVHFS and the DEMATEL-ANP approach is adopted to construct a comprehensive weighting framework. The following sections introduce the fundamental concepts and methodological foundations of these two methods.

3.1 Basic Definitions of IVHFS

The fundamental definitions of IVHFS and interval-valued hesitant fuzzy element (IVHFE) are introduced as follows [27]:

Definition 1: Let any non-empty subset be X, and $\tilde{E} = \left\{\left\langle x_i, \tilde{h}_{\tilde{E}}(x_i)\right\rangle | x_i \in X, i = 1, 2, \ldots, n\right\}$ be IVHFS, where $\tilde{h}_{\tilde{E}}(x_i) = \bigcup_{\tilde{\gamma} \in \tilde{h}_{\tilde{E}}(x_i)} \{\tilde{\gamma}\}$ is the basic unit of IVHFS, referred to as an IVHFE. Here, $\tilde{\gamma} = [\tilde{\gamma}^L, \tilde{\gamma}^U]$ is a set of interval numbers, where $\tilde{\gamma}^L = \inf \tilde{\gamma}$ and $\tilde{\gamma}^U = \sup \tilde{\gamma}$ denote the lower and upper bounds, respectively.

From Definition 1, it is evident that the IVHFS provides a complex form of information representation. To facilitate the comparison of the size of different IVHFE, the following algorithm is introduced:

Definition 2: Let $\tilde{h} = \cup_{[\tilde{\gamma}^L,\tilde{\gamma}^U]\in\tilde{h}} \{[\tilde{\gamma}^L, \tilde{\gamma}^U]\}$, $\tilde{h}_1 = \cup_{[\tilde{\gamma}_1^L,\tilde{\gamma}_1^U]\in\tilde{h}_1} \{[\tilde{\gamma}_1^L, \tilde{\gamma}_1^U]\}$, $\tilde{h}_2 = \cup_{[\tilde{\gamma}_2^L,\tilde{\gamma}_2^U]\in\tilde{h}_2} \{[\tilde{\gamma}_2^L, \tilde{\gamma}_2^U]\}$, and let β be a real constant. The basic arithmetic operations are defined as:

(a) $\tilde{h}^c = \cup_{[1-\tilde{\gamma}^L,1-\tilde{\gamma}^U]\in\tilde{h}} \{[1-\tilde{\gamma}^L, 1-\tilde{\gamma}^U]\}$;

(b) $\beta\tilde{h} = \cup_{[\tilde{\gamma}^L,\tilde{\gamma}^U]\in\tilde{h}} \left\{\left[1-\left(1-\tilde{\gamma}^L\right)^\beta, 1-\left(1-\tilde{\gamma}^U\right)^\beta\right]\right\}, \beta > 0$;

(c) $\tilde{h}_1 \cup \tilde{h}_2 = \cup_{[\tilde{\gamma}_1^L,\tilde{\gamma}_1^U]\in\tilde{h}_1,[\tilde{\gamma}_2^L,\tilde{\gamma}_2^U]\in\tilde{h}_1} \left\{\left[\max\left(\tilde{\gamma}_1^L, \tilde{\gamma}_2^L\right), \max\left(\tilde{\gamma}_1^U, \tilde{\gamma}_2^U\right)\right]\right\}$;

(d) $\tilde{h}_1 \oplus \tilde{h}_2 = \cup_{[\tilde{\gamma}_1^L,\tilde{\gamma}_1^U]\in\tilde{h}_1,[\tilde{\gamma}_2^L,\tilde{\gamma}_2^U]\in\tilde{h}_1} \left\{\left[\tilde{\gamma}_1^L + \tilde{\gamma}_2^L - \tilde{\gamma}_1^L \cdot \tilde{\gamma}_2^L, \tilde{\gamma}_1^U + \tilde{\gamma}_2^U - \tilde{\gamma}_1^U \cdot \tilde{\gamma}_2^U\right]\right\}$.

In the process of assigning weights to CI evaluation indicators, this study uses IVHFNs to quantify experts' subjective assessments of the interrelationships among indicators. However, these assessments primarily reflect the presence or absence of influence between indicators, without directly capturing the intensity of such influence. Since this study emphasizes the mutual influence among indicators, a key objective is to accurately determine the strength of these relationships and thereby construct a direct influence matrix. To address this, the score function of IVHFEs proposed by [27] is adopted to process the group evaluation data. The score function effectively reflects the degree to which a decision-making unit possesses a certain indicator, making it well-suited for quantifying the strength of inter-indicator relationships. The resulting scores are then used to measure the degree of mutual influence between indicators, with higher scores indicating stronger influence and lower scores reflecting weaker influence.

Definition 3: Let any IVHFE be $\tilde{h}_\alpha = \cup_{[\tilde{\gamma}_\alpha^L,\tilde{\gamma}_\alpha^U]\in\tilde{h}_\alpha} \{[\tilde{\gamma}_\alpha^L, \tilde{\gamma}_\alpha^U]\}$, then the score function of an IVHFE defined on X is expressed as:

$$s\left(\tilde{h}_\alpha\right) = \frac{1}{\#\tilde{h}_\alpha} \sum_{[\tilde{\gamma}_\alpha^L,\tilde{\gamma}_\alpha^U]\in\tilde{h}_\alpha} \left[\frac{\tilde{\gamma}_\alpha^L + \tilde{\gamma}_\alpha^U}{2}\right] \tag{1}$$

where $\#\tilde{h}_\alpha$ represents an IVHFE $\tilde{h}_\alpha$ containing interval numbers.

3.2 IVHFS-DEMATEL-ANP Approach

The development of fuzzy set theory has provided an effective means for addressing uncertainty in decision-making problems. In particular, IVHFS offer a stronger way to represent experts' hesitation and imprecise judgments during the evaluation process. In this study, IVHFEs are employed as a practical means to uniformly encode and aggregate multiple experts' interval evaluations rather than to represent individual hesitation in the strict sense. This adaptation facilitates the integration of fuzzy information into the proposed framework for CI evaluation [74]. However, fuzzy set theory alone is often insufficient to fully represent the complex causal relationships among indicators. To address this limitation, the integration of the DEMATEL method with the ANP, known as DEMATEL-ANP approach, has been employed to identify and quantify the interdependencies and causal relationships among indicators. In light of this, this study proposes a novel approach that combines IVHFS with the DEMATEL-ANP approach to more accurately determine the weights of evaluation indicators while simultaneously providing a comprehensive representation of their interactions within the system. This integrated approach provides stronger support for making decisions in CI. Fig. 2 depicts the proposed approach of the detailed workflow of the research process. The procedure of proposed approach is outlined below.

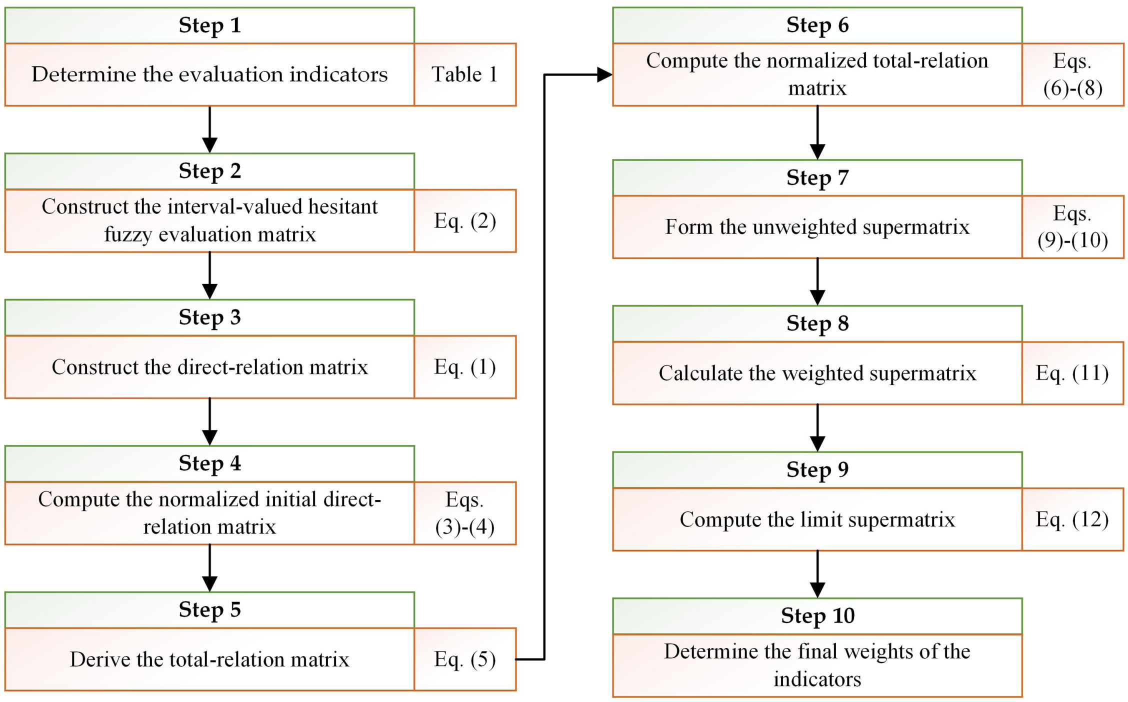

Figure 2: Flowchart of the proposed IVHFS-DEMATEL-ANP approach

Step 1: Determine the evaluation indicators

For our research aims, we selected the three main dimensions and 23 indicators presented in Table 1.

Step 2: Construct the interval-valued hesitant fuzzy evaluation matrix

A group of experts in CI is invited to form an evaluation panel. The degree of mutual influence among peer-level indicators in the CI evaluation system is assessed using IVHFNs, denoted as $\tilde{a}_{ij} = \bigcup_{\tilde{\gamma}_{ij}\in\tilde{a}_{ij}} \{\tilde{\gamma}_{ij}\} = \bigcup_{[\tilde{\gamma}^L_{ij},\tilde{\gamma}^U_{ij}]\in\tilde{a}_{ij}} \{[\tilde{\gamma}^L_{ij},\tilde{\gamma}^U_{ij}]\}$, where $\tilde{\gamma}_{ij} = [\tilde{\gamma}^L_{ij},\tilde{\gamma}^U_{ij}]$ is an interval number and represents the degree of the impact of the i^{th} indicator on the j^{th} indicator. Therefore, the interval-valued hesitant fuzzy evaluation matrix $\tilde{A}_q$ can be constructed as:

