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Research on Safety Resilience of Prefabricated Building Systems Based on Improved ISM-BN

Wei Liu [1,2,*] and Qing Ye [1,2,*]

[1] School of Civil Engineering and Architecture, East China Jiaotong University, Nanchang 330013, China
[2] Jiangxi Provincial Key Laboratory of Traffic Infrastructure Safety, East China Jiaotong University, Nanchang 330013, China
* Correspondence: liuwei@ecjtu.edu.cn (W.L.); 2024018085901077@ecjtu.edu.cn (Q.Y.)

Abstract

To reveal the influencing mechanism of safety resilience in prefabricated building systems (PBS), identify key risk nodes, and support targeted resilience enhancement, this study develops an improved ISM–BN analytical model. Based on 136 domestic safety accident cases involving prefabricated buildings (PB) from 2016 to 2025, and combined with bibliometric analysis, 13 causal factors were identified and an indicator system was established. Grey Relational Analysis (GRA) was introduced to improve the traditional Interpretive Structural Modeling (ISM) method, through which the causal factors were divided into four hierarchical levels and the hierarchical relationships among the factors and levels were clarified. Subsequently, the hierarchical structure derived from the improved ISM was mapped into a Bayesian Network (BN), and parameter learning was conducted using accident data. Through backward diagnosis and sensitivity analysis, five key risk nodes and two critical transmission paths were identified, based on which targeted improvement strategies were proposed. The results can provide methodological support and decision-making references for key risk control and resilience enhancement in PBS.

Keywords: prefabricated building; safety resilience; causative factors; risk transmission; improved ISM-BN

1. Introduction

The global construction industry is accelerating its transition toward greener, more industrialized, and more intelligent development. Prefabricated buildings (PB), characterized by standardized design, factory-based production, and assembly-oriented construction, are widely regarded as an important pathway for promoting the transformation and upgrading of the construction sector [1,2]. In general, PB refer to a type of building in which structural components are prefabricated in factories, transported to the construction site, and then assembled through processes such as hoisting, connection, and installation [3,4]. Compared with traditional cast-in-place buildings, they offer significant advantages in terms of resource conservation, construction efficiency, quality control, and green low-carbon development [5,6].

However, the rapid development of PB has not reduced the complexity of safety management [7]. On the contrary, their multi-stage, multi-actor, and multi-factor coupling characteristics impose higher demands on traditional safety management approaches [8,9]. Unlike conventional cast-in-place construction, the construction process of PB spans multiple stages, including design and development, component production, logistics and

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transportation, on-site hoisting, joint connection, and assembly construction. These stages are closely interconnected, and continuous coordination is required among multiple participants, such as design institutions, component manufacturers, transportation units, and construction contractors [10]. Once quality deviations, information mismatches, or organizational failures occur in any stage, risks may be transmitted and amplified along the system chain [11]. Therefore, the traditional safety management approach centered on risk identification and accident prevention alone is no longer sufficient to adequately explain or cope with the complex disturbances faced by prefabricated building systems (PBS).

Against this background, resilience theory provides a new analytical perspective for safety research on PB [12]. Resilience emphasizes a system's ability to maintain or reconstruct its critical functions through absorption, resistance, recovery, and adaptation when confronted with shocks, disturbances, and uncertainty [13]. Chen et al. [14] and Wang et al. [15] introduced resilience theory into PB research with promising results. Accordingly, this study incorporates the concept of resilience into the study of PB safety helps overcome the limitations of traditional risk management and enables a system-level understanding of how safety states are formed, weakened, and enhanced. In essence, the safety resilience of a PBS arises from the system's capability to respond to external shocks and internal disorder under the coupling effects of multiple interacting factors. Only by revealing the key factors affecting safety resilience and their internal relationships from a systems perspective can the evolutionary mechanism of safety problems in PB be more accurately understood, thereby providing theoretical support for shifting safety governance from passive control to proactive enhancement. Although safety resilience has gradually become an important perspective in construction safety research, its application in the field of PB remains relatively limited. Accordingly, this study focuses on PB as a typical type of construction system with complex-system characteristics and seeks to address the following core questions from a safety resilience perspective:

(1) What key causal factors constitute the safety resilience of the PBS, and what hierarchical structure exists among these factors?
(2) During the formation and evolution of safety resilience in the PBS, which factors play critical roles, and what are their transmission paths and underlying mechanisms?

