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Risk Assessment for Digital Transformation Projects in Construction Enterprises: An Enhanced FMEA Model

Tangzhenhao Li
School of Economics and Management,
Tongji University, 1239 Siping Road, Shanghai 200092, PR China
Cranfield School of Management,
Cranfield University, College Road, Bedford MK43 0AL, UK
Email: li-tanghao@163.com
Jianxin You
School of Economics and Management,
Tongji University, 1239 Siping Road, Shanghai 200092, PR China
Email: yjx2256@vip.sina.com
Emel Aktas
Cranfield School of Management,
Cranfield University, College Road, Bedford MK43 0AL, UK
Email: emel.aktas@cranfield.ac.uk
Yongxin Dong*
School of Law and Criminal Justice
East China University of Political Science and Law, Shanghai 201620, PR China
Email: dy893291318@sina.cn
*Corresponding author
Miying Yang
Cranfield School of Management,
Cranfield University, College Road, Bedford MK43 0AL, UK
Email: Miying.Yang@cranfield.ac.uk

Author contributions:
Tangzhenhao Li: Writing – original draft\ Data curation
Jianxin You: Conceptualization\ Investigation
Emel Aktas: Writing – review and editing
Yongxin Dong: Methodology\ Validation
Miying Yang: Writing – review and editing

Highlights:
- A novel multiple criteria Failure Mode and Effects Analysis (FMEA) is proposed.
- We analyzed digital transformation risks in a construction industry case study.
- Results substantiate applying FMEA and fuzzy logic on digital transformation risk.
- Results help construction managers mitigate digital transformation risks.

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Abstract

The digital transformation of the construction industry is crucial for advancing global digital economies, but it involves significant risks that require a standardized and robust assessment methodology. This paper presents an enhanced Failure Mode and Effect Analysis (FMEA) model that integrates the Multiple Attribute Border Approximation Area Comparison (MABAC) method with Grey Relational Analysis (GRA). Unlike previous approaches, this integration aligns grey relational changes with border approximation vector components, capturing both positive and negative correlations between modes. This enhances the prioritization process by distinguishing failure modes that may amplify or mitigate each other's impact, leading to more precise risk assessments and mitigation strategies. The model also employs interval numbers instead of crisp numbers to reduce information loss from decision-making ambiguities caused by heterogeneous expert evaluations. Applied in a real-life case study, the improved model effectively accommodates biases and hesitations in expert decision-making, enhancing the accuracy and reliability of risk assessments in digital transformation projects. The findings highlight the model's potential as a comprehensive and reliable framework for identifying, prioritizing, and mitigating risks in the digital transformation of the construction industry.

Keywords: Failure Mode and Effect Analysis, Digital Transformation, Multi-attributive Border

Approximation Area Comparison Method, Grey Relational Analysis, Construction Sector

1 Introduction

The digital economy has become a key driver reshaping modern economic systems and promoting sustainable growth worldwide (Shang et al., 2023). In 2022, China's digital economy reached 7.3 trillion US dollars, representing over 41% of its GDP (CAICT, 2023). Central to this economic shift is digital transformation (DT) (Qiao et al., 2024), defined as the process of leveraging digital technologies to fundamentally change an organization's operations, culture, and customer experiences to meet changing business and market requirements (Battistoni et al., 2023). In the construction industry, a traditional yet vital sector of the economy, DT is essential for addressing challenges such as intense competition, an aging workforce, and low productivity (Bhattacharya & Momaya, 2021). For individual construction companies, DT provides a pathway to improve management efficiency, enhance safety, and drive innovation (Koscheyev et al., 2019). However, these transformations also bring substantial risks at the company level, where the complexity of construction projects and their dynamic environments introduce various uncertainties that need careful management (Criado-Perez et al., 2022). Despite the critical need for effective risk management in company-level DT, most studies emphasize technological implementation rather than focusing on identifying and managing these risks (Musarat et al., 2022). This gap calls for a structured approach to assess the risks associated with DT projects within companies.

Traditional risk assessment methods typically rely on consistent and comprehensive data (Dou et al., 2024), which is often challenging to gather in rapidly evolving digital environments.

Consequently, reliance on historical data alone can lead to incomplete or misleading risk assessments. In such situations, expert judgment becomes crucial, making the Failure Mode and Effects Analysis (FMEA) model a suitable approach (Liu et al., 2024). FMEA uses expert insights to evaluate and prioritize risks systematically, particularly when reliable data is scarce (Liu et al., 2019). However, conventional FMEA has limitations, such as subjective judgments, assumptions that risks are independent, and insufficient handling of uncertainty (Samira et al., 2015). These limitations can undermine the reliability of risk assessments in complex DT scenarios.

To overcome these limitations, an enhanced FMEA model that integrates the MABAC method with GRA is proposed. MABAC enables a comprehensive evaluation of multiple criteria in decision-making (Pamučar & Ćirović, 2015), while GRA strengthens the analysis by examining the relationships between factors, thereby capturing interdependencies among risks (Liu et al., 2011). The model also employs interval-valued intuitionistic fuzzy numbers (IVIFNs) to manage uncertainty in expert assessments. Unlike traditional fuzzy numbers, IVIFNs allow experts to express both confidence in their assessments and any hesitation or uncertainty (Li et al., 2020). This dual expression reflects the reality of decision-making under uncertainty, where judgments are not always absolute but often accompanied by a degree of doubt. To further ensure consistency in comparing risk factors, the model uses matrix spectral norms, a mathematical tool used to measure the size or magnitude of a matrix, helping determine how much influence a set of risks can have on the overall analysis (Ishizaka et al., 2021). These methodological enhancements improve the precision and reliability of risk assessments, offering more robust support for decision-makers in managing DT risks.

An illustrative case study is conducted with a large construction enterprise in China to demonstrate the practical applicability and effectiveness of the enhanced FMEA model in assessing DT risks. In the case study, 23 potential failure modes related to DT projects were identified from the literature and evaluated by experts. Given the diverse nature of these failure modes—covering technological, organizational, and environmental aspects—the Technology–Organization–Environment (TOE) framework was employed to systematically categorize these risks (Zhu & Yan, 2022). To better align with the specific needs of construction projects characterized by resource management and supply chain dependencies, the framework was expanded with two additional categories—Resources and Industry Chain, based on expert input. This comprehensive categorization facilitated a more focused risk assessment and supported the effective application of the enhanced FMEA model.

The article is organized as follows: Section 2 reviews the relevant literature. Section 3 outlines the proposed model. Section 4 presents an illustrative case of the enhanced FMEA method, along with the results and discussion. Section 5 offers theoretical and managerial insights. Finally, Section 6 concludes with future research directions.

2 Literature review

2.1 Risk of digital transformation

DT is crucial for enhancing operational efficiency and driving innovation in today's data-driven era (Battistoni et al., 2023). While scholars have explored the processes, necessity, and advantages of DT, they have also highlighted challenges, particularly those exacerbated by disruptions such as the COVID-19 pandemic and declining globalization, which have disrupted supply chains and underscored the need for robust digital strategies to guide the DT process

(Ivanov, 2024). In discrete manufacturing companies, challenges like weak application foundations, lack of critical technology, and data aggregation difficulties have been identified (Möller et al., 2021). Case studies of listed companies reveal additional hurdles, including a shortage of internal digital talent, limited external technological expertise, and difficulties in securing funds for digital initiatives (Wang et al., 2020). Furthermore, expert interviews have pinpointed risks in DT, emphasizing that poor risk assessment and preparation often lead to project failures (Gölcük, 2020). These studies collectively stress the importance of developing effective risk assessment methods to support the success of DT projects.

The McKinsey Global Institute's report ranks the construction sector near the bottom in global DT indices, revealing substantial room for improvement (Agarwal et al., 2016). To change this situation, companies within this sector must prioritize DT, where they face not only the challenges of DT adoption but also the need to manage associated risks effectively (Pfnür & Wagner, 2020). However, current research primarily focuses on technological advancements, with insufficient attention given to the risk management strategies that companies need to implement. While factors influencing DT, such as technological readiness and organizational commitment, have been identified by Liu (2023), the specific risks companies face during this process remain underexplored. Therefore, a deeper understanding of these risks is essential for companies to successfully navigate their DT projects and achieve long-term growth. (Samuelson & Stehn, 2023).

2.2 FMEA model

DT projects involve complex risks that are difficult to quantify and predict using conventional risk assessment methods. Unlike traditional industrial risks, DT projects face

challenges such as rapid technological evolution, high uncertainty, and dynamic interactions between failure modes. FMEA is a widely used risk assessment tool, but its effectiveness in DT projects is limited by its reliance on expert judgments and deterministic scoring criteria. In this section, we discuss the fundamentals of FMEA and its existing limitations, providing the motivation for an improved risk assessment approach tailored for DT applications.

FMEA is a well-established risk management tool valued for its systematic approach and ability to integrate multidisciplinary perspectives (Liu et al., 2019). FMEA involves identifying potential failure modes based on expert knowledge and scoring them on a scale for Severity (S), Occurrence (O), and Detection (D) (J. Liu et al., 2023). The Risk Priority Number (RPN) is then calculated to prioritize mitigation efforts, with higher RPNs indicating higher risks (Liu et al., 2013).