$$\tilde{A}_q = \left(\tilde{a}_{qij}\right)_{m\times m} = \begin{bmatrix} \bigcup_{[\tilde{\gamma}_{11}^L,\tilde{\gamma}_{11}^U]\in\tilde{a}_{11}} \{[\tilde{\gamma}_{11}^L,\tilde{\gamma}_{11}^U]\} & \cdots & \bigcup_{[\tilde{\gamma}_{1j}^L,\tilde{\gamma}_{1j}^U]\in\tilde{a}_{1j}} \{[\tilde{\gamma}_{1j}^L,\tilde{\gamma}_{1j}^U]\} & \cdots & \bigcup_{[\tilde{\gamma}_{1m}^L,\tilde{\gamma}_{1m}^U]\in\tilde{a}_{1m}} \{[\tilde{\gamma}_{1m}^L,\tilde{\gamma}_{1m}^U]\} \\ \vdots & & \vdots & & \vdots \\ \bigcup_{[\tilde{\gamma}_{i1}^L,\tilde{\gamma}_{i1}^U]\in\tilde{a}_{i1}} \{[\tilde{\gamma}_{i1}^L,\tilde{\gamma}_{i1}^U]\} & \cdots & \bigcup_{[\tilde{\gamma}_{ij}^L,\tilde{\gamma}_{ij}^U]\in\tilde{a}_{ij}} \{[\tilde{\gamma}_{ij}^L,\tilde{\gamma}_{ij}^U]\} & \cdots & \bigcup_{[\tilde{\gamma}_{im}^L,\tilde{\gamma}_{im}^U]\in\tilde{a}_{im}} \{[\tilde{\gamma}_{im}^L,\tilde{\gamma}_{im}^U]\} \\ \vdots & & \vdots & & \vdots \\ \bigcup_{[\tilde{\gamma}_{m1}^L,\tilde{\gamma}_{m1}^U]\in\tilde{a}_{m1}} \{[\tilde{\gamma}_{m1}^L,\tilde{\gamma}_{m1}^U]\} & \cdots & \bigcup_{[\tilde{\gamma}_{mj}^L,\tilde{\gamma}_{mj}^U]\in\tilde{a}_{mj}} \{[\tilde{\gamma}_{mj}^L,\tilde{\gamma}_{mj}^U]\} & \cdots & \bigcup_{[\tilde{\gamma}_{mm}^L,\tilde{\gamma}_{mm}^U]\in\tilde{a}_{mm}} \{[\tilde{\gamma}_{mm}^L,\tilde{\gamma}_{mm}^U]\} \end{bmatrix} \tag{2}$$

where $q = D$ represents matrix for first-level indicators and $q = C$ represents the matrix for second-level indicators.

Step 3: Construct the direct-relation matrix

The direct-relation matrix T^q for the first-level and second-level indicators can be obtained by using Eq. (1) to process the interval-valued hesitant fuzzy evaluation matrix $\tilde{A}_q$ from Step 2, where $q \in \{D, C\}$.

Step 4: Compute the normalized initial direct-relation matrix

The normalized initial direct-relation matrix T_q^N for the first-level and second-level indicators can be obtained by using Eqs. (3) and (4):

$$T_q^N = s_q \times T_q \tag{3}$$

where

$$s_q = \min\left[\frac{1}{\max_i \sum_{j=1}^n \left|a_{qij}\right|}, \frac{1}{\max_j \sum_{i=1}^n \left|a_{qij}\right|}\right], q \in \{D, C\} \tag{4}$$

Step 5: Derive the total-relation matrix

The total-relation matrix T_q^I for the first-level and second-level indicators can be derived by using Eq. (5) to process the normalized initial direct-relation matrix T_q^N from Step 4.

$$T_q^I = T_q^N + T_q^N \cdot T_q^N + T_q^N \cdot T_q^N \cdot T_q^N + \cdots = T_q^N \left(I - T_q^N\right)^{-1}, q \in \{D, C\} \tag{5}$$

where I is an $m \times m$ identity matrix.

Step 6: Compute the normalized total-relation matrix

The normalized total-relation matrix T_q^α for the first-level and second-level indicators can be obtained by using Eqs. (6)–(8) to process the total-relation matrix T_q^I from Step 5.

$$T_q^\alpha = \left[t_{qij}^\alpha\right]_{m\times m} = \begin{bmatrix} t_{q11}/d_{q1} & \cdots & t_{q1j}/d_{q1} & \cdots & t_{q1m}/d_{q1} \\ \vdots & & \vdots & & \vdots \\ t_{qi1}/d_{qi} & \cdots & t_{qij}/d_{qi} & \cdots & t_{qim}/d_{qi} \\ \vdots & & \vdots & & \vdots \\ t_{qm1}/d_{qm} & \cdots & t_{qmj}/d_{qm} & \cdots & t_{qmm}/d_{qm} \end{bmatrix} = \begin{bmatrix} t_{q11}^\alpha & \cdots & t_{q1j}^\alpha & \cdots & t_{q1m}^\alpha \\ \vdots & & \vdots & & \vdots \\ t_{qi1}^\alpha & \cdots & t_{qij}^\alpha & \cdots & t_{qim}^\alpha \\ \vdots & & \vdots & & \vdots \\ t_{qm1}^\alpha & \cdots & t_{qmj}^\alpha & \cdots & t_{qmm}^\alpha \end{bmatrix} \tag{6}$$

where $q \in \{D\}$ and $d_{qi} = \sum_{j=1}^m t_{qij}, i = 1, 2, \ldots, m$.

Note that, to avoid the equal-weight problem in traditional ANP, the normalization of the total-relation matrix for second-level indicators T^{α}_{Cij} is performed as shown in Eq. (7):

$$T^{\alpha}_{q} = \begin{bmatrix} T^{\alpha}_{q11} & \cdots & T^{\alpha}_{q1j} & \cdots & T^{\alpha}_{q1m} \\ \vdots & & \vdots & & \vdots \\ T^{\alpha}_{qi1} & \cdots & T^{\alpha}_{qij} & \cdots & T^{\alpha}_{qim} \\ \vdots & & \vdots & & \vdots \\ T^{\alpha}_{qm1} & \cdots & T^{\alpha}_{qmj} & \cdots & T^{\alpha}_{qmm} \end{bmatrix}, q \in \{C\} \tag{7}$$

Taking the second-level indicator T^{α}_{C21} as an example, Eq. (8) is a normalization process of the sub-matrix.

$$T^{\alpha}_{C21} = \begin{bmatrix} t^{11}_{21}/d^{1}_{21} & \cdots & t^{1j}_{21}/d^{1}_{21} & \cdots & t^{1m_1}_{21}/d^{1}_{21} \\ \vdots & & \vdots & & \vdots \\ t^{i1}_{21}/d^{i}_{21} & \cdots & t^{ij}_{21}/d^{i}_{21} & \cdots & t^{im_1}_{21}/d^{i}_{21} \\ \vdots & & \vdots & & \vdots \\ t^{m_2 1}_{21}/d^{m_2}_{21} & \cdots & t^{m_2 j}_{21}/d^{m_2}_{21} & \cdots & t^{m_2 m_1}_{21}/d^{m_2}_{21} \end{bmatrix} = \begin{bmatrix} t^{\alpha 11}_{21} & \cdots & t^{\alpha 1j}_{21} & \cdots & t^{\alpha 1m_1}_{21} \\ \vdots & & \vdots & & \vdots \\ t^{\alpha i1}_{21} & \cdots & t^{\alpha ij}_{21} & \cdots & t^{\alpha im_1}_{21} \\ \vdots & & \vdots & & \vdots \\ t^{\alpha m_2 1}_{21} & \cdots & t^{\alpha m_2 j}_{21} & \cdots & t^{\alpha m_2 m_1}_{21} \end{bmatrix} \tag{8}$$

where $d^{i}_{21} = \sum_{j=1}^{m_1} t^{ij}_{21}, i = 1, 2, \ldots, m_2$.

Step 7: Form the unweighted supermatrix

The unweighted supermatrix W is constructed by transposing each block of the normalized total-relation matrix, as shown in Eq. (9):

$$W = \left(T^{\alpha}_{q}\right)' = \begin{bmatrix} W_{11} & \cdots & W_{i1} & \cdots & W_{m1} \\ \vdots & & \vdots & & \vdots \\ W_{1j} & \cdots & W_{ij} & \cdots & W_{mj} \\ \vdots & & \vdots & & \vdots \\ W_{1m} & \cdots & W_{im} & \cdots & W_{mm} \end{bmatrix} \tag{9}$$

where $W_{ij} = \left(T^{\alpha}_{qij}\right), i = 1, 2, \ldots, m, j = 1, 2, \ldots, m; q \in \{C\}$.

For instance, the second-level indicator T^{α}_{C21} is performed as shown in Eq. (10):

$$W_{C21} = \left(T^{\alpha}_{C21}\right)' = \begin{bmatrix} t^{11}_{21}/d^{1}_{21} & \cdots & t^{i1}_{21}/d^{i}_{21} & \cdots & t^{m_2 1}_{21}/d^{m_2}_{21} \\ \vdots & & \vdots & & \vdots \\ t^{1j}_{21}/d^{1}_{21} & \cdots & t^{ij}_{21}/d^{i}_{21} & \cdots & t^{m_2 j}_{21}/d^{m_2}_{21} \\ \vdots & & \vdots & & \vdots \\ t^{1m_1}_{21}/d^{1}_{21} & \cdots & t^{im_1}_{21}/d^{i}_{21} & \cdots & t^{m_2 m_1}_{21}/d^{m_2}_{21} \end{bmatrix} = \begin{bmatrix} t^{\alpha 11}_{21} & \cdots & t^{\alpha i1}_{21} & \cdots & t^{\alpha m_2 1}_{21} \\ \vdots & & \vdots & & \vdots \\ t^{\alpha 1j}_{21} & \cdots & t^{\alpha ij}_{21} & \cdots & t^{\alpha m_2 j}_{21} \\ \vdots & & \vdots & & \vdots \\ t^{\alpha 1m_1}_{21} & \cdots & t^{\alpha im_1}_{21} & \cdots & t^{\alpha m_2 m_1}_{21} \end{bmatrix} \tag{10}$$

Step 8: Calculate the weighted supermatrix

The weighted supermatrix W_k is obtained by multiplying the normalized total-relation matrix T_q^α by the unweighted supermatrix W, as shown in Eq. (11):

$$W_k = T_q^\alpha \times W = \begin{bmatrix} t_{q11}^\alpha \times W_{11} & \cdots & t_{q1i}^\alpha \times W_{i1} & \cdots & t_{q1n}^\alpha \times W_{n1} \\ \cdots & & \vdots & & \cdots \\ t_{qj1}^\alpha \times W_{1j} & \cdots & t_{qji}^\alpha \times W_{ij} & \cdots & t_{qjn}^\alpha \times W_{nj} \\ \cdots & & \vdots & & \cdots \\ t_{qn1}^\alpha \times W_{1n} & \cdots & t_{qni}^\alpha \times W_{in} & \cdots & t_{qnn}^\alpha \times W_{nn} \end{bmatrix}, q \in \{D\} \tag{11}$$

Step 9: Compute the limit supermatrix

The limit the weighted supermatrix W_k^δ is computed by raising the weighted supermatrix W_k to a sufficiently large power k, as Eq. (12), until the supermatrix has converged and become a long-term stable supermatrix to get the global priority vectors or called the weights of the indicators.

$$W_k^\delta = \lim_{\delta \to \infty} W_k^\delta \tag{12}$$

Step 10: Determine the final weights of the indicators

The final indicator weights are located in the corresponding columns of the limit supermatrix. The indicator with the highest overall priority value is identified as the most important.