Aiming to improve the safety resilience of the PBS, this study constructs a safety resilience measurement index system around the characteristics of multi-stage continuity, multi-actor coordination, and multi-factor coupling in the prefabricated construction process, and proposes an integrated analytical framework combining an improved Interpretive Structural Modeling (ISM) approach with a Bayesian Network (BN). Compared with existing studies on PB, which often rely on expert experience to construct inter-indicator relationships or focus mainly on static evaluation results, the main improvements of this study are twofold. First, 136 PB accident cases in China from 2016 to 2025, mainly involving prefabricated concrete buildings and steel prefabricated building, were collected and systematically organized as a self-compiled dataset to identify key causal factors. Grey Relational Analysis (GRA)and K-means clustering were then introduced to improve the traditional ISM method, thereby reducing subjectivity in determining factor relationships and revealing the hierarchical relationships and transmission structure among causal factors. Second, the hierarchical structure generated by the improved ISM was mapped into the BN. Through forward inference, posterior probability diagnosis, and sensitivity analysis, the safety resilience level of the system was quantitatively evaluated, and key risk nodes and transmission paths were identified. The study not only achieves a quantitative evaluation of the safety resilience level of the PBS, but also identifies the key causal factors and critical transmission paths that affect system resilience, thereby revealing the formation logic of system safety resilience and the mechanism of risk evolution. The findings can provide a scientific basis for safety governance, key risk prevention and control, and resilience enhancement strategies in PB projects, while also offering methodological support for safety resilience research on complex engineering systems.

2. Literature Review

2.1. Safety Management of PB

As an important approach to construction industrialization, PB offer advantages such as resource conservation, improved construction efficiency, and enhanced safety conditions for certain operations. However, PB differ substantially from traditional cast-in-place buildings in terms of construction organization, workspace conditions, component transportation and hoisting processes, and on-site assembly logic. Therefore, traditional construction safety management models cannot be directly applied to PB scenarios [16]. Against this background, safety management in PB has gradually attracted increasing academic attention. Existing studies have mainly focused on the identification of safety influencing factors and safety risk assessment. In terms of safety influencing factor identification, Yang et al. [17] conducted a coupling analysis of safety risk factors in PB construction based on an N-K modified complex network. By incorporating accident cases to identify key risk factors, they found that on-site information communication, cross-operation safety, and the natural construction environment significantly increased the likelihood of construction safety accidents. Zhong and Li [18] focused on hoisting safety in PB. They identified hazardous factors during the construction process using Failure Mode and Effects Analysis, and further analyzed the interactions, criticality, and hierarchical relationships among these factors through a Grey-DEMATEL-ISM approach. Their results indicated that the skill level of hoisting equipment operators, the number of on-site safety management personnel, and the compatibility between prefabricated components and hoisting equipment were important root factors affecting hoisting safety. In terms of safety risk assessment, Lv et al. [19] examined safety risks from the perspective of design–construction phase linkage and used a structural equation model (SEM) to demonstrate that risk control in the design phase has a significant impact on construction-phase safety risks. Li et al. [20] developed a risk indicator system for safety risk assessment in PB construction in China, applied SEM to analyze the relationships among three categories of risk factors—objects, workers, and management—and further validated the evaluation results using a cloud model. Meanwhile, digital technologies have also been increasingly integrated into PB safety management. Shen and Xu [21] developed a safety risk monitoring system for PB based on BIM and ontology technology, enabling the sharing, reuse, and visualization of risk knowledge. Liu and Meng [22] proposed a digital twin-based coupling framework for hoisting safety risks by integrating IoT, BIM, the Apriori algorithm, and complex networks, thereby realizing the dynamic perception and visual analysis of interrelationships among risk factors. Liao and Mo [7] developed a safety consultation and question-answering system for PB based on large language models and retrieval-augmented generation technology, providing real-time safety knowledge support for on-site personnel.