While FMEA provides valuable risk information that can enhance the performance and reliability of products and services (Giannakis & Papadopoulos, 2016), it has notable limitations. These include difficulties in handling large expert groups, analyzing heterogeneous information, and addressing incomplete or dynamic risk assessments, which are caused by variations in expert opinions, inconsistent data availability, and the evolving nature of DT projects (Samira et al., 2015). Various methods have been proposed to enhance FMEA's effectiveness. For example, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) has been integrated to improve decision support by providing a clearer ranking of risks (Braglia et al., 2003). Hybrid methods like FMEA-CODAS address the equal weighting issue of S, O, and D, where each risk component is often given equal importance despite their differing impacts (Almeraz-Durán et al., 2021). Other approaches, such as the Choquet integral, account for

mutual risk influences (Zhang et al., 2021), and methods like Personalized Linguistic Preference Relations (PLPRs) and Group Linguistic Decision Systems (GLDS) consider group and individual risk attitudes (Liu et al., 2018b).

These advancements have improved the precision and reliability of FMEA models, but the broad range of expert domains and varying expertise levels in construction enterprises pose challenges for aggregating expert opinions consistently (Takva et al., 2023). The rigid scoring system in conventional FMEA, which uses integers between 1 and 10, may also lead to oversimplification or inaccuracies in expert assessments (Gölcük, 2020). To address this, methods such as fuzzy numbers and interval numbers have been introduced to incorporate uncertainty into the analysis of the problem (Li et al., 2020; Song et al., 2014). Additionally, the MABAC method has been employed to determine priority rankings by calculating the distance between each risk and an ideal point, categorizing risks into upper, middle, and lower zones, which indicate different levels of severity (Pfnür & Wagner, 2020). The definitions of these zones are context-dependent, requiring careful calibration to reflect the specific characteristics of the assessed project. Similarly, GRA is utilized for handling incomplete data and evaluating the correlation between various risk factors, such as technological challenges, organizational readiness, and market conditions (Hashemi et al., 2015). This method calculates the geometric proximity between sequences, which refers to the similarity or closeness of different data series based on their shape and trend over time. In the context of risk assessment, this approach helps identify which risk factors exhibit similar patterns of change or influence, enabling a more comprehensive understanding of their interrelationships (Liu et al., 2011).

While existing improved FMEA models offer some advancements, their applicability to

the challenges of DT in construction enterprises remains uncertain. This highlights the need for further development of risk assessment models that are specifically designed to address these challenges in this field.

2.3 Fundamental definitions

Risk evaluation in DT projects is inherently uncertain, as emerging technologies and digital ecosystems introduce a high degree of unpredictability. Traditional FMEA methods struggle to accommodate the subjectivity, hesitation, and inconsistency in expert judgments, which are particularly prevalent in DT-related risk assessments. To address this issue, this section introduces mathematical approaches used in our novel model, which provide a more flexible and robust framework for quantifying expert opinions under uncertainty.

Intuitionistic fuzzy numbers (IFNs) (Atanassov, 1999b) and interval-valued intuitionistic fuzzy set (IVIFS) (Atanassov, 1999a) are introduced in formulating the improved model to capture the uncertainty in failure assessment. They are defined respectively as:

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle | x \in X\} \quad (1)$$

where μ_A: X → [0,1] means the membership degree and ν_A: X → [0,1] means the non-membership degree of the element $x \in X$ to A, respectively, with the condition that for all $x \in X$,

$$\tilde{A} = \{\langle x, \tilde{\mu}_{\tilde{A}}(x), \tilde{\nu}_{\tilde{A}}(x)\rangle | x \in X\} \quad (2)$$

where $\tilde{\mu}_{\tilde{A}} = [\mu_A^L(x), \mu_A^R(x)] \subseteq [0,1]$ and $\tilde{\nu}_{\tilde{A}} = [\nu_A^L(x), \nu_A^R(x)] \subseteq [0,1]$ are intervals denoting the membership and non-membership degrees of the element $x \in X$ to $\tilde{A}$, respectively, with the condition $\mu_A^R(x) + \nu_A^R(x) \leq 1$ for all $x \in X$.Due to the uncertainty and vagueness of subjective judgments, IVIFNs are introduced to transform the assessment language, thereby more effectively handling the imprecise and ambiguous information during the evaluation process. Let $\alpha_i = ([\underline{\mu}_{\alpha_i}, \bar{\mu}_{\alpha_i}], [\underline{\nu}_{\alpha_i}, \bar{\nu}_{\alpha_i}]), (i = 1,2)$ be IVIFNs, and α also be

an IVIFN.

The scoring function of IVIFNs is expressed as:

$$S(\alpha) = \frac{1}{2}(\underline{\mu}_\alpha + \bar{\mu}_\alpha - \underline{\nu}_\alpha - \bar{\nu}_\alpha) \quad (3)$$

The precise function of IVIFNs is expressed as:

$$H(\alpha) = \frac{1}{2}\left(\underline{\mu}_\alpha + \bar{\mu}_\alpha + \underline{\nu}_\alpha + \bar{\nu}_\alpha\right) \quad (4)$$

The interval intuitionistic fuzzy distance between IVIFNs α_1 and α_2 is determined by:

$$\begin{aligned} & d_{\mathrm{IVIFD}}(\alpha_1, \alpha_2) \\ & = |\alpha_1 - \alpha_2| \\ & = \frac{1}{2}\sqrt{\left((\underline{\mu}_{\alpha_1} - \underline{\mu}_{\alpha_2})^2 + (\bar{\mu}_{\alpha_1} - \bar{\mu}_{\alpha_2})^2 + (\underline{\nu}_{\alpha_1} - \underline{\nu}_{\alpha_2})^2 + (\bar{\nu}_{\alpha_1} - \bar{\nu}_{\alpha_2})^2\right)} \end{aligned} \quad (5)$$

The Interval-valued Intuitionistic Fuzzy Weighted Average (IVIFWA) operator is introduced to aggregate all individual risk assessment matrices into the collective risk assessment matrix. It is defined as follows (Chen et al., 2012):

$$\begin{aligned} & \mathrm{IVIFWA}(\alpha_1, \alpha_2, \cdots, \alpha_n) \\ & = \Sigma_{i=1}^{n} \omega_i \alpha_i \\ & = \left(\left[1 - \prod_{i=1}^{n}\left(1 - \underline{\mu}_{\alpha_i}\right)^{\omega_i}, 1 - \prod_{i=1}^{n}\left(1 - \bar{\mu}_{\alpha_i}\right)^{\omega_i}\right], \left[\prod_{i=1}^{n}\left(\underline{\nu}_{\alpha_i}\right)^{\omega_i}, \prod_{i=1}^{n}\left(\bar{\nu}_{\alpha_i}\right)^{\omega_i}\right]\right) \end{aligned} \quad (6)$$

where $\omega_i \in [0,1]$, $\sum_{i=1}^{n} \omega_i = 1$, $\omega = (\omega_1, \omega_2, \cdots, \omega_n)^T$ is the corresponding weight vector for α_i $(i = 1,2,\cdots,n)$.

Entropy conveys the inherent strength of information to decision-makers. Cross-entropy works by minimizing the difference between the true distribution and the predicted distribution. Let $\tilde{A}^{(k)} = \left[\left(\left[a_i^{(k)}, b_i^{(k)}\right], \left[c_i^{(k)}, d_i^{(k)}\right]\right)\right]_{m\times n}$ $(i = 1,2)$ be two IVIFNs on a non-empty set $X = \{x_1, x_2, \cdots, x_n\}$. The cross-entropy $P\left(\tilde{A}^{(1)}, \tilde{A}^{(2)}\right)$ between $\tilde{A}_1$ and $\tilde{A}_2$ is defined as follows (De Boer et al., 2005):

$$P\left(\tilde{A}^{(1)},\tilde{A}^{(2)}\right)=\sum_{n=1}^{n}\left(\frac{y^{(1)}+2}{4}ln\frac{2(y^{(1)}+2)}{y^{(1)}+2+y^{(2)}+2}+\frac{-y^{(1)}+2}{4}ln\frac{2(-y^{(1)}+2)}{-y^{(1)}+2-y^{(2)}+2}\right) \quad (7)$$

where $y^{(1)}=a_i^{(1)}+b_i^{(1)}-c_i^{(1)}-d_i^{(1)}$and $y^{(2)}=a_i^{(2)}+b_i^{(2)}-c_i^{(2)}-d_i^{(2)}$.

A sorting vector allows for sorting operations without altering the original data. Let $a=[\underline{a},\bar{a}]$ and $b=[\underline{b},\bar{b}]$ be interval numbers with lengths $L(a)=\bar{a}-\underline{a}$ and $L(b)=\bar{b}-\underline{b}$, respectively. The possibility degree that $a\geq b$ is denoted as:

$$p(a\geq b)=max\left(1-max\left(\frac{b^{+}-a^{-}}{L(a)+L(b)},0\right),0\right) \quad (8)$$

Given a set of interval numbers $a_i=[\underline{a}_i,\bar{a}_i]$, the corresponding possibility degree sorting matrix $P=(P_{ij})_{n\times n}$ is constructed, where $P_{ij}=p(a_i\geq a_j)$. The interval numbers are sorted based on the values of sorting vector (Li et al., 2020), which is represented by:

$$\omega_i=\frac{\sum_{j=1}^{n}P_{ij}+\frac{n}{2}-1}{n(n-1)} \quad (9)$$

The spectral norm of matrix $A\in\mathbb{R}^{m\times n}$ is denoted as (Ishizaka et al., 2021):

$$\|A\|_2=\sqrt{\lambda_{max}(A^TA)} \quad (10)$$

where $A^T$is the transpose of matrix A, $\lambda_{max}(\mathrm{AA}^T)$is the largest eigenvalue of the matrix A^TA.