4 Results

4.1 Implementation and Computation

To demonstrate the applicability of proposed method, CI evaluation within a smart factory in the electronic assembly sector is selected as an illustrative example. The dynamic and information-intensive nature of smart manufacturing environments, along with the need for timely and accurate decision-making, highlights the importance of developing advanced decision-support systems. CI plays a critical role in enabling smart factories to effectively adapt to changes in production demands, technology integration, and industrial market conditions. For this case study, a panel of five experts was assembled to conduct the CI evaluation. The panel consisted of managers from manufacturing enterprises and academic scholars, all with more than ten years of practical experience in smart manufacturing and industrial intelligence. Based on their professional knowledge and experience, the experts assessed the degree of influence among the evaluation indicators.

Considering the uncertainty and hesitations in the evaluation process, particularly since different experts may express varying degrees of confidence or assign different values, the indicators in this study were evaluated using a five-point linguistic scale shown in Table 2. For example, when assessing the influence of indicator $\tilde{a}_1$ on indicator $\tilde{a}_3$, Experts A, C, and D provided ratings in the lower part of the low interval [0.2, 0.3], whereas Experts B and E provided ratings in the upper part [0.3,0.4]. The aggregated evaluation is thus represented as { [0.2, 0.3], [0.3, 0.4]}. It is worth noting that while the aggregation of evaluation values follows [75], our study differs by adopting a purely qualitative representation without incorporating probabilities.

Table 2: Linguistic terms for indicator ratings

Linguistic terms	Fuzzy interval number
Very low (VL)	[0.0, 0.2]
Low (L)	[0.2, 0.4]
Medium (M)	[0.4, 0.6]
High (H)	[0.6, 0.8]
Very high (VH)	[0.8, 1.0]

The evaluation results for the first-level and second-level CI indicators are summarized in Tables 3 and 4. As shown in Tables 3 and 4, the direct-relation matrices for the first-level and second-level CI indicators are calculated using Eq. (1). Subsequently, the initial direct-relation matrices and the normalized initial direct-relation matrices for the first-level and second-level CI indicators were obtained by applying Eqs. (3) and (4) (Tables 5–8). Thereafter, the total-relation matrices and the normalized total-relation matrices for the first-level and second-level CI indicators were derived using Eqs. (5)–(7) (Tables 9–12). According to Eq. (9), the normalized total-relation matrix of the second-level indicators was transposed to generate the unweighted supermatrix (Table 13), and Eq. (11) was applied to construct the weighted supermatrix (Table 14). Finally, the limit of the weighted supermatrix was calculated to obtain the convergent weight matrix (Table 15). The weight distribution of each CI indicator is illustrated in Fig. 3, and the corresponding ranking results are reported in Table 16.

Table 3: Interval-valued hesitant fuzzy evaluation matrix of first-level CI indicators

	C1	C2	C3
C1	0.000	[0.3, 0.4]	[0.2, 0.3] [0.3, 0.4]
C2	[0.5, 0.7]	0.000	[0.6, 0.7]
C3	[0.4, 0.6]	[0.2, 0.3] [0.3, 0.4]	0.000

4.2 Sensitivity Analysis

To evaluate the robustness of the proposed framework, a sensitivity analysis was conducted by perturbing the expert inputs by ±10% and ±20%. As shown in Fig. 4, the method remains highly stable under positive perturbations (+10% and +20%), with only three indicators (C16, C23, C26) exhibiting minor changes. In contrast, negative perturbations had a stronger impact: −10% affected two indicators (C21, C24), while −20% influenced four indicators (C14, C15, C21, C24). Importantly, however, the top four indicators (C32, C31, C34, C35) remained unchanged across all scenarios, demonstrating that the highest-priority factors are robust even when lower-ranked indicators fluctuate considerably.

Table 4: Interval-valued hesitant fuzzy evaluation matrix of second-level CI indicators

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23
D11	0	[0.4, 0.6]	[0.7, 0.8]	[0.5, 0.6]	[0.3, 0.5] [0.4, 0.5]	[0.6, 0.8]	[0.6, 0.7]	[0.5, 0.6]	[0.8, 0.9]	[0.3, 0.5]	[0.4, 0.5]	[0.4, 0.6]
D12	[0.4, 0.6]	0	[0.3, 0.5]	[0.4, 0.6]	[0.5, 0.6]	[0.6, 0.7]	[0.5, 0.6]	[0.5, 0.6]	[0.7, 0.8]	[0.2, 0.4]	[0.3, 0.4]	[0.4, 0.6]
D13	[0.2, 0.3]	[0.1, 0.2]	0	[0.3, 0.5]	[0.6, 0.8]	[0.5, 0.6]	[0.6, 0.7]	[0.4, 0.6]	[0.3, 0.4] [0.4,0.5]	[0.3, 0.4]	[0.2, 0.3]	[0.3, 0.4]
D14	[0.3, 0.4]	[0.5, 0.7]	[0.7, 0.8]	0	[0.5, 0.7]	[0.6, 0.9]	[0.6, 0.7]	[0.5, 0.7]	[0.5, 0.6]	[0.4, 0.6]	[0.4, 0.6]	[0.6, 0.7]
D15	[0.2, 0.3] [0.3, 0.4]	[0.1, 0.2]	[0.1, 0.2]	[0.3, 0.4]	0	[0.3, 0.5]	[0.5, 0.7]	[0.3, 0.5]	[0.4, 0.5]	[0.2, 0.3]	[0.2, 0.3]	[0.2, 0.4]
D16	[0.2, 0.3]	[0.2, 0.3]	[0.3, 0.4]	[0.2, 0.4]	[0.5, 0.6]	0	[0.4, 0.6]	[0.5, 0.6]	[0.6, 0.7]	[0.3, 0.5]	[0.3, 0.4]	[0.4, 0.5]
D17	[0.3, 0.4]	[0.1, 0.2]	[0.3, 0.4]	[0.3, 0.4]	[0.4, 0.6]	[0.4, 0.6]	0	[0.4, 0.5]	[0.4, 0.5]	[0.2, 0.3]	[0.2, 0.3]	[0.3, 0.4]
D18	[0.1, 0.2]	[0.3, 0.4]	[0.4, 0.6]	[0.6, 0.7]	[0.5, 0.6]	[0.6, 0.7]	[0.6, 0.7]	0	[0.3, 0.4]	[0,3, 0.4]	[0.3, 0.4]	[0.3, 0.5]
D19	[0.2, 0.3]	[0.1, 0.2]	[0.5, 0.6]	[0.5, 0.6]	[0.6, 0.7]	[0.4, 0.6]	[0.5.0.7]	[0.3, 0.4]	0	[0.3, 0.5]	[0.5, 0.7]	[0.4, 0.5]
D21	[0.5, 0.6]	[0.4, 0.5]	[0.4, 0.6]	[0.5, 0.6]	[0.5, 0.7]	[0.6, 0.7]	[0.7, 0.8]	[0.5, 0.8]	[0.6, 0.7]	0	[0.6, 0.7]	[0.6, 0.7]
D22	[0.3, 0.4]	[0.5, 0.6] [0.6, 0.7]	[0.2, 0.3] [0.4, 0.6]	[0.1, 0.2]	[0.6, 0.7]	[0.4, 0.5]	[0.5, 0.6]	[0.8, 0.9]	[0.7, 0.8]	[0.4, 0.6]	0	[0.8, 0.9]
D23	[0.3, 0.5]	[0.4, 0.5]	[0.1, 0.3]	[0.5, 0.6]	[0.6, 0.7]	[0.4, 0.5]	[0.5, 0.6]	[0.8, 0.9]	[0.7, 0.8]	[0.5, 0.7]	[0.3, 0.4]	0
D24	[0.3, 0.5]	[0.1, 0.2]	[0.3, 0.4]	[0.5, 0.7]	[0.5, 0.6]	[0.6, 0.7]	[0.4, 0.5] [0.5, 0.6]	[0.7, 0.8]	[0.5, 0.6]	[0.5, 0.6]	[0.5, 0.6]	[0.5, 0.6] [0.6, 0.7] [0.7, 0.8]
D25	[0.2, 0.3]	[0.4, 0.6]	[0.6, 0.7] [0.8, 0.9]	[0.4, 0.5]	[0.3, 0.4]	[0.5, 0.6]	[0.6, 0.8]	[0.4, 0.5] [0.5, 0.6]	[0.6, 0.7]	[0.4, 0.5]	[0.3, 0.4]	[0.7, 0.8]
D26	[0.1, 0.2]	[0.1, 0.2] [0.2, 0.3]	[0.6, 0.7]	[0.7, 0.8]	[0.6, 0.7]	[0.2, 0.3]	[0.3, 0.4]	[0.4, 0.5]	[0.8, 0.9]	[0.5, 0.6]	[0.6, 0.7]	[0.6, 0.7]
D27	[0.1, 0.2]	[0.2, 0.3] [0.5, 0.6]	[0.4, 0.6]	[0.4, 0.6]	[0.3, 0.5]	[0.4, 0.5] [0.5, 0.6] [0.8, 0.9]	[0.5, 0.6]	[0.3, 0.4]	[0.2, 0.3]	[0.1, 0.3]	[0.3, 0.4]	[0.3, 0.5]
D28	[0.1, 0.2]	[0.4, 0.5]	[0.3, 0.4]	[0.5, 0.6]	[0.2, 0.3]	[0.5. 0.7]	[0.6, 0.7]	[0.4, 0.5]	[0.6, 0.7]	[0.3, 0.4]	[0.5, 0.6]	[0.6, 0.7]
D31	[0.3, 0.4]	[0.2, 0.3]	[0.2, 0.5]	[0.5, 0.6]	[0.1, 0.3]	[0.7, 0.8]	[0.5, 0.6]	[0.4, 0.6]	[0.5, 0.6]	[0.5, 0.6]	[0.3, 0.4]	[0.3, 0.4]
D32	[0.2, 0.3]	[0.3, 0.4]	[0.2, 0.3]	[0.6, 0.7]	[0.2, 0.4]	[0.3, 0.4]	[0.3, 0.5]	[0.6, 0.7]	[0.2, 0.3]	[0.4, 0.5]	[0.7, 0.9]	[0.5, 0.6]
D33	[0.1, 0.2]	[0.2, 0.5]	[0.7, 0.8]	[0.3, 0.5]	[0.6, 0.8]	[0.6, 0.8]	[0.7, 0.8]	[0.5, 0.6]	[0.6, 0.7]	[0.8, 0.9]	[0.5, 0.6] [0.6, 0.7]	[0.6, 0.7]
D34	[0.1, 0.3]	[0.5, 0.6]	[0.4, 0.6]	[0.7, 0.9]	[0.7, 0.8]	[0.8, 0.9]	[0.8, 0.9]	[0.6, 0.7] [0.7, 0.8]	[0.8, 0.9]	[0.6, 0.7]	[0.3, 0.5]	[0.2, 0.4]
D35	[0.3, 0.4]	[0.4, 0.5]	[0.4, 0.5]	[0.1, 0.3]	[0.6, 0.8]	[0.6, 0.7]	[0.6, 0.7]	[0.3, 0.5]	[0.5, 0.6]	[0.3, 0.5]	[0.6, 0.7]	[0.4, 0.5]
D36	[0.2, 0.3]	[0.5, 0.6]	[0.6, 0.7]	[0.3, 0.5]	[0.5, 0.6]	[0.4, 0.6]	[0.8, 0.9]	[0.5, 0.6]	[0.4, 0.6]	[0.2, 0.4]	[0.5, 0.6]	[0.4, 0.6]