Overall, existing studies have made notable progress in risk analysis, process monitoring, and technology-enabled safety management for PB, but several limitations remain. Most existing studies focus on individual construction stages, such as hoisting and assembly, while lacking a systematic investigation of whole-process safety management across design, production, transportation, and construction. In addition, previous research has mainly concentrated on risk factor identification and static evaluation, with insufficient attention paid to the hierarchical relationships, transmission paths, and coupling mechanisms among influencing factors. Therefore, it is necessary to further identify the key factors affecting safety management in PB from a systems perspective and to reveal their internal relationships and mechanisms of action.

2.2. Safety Resilience

With increasing uncertainty in the global security situation and economic environment, resilience has gradually become a prominent concept and research topic. Against this background, introducing resilience into safety management research is of considerable theoretical and practical significance. Examining safety issues from the perspective of resilience theory may provide a new perspective for the safety management of PB projects. As an emerging concept developed at the intersection of multiple disciplines, safety resilience has been gradually applied in fields such as urban planning [23,24], ecological management [25] and socio-economic systems [26], and has generated relatively rich research outcomes.

In engineering, research on safety resilience has gradually expanded. Kou and Liu [27,28] explicitly introduced resilience theory into civil engineering construction safety research to improve the safety stability and control level of engineering projects, and on this basis established an evaluation index system for construction safety resilience. In another study, they examined the interrelationships among construction safety resilience elements from a network perspective and pointed out that factors such as safety behavior and risk prevention play key roles in resilience enhancement. Through bibliometric analysis, Hu and Li [29] found that existing research on construction safety resilience mainly focuses on three major streams: structural resilience, psychological resilience, and managerial resilience, indicating that construction safety resilience has been understood from multiple levels, including physical systems, individual behavior, and organizational management. Xu and Zhou [30] conducted a quantitative classification and prediction of tower crane construction safety resilience based on a historical accident database. Guo et al. [31] constructed an evaluation index system for the safety resilience of major railway projects by integrating AISM with systematic cluster analysis.

In contrast, research on safety resilience in the field of PB is still in its infancy. Wang et al. [32] introduced resilience theory into the safety management of PB, investigated the safety control mechanisms of PB across stages from decision-making to construction, and established a whole-process safety resilience evaluation index system for PB. This indicates that the academic community has begun to shift gradually from traditional safety risk research toward safety resilience research. However, existing studies still rely heavily on expert judgment or prior assumptions, and the hierarchical relationships, transmission paths, and structural characteristics among factors have not yet been objectively characterized. Consequently, the objectivity and reproducibility of existing models still require further improvement.

3. Model and Method

To investigate the safety resilience of PBS in depth, this study adopts an integrated framework combining improved ISM approach and BN, as shown in Figure 1, to reveal the complex relationships and mechanisms among safety-related factors within the system. First, based on 136 domestic PB accident reports collected from 2016 to 2025, the key factors affecting system safety resilience were extracted and identified, and an influencing-factor system for safety resilience was established. Subsequently, GRA was introduced to optimize the inter-factor relationships in ISM, while K-means clustering was employed to determine the threshold for adjacency identification, thereby enabling the construction of a more accurate adjacency matrix and the analysis of the hierarchical structure of the factors. Finally, BN was developed for probabilistic modeling and inference, through which the posterior probabilities of the factors under different conditions were evaluated, and the most critical causal factors and their influence paths were identified by sensitivity analysis.