In summary, the limitations of conventional FMEA methods in DT projects highlight the need for an improved risk assessment framework that effectively captures uncertainty and expert judgment variations. The proposed model integrates MABAC and GRA to enhance the prioritization and evaluation of risks in DT projects. MABAC enables a comprehensive multi-criteria decision-making process, ensuring that risk factors are assessed holistically rather than in isolation. GRA strengthens this analysis by capturing interdependencies between risk factors, which is crucial for understanding cascading risks in networked digital environments. Furthermore, IVIFNs improve uncertainty handling by allowing experts to express both confidence and hesitation in their assessments, accommodating the ambiguity and evolving

nature of DT risks. By integrating these methodological enhancements, the proposed approach provides a more precise and resilient framework for managing risks in DT projects. It offers decision-makers a structured, mathematically robust, and adaptive tool to navigate the uncertainties inherent in digital transformation initiatives.

3 The proposed methodology

3.1. Research design

This paper introduces a novel FMEA approach based on MABAC and GRA for assessing the risk levels of failure modes. This method integrates expert judgments with objective analysis, enhancing the reliability of risk assessments by reducing subjectivity and aligning weights with the structural characteristics of the data.

First, the method transforms the heterogeneous expert evaluation data into IVIFNs to construct a risk assessment matrix for potential failure modes. Next, matrix norms are applied to determine the objective weights of experts, addressing the shortcomings of traditional methods in considering the positional characteristics of evaluation data. These objective weights are then combined with subjective weights to create a weighted risk assessment matrix. Using this weighted matrix, the distances and grey relational degrees between the sample data and boundary approximation area vectors are calculated. Finally, a segmented function integrates MABAC and GRA, allowing for the computation of distance interval numbers for each risk factor. This process corrects the heterogeneity of evaluation information and the fuzziness caused by hesitation in decision-making. The risk ranking is then performed using a possibility-based sorting method. Figure 1 provides a flowchart of the proposed approach.

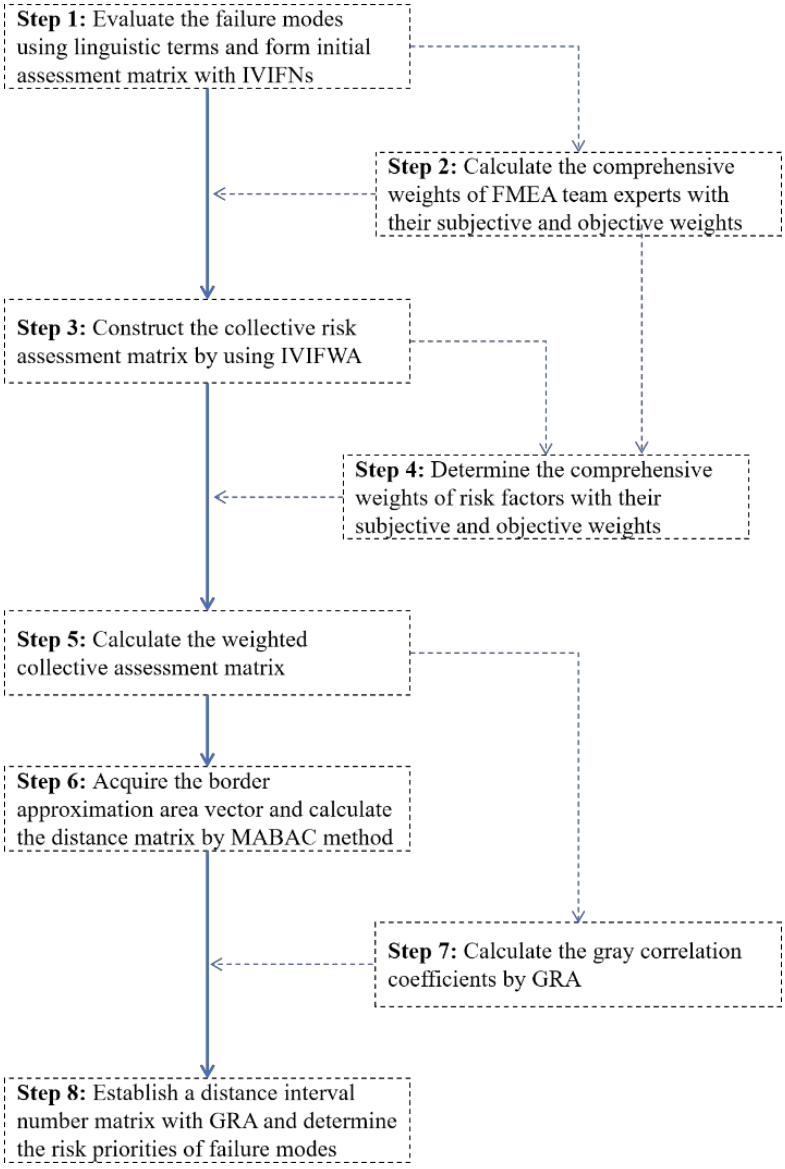


Fig. 1. Flowchart of the proposed approach

3.2 FMEA application enhanced with MABAC and GRA

Step 1. Form an initial assessment matrix

A team of FMEA experts is assembled to assess the primary failure modes in the DT process of construction enterprises, focusing on the risk factors S, O, and D. Linguistic Terms are used in the expert evaluations. These terms were then converted into IVIFNs to generate the fuzzy evaluation matrix, as outlined in Table 1.

Table 1.
Commonly used terms for risk assessment factors and their corresponding IVIFNs

Linguistic Terms	IVIFNs
Extremely Low (EL)	([0.10,0.10],[0.90,0.90])
Very Low (VL)	([0.15,0.20],[0.60,0.75])
Low (L)	([0.25,0.35],[0.50,0.60])
Moderately Low (ML)	([0.35,0.45],[0.40,0.55])
Medium (M)	([0.50,0.50],[0.50,0.50])
Moderately High (MH)	([0.45,0.60],[0.15,0.25])
High (H)	([0.60,0.75],[0.10,0.20])
Very High (VH)	([0.75,0.85],[0.05,0.15])
Extremely High (EH)	([0.90,0.90],[0.10,0.10])
Exceptionally High (EXH)	([0.99,0.99],[0.01,0.01])

Step 2. Calculate the weights of experts

According to previous research (Yue, 2012; Zhang & Xu, 2015), assuming the subjective weights of the FMEA experts are $\hat{\lambda}^{(k)}(k = 1,2,\cdots,l)$. Let the evaluation matrices of FMEA experts be:

$$X^{(k)} = \left[x_{ij}^{(k)}\right]_{m\times n} = \left[\left(\left[a_{ij}^{(k)}, b_{ij}^{(k)}\right], \left[c_{ij}^{(k)}, d_{ij}^{(k)}\right]\right)\right]_{m\times n} \tag{11}$$

where $i = 1,2,\cdots,m$, $j = 1,2,\cdots,n$ and $k = 1,2,\cdots,l$.

The elements of $Y^{(k)}$ are defined as the traditional matrix of real numbers, where each element corresponds to the elements of the original IVIFNs matrix $X^{(k)}$:

$$Y^{(k)} = \left[y_{ij}^{(k)}\right]_{m\times 4n} = \begin{bmatrix} a_{11}^{(k)} & b_{11}^{(k)} & c_{11}^{(k)} & d_{11}^{(k)} & \cdots & a_{1n}^{(k)} & b_{1n}^{(k)} & c_{1n}^{(k)} & d_{1n}^{(k)} \\ a_{21}^{(k)} & b_{21}^{(k)} & c_{21}^{(k)} & d_{21}^{(k)} & \cdots & a_{2n}^{(k)} & b_{2n}^{(k)} & c_{2n}^{(k)} & d_{2n}^{(k)} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ a_{m1}^{(k)} & b_{m1}^{(k)} & c_{m1}^{(k)} & d_{m1}^{(k)} & \cdots & a_{mn}^{(k)} & b_{mn}^{(k)} & c_{mn}^{(k)} & d_{mn}^{(k)} \end{bmatrix}_{m\times 4n} \tag{12}$$

where $i = 1,2,\cdots,m$, $j = 1,2,\cdots,n$ and $k = 1,2,\cdots,l$.

When determining the objective weights for experts, the norm of the matrix difference is calculated separately:

$$z^{(k)} = \|Y^{(k)} - \bar{Y}\|_2, \ k = 1,2,\cdots,l \tag{13}$$

where $\bar{Y}$ is the average matrix.