	D24	**D25**	**D26**	**D27**	**D28**	**D31**	**D32**	**D33**	**D34**	**D35**	**D36**
D11	[0.2, 0.4]	[0.3, 0.4]	[0.6, 0.8]	[0.7, 0.8]	[0.4, 0.6]	[0.3, 0.4]	[0.5, 0.7]	[0.1, 0.3] [0.2, 0.3]	[0.2, 0.4]	[0.3, 0.5]	[0.1, 0.2]
D12	[0.2, 0.3]	[0.2, 0.3]	[0.5, 0.6] [0.6, 0.7]	[0.5, 0.7]	[0.5, 0.6]	[0.2, 0.4]	[0.6, 0.7]	[0.3, 0.4]	[0.2, 0.3]	[0.2, 0.3]	[0.2, 0.3]
D13	[0.2, 0.4]	[0.1, 0.3]	[0.6, 0.7]	[0.5, 0.6]	[0.7, 0.8]	[0.4, 0.6]	[0.3, 0.5]	[0.2, 0.4]	[0.3, 0.5]	[0.2, 0.3]	[0.1, 0.2]
D14	[0.4, 0.6]	[0.3, 0.5] [0.4, 0.5]	[0.6, 0.7]	[0.6, 0.8]	[0.5, 0.7]	[0.5, 0.7]	[0.3, 0.4]	[0.3, 0.5]	[0.3, 0.4]	[0.3, 0.5]	[0.3, 0.4]
D15	[0.2, 0.3]	[0.1, 0.2]	[0.3, 0.5]	[0.3, 0.4]	[0.3, 0.4]	[0.2, 0.3]	[0.3, 0.5]	[0.2, 0.3]	[0.4, 0.5]	[0.1, 0.2]	[0.1, 0.2]
D16	[0.3, 0.4]	[0.2, 0.3]	[0.4, 0.6]	[0.5, 0.7]	[0.5, 0.6]	[0.3, 0.4]	[0.3, 0.5]	[0.3, 0.5]	[0.2, 0.3]	[0.1, 0.2]	[0.1, 0.2]
D17	[0.1, 0.2]	[0.2, 0.3]	[0.3, 0.4]	[0.5, 0.6]	[0.3, 0.5]	[0.2, 0.4]	[0.3, 0.4]	[0.2, 0.3]	[0.3, 0.4]	[0.4, 0.5]	[0.2, 0.3]

(Continued)

Table 5 (continued)

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23
D18	[0.2, 0.4]	[0.2, 0.3]	[0.4, 0.6]	[0.6, 0.8]	[0.5, 0.6]	[0.3, 0.4]	[0.1, 0.2]	[0.1, 0.3]	[0.4, 0.5]	[0.2, 0.3]	[0.1, 0.2] [0.2, 0.3]	
D19	[0.3, 0.4]	[0.3, 0.4]	[0.6, 0.7]	[0.7. 0.8]	[0.4, 0.5]	[0.2, 0.4]	[0.3, 0.4]	[0.4, 0.5]	[0.2, 0.3]	[0.2, 0.4]	[0.1, 0.2]	
D21	[0.5, 0.6]	[0.3, 0.4]	[0.7, 0.8]	[0.8, 0.9]	[0.3, 0.5]	[0.7, 0.8]	[0.6, 0.7]	[0.5, 0.6]	[0.3, 0.5]	[0.4. 0.5]	[0.3, 0.5]	
D22	[0.2, 0.4]	[0.3, 0.5] [0.4, 0.6] [0.5, 0.7]	[0.5, 0.7]	[0.3, 0.4]	[0.2, 0.3] [0.6, 0.7]	[0.3, 0.4]	[0.6, 0.7]	[0.6, 0.7]	[0.3, 0.4]	[0.4, 0.6]	[0.3, 0.4]	
D23	[0.5, 0.6]	[0.3, 0.4]	[0.6, 0.7]	[0.5, 0.6]	[0.4, 0.6]	[0.7, 0.8]	[0.3, 0.4] [0.4, 0.5] [0.5, 0.6]	[0.2, 0.4]	[0.2, 0.3]	[0.6, 0.7]	[0.6, 0.7]	
D24	0	[0.2, 0.4]	[0.7, 0.9]	[0.6, 0.8]	[0.5, 0.6]	[0.6, 0.7]	[0.2, 0.4]	[0.2, 0.4]	[0.7, 0.9]	[0.3, 0.5]	[0.5, 0.6]	
D25	[0.7, 0.8]	0	[0.1, 0.3] [0.5, 0.7]	[0.6, 0.7]	[0.5, 0.6]	[0.3, 0.4]	[0.3, 0.4]	[0.3, 0.4]	[0.5, 0.6]	[0.3, 0.4]	[0.6, 0.8]	
D26	[0.7, 0.9]	[0.1, 0.3]	0	[0.5, 0.6]	[0.3, 0.5]	[0.2, 0.3]	[0.6, 0.7]	[0.2, 0.3]	[0.6, 0.7]	[0.5, 0.6]	[0.2, 0.3]	
D27	[0.4, 0.5]	[0.3, 0.4]	[0.4, 0.6]	0	[0.4, 0.6]	[0.3, 0.4]	[0.3, 0.4]	[0.4, 0.5]	[0.3, 0.5]	[0.4, 0.6]	[0.2, 0.3]	
D28	[0.2, 0.3]	[0.2, 0.3]	[0.3, 0.5]	[0.3, 0.4]	0	[0.4, 0.6]	[0.3, 0.5]	[0.3, 0.4]	[0.2, 0.3]	[0.4, 0.6]	[0.4, 0.6]	
D31	[0.2, 0.3]	[0.7, 0.8]	[0.6, 0.7]	[0.4, 0.5]	[0.7, 0.9]	0	[0.3, 0.5]	[0.3, 0.5]	[0.3, 0.4]	[0.5, 0.6]	[0.2, 0.4]	
D32	[0.6, 0.7] [0.7, 0.8]	[0.6, 0.7]	[0.6, 0.8]	[0.5, 0.7]	[0.4, 0.5]	[0.3, 0.4]	0	[0.2, 0.3]	[0.1, 0.3]	[0.2, 0.4]	[0.3, 0.4]	
D33	[0.5, 0.6]	[0.4, 0.6]	[0.7, 0.8]	[0.4, 0.6]	[0.5, 0.6]	[0.4, 0.6]	[0.6, 0.8]	0	[0.5, 0.7]	[0.2, 0.3]	[0.6, 0.8]	
D34	[0.3, 0.5] [0.5, 0.6] [0.8, 0.9]	[0.3, 0.4]	[0.4, 0.6]	[0.2, 0.4]	[0.6, 0.8]	[0.2, 0.3]	[0.4, 0.5]	[0.1, 0.2]	0	[0.5, 0.6]	[0.2, 0.4]	
D35	[0.4, 0.6]	[0.2, 0.3]	[0.2, 0.3]	[0.4, 0.5]	[0.5, 0.6]	[0.6, 0.8]	[0.5, 0.6]	[0.3, 0.4]	[0.6, 0.7]	0	[0.4, 0.6]	
D36	[0.3, 0.5]	[0.1, 0.3]	[0.7, 0.8]	[0.2, 0.4]	[0.5, 0.6]	[0.6, 0.7]	[0.3, 0.5]	[0.4, 0.5]	[0.4, 0.5]	[0.5, 0.7]	0	

Table 5: Initial direct-relation matrix of first-level CI indicators

	C1	C2	C3
C1	0.000	0.350	0.300
C2	0.600	0.000	0.650
C3	0.500	0.325	0.000

Table 6: Initial direct-relation matrix of second-level CI indicators

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23	D24	D25	D26	D27	D28	D31	D32	D33	D34	D35	D36
D11	0.000	0.500	0.750	0.550	0.425	0.700	0.650	0.550	0.850	0.400	0.450	0.500	0.300	0.350	0.700	0.750	0.500	0.350	0.600	0.225	0.300	0.400	0.150
D12	0.500	0.000	0.400	0.500	0.550	0.650	0.550	0.550	0.750	0.300	0.350	0.500	0.250	0.250	0.600	0.600	0.550	0.300	0.650	0.350	0.250	0.250	0.250
D13	0.250	0.150	0.000	0.400	0.700	0.550	0.650	0.500	0.400	0.350	0.250	0.350	0.300	0.200	0.650	0.550	0.750	0.450	0.400	0.300	0.400	0.250	0.150
D14	0.350	0.600	0.750	0.000	0.600	0.750	0.650	0.600	0.550	0.500	0.500	0.650	0.500	0.425	0.650	0.700	0.600	0.600	0.350	0.400	0.350	0.400	0.350
D15	0.300	0.150	0.150	0.350	0.000	0.400	0.600	0.400	0.450	0.250	0.250	0.300	0.250	0.150	0.400	0.350	0.350	0.250	0.400	0.250	0.450	0.150	0.150
D16	0.250	0.250	0.350	0.300	0.550	0.000	0.500	0.550	0.650	0.400	0.350	0.450	0.350	0.250	0.500	0.600	0.550	0.350	0.400	0.400	0.250	0.150	0.150
D17	0.350	0.150	0.350	0.350	0.500	0.500	0.000	0.450	0.450	0.250	0.250	0.350	0.150	0.250	0.350	0.550	0.400	0.300	0.350	0.250	0.350	0.450	0.250
D18	0.150	0.350	0.500	0.650	0.550	0.650	0.650	0.000	0.350	0.350	0.350	0.400	0.300	0.250	0.500	0.700	0.550	0.350	0.150	0.200	0.450	0.250	0.200
D19	0.250	0.150	0.550	0.550	0.650	0.500	0.600	0.350	0.000	0.400	0.600	0.450	0.350	0.350	0.650	0.750	0.450	0.300	0.350	0.450	0.250	0.300	0.150
D21	0.550	0.450	0.500	0.550	0.600	0.650	0.750	0.650	0.650	0.000	0.650	0.650	0.550	0.350	0.750	0.850	0.400	0.750	0.650	0.550	0.400	0.450	0.400
D22	0.350	0.600	0.375	0.150	0.650	0.450	0.550	0.850	0.750	0.500	0.000	0.850	0.450	0.500	0.600	0.350	0.450	0.350	0.650	0.650	0.350	0.500	0.350
D23	0.400	0.450	0.200	0.550	0.650	0.450	0.550	0.850	0.750	0.600	0.350	0.000	0.550	0.350	0.650	0.550	0.500	0.750	0.450	0.300	0.250	0.650	0.650
D24	0.400	0.150	0.350	0.600	0.550	0.650	0.500	0.750	0.550	0.550	0.550	0.650	0.000	0.300	0.800	0.700	0.550	0.650	0.300	0.300	0.800	0.400	0.550
D25	0.250	0.500	0.750	0.450	0.350	0.550	0.700	0.500	0.650	0.450	0.350	0.750	0.750	0.000	0.400	0.650	0.550	0.350	0.350	0.350	0.550	0.350	0.700
D26	0.150	0.200	0.650	0.750	0.650	0.250	0.350	0.450	0.850	0.550	0.650	0.650	0.800	0.200	0.000	0.550	0.400	0.250	0.650	0.250	0.650	0.550	0.250
D27	0.150	0.400	0.500	0.500	0.400	0.617	0.550	0.350	0.250	0.200	0.350	0.400	0.450	0.350	0.500	0.000	0.500	0.350	0.350	0.450	0.400	0.500	0.250
D28	0.150	0.450	0.350	0.550	0.250	0.600	0.650	0.450	0.650	0.350	0.550	0.650	0.250	0.250	0.400	0.350	0.000	0.500	0.400	0.350	0.250	0.500	0.500
D31	0.350	0.250	0.350	0.550	0.200	0.750	0.550	0.500	0.550	0.550	0.350	0.350	0.250	0.750	0.650	0.450	0.750	0.000	0.400	0.400	0.350	0.550	0.300
D32	0.250	0.350	0.250	0.650	0.300	0.350	0.400	0.650	0.250	0.450	0.800	0.550	0.700	0.650	0.700	0.600	0.450	0.350	0.000	0.250	0.200	0.300	0.350
D33	0.150	0.350	0.750	0.400	0.700	0.700	0.750	0.550	0.650	0.850	0.550	0.650	0.550	0.500	0.750	0.500	0.550	0.500	0.700	0.000	0.600	0.250	0.700
D34	0.200	0.550	0.500	0.750	0.750	0.850	0.850	0.700	0.850	0.650	0.400	0.300	0.600	0.350	0.500	0.300	0.700	0.250	0.450	0.150	0.000	0.550	0.300
D35	0.350	0.450	0.450	0.200	0.700	0.650	0.650	0.400	0.550	0.400	0.650	0.450	0.500	0.250	0.250	0.450	0.550	0.700	0.550	0.350	0.650	0.000	0.500
D36	0.250	0.550	0.650	0.400	0.550	0.500	0.850	0.550	0.500	0.300	0.550	0.500	0.400	0.200	0.750	0.300	0.550	0.650	0.400	0.450	0.450	0.600	0.000