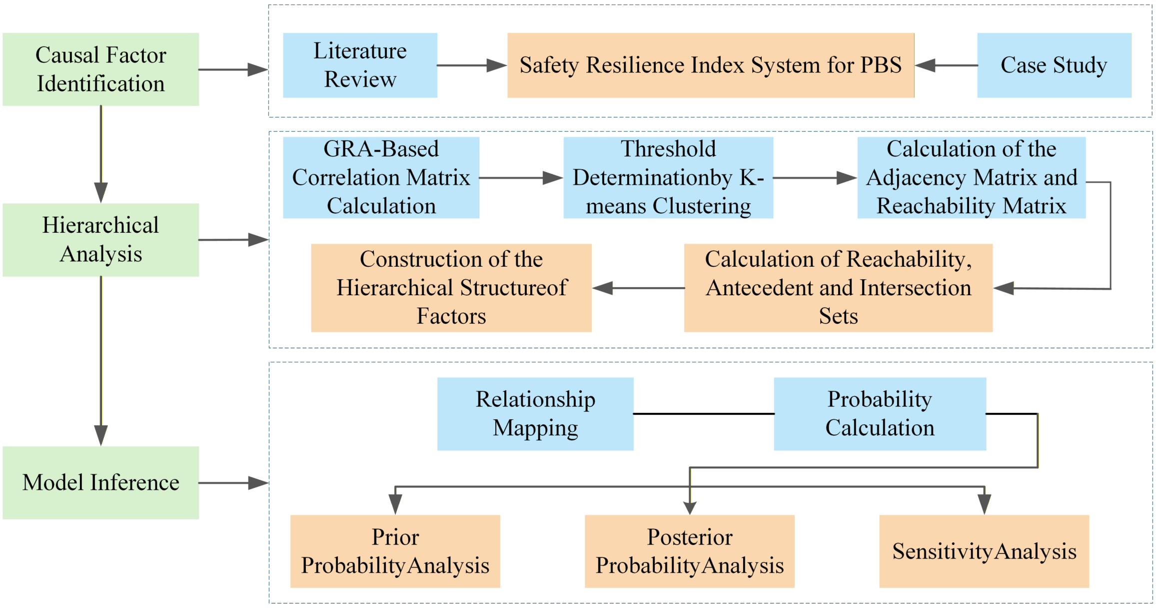

Figure 1. Research framework.

3.1. Data Sources

To comprehensively analyze the causal factors affecting the safety resilience of the PBS and to ensure the authenticity and representativeness of the research data. This study followed the principles of typicality, completeness, and accessibility, and collected publicly available accident investigation reports related to PB safety in China from 2016 to 2025 as research samples. Considering the typical characteristics of PBS, such as factory prefabrication, transportation and hoisting, and on-site assembly, it should be noted that the PBS discussed in this study mainly refer to prefabricated concrete buildings and steel PB that are commonly used in engineering practice in China. This study focuses on safety management issues and risk transmission mechanisms in processes such as component production, transportation, storage, hoisting, connection, and on-site installation, rather than conducting a unified evaluation of the structural mechanical performance of different material systems.

Based on this scope, accident cases were systematically retrieved and screened using keywords such as "prefabricated building," "prefabricated components," "steel structure," "hoisting," and "assembly." All cases were collected from official accident investigation reports publicly released by the Ministry of Emergency Management of the People's Republic of China, provincial and municipal emergency management departments, housing and urban–rural development authorities, and local government websites. After removing duplicates and conducting screening and data cleaning, 136 representative PB safety accident cases were finally selected as the research samples. The sample accidents mainly include mechanical injury, falling from height, struck-by-object accidents, vehicle injury, collapse, and other types of accidents. Among them, mechanical injury accounted for the largest number of cases, with 36 cases, followed by falling from height with 31 cases and struck-by-object accidents with 26 cases. Collapse, vehicle injury, and other types of accidents accounted for 18, 13, and 12 cases, respectively. The specific distribution of accident types is shown in Figure 2. These reports provide relatively complete information on the time, location, process, causal analysis, and consequences of the accidents, and can therefore realistically reflect the formation and transmission characteristics of safety risks during the construction process of PB.