The resulting matrix $z^{(k)}$ is normalized to $\bar{z}^{(k)} = z^{(k)} / \sum_{k=1}^{l} z^{(k)}$. Consequently, the objective weights for the l experts are assigned as follows:

$$\tilde{\lambda}^{(k)} = \frac{1-\bar{z}^{(k)}}{\sum_{k=1}^{l}(1-\bar{z}^{(k)})},\ k = 1,2,\cdots,l \tag{14}$$

To ensure both subjective and objective factors contribute proportionally to the final expert weight, we adopt a multiplicative fusion method with normalization rather than a simple weighted sum. The final weight is calculated as (Chunyou et al., 2017):

$$\lambda^{(k)} = \frac{\hat{\lambda}^{(k)}\tilde{\lambda}^{(k)}}{\sum_{k=1}^{l}\hat{\lambda}^{(k)}\tilde{\lambda}^{(k)}},\ k = 1,2,\cdots,l \tag{15}$$

Step 3. Construct the collective assessment matrix

Using the IVIFWA operator, the evaluation opinions of FMEA experts are aggregated to obtain the collective risk assessment matrix. The opinions of each expert are aggregated to form the collective assessment matrix $[\alpha_{ij}]_{m\times n}$:

$$\begin{aligned}
&\alpha_{ij} = \left([a_{ij}, b_{ij}], [c_{ij}, d_{ij}]\right) \\
&= \mathrm{IVIFWA}\left(x_{ij}^{(1)}, x_{ij}^{(2)}, \cdots, x_{ij}^{(l)}\right) \\
&= \sum_{k=1}^{l} \lambda_k\, x_{ij}^{(k)} \\
&= \left(\left[1 - \prod_{k=1}^{l}\left(1 - a_{ij}^{(k)}\right)^{\lambda_k}, 1 - \prod_{k=1}^{l}\left(1 - b_{ij}^{(k)}\right)^{\lambda_k}\right], \left[\prod_{k=1}^{l}\left(c_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(d_{ij}^{(k)}\right)^{\lambda_k}\right]\right)
\end{aligned} \tag{16}$$

where $\alpha_{ij} = ([\underline{\mu}_{ij}, \bar{\mu}_{ij}], [\underline{\nu}_{ij}, \bar{\nu}_{ij}]),\ i = 1,2,\cdots,m,\ \ j = 1,2,\cdots,n,\ \ k = 1,2,\cdots,l$ represents the collective assessment results of l experts on the failure mode FM_i concerning the risk factor RF_j.

Step 4. Determine the wights of risk factors

Assuming there are l experts evaluating the weights of n risk factors, the evaluation value of the k-th expert for the weight of the j-th risk factor is denoted as $c_j^{(k)}$. The subjective weight vector for risk factors is:

$$c_j = \sum_{k=1}^{l} \lambda^{(k)} c_j^{(k)} \tag{17}$$

where $\sum_{j=1}^{n} c_j^{(k)} = 1,\ k = 1,2,\cdots,l.$

For a risk factor RF_j $(j = 1,2,\cdots,n)$, the deviation in the symmetrical form of failure mode FM_i $(i = 1,2,\cdots,m)$ concerning other failure modes is defined as (Liu et al., 2019):

$$D_{ij} = \sum_{g=1}^{m} P^*(\tilde{x}_{ij}, \tilde{x}_{gj}) = \frac{1}{2}\sum_{g=1}^{m}\left(P(\tilde{x}_{ij}, \tilde{x}_{gj}) + P(\tilde{x}_{gj}, \tilde{x}_{ij})\right) \tag{18}$$

For the risk factor RF_j, the overall deviation of all failure modes concerning other failure modes is given by:

$$\begin{aligned} D_j &= \frac{1}{2}\sum_{i=1}^{m}\sum_{g=1}^{m}\left(P(\tilde{x}_{ij}, \tilde{x}_{gj}) + P(\tilde{x}_{gj}, \tilde{x}_{ij})\right) \\ &= \sum_{i=1}^{m}\sum_{g=1}^{m} P\left(\tilde{x}_{ij}, \tilde{x}_{gj}\right) = \sum_{i=1}^{m}\sum_{g=1}^{m} P\left(\tilde{x}_{gj}, \tilde{x}_{ij}\right) \end{aligned} \tag{19}$$

Assuming the objective weight for the j-th risk factor is denoted as v_j, the objective weight vector for risk factors is given by:

$$v_j = \frac{1 - D_j}{\sum_{j=1}^{n}(1 - D_j)},\quad j = 1,2,\cdots,n \tag{20}$$

This paper adopts a method of multiplicative synthesis to combine subjective weights and objective weights, namely the weight vector:

$$w_j = \frac{c_j v_j}{\sum_{j=1}^{n} c_j v_j},\quad j = 1,2,\cdots,n \tag{21}$$

Step 5. Calculate the weighted collective risk assessment matrix

Based on Step 4, and considering the evaluation information from expert weights, further calculate the weighted collective risk assessment matrix:

$$\begin{aligned} r_{ij} &= \left([\hat{a}_{ij}, \hat{b}_{ij}], [\hat{c}_{ij}, \hat{d}_{ij}]\right) \\ &= \sum_{j=1}^{n} w_j\, \alpha_{ij} \\ &= \left(\left[1 - \prod_{j=1}^{n}(1 - a_{ij})^{w_j}, 1 - \prod_{j=1}^{n}(1 - b_{ij})^{w_j}\right], \left[\prod_{j=1}^{n}(c_{ij})^{w_j}, \prod_{j=1}^{n}(d_{ij})^{w_j},\right]\right) \end{aligned} \tag{22}$$

where $i = 1,2,\cdots,m,\ j = 1,2,\cdots,n,$ w_j represents the weights for risk factors S, O, and D.

Step 6. Calculate the BBA and distance matrix

Based on the operational definition of IVIFNs, BAA vector is calculated as:

$$g_j = \prod_{i=1}^{m}(r_{ij})^{1/m}$$
$$= \left(\left[\prod_{i=1}^{m}\hat{a}_{ij}^{1/m}, \prod_{i=1}^{m}\hat{b}_{ij}^{1/m}\right], \left[1-\prod_{i=1}^{m}(1-\hat{c}_{ij})^{1/m}, 1-\prod_{i=1}^{m}(1-\hat{d}_{ij})^{1/m}\right]\right) \quad (23)$$

where $j = 1,2,\cdots,n$.

Based on the definition of the Euclidean distance operator, the distance matrix is determined as:

$$d_{ij} = \begin{cases} d(r_{ij}, g_j), & if\ r_{ij} \geq g_j \\ -d(r_{ij}, g_j), & if\ r_{ij} < g_j \end{cases} \quad (24)$$

where $i = 1,2,\cdots,m,\ j = 1,2,\cdots,n$.

Step 7. Calculate the grey correlation coefficients

Based on the weighted risk assessment matrix, the grey correlation coefficient ρ_{ij} is calculated:

$$\rho_{ij} = \frac{\min\limits_{1\leq j\leq n}\min\limits_{1\leq i\leq m}\left(d(r_{ij},g_j)\right)+\xi\max\limits_{1\leq j\leq n}\max\limits_{1\leq i\leq m}\left(d(r_{ij},g_j)\right)}{d(r_{ij},g_j)+\xi\max\limits_{1\leq j\leq n}\max\limits_{1\leq i\leq m}\left(d(r_{ij},g_j)\right)} \quad (25)$$

In this study, ξ is determined as 0.5 (Hashemi et al., 2015). Based on previous relationship of d_{ij} and MABAC method, the grey relational matrix with compatibility can be defined as follows in the definition of grey correlation coefficient:

$$\rho'_{ij} = \begin{cases} \rho_{ij}, & if\ \ r_{ij} \geq g_j \\ -\rho_{ij}, & if\ \ r_{ij} < g_j \end{cases} \quad (26)$$

where $i = 1,2,\cdots,m,\ j = 1,2,\cdots,n$.

Step 8. Determine the risk priorities by a distance interval number matrix with GRA

The entry d_{ij} of the distance matrix and the entry ρ'_{ij} of the grey relational matrix are normalized separately:

$$\hat{d}_{ij} = d_{ij}/\sqrt{\sum_{i=1}^{m} |d_{ij}|}, \quad j = 1,2,\cdots,n \tag{27}$$

$$\hat{\rho}'_{ij} = \rho'_{ij}/\sqrt{\sum_{i=1}^{m} |\rho'_{ij}|}, \quad j = 1,2,\cdots,n \tag{28}$$

The following distance interval number operator definition method is adopted to establish a distance interval number matrix with GRA:

$$\tilde{d}_{ij} = \left[min\left(\hat{d}_{ij}, \hat{\rho}_{ij'}\right), max\left(\hat{d}_{ij}, \hat{\rho}_{ij'}\right)\right] \tag{29}$$

According to the possibility degree sorting method, the risk priority ranking of failure modes is obtained by arranging the distance interval numbers in descending order.

4 An illustrative case

Ethical approval for this study was granted by the Ethics Committee of Tongji University on December 18, 2023. The study was conducted from January to February 2024, involving five experts (four males and one female). The experts assessed twenty-three failure modes using Linguistic Terms to evaluate risk factors S, O, and D. The collected data were then analyzed using the proposed enhanced FMEA model.