Table 7: Normalized initial direct-relation matrix of first-level CI indicators

	C1	C2	C3
C1	0.000	0.280	0.240
C2	0.480	0.000	0.520
C3	0.400	0.260	0.000

Table 8: Normalized initial direct-relation matrix of second-level CI indicators

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23	D24	D25	D26	D27	D28	D31	D32	D33	D34	D35	D36
D11	0.000	0.037	0.056	0.041	0.031	0.052	0.048	0.041	0.063	0.030	0.033	0.037	0.022	0.026	0.052	0.056	0.037	0.026	0.044	0.017	0.022	0.030	0.011
D12	0.037	0.000	0.030	0.037	0.041	0.048	0.041	0.041	0.056	0.022	0.026	0.037	0.019	0.019	0.044	0.044	0.041	0.022	0.048	0.026	0.019	0.019	0.019
D13	0.019	0.011	0.000	0.030	0.052	0.041	0.048	0.037	0.030	0.026	0.019	0.026	0.022	0.015	0.048	0.041	0.056	0.033	0.030	0.022	0.030	0.019	0.011
D14	0.026	0.044	0.056	0.000	0.044	0.056	0.048	0.044	0.041	0.037	0.037	0.048	0.037	0.031	0.048	0.052	0.044	0.044	0.026	0.030	0.026	0.030	0.026
D15	0.022	0.011	0.011	0.026	0.000	0.030	0.044	0.030	0.033	0.019	0.019	0.022	0.019	0.011	0.030	0.026	0.026	0.019	0.030	0.019	0.033	0.011	0.011
D16	0.019	0.019	0.026	0.022	0.041	0.000	0.037	0.041	0.048	0.030	0.026	0.033	0.026	0.019	0.037	0.044	0.041	0.026	0.030	0.030	0.019	0.011	0.011
D17	0.026	0.011	0.026	0.026	0.037	0.037	0.000	0.033	0.033	0.019	0.019	0.026	0.011	0.019	0.026	0.041	0.030	0.022	0.026	0.019	0.026	0.033	0.019
D18	0.011	0.026	0.037	0.048	0.041	0.048	0.048	0.000	0.026	0.026	0.026	0.030	0.022	0.019	0.037	0.052	0.041	0.026	0.011	0.015	0.033	0.019	0.015

(Continued)

Table 8 (continued)

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23	D24	D25	D26	D27	D28	D31	D32	D33	D34	D35	D36
D19	0.019	0.011	0.041	0.041	0.048	0.037	0.044	0.026	0.000	0.030	0.044	0.033	0.026	0.026	0.048	0.056	0.033	0.022	0.026	0.033	0.019	0.022	0.011
D21	0.041	0.033	0.037	0.041	0.044	0.048	0.056	0.048	0.048	0.000	0.048	0.048	0.041	0.026	0.056	0.063	0.030	0.056	0.048	0.041	0.030	0.033	0.030
D22	0.026	0.044	0.028	0.011	0.048	0.033	0.041	0.063	0.056	0.037	0.000	0.063	0.033	0.037	0.044	0.026	0.033	0.026	0.048	0.048	0.026	0.037	0.026
D23	0.030	0.033	0.015	0.041	0.048	0.033	0.041	0.063	0.056	0.044	0.026	0.000	0.041	0.026	0.048	0.041	0.037	0.056	0.033	0.022	0.019	0.048	0.048
D24	0.030	0.011	0.026	0.044	0.041	0.048	0.037	0.056	0.041	0.041	0.041	0.048	0.000	0.022	0.059	0.052	0.041	0.048	0.022	0.022	0.059	0.030	0.041
D25	0.019	0.037	0.056	0.033	0.026	0.041	0.052	0.037	0.048	0.033	0.026	0.056	0.056	0.000	0.030	0.048	0.041	0.026	0.026	0.026	0.041	0.026	0.052
D26	0.011	0.015	0.048	0.056	0.048	0.019	0.026	0.033	0.063	0.041	0.048	0.048	0.059	0.015	0.000	0.041	0.030	0.019	0.048	0.019	0.048	0.041	0.019
D27	0.011	0.030	0.037	0.037	0.030	0.046	0.041	0.026	0.019	0.015	0.026	0.030	0.033	0.026	0.037	0.000	0.037	0.026	0.026	0.033	0.030	0.037	0.019
D28	0.011	0.033	0.026	0.041	0.019	0.044	0.048	0.033	0.048	0.026	0.041	0.048	0.019	0.019	0.030	0.026	0.000	0.037	0.030	0.026	0.019	0.037	0.037
D31	0.026	0.019	0.026	0.041	0.015	0.056	0.041	0.037	0.041	0.041	0.026	0.026	0.019	0.056	0.048	0.033	0.056	0.000	0.030	0.030	0.026	0.041	0.022
D32	0.019	0.026	0.019	0.048	0.022	0.026	0.030	0.048	0.019	0.033	0.059	0.041	0.052	0.048	0.052	0.044	0.033	0.026	0.000	0.019	0.015	0.022	0.026
D33	0.011	0.026	0.056	0.030	0.052	0.052	0.056	0.041	0.048	0.063	0.041	0.048	0.041	0.037	0.056	0.037	0.041	0.037	0.052	0.000	0.044	0.019	0.052
D34	0.015	0.041	0.037	0.056	0.056	0.063	0.063	0.052	0.063	0.048	0.030	0.022	0.044	0.026	0.037	0.022	0.052	0.019	0.033	0.011	0.000	0.041	0.022
D35	0.026	0.033	0.033	0.015	0.052	0.048	0.048	0.030	0.041	0.030	0.048	0.033	0.037	0.019	0.019	0.033	0.041	0.052	0.041	0.026	0.048	0.000	0.037
D36	0.019	0.041	0.048	0.030	0.041	0.037	0.063	0.041	0.037	0.022	0.041	0.037	0.030	0.015	0.056	0.022	0.041	0.048	0.030	0.033	0.033	0.044	0.000

Table 9: Total-relation matrix of first-level CI indicators

	C1	C2	C3
C1	0.583	0.627	0.706
C2	1.260	0.655	1.163
C3	0.961	0.681	0.585

Table 10: Total-relation matrix of second-level CI indicators

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23	D24	D25	D26	D27	D28	D31	D32	D33	D34	D35	D36
D11	0.065	0.115	0.157	0.149	0.152	0.176	0.180	0.161	0.189	0.125	0.135	0.150	0.119	0.101	0.177	0.178	0.153	0.122	0.143	0.096	0.112	0.118	0.086
D12	0.094	0.072	0.123	0.136	0.149	0.161	0.161	0.150	0.170	0.109	0.119	0.140	0.106	0.087	0.158	0.156	0.145	0.109	0.137	0.097	0.100	0.099	0.086
D13	0.071	0.076	0.084	0.119	0.148	0.143	0.156	0.135	0.134	0.104	0.102	0.118	0.101	0.077	0.149	0.140	0.149	0.111	0.110	0.086	0.103	0.092	0.073
D14	0.096	0.129	0.165	0.119	0.174	0.191	0.192	0.175	0.179	0.141	0.146	0.170	0.140	0.113	0.184	0.184	0.170	0.149	0.134	0.114	0.124	0.126	0.107
D15	0.062	0.061	0.077	0.095	0.076	0.109	0.127	0.106	0.113	0.079	0.083	0.094	0.079	0.059	0.109	0.104	0.099	0.079	0.091	0.067	0.089	0.068	0.058
D16	0.069	0.080	0.107	0.109	0.134	0.100	0.142	0.136	0.148	0.105	0.106	0.123	0.102	0.078	0.136	0.141	0.131	0.102	0.107	0.091	0.090	0.082	0.071
D17	0.070	0.067	0.098	0.102	0.121	0.125	0.095	0.118	0.122	0.086	0.090	0.105	0.079	0.072	0.114	0.126	0.111	0.090	0.095	0.073	0.089	0.095	0.071
D18	0.064	0.090	0.120	0.135	0.138	0.150	0.156	0.099	0.130	0.103	0.108	0.121	0.100	0.079	0.138	0.150	0.135	0.104	0.092	0.079	0.106	0.091	0.076
D19	0.074	0.080	0.130	0.134	0.151	0.146	0.159	0.132	0.112	0.113	0.132	0.132	0.110	0.091	0.157	0.161	0.134	0.106	0.112	0.101	0.098	0.100	0.077
D21	0.116	0.126	0.158	0.168	0.184	0.195	0.211	0.190	0.197	0.114	0.167	0.181	0.153	0.116	0.203	0.206	0.166	0.167	0.164	0.132	0.136	0.138	0.118
D22	0.093	0.126	0.135	0.127	0.173	0.165	0.180	0.188	0.188	0.138	0.108	0.180	0.134	0.115	0.176	0.156	0.154	0.127	0.151	0.128	0.121	0.129	0.106
D23	0.098	0.117	0.125	0.156	0.174	0.167	0.182	0.189	0.189	0.145	0.135	0.121	0.141	0.106	0.181	0.171	0.160	0.157	0.138	0.105	0.115	0.142	0.127
D24	0.098	0.098	0.138	0.162	0.170	0.184	0.182	0.185	0.179	0.144	0.150	0.169	0.105	0.104	0.194	0.183	0.166	0.152	0.129	0.107	0.155	0.127	0.121
D25	0.086	0.119	0.162	0.147	0.152	0.172	0.191	0.164	0.181	0.133	0.132	0.172	0.154	0.079	0.162	0.176	0.162	0.128	0.129	0.108	0.134	0.120	0.130
D26	0.077	0.095	0.149	0.164	0.168	0.146	0.160	0.156	0.189	0.137	0.150	0.161	0.155	0.091	0.128	0.164	0.146	0.117	0.146	0.097	0.138	0.129	0.095
D27	0.064	0.094	0.121	0.125	0.128	0.148	0.149	0.125	0.124	0.094	0.109	0.122	0.112	0.087	0.139	0.101	0.132	0.105	0.107	0.096	0.104	0.109	0.081
D28	0.069	0.102	0.116	0.135	0.125	0.154	0.164	0.140	0.159	0.111	0.129	0.147	0.103	0.085	0.141	0.134	0.103	0.122	0.117	0.095	0.097	0.115	0.103
D31	0.087	0.095	0.125	0.144	0.129	0.174	0.168	0.152	0.162	0.132	0.124	0.135	0.111	0.126	0.166	0.151	0.164	0.093	0.124	0.104	0.112	0.125	0.095
D32	0.079	0.100	0.115	0.148	0.134	0.143	0.153	0.161	0.139	0.123	0.152	0.148	0.141	0.117	0.168	0.158	0.141	0.117	0.093	0.092	0.100	0.106	0.097
D33	0.087	0.118	0.174	0.158	0.191	0.197	0.211	0.183	0.197	0.174	0.159	0.180	0.153	0.125	0.203	0.181	0.176	0.150	0.166	0.092	0.149	0.124	0.139
D34	0.083	0.122	0.144	0.168	0.180	0.193	0.201	0.177	0.195	0.147	0.136	0.142	0.143	0.104	0.168	0.153	0.172	0.120	0.136	0.094	0.095	0.132	0.100
D35	0.089	0.110	0.133	0.122	0.168	0.171	0.179	0.149	0.166	0.124	0.146	0.144	0.130	0.093	0.143	0.153	0.154	0.145	0.137	0.103	0.135	0.088	0.110
D36	0.084	0.118	0.150	0.139	0.161	0.163	0.195	0.162	0.166	0.119	0.142	0.150	0.125	0.091	0.180	0.145	0.157	0.144	0.129	0.111	0.124	0.133	0.076