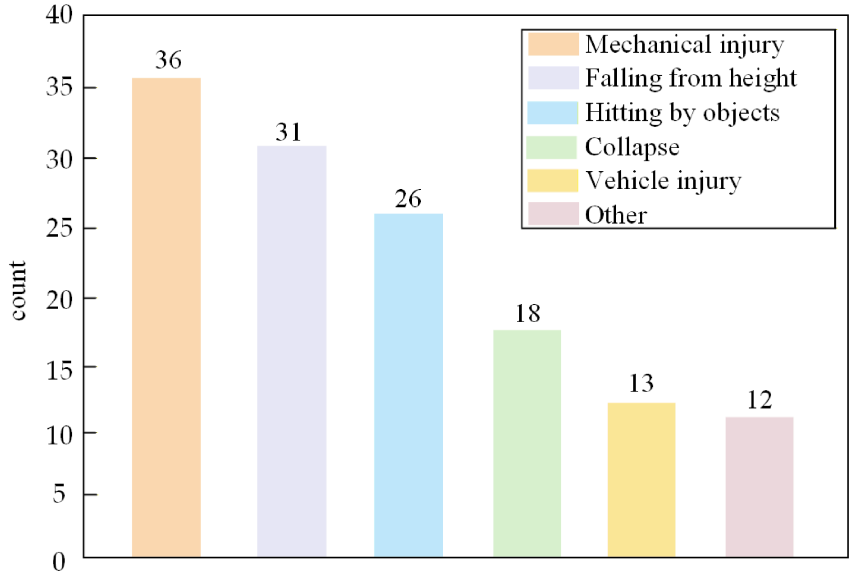

Figure 2. Statistical distribution of accident types in PB.

3.2. Improved ISM

ISM can reveal the structural relationships among factors in complex systems through matrix operations and hierarchical decomposition, and has therefore been widely applied in engineering safety and accident causation research [33]. However, conventional ISM usually relies on experts to assign binary values (0/1) when constructing the adjacency matrix, which introduces strong subjectivity and makes it difficult to reflect differences in the strength of inter-factor relationships, thereby affecting the objectivity and reproducibility of the results. To overcome this limitation, this study introduces GRA to improve the mechanism for generating the adjacency matrix. By quantifying the similarity of changing trends among factors and calculating grey relational coefficients, GRA provides an objective representation of the intrinsic degree of association among factors. On this basis, K-means clustering is applied to the relational coefficient matrix, and the clustering centers are used as thresholds to convert the relational coefficients into binary adjacency relationships (assigned as 1 when the coefficient is greater than or equal to the threshold, and 0 otherwise), thereby constructing a more data-supported adjacency matrix. Previous studies have shown that this approach can effectively improve the objectivity and applicability of ISM in the analysis of complex accident causation. For example, Xue et al. [34] integrated GRA into ISM and combined it with MICMAC to reveal the hierarchical relationships and interaction mechanisms among the causal factors of fall-from-height accidents in construction engineering. Hou et al. [35] employed the ISM-MICMAC approach to analyze the interaction mechanisms among influencing factors of hazardous chemical production explosion accidents, and further combined it with the Bow-tie model to identify the priority of prevention and control measures for accident causal factors. Given that the factors affecting the safety resilience of PBS are characterized by multi-source coupling, complex interrelationships, and long transmission chains, this study adopts the improved ISM method to enhance the objectivity of relationship identification and to provide a more reliable basis for subsequent hierarchical classification and path analysis.

(1) Define the data sequence

The reference sequence is a data sequence that can reflect the behavioral characteristics of the system, denoted as $Y_0 = \{y_0(k) \mid k = 1, 2, \ldots, n\}$; the comparison sequence is a data sequence composed of factors that can influence the system behavior, denoted as $Y_i = \{y_i(k) \mid k = 1, 2, \ldots, n\}$, and n is the number of sample points.

(2) Data dimensionless processing

The mean method is used to eliminate the differences in dimensions and orders of magnitude.

$$\overline{x_i}(k) = \frac{y_i(k)}{\frac{1}{n}\sum_{k=1}^{n} y_i(k)}, (i = 1, 2, \cdots, m) \tag{1}$$

(3) Calculate the correlation coefficient

The correlation coefficient between Y_i and Y_0 at the k-th point is:

$$\xi_i(k) = \frac{a + \rho b}{|y_0(k) - y_i(k)| + \rho b} \tag{2}$$

In the formula, a and b represent the minimum and maximum differences of the two levels respectively, where $a = \min_i \min_k |x_0(k) - x_i(k)|$, $b = \max_i \max_k |x_0(k) - x_i(k)|$; ρ is the resolution coefficient, which is generally taken as 0.5.