Besides, the application of the model is based on the following key assumptions:

- Availability of expert assessments: Sufficient and reliable expert evaluations are available for risk assessment.
- Applicability of FMEA to DT projects: FMEA remains a relevant framework for evaluating risks in DT environments.
- Static nature of risk evaluation: Risk evaluations are conducted at a specific point in time, without accounting for evolving risk conditions.
- Quantifiable risk relationships: Risk factors can be numerically assessed and prioritized.

4.1 Risk assessment process and key results

This section presents a case study demonstrating the proposed approach, focusing on the risk assessment of a DT project within a large Fortune Global 500 construction enterprise in China. The company, a leader in the Chinese construction industry, operates across various fields, including architectural design, urban planning, and public works. Committed to industry-leading DT, the company has launched a project that integrates information technology with factory production, embedding digital development throughout its entire industry chain.

Table 2.
Experts' profiles

Expert	Position	Expertise	Years of experience
1	Deputy director of construction management department of a municipal government	Construction regulations formulation, Construction project audit, Urban digital twin	13
2	Structural design team leader of a top design institute	Construction project design, Design optimization, Intelligent design	9
3	Senior consultant of an engineering consulting firm	Digital transformation consulting	7
4	Project manager of a key real estate company	Construction project management, Project optimization, Intelligent construction	11
5	Professor at a top civil engineering school	Architectural structural disaster prevention, Structural performance evaluation, Digital technology in construction	23

Given the construction industry's numerous subsectors, five experts, each with over five years of experience in DT, were selected from five sub-industries: consulting, design, regulation, construction, and research. These experts formed the evaluation team for this assessment, with their profiles detailed in Table 2. Before the evaluation, all experts received comprehensive information about the project to ensure they were well-informed. As per Duan et al. (2019) and

Liu et al. (2018a), the expert panel members considered is acceptable.

Drawing from literature and expert advice, the failure modes (FM_i) and their effects on the DT project in the construction enterprise were identified. Using the Technology–Organization–Environment (TOE) framework and expert feedback, these FM_i were categorized into five areas: Resources, Technology, Organization, Environment and Industry chain. Table 3 details each FM_i and the corresponding source literature. This study focuses exclusively on the failure modes and effects relevant to the implementation of the DT project, excluding risks from other processes.

Table 3.
Failure modes and effect of DT in construction enterprise

FM_i	**Failure Mode and Effect**	**Category**	**Reference**
FM_1	Limited fund in construction enterprises lead to slow progress in DT projects	Resource	(Kargas et al., 2023; Li et al., 2018)
FM_2	Difficulty in obtaining external funds may cause DT projects to be suspended		(Kargas et al., 2023; S. Liu et al., 2023; Zhu & Yan, 2022)
FM_3	Excessive investment in DT projects leads to a shortage of funds for other critical businesses		(S. Liu et al., 2023; Oludapo et al., 2024)
FM_4	Lack of DT leaders results in a lack of direction and strategic guidance		(Oludapo et al., 2024; Syed et al., 2023)
FM_5	Employees lack knowledge of DT, leading to frequent errors during implementation		(Kargas et al., 2023; Syed et al., 2023)
FM_6	Lack of compatible hardware and software systems increases the pressure and workload on internal R&D personnel	Technology	(Cheng & Teizer, 2013; Li et al., 2018; Linderoth et al., 2018; Zhu & Yan, 2022)
FM_7	Inconsistent data standards lead to discontinuity in business processes		(Cheng & Teizer, 2013; Li et al., 2018; Pfnür & Wagner, 2020)
FM_8	Complex data types affect the enterprise's data analysis capabilities		(Koscheyev et al., 2019; Sun et al., 2021; Zhu & Yan, 2022)

FM_9	Insufficient data asset sorting results in inadequate support for business decisions		(Gangwar, 2018; Linderoth et al., 2018; Zhu & Yan, 2022)
FM_{10}	Lack of a company-wide strategic system causes DT projects to lack comprehensive planning and consistency		(Kargas et al., 2023; Papavasiliou et al., 2024)
FM_{11}	Lack of coordination mechanisms with existing businesses leads to conflicts between new and existing businesses		(Oludapo et al., 2024; Papavasiliou et al., 2024)
FM_{12}	Lack of information transmission mechanisms forms "data silos," resulting in low collaboration efficiency	Organization	(Ghafoori et al., 2024; Oludapo et al., 2024; Saihi et al., 2023)
FM_{13}	Absence of learning and training mechanisms reduces the digital productivity of the enterprise		(Shang et al., 2024; Syed et al., 2023)
FM_{14}	Lack of performance evaluation mechanisms causes employees to pay less attention to DT projects		(Narbariya et al., 2022; Syed et al., 2023)
FM_{15}	Inconsistencies between management and employee goals lead to low execution efficiency		(Christodoulou et al., 2022; Kargas et al., 2023; Saihi et al., 2023)
FM_{16}	Lack of vigilance towards changes in the industry environment weakens market adaptability		(Ghafoori et al., 2024; Papavasiliou et al., 2024)
FM_{17}	Employees' lack of recognition of DT leads to low motivation and participation		(Papavasiliou et al., 2024; Saihi et al., 2023)
FM_{18}	The enterprise lacks an innovative atmosphere, resulting in a scarcity of employee innovations	Environment	(Escoz Barragan et al., 2024; Kargas et al., 2023)
FM_{19}	Absence of an innovation reward culture leads to insufficient employee innovation motivation		(Kiefer et al., 2021; Papavasiliou et al., 2024)
FM_{20}	Lack of strong DT consulting services causes the enterprise to have cognitive biases about projects		(Bode et al., 2022; Bode et al., 2021)
FM_{21}	Lack of control over cloud platforms and other third-party services increases the risk of data leakage	Industry Chain	(Cheng & Teizer, 2013; Forcael et al., 2020; Li et al., 2018; Yee-Loong Chong & Ooi, 2008)
FM_{22}	Lack of cooperation in the industry		(Craveiro et al., 2019; H.

	chain hinders the realization of comprehensive digital solutions for the enterprise	Liu et al., 2023; Szalavetz, 2020)
FM_{23}	Lack of business cooperation with customers, suppliers, and competitors leads to strategic deviations in DT projects	(Li et al., 2022; Szalavetz, 2020)

Five experts initially assessed twenty-three failure modes using Linguistic Terms for risk factors S, O, and D, with detailed results available in Appendix A1. To finalize the semantic evaluations, subjective weights were assigned based on each expert's experience and expertise, resulting in weights of 0.25, 0.15, 0.1, 0.2, and 0.3 for Experts 1 to 5, respectively. Based on Step 2, the objective weights were determined as 0.2071, 0.2056, 0.2064, 0.2088, and 0.1722. These were combined with the subjective weights, yielding final expert weights of 0.2632, 0.1568, 0.1049, 0.2123, and 0.2627.

The entropy method was used to determine the objective weights of the risk factors, considering their inherent significance. The calculated objective weights for S, O, and D were 0.28467, 0.41982, and 0.29551, respectively. The final weights for S, O, and D were determined by combining these with the subjective weights as 0.3148, 0.3977, and 0.2875. Based on these, the aggregated failure mode evaluations were calculated, with the weighted assessment matrix available in Appendix A2. Additionally, the grey relational matrix (Appendix A3) was computed using $\xi = 0.5$ (Hashemi et al., 2015), which balances the impact of extreme values and ensures robust and reliable correlation analysis results. Considering the dominant nested loops and sorting steps, the overall time complexity of this case is $O(m * n * p + m \log m)$, where m is the number of failure modes, n is the number of criteria and p is the number of experts, in this case $m = 23$ *(failure modes)*, $n = 12$ *(criteria)*, $p = 5$ *(experts)*, which remains practical for real-world applications.

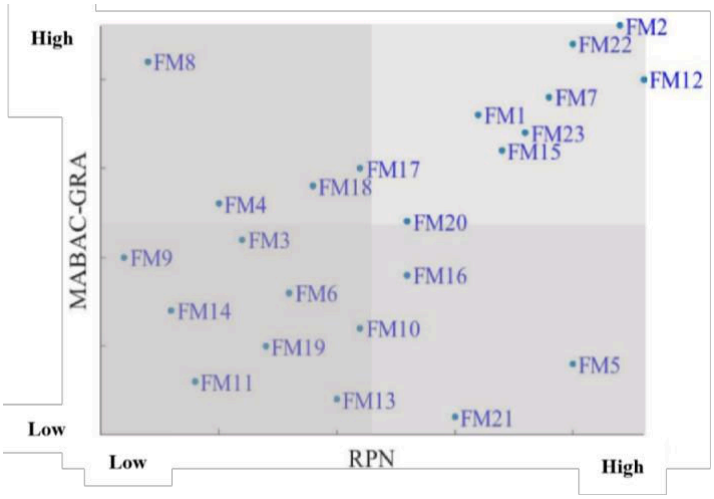
The comparative ranking results are shown in Table 4. To demonstrate the reliability of the proposed FMEA model, a comparison with existing failure ranking methods is necessary (Liu et al., 2017). Therefore, Table 4 presents the ranking results computed using the MABAC-GRA method alongside those from the conventional FMEA method (RPN) (Faghih-Roohi et al., 2020) , the IF-TOPSIS enhanced FMEA method (Liu et al., 2019), and one of the latest FMEA methods using evidential BWM and SMAA-MARCOS (Ju et al., 2024), enabling a comprehensive comparative analysis.