Table 11: Normalized total-relation matrix of first-level CI indicators

	C1	C2	C3
C1	0.304	0.327	0.368
C2	0.409	0.213	0.378
C3	0.432	0.306	0.263

Table 12: Normalized total-relation matrix of second-level CI indicators

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23	D24	D25	D26	D27	D28	D31	D32	D33	D34	D35	D36
D11	0.048	0.085	0.117	0.111	0.113	0.131	0.134	0.120	0.140	0.110	0.119	0.132	0.104	0.089	0.155	0.157	0.134	0.180	0.211	0.141	0.166	0.175	0.127
D12	0.078	0.059	0.101	0.112	0.122	0.132	0.132	0.123	0.140	0.107	0.116	0.137	0.104	0.086	0.155	0.153	0.142	0.174	0.218	0.154	0.159	0.158	0.137
D13	0.066	0.071	0.079	0.112	0.139	0.134	0.146	0.127	0.126	0.111	0.108	0.126	0.107	0.082	0.159	0.149	0.158	0.194	0.192	0.149	0.179	0.160	0.127
D14	0.068	0.088	0.112	0.080	0.115	0.132	0.133	0.122	0.126	0.113	0.117	0.136	0.112	0.090	0.148	0.148	0.136	0.197	0.177	0.152	0.164	0.167	0.142
D15	0.075	0.074	0.093	0.115	0.092	0.132	0.154	0.128	0.137	0.113	0.118	0.133	0.112	0.084	0.154	0.147	0.140	0.174	0.202	0.149	0.197	0.150	0.129
D16	0.067	0.078	0.104	0.106	0.131	0.098	0.138	0.132	0.144	0.114	0.115	0.133	0.110	0.085	0.148	0.153	0.142	0.187	0.198	0.168	0.166	0.151	0.131
D17	0.077	0.073	0.107	0.111	0.131	0.136	0.103	0.128	0.133	0.110	0.115	0.134	0.101	0.091	0.146	0.161	0.142	0.175	0.185	0.143	0.173	0.185	0.138
D18	0.059	0.083	0.111	0.125	0.127	0.139	0.144	0.092	0.120	0.111	0.115	0.130	0.107	0.085	0.148	0.161	0.144	0.190	0.168	0.144	0.193	0.167	0.138
D19	0.067	0.072	0.116	0.120	0.135	0.130	0.143	0.118	0.100	0.110	0.128	0.129	0.107	0.089	0.152	0.156	0.130	0.179	0.189	0.170	0.164	0.168	0.130
D21	0.075	0.081	0.102	0.109	0.119	0.126	0.136	0.123	0.128	0.087	0.128	0.138	0.117	0.089	0.156	0.158	0.127	0.196	0.192	0.154	0.159	0.162	0.138
D22	0.068	0.091	0.098	0.092	0.126	0.120	0.131	0.137	0.137	0.119	0.093	0.155	0.116	0.099	0.152	0.134	0.133	0.167	0.198	0.168	0.158	0.170	0.139
D23	0.070	0.083	0.090	0.112	0.124	0.120	0.130	0.135	0.135	0.125	0.116	0.104	0.122	0.091	0.156	0.147	0.138	0.200	0.176	0.135	0.147	0.181	0.161
D24	0.071	0.070	0.099	0.116	0.122	0.132	0.130	0.133	0.128	0.119	0.123	0.139	0.086	0.086	0.159	0.151	0.136	0.192	0.164	0.135	0.196	0.161	0.153
D25	0.063	0.086	0.118	0.107	0.111	0.125	0.139	0.119	0.131	0.114	0.113	0.147	0.131	0.067	0.139	0.150	0.139	0.171	0.172	0.144	0.180	0.160	0.173
D26	0.059	0.073	0.115	0.125	0.129	0.112	0.123	0.120	0.145	0.121	0.132	0.142	0.137	0.081	0.113	0.145	0.129	0.162	0.202	0.135	0.191	0.179	0.131
D27	0.060	0.087	0.112	0.116	0.119	0.137	0.138	0.116	0.115	0.105	0.121	0.137	0.124	0.097	0.155	0.113	0.147	0.175	0.178	0.160	0.172	0.181	0.134
D28	0.059	0.088	0.100	0.116	0.107	0.132	0.141	0.120	0.137	0.116	0.136	0.154	0.108	0.090	0.148	0.141	0.108	0.188	0.180	0.147	0.150	0.177	0.158
D31	0.070	0.077	0.102	0.116	0.105	0.141	0.136	0.123	0.131	0.119	0.111	0.122	0.100	0.113	0.150	0.136	0.148	0.143	0.190	0.159	0.171	0.191	0.146
D32	0.067	0.086	0.098	0.126	0.114	0.122	0.131	0.137	0.118	0.107	0.133	0.129	0.123	0.102	0.146	0.138	0.123	0.193	0.153	0.152	0.166	0.175	0.161
D33	0.058	0.078	0.115	0.104	0.126	0.130	0.139	0.121	0.130	0.129	0.118	0.133	0.113	0.092	0.150	0.134	0.130	0.183	0.203	0.113	0.182	0.151	0.169
D34	0.057	0.083	0.098	0.115	0.123	0.132	0.137	0.121	0.133	0.126	0.117	0.122	0.123	0.089	0.145	0.131	0.148	0.178	0.201	0.138	0.140	0.195	0.148
D35	0.069	0.086	0.103	0.095	0.130	0.133	0.139	0.116	0.129	0.114	0.135	0.132	0.119	0.086	0.132	0.140	0.142	0.202	0.191	0.143	0.188	0.123	0.153
D36	0.063	0.089	0.112	0.104	0.120	0.122	0.146	0.121	0.124	0.107	0.128	0.135	0.113	0.082	0.162	0.131	0.141	0.201	0.181	0.155	0.173	0.186	0.106

Table 13: Unweighted supermatrix of second-level CI indicators

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23	D24	D25	D26	D27	D28	D31	D32	D33	D34	D35	D36
D11	0.048	0.078	0.066	0.068	0.075	0.067	0.077	0.059	0.067	0.075	0.068	0.070	0.071	0.063	0.059	0.060	0.059	0.070	0.067	0.058	0.057	0.069	0.063
D12	0.085	0.059	0.071	0.088	0.074	0.078	0.073	0.083	0.072	0.081	0.091	0.083	0.070	0.086	0.073	0.087	0.088	0.077	0.086	0.078	0.083	0.086	0.089
D13	0.117	0.101	0.079	0.112	0.093	0.104	0.107	0.111	0.116	0.102	0.098	0.090	0.099	0.118	0.115	0.112	0.100	0.102	0.098	0.115	0.098	0.103	0.112
D14	0.111	0.112	0.112	0.080	0.115	0.106	0.111	0.125	0.120	0.109	0.092	0.112	0.116	0.107	0.125	0.116	0.116	0.116	0.126	0.104	0.115	0.095	0.104
D15	0.113	0.122	0.139	0.115	0.092	0.131	0.131	0.127	0.135	0.119	0.126	0.124	0.122	0.111	0.129	0.119	0.107	0.105	0.114	0.126	0.123	0.130	0.120
D16	0.131	0.132	0.134	0.132	0.132	0.098	0.136	0.139	0.130	0.126	0.120	0.120	0.132	0.125	0.112	0.137	0.132	0.141	0.122	0.130	0.132	0.133	0.122
D17	0.134	0.132	0.146	0.133	0.154	0.138	0.103	0.144	0.143	0.136	0.131	0.130	0.130	0.139	0.123	0.138	0.141	0.136	0.131	0.139	0.137	0.139	0.146
D18	0.120	0.123	0.127	0.122	0.128	0.132	0.128	0.092	0.118	0.123	0.137	0.135	0.133	0.119	0.120	0.116	0.120	0.123	0.137	0.121	0.121	0.116	0.121
D19	0.140	0.140	0.126	0.126	0.137	0.144	0.133	0.120	0.100	0.128	0.137	0.135	0.128	0.131	0.145	0.115	0.137	0.131	0.118	0.130	0.133	0.129	0.124
D21	0.110	0.107	0.111	0.113	0.113	0.114	0.110	0.111	0.110	0.087	0.119	0.125	0.119	0.114	0.121	0.105	0.116	0.119	0.107	0.129	0.126	0.114	0.107
D22	0.119	0.116	0.108	0.117	0.118	0.115	0.115	0.115	0.128	0.128	0.093	0.116	0.123	0.113	0.132	0.121	0.136	0.111	0.133	0.118	0.117	0.135	0.128
D23	0.132	0.137	0.126	0.136	0.133	0.133	0.134	0.130	0.129	0.138	0.155	0.104	0.139	0.147	0.142	0.137	0.154	0.122	0.129	0.133	0.122	0.132	0.135
D24	0.104	0.104	0.107	0.112	0.112	0.110	0.101	0.107	0.107	0.117	0.116	0.122	0.086	0.131	0.137	0.124	0.108	0.100	0.123	0.113	0.123	0.119	0.113
D25	0.089	0.086	0.082	0.090	0.084	0.085	0.091	0.085	0.089	0.089	0.099	0.091	0.086	0.067	0.081	0.097	0.090	0.113	0.102	0.092	0.089	0.086	0.082
D26	0.155	0.155	0.159	0.148	0.154	0.148	0.146	0.148	0.152	0.156	0.152	0.156	0.159	0.139	0.113	0.155	0.148	0.150	0.146	0.150	0.145	0.132	0.162
D27	0.157	0.153	0.149	0.148	0.147	0.153	0.161	0.161	0.156	0.158	0.134	0.147	0.151	0.150	0.145	0.113	0.141	0.136	0.138	0.134	0.131	0.140	0.131
D28	0.134	0.142	0.158	0.136	0.140	0.142	0.142	0.144	0.130	0.127	0.133	0.138	0.136	0.139	0.129	0.147	0.108	0.148	0.123	0.130	0.148	0.142	0.141
D31	0.180	0.174	0.194	0.197	0.174	0.187	0.175	0.190	0.179	0.196	0.167	0.200	0.192	0.171	0.162	0.175	0.188	0.143	0.193	0.183	0.178	0.202	0.201
D32	0.211	0.218	0.192	0.177	0.202	0.198	0.185	0.168	0.189	0.192	0.198	0.176	0.164	0.172	0.202	0.178	0.180	0.190	0.153	0.203	0.201	0.191	0.181
D33	0.141	0.154	0.149	0.152	0.149	0.168	0.143	0.144	0.170	0.154	0.168	0.135	0.135	0.144	0.135	0.160	0.147	0.159	0.152	0.113	0.138	0.143	0.155
D34	0.166	0.159	0.179	0.164	0.197	0.166	0.173	0.193	0.164	0.159	0.158	0.147	0.196	0.180	0.191	0.172	0.150	0.171	0.166	0.182	0.140	0.188	0.173