(4) Construct the correlation matrix

The correlation degree is obtained by calculating the mean of the correlation coefficients. Each factor is taken as Y_0 in turn, and the correlation degrees between every two factors are calculated to obtain a symmetric correlation degree matrix $G = [g_{ij}]_{m \times m}$. The formula for calculating the correlation degree is as follows:

$$r_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \tag{3}$$

(5) Threshold clustering and adjacency matrix generation

The K-means clustering algorithm is used to perform K-means clustering on all non-diagonal elements in G, and the threshold λ is obtained. Then, an adjacency matrix $A = [a_{ij}]_{m \times m}$ is constructed:

$$a_{ij} = \begin{cases} 0 & s_{ij} < \lambda \\ 1 & s_{ij} \geq \lambda \end{cases} (i, j = 1, 2, \cdots, 23) \tag{4}$$

(6) Calculate the reachability matrix

After introducing the identity matrix I, multiple Boolean operations are carried out. The operations stop when the adjacency matrix A satisfies Formula (7), and then the reachability matrix M can be obtained.

$$(A + I) \neq (A + I)^2 \neq \cdots \neq (A + I)^{K-1} = (A + I)^K \tag{5}$$

$$M = (A + I)^K \tag{6}$$

(7) Draw the hierarchical structure diagram of ISM

First, obtain the relationships of accident-causing factors based on the reachability matrix M, namely the reachable set $R(a_i)$, the antecedent set $Q(a_i)$, and the intersection $C(a_i) = R(a_i) \cap Q(a_i)$ respectively. Then, conduct hierarchical decomposition. When a certain condition is met, remove the elements that meet the condition, and classify the removed elements into the first level. Delete the elements in the first level and form a new analysis table. Repeat the above steps to determine the elements of the second level, and so on, until no new hierarchical elements can be decomposed. Finally, draw a hierarchical structure diagram of factors according to the hierarchical division results.

3.3. BN

BN is a probabilistic graphical model built on Bayesian probability theory, which can intuitively represent the conditional dependence relationships among random variables through a directed acyclic graph (DAG). Due to its remarkable advantages in handling uncertainty, characterizing the causal relationships of complex systems, and conducting probabilistic inference, BN has been widely applied in fields such as risk assessment, fault diagnosis, accident analysis, and uncertainty decision-making [36,37]. Compared with traditional static analysis methods, BN can not only describe the causal associations among various factors in the system but also reveal the key risk paths and influencing factors through forward inference and reverse diagnosis. Therefore, it is particularly suitable for the safety analysis and resilience assessment of complex engineering systems.

In this study, BN is used to construct a probabilistic inference model for the safety resilience of PBS. First, the network topology is determined based on the factor hierarchical structure and interaction relationships obtained from the improved ISM. Second, the node states and conditional probability tables are determined by combining accident case data and expert knowledge. Finally, Bayesian network is used to conduct inference analysis on the safety resilience of PBS, identify the key causal factors and their influence paths, and further reveal the degree of influence of different factors on the system's safety resilience. By combining BN with the improved ISM, this paper can further achieve quantitative analysis and mechanism explanation of the safety resilience of PBS on the basis of clarifying the hierarchical relationships among factors.

The model can be represented by a tuple: where G is a DAG with n nodes, used to depict the causal or conditional dependency structure among variables; P represents the joint probability distribution that matches the graph structure, i.e., the conditional probability distribution (CPD) of each node. This structure enables the Bayesian network to effectively capture the local dependency relationships between variables and support efficient probabilistic inference.

Bayes' theorem is the core foundation of Bayesian network (BN) inference, and its expression is as follows:

$$P(A|E) = \frac{P(E|A)P(A)}{P(E)} \tag{7}$$

Among them, $P(A)$ is the prior probability, $P(A|E)$ is the posterior probability, $P(E)$ is the evidence factor, and $P(E|A)$ is the likelihood function.

By adjusting the probability parameters of nodes in the network, the Bayesian network can perform diagnostic reasoning on the model. When conducting reasoning, given the observed evidence E, the posterior probability of each root node can be calculated to evaluate its possibility as a potential cause. The formula for calculating the posterior probability is as follows:

$$P(X_i|E) = \frac{P(E|X_i)P(X_i)}{\sum_j P(E|X_j)P(X_j)} \tag{8}$$

Among them, $P(\mathrm{X_i})$ and $P(\mathrm{X_j})$ are prior probabilities, $P(\mathrm{X_i}|E)$ is the posterior probability, and $P(E|\mathrm{X_i})$ and $P(E|X_j)$ are conditional probabilities.