Table 4.
Ranking Results of Failure Modes Based on the Improved FMEA Model

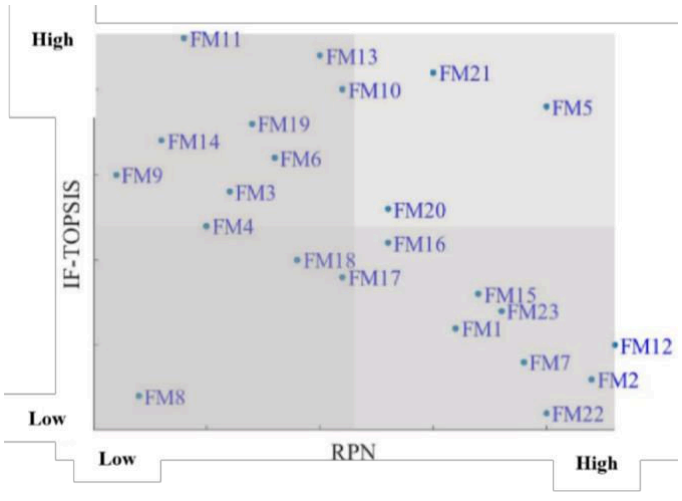
	S	O	D	RPN	IF-TOPSIS	MABAC-GRA	BWM-SMAA-MARCOS
FM1	8	3	8	8	18	6	23
FM2	6	7	8	2	21	1	21
FM3	1	7	9	18	10	13	15
FM4	3	3	6	19	12	11	20
FM5	8	7	5	3	5	20	12
FM6	2	6	9	16	9	16	13
FM7	10	4	6	5	20	5	5
FM8	1	9	3	22	22	3	4
FM9	1	4	4	23	7	14	2
FM10	8	2	8	12	4	18	3
FM11	4	6	2	20	1	21	6
FM12	6	9	8	1	19	4	8
FM13	7	3	6	14	2	22	14
FM14	3	6	2	21	8	17	22
FM15	6	4	9	7	16	8	9
FM16	8	3	6	10	13	15	17
FM17	8	4	4	12	15	9	11
FM18	2	7	8	15	14	10	10
FM19	7	3	5	17	6	19	19
FM20	8	9	2	10	11	12	16
FM21	3	8	7	9	3	23	18
FM22	7	8	5	3	23	2	1
FM23	8	7	4	6	17	7	7

4.2 Results and Discussion

Firstly, as shown in Table 4, the conventional RPN, IF-TOPSIS, the proposed MABAC-GRA methods, and BWM-SMAA-MARCOS methods, they produce different risk rankings for each failure mode (with 1 as the highest risk and 23 as the lowest). The Spearman rank correlation coefficients (Zar, 2005) among RPN and MABAC-GRA, RPN and IF-TOPSIS, and RPN and BWM-SMAA-MARCOS, are 0.399, -0.457, and 0.024 respectively, indicating that RPN and MABAC-GRA have more similar rankings compared to RPN and IF-TOPSIS, and PRN and BWM-SMAA-MARCOS.



a. Risk Scatter Plot between RPN and MABAC-GRA Methods



b. Risk Scatter Plot between RPN and IF-TOPSIS Methods

Fig. 2. Risk Scatter Plots for Different Evaluation Methods

Based on the final ranking results in Table 4, risk ranking scatter plots are shown in Fig. 2.

In both Fig. 2a and 2b, the horizontal axis represents the RPN ranking, where values increase to the right, indicating higher risk (1 = highest, 23 = lowest). The vertical axis in Fig. 2a and 2b represents the ranking results of the MABAC-GRA and IF-TOPSIS methods, respectively, with values increasing vertically to indicate higher risk (1 = highest, 23 = lowest).

Figure 2 shows that the MABAC-GRA method's rankings are positively correlated with those of the RPN method, while the IF-TOPSIS method shows a negative correlation with RPN. This suggests that MABAC-GRA aligns more closely with the basic FMEA model, providing more consistent and reliable rankings. In contrast, IF-TOPSIS introduces different considerations, leading to less alignment with RPN. This is consistent with the Spearman rank correlation results, indicating that IF-TOPSIS, as well as BWM-SMAA-MARCOS, may be less suitable for risk assessment in the DT of the construction sector. The variability in expert expertise contributes to differences in assessment criteria, leading to this disparity. The study introduces an objective weighting method to address this disparity issue and to more precisely determine expert importance, accounting for positional sensitivity in evaluation data. The integration of MABAC and GRA methods using a distance interval number operator further minimizes information loss during the transformation of diverse expert decision-making data. By effectively combining subjective and objective weights, the decision-making process is optimized. The results demonstrate that the proposed MABAC-GRA improved FMEA model is highly adaptable to the subjectivity challenges (Chakraborty et al., 2023; Silva et al., 2023) posed by diverse expert opinions in the risk assessment of DT projects in construction enterprises.

Secondly, according to the MABAC-GRA ranking results, the top five failure modes with

the highest risks in the enterprise's DT process are FM_2, FM_{22}, FM_8, FM_{12}, and FM_7. Except for FM_8, Figure 3a shows that the other four also rank high in the RPN, warranting specific analysis:

a) FM_2: DT in construction requires significant financial support for talent acquisition, hardware, and software. However, construction companies often face working capital issues and liquidity crises, (Mahmoudi et al., 2023) exacerbated by COVID-19 and industry pressures, particularly in countries like China (Deng et al., 2024; Liu et al., 2022). This makes securing external funding crucial. A construction firm's growth depends heavily on its ability to obtain capital for project investments (Paganin, 2021). Without adequate funding, tight cash flow not only jeopardizes ongoing projects but also threatens the company's financial stability. Thus, FM_2 is a critical risk in the DT of construction companies.

b) FM_{22}: The construction industry's interconnected nature, with its long industry chain—including consulting, exploration, design, construction, supervision, and operation—requires that DT aligns with industry characteristics. The chain involves multiple actors who interact dynamically and make decisions at various stages, which are crucial to the industry's overall functioning (Giorgi et al., 2020). However, these interactions are often fragmented and discontinuous, complicating DT efforts. Therefore, incorporating the entire construction industry chain into a DT project is vital (Leising et al., 2018). Projects that focus solely on individual enterprise needs, without integrating related businesses, risk becoming insular and limiting potential benefits. To fully leverage DT, fostering collaboration among all actors within the industry chain is essential. A lack of cooperation within the industry chain could significantly hinder the development of digital solutions

for the enterprise.

c) FM_7: The construction industry generates vast amounts of unstructured data, including drawings and models. Effectively storing and extracting value from this data according to unified standards poses significant challenges. When data from different sources lacks standardization, it becomes difficult to merge and analyze, leading to fragmented information. This fragmentation disrupts workflows, causing delays, errors, and inefficiencies, which in turn hinder continuous business operations and expose organizations to unacceptable risks (Sadiq et al., 2007).

d) FM_{12}: Like many projects in construction companies, DT involves multiple departments. The lack of robust communication mechanisms often leads to 'data silos,' which hinder business operations and data analysis across departments, systems, and units (Abdel-Aty & Negri, 2024). Unlike traditional projects, DT is data-driven and data-intensive. However, current data management in construction relies on traditional siloed approaches, with low digitalization, heterogeneous data sources, and poor data quality (Hernández et al., 2023). These issues exacerbate the data silo effect, impeding collaboration as teams struggle to access necessary data from other departments. This lack of access results in redundant efforts, miscommunication, and delays, posing significant risks to the DT project.

e) FM_8: In the construction industry, multiple stakeholders from different subsectors have distinct data needs, leading to significant data fragmentation (Hernández et al., 2023). Despite efforts to address this issue, the heterogeneous nature of building-related data continues to hinder integration (Koh et al., 2017). A universally accepted data treatment methodology has yet to be established across domains (Fan et al., 2021). This gap indicates

that current enterprise data analysis capabilities struggle to handle complex data types, posing a significant challenge to DT projects. Although this issue may appear less risky in the RPN ranking, the high risk identified through the MABAC-GRA model highlights the advantages of the improved assessment approach.