(Continued)

Table 13 (continued)

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23	D24	D25	D26	D27	D28	D31	D32	D33	D34	D35	D36
D35	0.175	0.158	0.160	0.167	0.150	0.151	0.185	0.167	0.168	0.162	0.170	0.181	0.161	0.160	0.179	0.181	0.177	0.191	0.175	0.151	0.195	0.123	0.186
D36	0.127	0.137	0.127	0.142	0.129	0.131	0.138	0.138	0.130	0.138	0.139	0.161	0.153	0.173	0.131	0.134	0.158	0.146	0.161	0.169	0.148	0.153	0.106

Table 14: Weighted supermatrix of CI indicators

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23	D24	D25	D26	D27	D28	D31	D32	D33	D34	D35	D36
D11	0.015	0.024	0.020	0.021	0.023	0.021	0.023	0.018	0.020	0.024	0.022	0.023	0.023	0.021	0.019	0.019	0.019	0.026	0.025	0.021	0.021	0.026	0.023
D12	0.026	0.018	0.022	0.027	0.023	0.024	0.022	0.025	0.022	0.027	0.030	0.027	0.023	0.028	0.024	0.028	0.029	0.028	0.032	0.029	0.031	0.032	0.033
D13	0.036	0.031	0.024	0.034	0.028	0.032	0.033	0.034	0.035	0.033	0.032	0.029	0.032	0.038	0.037	0.037	0.033	0.037	0.036	0.042	0.036	0.038	0.041
D14	0.034	0.034	0.034	0.024	0.035	0.032	0.034	0.038	0.037	0.036	0.030	0.037	0.038	0.035	0.041	0.038	0.038	0.043	0.047	0.038	0.042	0.035	0.038
D15	0.034	0.037	0.042	0.035	0.028	0.040	0.040	0.039	0.041	0.039	0.041	0.041	0.040	0.036	0.042	0.039	0.035	0.039	0.042	0.046	0.045	0.048	0.044
D16	0.040	0.040	0.041	0.040	0.040	0.030	0.041	0.042	0.040	0.041	0.039	0.039	0.043	0.041	0.037	0.045	0.043	0.052	0.045	0.048	0.049	0.049	0.045
D17	0.041	0.040	0.045	0.041	0.047	0.042	0.031	0.044	0.043	0.045	0.043	0.043	0.043	0.045	0.040	0.045	0.046	0.050	0.048	0.051	0.051	0.051	0.054
D18	0.036	0.038	0.039	0.037	0.039	0.040	0.039	0.028	0.036	0.040	0.045	0.044	0.043	0.039	0.039	0.038	0.039	0.045	0.051	0.044	0.045	0.043	0.045
D19	0.043	0.043	0.038	0.038	0.042	0.044	0.041	0.037	0.030	0.042	0.045	0.044	0.042	0.043	0.047	0.038	0.045	0.048	0.044	0.048	0.049	0.047	0.046
D21	0.045	0.044	0.045	0.046	0.046	0.047	0.045	0.045	0.045	0.019	0.025	0.027	0.025	0.024	0.026	0.022	0.025	0.045	0.040	0.049	0.048	0.043	0.041
D22	0.049	0.048	0.044	0.048	0.048	0.047	0.047	0.047	0.052	0.027	0.020	0.025	0.026	0.024	0.028	0.026	0.029	0.042	0.050	0.045	0.044	0.051	0.048
D23	0.054	0.056	0.052	0.056	0.054	0.054	0.055	0.053	0.053	0.029	0.033	0.022	0.030	0.031	0.030	0.029	0.033	0.046	0.049	0.050	0.046	0.050	0.051
D24	0.043	0.043	0.044	0.046	0.046	0.045	0.041	0.044	0.044	0.025	0.025	0.026	0.018	0.028	0.029	0.026	0.023	0.038	0.046	0.043	0.046	0.045	0.043
D25	0.036	0.035	0.033	0.037	0.034	0.035	0.037	0.035	0.036	0.019	0.021	0.019	0.018	0.014	0.017	0.021	0.019	0.043	0.039	0.035	0.034	0.032	0.031
D26	0.064	0.063	0.065	0.060	0.063	0.060	0.060	0.061	0.062	0.033	0.032	0.033	0.034	0.030	0.024	0.033	0.031	0.057	0.055	0.057	0.055	0.050	0.061
D27	0.064	0.063	0.061	0.060	0.060	0.063	0.066	0.066	0.064	0.034	0.029	0.031	0.032	0.032	0.031	0.024	0.030	0.051	0.052	0.051	0.050	0.053	0.050
D28	0.055	0.058	0.065	0.056	0.057	0.058	0.058	0.059	0.053	0.027	0.028	0.029	0.029	0.029	0.027	0.031	0.023	0.056	0.046	0.049	0.056	0.054	0.053
D31	0.078	0.075	0.084	0.085	0.075	0.081	0.076	0.082	0.077	0.060	0.051	0.061	0.059	0.052	0.050	0.053	0.058	0.037	0.051	0.048	0.047	0.053	0.053
D32	0.091	0.094	0.083	0.077	0.087	0.085	0.080	0.072	0.082	0.059	0.061	0.054	0.050	0.053	0.062	0.054	0.055	0.050	0.040	0.053	0.053	0.050	0.047
D33	0.061	0.066	0.064	0.065	0.064	0.072	0.062	0.062	0.073	0.047	0.051	0.041	0.041	0.044	0.041	0.049	0.045	0.042	0.040	0.030	0.036	0.038	0.041
D34	0.071	0.069	0.077	0.071	0.085	0.071	0.075	0.083	0.071	0.049	0.048	0.045	0.060	0.055	0.058	0.053	0.046	0.045	0.044	0.048	0.037	0.049	0.045
D35	0.075	0.068	0.069	0.072	0.065	0.065	0.080	0.072	0.072	0.049	0.052	0.055	0.049	0.049	0.055	0.055	0.054	0.050	0.046	0.040	0.051	0.032	0.049
D36	0.055	0.059	0.055	0.061	0.056	0.056	0.060	0.060	0.056	0.042	0.042	0.049	0.047	0.053	0.040	0.041	0.048	0.038	0.042	0.044	0.039	0.040	0.028

Table 15: Convergent limit supermatrix of CI indicators

	D11	D12	D13	D14	D15	D16	D17	D18	D19	D21	D22	D23	D24	D25	D26	D27	D28	D31	D32	D33	D34	D35	D36
D11	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022
D12	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027
D13	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
D14	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038
D15	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041
D16	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043
D17	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046
D18	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
D19	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044
D21	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
D22	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
D23	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044
D24	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
D25	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030
D26	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049
D27	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047
D28	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045
D31	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061
D32	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062
D33	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
D34	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057	0.057
D35	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056
D36	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047

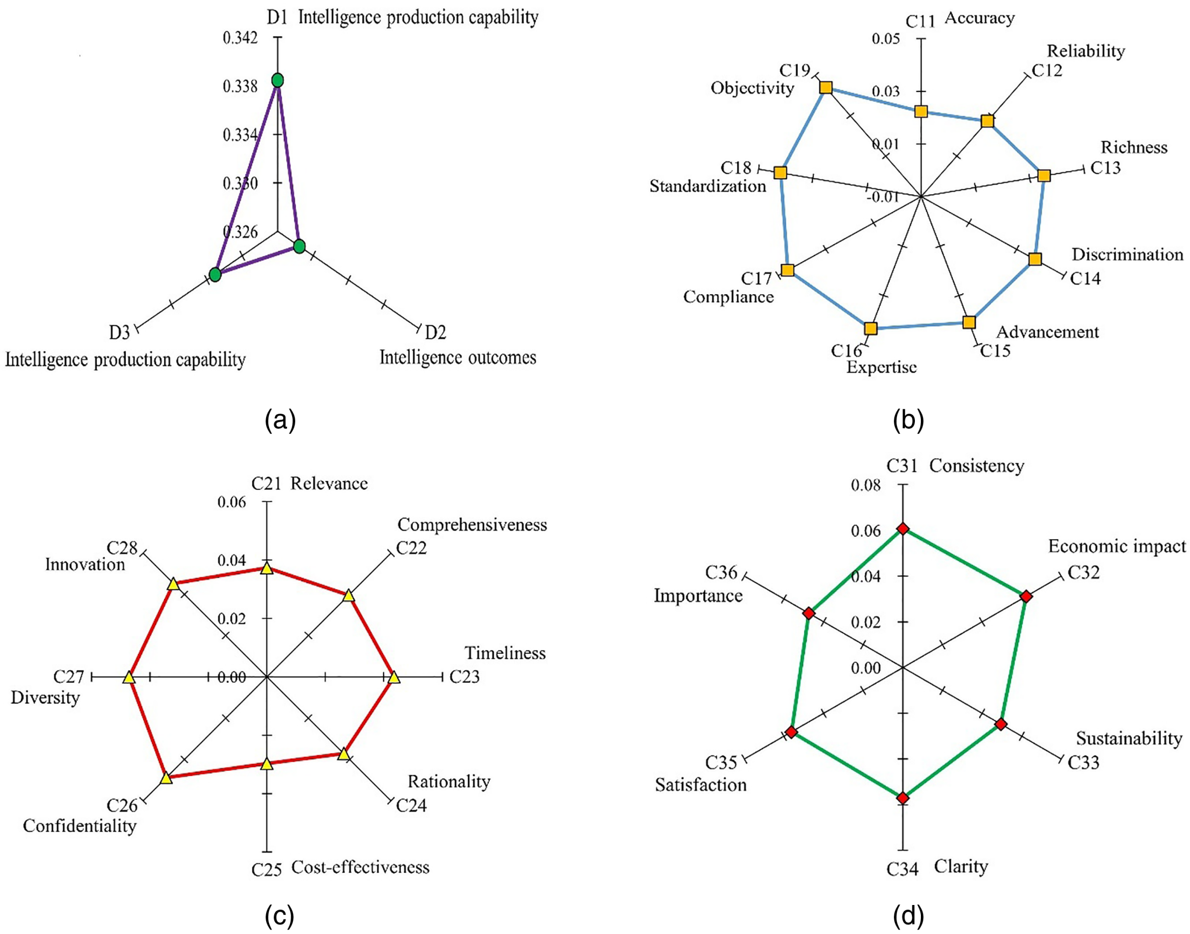

Figure 3: Final weights of (**a**) D1 to D3 indicators; (**b**) C11 to C19 indicators; (**c**) C21 to C28 indicators; (**d**) C31 to C36 indicators