Sensitivity analysis is an important means to identify key nodes in the study of failure risk. Among them, the rate of variation (ROV) is a commonly used sensitivity analysis method, which quantifies the impact on the system output by comparing the change degree between the posterior probability and the prior probability of a node under different evidence. Specifically, the ROV value of a node can be calculated by the following formula:

$$\mathrm{ROV}(X_i) = \frac{\varphi(X_i) - \phi(X_i)}{\phi(X_i)} \tag{9}$$

Among them, $\phi(X_i)$ represents the prior probability of node X_i, and $\varphi(X_i)$ is its posterior probability. The larger the ROV value, the more sensitive the node is to the system output, indicating that it is a critical risk unit.

4. Model Analysis

Based on the improved ISM-BN model established in the previous section, model parameter estimation and result analysis were further carried out. First, the prior probabilities of the root nodes were obtained by integrating expert judgments through the DUOWA operator, while the conditional probabilities were calculated from a dataset of 136 accident investigation reports. Subsequently, these parameters were imported into Netica software, and forward inference, backward diagnosis, and sensitivity analysis were conducted in sequence to comprehensively evaluate the safety resilience level of the PBS and identify the key causal factors.

4.1. Identification of Causal Factors

To systematically identify the safety risks in the PBS and address the limitations of traditional safety management, this study integrates multi-source data and bibliometric analysis. First, 136 accident cases related to PBS from 2016 to 2025 were collected. Meanwhile, CNKI and Web of Science were used as the main data sources, with keywords such as "prefabricated building safety risk" and "safety resilience research" to retrieve representative literature. High-frequency risk factors were identified through frequency statistics. Combined with relevant codes and standards, the causal factors were then classified, screened, and de-duplicated, leading to the preliminary construction of a safety resilience indicator system for PBS comprising 13 causal factors. These factors were further categorized into four dimensions, namely predictive resilience, absorptive resilience, adaptive resilience, and restorative resilience, as shown in Table 1.

Table 1. Safety resilience indicator system for the PBS.

Resilience Dimension	Influencing Factor	Description
Predictive resilience (A)	Prefabricated component factor (A1)	Refers to the risk of failure of prefabricated components during factory production, transportation, and storage.
	Safety information factor (A2)	Refers to the capacity for transmission, recording, and traceability of safety management information, including the timeliness and accuracy of safety briefings, technical disclosures, and accident reporting.
	Hazard inspection factor (A3)	Refers to the ability to identify, assess, and rectify on-site hazards, including routine inspections, special inspections, and monitoring of major hazard sources.
	Equipment factor (A4)	Covers the operating condition and maintenance management of construction machinery and equipment, such as hoisting machinery and lifting equipment.

Table 1. *Cont.*

Resilience Dimension	Influencing Factor	Description
Absorptive resilience (B)	Safety protection factor (B1)	Refers to the provision and maintenance of on-site safety protection facilities, including edge protection, opening protection, work-at-height protection, and temporary electricity protection.
	Temporary structure factor (B2)	Refers to the stability of temporary facilities such as temporary supports, scaffolds, and operation platforms.
	Critical process technology factor (B3)	Refers to the technical control level of critical construction processes such as hoisting, connection, and grouting, including lifting-point design, grouting compactness, and joint connection quality.
Adaptive resilience (C)	Site management factor (C1)	Refers to the overall management capability of on-site organization and coordination, personnel management, and material management, including construction organization design, process coordination, and coordination of cross operations.
	Worker factor (C2)	Refers to workers' technical competence, safety awareness, operational skills, and psychological state.
	Primary safety responsibility factor (C3)	Refers to the extent to which participating parties, such as owners, contractors, and supervision units, fulfill their primary responsibilities for work safety, including safety investment, institutional development, and responsibility implementation.
	Emergency response factor (C4)	Refers to emergency preparedness and response capacity, including emergency plan preparation, drills, emergency material reserves, and accident handling capability.
Restorative resilience (D)	Supervision factor (D1)	Refers to the strength of supervision and inspection by government regulators and supervision units on site, including the review of special safety plans, on-site supervision of critical processes, and follow-up of hazard rectification.
	Overall improvement factor (D2)	Refers to the ability to improve the overall safety resilience of the system through technological innovation, management innovation, and the improvement of standards and regulations.