The risks associated with FM_{19}, FM_5, FM_{11}, FM_{13}, and FM_{21} are identified as the lowest, allowing the company to reduce focus on these specific risk factors. Notably, FM_{19}, FM_{11}, and FM_{13} also exhibited low risks in the RPN rankings, underscoring their minimal impact on operational concerns:

a) FM_5: Employee knowledge is crucial for effective change (Jones et al., 2005). A workforce skilled in digital technologies enhances their utilization at the firm level (Cetindamar et al., 2024). Thus, organizations must employ digitally skilled workers to maximize the benefits of their technology investments (Rocha et al., 2023). Job seekers often find large companies attractive due to their friendly and open access culture, teamwork, compensation, training and development (Marinakou, 2019). As a leading construction enterprise, the analyzed company benefits from this talent attraction effect, making the risk of a talent shortage minimal in its DT project. The MABAC-GRA model accurately reflects this reality, showing greater consistency with the actual situation.

b) FM_{21}: The construction industry has adopted cloud computing, like cloud-based BIM, and third-party software to support DT (Cabrera-Silva et al., 2021). Traditional design and management systems increasingly depend on third-party resources, such as cloud centers and edge nodes (Xu et al., 2022). A significant risk in this context is the unauthorized disclosure and data leakage of shared information (Bhargava et al., 2013). However, due

to strict contractual obligations and compliance with Chinese regulations, such as the "Cybersecurity Law" and the "Personal Information Protection Law," the risk of operational consequences from information leakage is minimal in DT projects in China, even when using third-party services.

c) FM_{11}, FM_{13} and FM_{19}: Effective coordination is essential for successful construction projects (Fauzi et al., 2023). A lack of coordination can lead to cost overruns, delays, unmet project requirements, and strained client relationships (Wang et al., 2018). Furthermore, the success of DT depends on employees' ability to effectively leverage new technologies (Cui et al., 2021; Rocha et al., 2023). Therefore, organizations investing in digital technologies must also invest in training their employees to maximize the benefits of these tools. Additionally, fostering an innovative culture that supports and rewards innovation is crucial for the performance of DT projects (Amabile et al., 2004; Sagbas et al., 2023). However, despite the importance of these factors, these three failure modes exhibit low risks according to both the RPN and proposed MABAC-GRA rankings. This may be because the company, a Fortune Global 500 leader in the construction industry, has already established mature institutional processes, robust training programs, and a strong corporate culture. These factors likely reduce the risks associated with coordination, employee training, and innovation, resulting in lower operational risks in these areas.

The proposed FMEA model outperforms the original RPN method in risk identification and ranking, offering more accurate and reliable results. Supported by literature and real-world evidence, this model's precision enhances decision-making and risk management in projects.

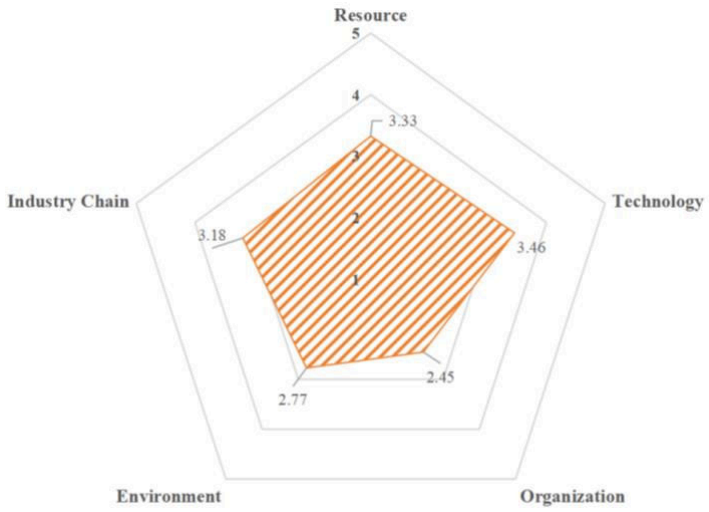


Fig. 3. Risk Assessment of Failure Mode Groups

Finally, according to Table 3, the 23 risk factors were grouped into five failure modes: Resources, Technology Organization, Environment and Industry Chain. After assigning ranks on a 1-5 scale, average ordinal values for each group were calculated, resulting in the risk assessment radar chart in Fig. 3. The chart rates risk from 1 (lowest) to 5 (highest), with intermediate values indicating varying risk levels.

The chart reveals that Technology carries the highest risk, while Organization has the lowest. This highlights the importance of focusing on digital technology in risk management for DT projects. Despite the use of digital platforms, construction companies often fall short of necessary digital technology standards, with inadequate technical support hindering development (Criado-Perez et al., 2022). Therefore, investment in technology is critical (Gu & London, 2010), alongside managing associated risks. The low risk in Organization reflects the company's mature management mechanisms, effectively mitigating organizational challenges.

5 Insights

From a theoretical perspective, this study advances FMEA model development and DT risk assessment literature in several ways. It introduces an enhanced FMEA model that

integrates MABAC and GRA methods, specifically tailored for assessing DT project risks in the construction industry. The illustrative case shows that this MABAC-GRA method assesses risks more accurately and reliably compared to the original FMEA's RPN method and the IF-TOPSIS method. This suggests that previous FMEA models may not be suitable for DT risk assessment in construction. The proposed model addresses weight ambiguity due to positional changes in matrix elements, improving the resolution of weights and resulting in more precise calculations of combined expert weights. Additionally, the combination of MABAC and GRA corrects evaluation information heterogeneity and the fuzzy distance caused by hesitation in human decision-making, providing substantial enhancements to FMEA and fuzzy number literature, and offering a robust framework for digital risk assessment theories.

Moreover, while previous literature discusses various risks in DT projects, this study confirms that insufficient funding is a significant risk for construction companies. However, not all risks from earlier studies are universally applicable; for example, large companies may not face a shortage of DT talent due to their ability to attract skilled workers. A successful DT strategy involves not just technology but also culture, management, and human resources (Ismail et al., 2017). Although extensively researched, the specific impact of technology on these projects has been less studied. (Tsiavos & Kitsios, 2021). This study highlights that technology plays a pivotal role, emerging as the most significant risk factor in the DT of the construction industry.

From a managerial perspective, this study provides valuable insights for project managers seeking to mitigate risks in DT projects within construction enterprises. The developed method could be integrated into software tools used by these enterprises to manage risks. Key actionable

recommendations include:

a) **Ensuring adequate fundings**: DT in the construction industry requires substantial capital, often constrained by low margins and limited financial flexibility. Adequate funding, especially for technology investments, is crucial for project success. Construction companies should accurately budget and develop advanced funding plans to avoid financial pitfalls.

b) **Developing data standards:** Unified data standards are essential for high data quality in DT projects. While industry-wide standards may be challenging to establish, construction companies should create internal standards, including data categorization methods, master data identification, and data architecture development. This will improve data organization and communication, enhancing project efficiency.

c) **Enhancing internal and external cooperation:** The construction industry often suffers from fragmentation and poor collaboration (Criado-Perez et al., 2022). To address this, companies can implement integrated communication platforms, form cross-functional teams, and develop feedback mechanisms. These strategies reduce data silos, improve collaborative efficiency, and increase the success rate of DT projects.

d) **Special notions:** The analyzed company, as a leader in the construction industry, has distinct advantages, such as resource acquisition, substantial financial investment, comprehensive institutional frameworks, and strong industry influence. In contrast, smaller or single-business construction companies may excel in areas like corporate culture, institutional flexibility, and collaboration speed. To achieve accurate risk assessments, these differences necessitate tailored evaluations and further analysis using the proposed

model. This approach ensures that risk assessments align with the unique challenges and strengths of each enterprise, enhancing the strategic value of the analysis. Moreover, the failure modes used in the case study focus specifically on DT risks, not other processes. If risk assessments are needed for other aspects of DT, new failure modes can be independently generated and ranked using the proposed method. Additionally, geographical factors do not limit the model's applicability; construction companies worldwide can adapt the model to assess and prioritize risks relevant to their context.

6 Conclusion and Research Directions

This study proposed an FMEA model integrating MABAC and GRA to prioritize failure mode risks, using a DT project in a construction enterprise as a case study. The model offers several key advantages:

(1) By employing IVIFNs, the model unifies heterogeneous information and accounts for the positional relationships in the risk factor evaluation matrix. This enhances the accuracy, objectivity, and reliability of expert weight calculations in practical applications.

(2) The model combines MABAC and GRA, overcoming GRA's limitations in analyzing correlations between identical factors across different evaluation sequences. This integration leverages the strengths of both methods.

(3) The introduction of distance interval number operators, coupled with a probability-based ranking method, allows the model to accommodate a wide range of decision-maker subjectivities and preference fluctuations. This approach minimizes information loss and considers evaluative tendencies and hesitations, improving the robustness of expert evaluations.

This study confirmed the reliability of the proposed FMEA model through a detailed case

analysis, offering management strategies to mitigate DT risks in the construction industry. The model identified the top five failure modes posing the highest risks: FM2 (difficulty in obtaining external funds), FM22 (lack of cooperation in the industry chain), FM8 (complex data types affecting analysis capabilities), FM12 (data silos reducing collaboration efficiency), and FM7 (inconsistent data standards disrupting business processes). To mitigate these risks, enterprises should closely monitor financial stability, ensuring sufficient cash flow and support during DT. Enhancing both external cooperation and internal communication is crucial to reducing strategic risks. Prioritizing the establishment of consistent data standards is also essential to avoid undermining digital efforts.

While the proposed approach enhances conventional FMEA for DT projects, it has several limitations. First, the model relies on expert input, which may introduce subjectivity and potential biases. Although IVIFNs help capture uncertainty in expert judgments, the selection of subjective expert weights could be improved through more systematic methodologies. Second, the model assumes a static risk evaluation framework, which does not explicitly account for the evolving nature of risks in DT projects. Future research could explore dynamic risk modeling techniques to enhance adaptability. Third, the computational complexity of the MABAC-GRA integration increases with larger datasets, potentially limiting scalability in real-time applications. Lastly, while this study focuses on DT risks, its application in traditional industries undergoing digital transformation requires further investigation to assess generalizability.