Table 16: Ranking results of each CI indicator

First-level index	Weight	Ranking	Second-level index	Weight	Ranking	Global weight	Global ranking
Intelligence production capability (D1)	0.339	1	Accuracy (C11)	0.066	9	0.022	23
			Reliability (C12)	0.081	8	0.027	22
			Richness (C13)	0.104	7	0.035	20
			Discrimination (C14)	0.111	6	0.038	17
			Advancement (C15)	0.121	5	0.041	15
			Expertise (C16)	0.128	3	0.043	13
			Compliance (C17)	0.136	1	0.046	9
			Standardization (C18)	0.124	4	0.042	14
			Objectivity (C19)	0.130	2	0.044	11
Intelligence outcomes (D2)	0.328	3	Relevance (C21)	0.114	6	0.037	18

(Continued)

Table 16 (continued)

First-level index	Weight	Ranking	Second-level index	Weight	Ranking	Global weight	Global ranking
			Comprehensiveness (C22)	0.121	5	0.040	16
			Timeliness (C23)	0.132	4	0.044	11
			Rationality (C24)	0.113	7	0.037	18
			Cost-effectiveness (C25)	0.090	8	0.030	21
			Confidentiality (C26)	0.148	1	0.049	5
			Diversity (C27)	0.144	2	0.047	7
			Innovation (C28)	0.138	3	0.045	10
User experience effectiveness (D3)	0.333	2	Consistency (C31)	0.182	2	0.061	2
			Economic impact (C32)	0.187	1	0.062	1
			Sustainability (C33)	0.149	5	0.049	5
			Clarity (C34)	0.171	3	0.057	3
			Satisfaction (C35)	0.169	4	0.056	4
			Importance (C36)	0.142	6	0.047	7

5 Discussion

This study applied the proposed approach in a case company to analyze and illustrate the causal relationships among evaluation indicators. Based on this analysis, an unweighted supermatrix was constructed to reflect the relative importance of each indicator, and a weighted supermatrix was subsequently developed by considering each indicator's contribution to the overall system. Through the convergence of the limit supermatrix, the global weights of all indicators were obtained, as presented in Table 16. The proposed approach allows for the determination of both the local weights, representing the importance of indicators within their respective hierarchical levels, and global weights, capturing their significance across the entire system. This dual weighting is essential for accurately assessing the absolute importance of each indicator within the CI evaluation framework, thereby enhancing the reliability and comprehensiveness of the results. Sensitivity analysis further confirmed the robustness of the framework, showing that while a few lower-ranked indicators experienced minor variations under perturbations, the top priorities remained stable.

As shown in Table 16, the first-level indicators are ranked in the following order: intelligence production capability (D1), user experience effectiveness (D3), and intelligence outcomes (D2). This ranking reflects the core purpose of competitive intelligence, which is to obtain strategically valuable information resources that enhance an organization's responsiveness and competitive advantage in a smart factor. The quality, precision, and usability of intelligence are directly linked to production capability, forming the foundation for both strategic decision-making and tactical actions. Therefore, it is reasonable that this indicator holds the highest priority in the overall evaluation model. Examining the global weight rankings, the top three indicators all belong to the part of user experience effectiveness (D3), specifically economic impact (C32), consistency (C31), and clarity (C34). This indicates the critical role of user experience in determining the ultimate effectiveness of CI. Economic impact (C32) indicates the financial advantages gained through the application of intelligence, serving as an important indicator of the system's overall commercial value. Consistency (C31) refers to the stability and reliability of intelligence outputs which are essential for building user trust and dependence. Clarity (C34) emphasizes the intelligibility and ease of understanding of intelligence content, directly influencing the efficiency of information dissemination and the effectiveness of user cognition.

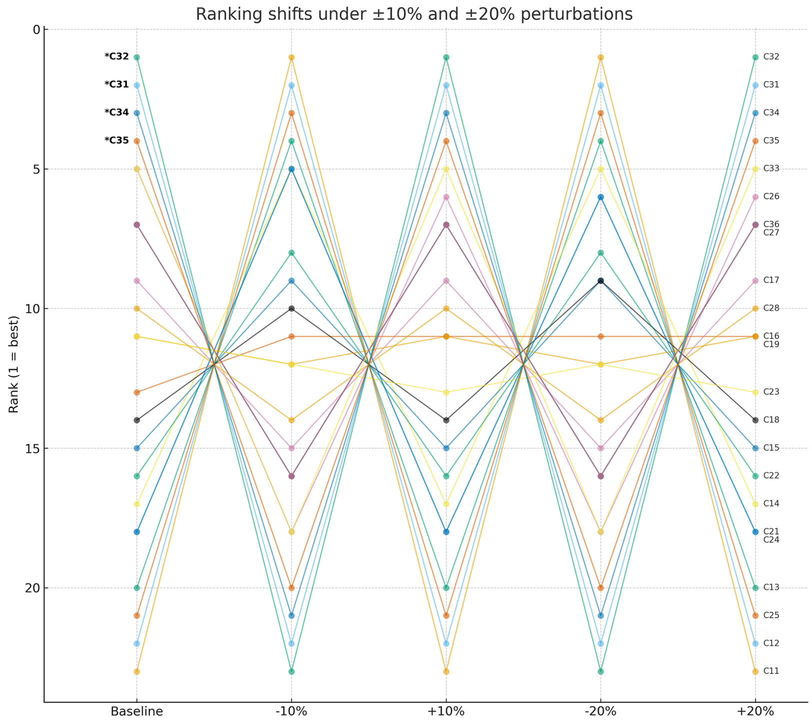

Figure 4: Sensitivity analysis through changes in the expert inputs

Further analysis of the second-level indicators reveals that within the dimension of intelligence production capability (D1), compliance (C17) holds the highest weight (global weight = 0.046; ranked 9th overall). Compliance is fundamental to the intelligence production process, ensuring that data collection and processing conform to relevant laws, industry standards, and ethical principles. In an environment where data governance and privacy protection are increasingly prioritized, legally compliant intelligence can be effectively integrated into corporate strategies and reduce potential risks. Within the dimension of intelligence outcomes (D2), confidentiality (C26) emerges as the most important indicator (global weight = 0.049; ranked 5th overall). The confidentiality of intelligence outputs determines their strategic value and security level. High-quality CI often involves trade secrets or strategic plans, and any unauthorized disclosure can result in substantial losses. Therefore, establishing a secure confidential mechanism is essential to protect intelligence during transmission and use. Finally, in the dimension of user experience effectiveness (D3), economic impact (C32) holds the highest global weight (global weight = 0.062; ranked 1st overall). This finding reflects that the ultimate benchmark for a CI system lies in its ability to create tangible economic value. Regardless of the quality of intelligence, if it cannot be translated into measurable financial outcomes, its practical significance will be questioned. Thus, economic impact not only assesses the return on investment in intelligence but also directly indicates the system's contribution to enhancing a company's core competitiveness.

6 Conclusions

CI represents the initial and critical step in development of effective competitive strategies. High-quality CI plays a key role in enabling companies to identify key differences between user demands and perceptions regarding their own products and those of competitors. Effectively addressing these discrepancies is recognized as one of the essential challenges that organizations must overcome to achieve and sustain strategic advantage. Although existing research has primarily focused on the processes, operational steps, strategic objectives, and organizational benefits of CI, relatively limited attention has been paid to the systematic evaluation of corporate CI capabilities.

To construct an effective evaluation system for company CI, this study systematically collected and analyzed a representative body of CI-related literature. Based on the essential functional attributes of intelligence, 23 indicators were selected across three key dimensions: intelligence production capability, intelligence outcomes, and user experience effectiveness. Using these indicators, a comprehensive evaluation framework for company CI was established. Recognizing the hesitation and uncertainty that often characterize corporate decision-making in CI, this study proposed an integrated IVHFS and DEMATEL-ANP framework. This framework not only extends the capabilities of traditional MCDM techniques in handling uncertainty and subjective hesitations but also effectively captures the structural relationships and causal relationships among evaluation indicators. By doing so, it enables the identification and quantification of indicator weights based on their mutual influence within the system. A case study conducted in a smart factory specializing in electronic assembly was used to validate the proposed approach, confirming its effectiveness, theoretical soundness, and practical relevance in complex manufacturing environments. Furthermore, the sensitivity analysis demonstrated the robustness of the framework: although a few lower-ranked indicators exhibited minor shifts under $\pm 10\%$ and $\pm 20\%$ perturbations, the top four indicators (C32, C31, C34, C35) remained unchanged across all scenarios, underscoring the stability of the key priorities.

This study makes contributions in three main aspects. First, the introduction of IVHFS enables a more realistic representation of expert hesitation and uncertain judgments, thereby enhancing the expressiveness and reliability of the input data. Second, the hybrid DEMATEL-ANP approach reveals the complex interrelationships among evaluation indicators, resulting in weight assignments with proved validity and consistency. Third, the comprehensive integration of these methodologies significantly improves the adaptability of the evaluation framework to multi-dimensional and complex decision-making problems. In particular, it strengthens the system's ability to support competitive intelligence evaluation in smart factory environments, where decision-making must account for high levels of fuzziness, indicator interdependence, and operational dynamism.

The findings of this study provide valuable insights for integrating fuzzy logic, multi-layered structures, and system dynamics analysis. Future research could extend this work by incorporating ranking methods such as TOPSIS or VIKOR, applying machine learning to optimize weight-learning, or adopting more rigorous protocols (e.g., content analysis or multi-round Delphi) to strengthen the validity of the 23 indicators. Furthermore, defuzzification inevitably results in partial loss of hesitation information, as the score function used in this study ignores the interval width and deviation; future research could address this limitation by integrating entropy- or dispersion-based measures alongside the score function to distinguish cases with identical averages but differing levels of uncertainty.

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