Future work could focus on enhancing the practical applicability and computational efficiency of the proposed model. One direction is to develop an Excel-based or web-based

decision-support platform, enabling practitioners to apply the model without extensive programming knowledge. Additionally, integrating machine learning techniques could optimize expert weight assignment, reducing subjectivity and improving risk evaluation accuracy. Another potential improvement is to incorporate dynamic risk modeling, utilizing Hidden Markov Models (HMMs), Bayesian updating, or reinforcement learning to adaptively adjust risk rankings over time. Finally, optimizing computational efficiency through parallel computing or heuristic-based techniques could enhance scalability for large-scale applications, making the model more suitable for real-time decision-making in complex digital transformation projects.

Code Availability Statement

The implementation of the proposed MABAC-GRA risk assessment model is publicly available at https://github.com/yxdong216/RiskAssessment4DT_Construction. This repository ensures transparency and facilitates reproducibility for further research and practical applications.

Appendix

A1. Linguistic assessment on failure modes by the FMEA team members

	S					O					D				
	TM1	TM2	TM3	TM4	TM5	TM1	TM2	TM3	TM4	TM5	TM1	TM2	TM3	TM4	TM5
FM1	H	VH	EXH	VH	L	H	VH	VH	MH	ML	EXH	VH	EL	EL	ML
FM2	VH	M	EXH	L	VH	VH	L	EXH	VH	VH	EXH	EH	EL	VL	ML
FM3	M	EXH	EXH	EXH	VH	ML	VH	VH	EL	VL	VH	EH	L	EL	VL
FM4	L	EH	EXH	VH	EH	ML	EH	EXH	ML	VH	ML	L	L	MH	H
FM5	H	EH	MH	H	VH	M	VH	EXH	L	VH	L	L	EL	MH	VH
FM6	ML	H	EXH	VH	H	M	MH	EXH	VH	H	M	EH	M	VL	ML
FM7	EH	EH	EXH	H	H	EH	L	EXH	VH	VH	EH	H	MH	L	L
FM8	EH	H	EH	H	VH	EH	EH	EXH	VH	VH	EH	EH	L	L	ML
FM9	EXH	H	VH	H	EH	EXH	EH	EXH	H	VH	ML	M	L	L	MH
FM10	EXH	VH	VH	H	EH	EXH	MH	EH	MH	VH	VL	MH	L	ML	H
FM11	H	EH	EXH	EH	EH	H	VH	VH	ML	ML	L	EH	L	VL	ML
FM12	MH	EH	EXH	MH	VH	EXH	EH	EXH	EH	ML	VL	EH	L	L	ML
FM13	M	VH	VH	MH	EH	MH	ML	EXH	ML	EH	M	VH	L	L	ML
FM14	EH	VH	VH	ML	H	EH	VH	EXH	H	M	ML	VL	L	L	M
FM15	M	VH	EXH	EH	VH	VH	VH	EXH	VH	VH	ML	VL	L	VH	VH
FM16	H	EH	EH	H	ML	EH	EH	EXH	VH	H	VL	L	M	VH	M
FM17	MH	EH	EH	EH	H	EXH	ML	EXH	MH	VH	M	L	L	M	ML
FM18	MH	EH	VH	EH	H	EXH	EH	EXH	MH	H	M	VL	L	L	M
FM19	M	EH	VH	ML	M	H	EH	VH	VH	H	M	VL	MH	VL	MH
FM20	MH	H	H	VH	VH	ML	EH	EH	MH	VH	H	VH	VL	VL	ML
FM21	M	VH	VH	EH	H	ML	MH	EH	MH	L	MH	L	L	ML	VH
FM22	EXH	EH	EH	VH	EH	VH	EH	EXH	M	H	ML	EH	EL	VL	M
FM23	EXH	EH	VH	H	VH	MH	H	VH	M	H	L	ML	M	ML	ML

A2. The weighted collect assessment matrix

	S	O	D
FM1	([0.4487,0.5016],[0.3976,0.4706])	([0.3311,0.4250],[0.4180,0.5721])	([0.5881,0.5944],[0.3924,0.4056])
FM2	([0.4771,0.5271],[0.3819,0.4711])	([0.4106,0.4565],[0.4575,0.5417])	([0.6262,0.6262],[0.3738,0.3738])
FM3	([0.3434,0.3740],[0.5656,0.6260])	([0.5855,0.6090],[0.3404,0.3889])	([0.3576,0.3836],[0.5685,0.6075])

FM4	([0.1571,0.2122],[0.6889,0.7826])	([0.4663,0.4964],[0.4466,0.4994])	([0.6313,0.6353],[0.3576,0.3625])
FM5	([0.1706,0.2371],[0.6498,0.7319])	([0.4129,0.4747],[0.4155,0.5209])	([0.4938,0.5058],[0.4588,0.4769])
FM6	([0.2420,0.2955],[0.6039,0.7045])	([0.3910,0.4661],[0.4070,0.4950])	([0.5294,0.5294],[0.4706,0.4706])
FM7	([0.4485,0.4793],[0.4625,0.5150])	([0.4073,0.4783],[0.4037,0.5010])	([0.5588,0.5693],[0.3999,0.4157])
FM8	([0.4485,0.4793],[0.4625,0.5150])	([0.4707,0.5325],[0.3615,0.4567])	([0.5611,0.5658],[0.4257,0.4316])
FM9	([0.4913,0.5249],[0.4160,0.4629])	([0.4085,0.4607],[0.4466,0.5268])	([0.2803,0.3378],[0.5384,0.6262])
FM10	([0.4687,0.4943],[0.4420,0.4821])	([0.3894,0.4708],[0.3725,0.4940])	([0.2028,0.2527],[0.6557,0.7365])
FM11	([0.2385,0.2953],[0.6071,0.6822])	([0.5130,0.5300],[0.4371,0.4700])	([0.3576,0.3836],[0.5685,0.6075])
FM12	([0.3287,0.3596],[0.5493,0.5986])	([0.5037,0.5260],[0.4308,0.4740])	([0.6313,0.6353],[0.3576,0.3625])
FM13	([0.1754,0.2056],[0.7173,0.7642])	([0.4759,0.5323],[0.3668,0.4677])	([0.4238,0.4516],[0.4947,0.5451])
FM14	([0.3196,0.3550],[0.5817,0.6355])	([0.2851,0.3599],[0.4995,0.6270])	([0.5296,0.5523],[0.4039,0.4450])
FM15	([0.2919,0.3364],[0.5792,0.6636])	([0.3453,0.4399],[0.3938,0.5563])	([0.6313,0.6353],[0.3576,0.3625])
FM16	([0.2616,0.3328],[0.5363,0.6444])	([0.3759,0.4152],[0.5162,0.5691])	([0.5743,0.5743],[0.4257,0.4257])
FM17	([0.3381,0.3689],[0.5449,0.5882])	([0.3708,0.4275],[0.4732,0.5599])	([0.5611,0.5658],[0.4257,0.4316])
FM18	([0.3381,0.3689],[0.5449,0.5882])	([0.3866,0.4311],[0.4826,0.5469])	([0.5296,0.5523],[0.4039,0.4450])
FM19	([0.2281,0.2716],[0.6464,0.7231])	([0.3780,0.4060],[0.5335,0.5790])	([0.4936,0.5317],[0.3871,0.4520])
FM20	([0.2196,0.3060],[0.5207,0.6351])	([0.4175,0.5123],[0.3362,0.4765])	([0.4726,0.4933],[0.4626,0.4958])
FM21	([0.2402,0.2795],[0.6157,0.6716])	([0.2454,0.3328],[0.5130,0.6355])	([0.4958,0.5201],[0.4330,0.4770])
FM22	([0.4389,0.4694],[0.4721,0.5306])	([0.5501,0.5676],[0.4002,0.4243])	([0.5550,0.5550],[0.4450,0.4450])
FM23	([0.4035,0.4301],[0.5160,0.5513])	([0.3863,0.4494],[0.4430,0.5353])	([0.4973,0.5237],[0.4240,0.4763])

A3. Grey Correlation Matrix（$\xi = 0.5$）

	S	O	D		S	O	D		S	O	D
FM1	0.9105	0.7446	0.8034	FM9	0.9311	0.7841	0.5866	FM17	0.7418	0.7466	0.7686
FM2	0.9387	0.7756	0.8428	FM10	0.8912	0.8123	0.5281	FM18	0.7418	0.7529	0.7583
FM3	0.7285	1.0000	0.6075	FM11	0.6628	0.8605	0.6075	FM19	0.6389	0.7213	0.7443
FM4	0.5957	0.8213	0.8579	FM12	0.7330	0.8574	0.8579	FM20	0.6894	0.8535	0.6997
FM5	0.6189	0.8008	0.7135	FM13	0.5958	0.8774	0.6606	FM21	0.6602	0.6639	0.7240
FM6	0.6593	0.8015	0.7268	FM14	0.7114	0.6841	0.7583	FM22	0.8421	0.9210	0.7543
FM7	0.8580	0.8101	0.7814	FM15	0.6943	0.7631	0.8579	FM23	0.7964	0.7725	0.7278
FM8	0.8580	0.8818	0.7686	FM16	0.7011	0.7305	0.7765				

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