4.2. Improved ISM Analysis

After collecting, screening, and coding 136 PB safety accident reports in China from 2016 to 2025, the occurrence frequencies of the 13 causal factors in each year were calculated, and the original data sequences were constructed accordingly. For each analysis, the annual occurrence frequency of one causal factor was taken as the reference sequence, while the occurrence frequencies of the remaining causal factors were used as comparison sequences. MATLAB was then employed to calculate the grey relational degree among the factors according to Equations (1)–(5), thereby obtaining the grey relational degree matrix. To reduce the dependence of traditional ISM on expert subjective judgment when constructing adjacency relationships, this study further applied K-means clustering to classify the off-diagonal elements of the grey relational degree matrix.

Since the ISM adjacency matrix requires the relationships among factors to be transformed into binary 0/1 relationships, the grey relational degrees were divided into two categories: "strong correlation" and "weak correlation". Therefore, the number of clusters was set as K = 2. After 10 iterations, the two cluster centers were obtained as 0.7489 and

0.6330, respectively. The two cluster centers were then used as alternative thresholds for comparative analysis. The results showed that when the threshold was set to 0.7489, the hierarchical relationships among the causal factors were clearer, and the factor transmission paths were more consistent with the practical characteristics of safety resilience in PBS. Therefore, the higher cluster center, 0.7489, was finally selected as the correlation threshold. According to Equation (6), the grey relational degree matrix was converted into the adjacency matrix A, as shown in Table A1. On this basis, the identity matrix was introduced, and the reachability matrix M was obtained through Boolean operations, as shown in Table 2. Furthermore, the reachable set, antecedent set, and intersection set of each factor were calculated, and hierarchical decomposition was performed, as shown in Table A2.

The results show that the influencing factors of safety resilience in the PBS can be divided into four hierarchical levels, namely, $L_1 = \{A1, A4, B2, B3\}$, $L_2 = \{B1, C2, C4\}$, $L_3 = \{A2, A3, C1\}$, $L_4 = \{C3, D1, D2\}$. Among them, L_1 represents the surface-level factors, which mainly reflect the direct manifestations of system safety resilience; L_2 and L_3 represent the intermediate factors, which play a bridging role in the transmission from deep-rooted factors to surface-level factors; and L_4 represents the deep-rooted factors, which serve as the fundamental driving forces affecting the safety resilience of the PBS. The resulting hierarchical structure of the factors is shown in Figure 3. These findings indicate that the formation of safety resilience in the PBS is not the result of any single factor acting independently, but rather a dynamic evolutionary process in which deep-rooted factors are progressively transmitted through intermediate factors and ultimately manifested in surface-level factors. This provides a structural basis for subsequent analysis.

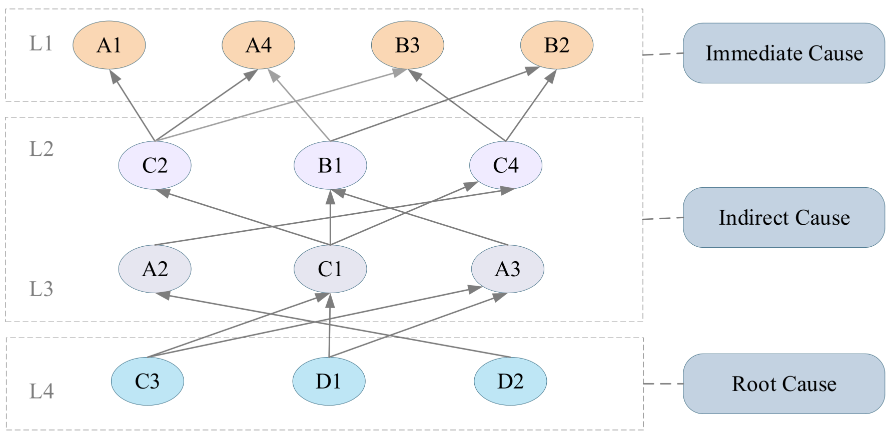

Figure 3. Hierarchical structure of the factors.

Table 2. Reachability matrix M.

	A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	C4	D1	D2
A1	1	0	0	0	0	0	0	0	0	0	0	0	0
A2	0	1	0	0	0	1	1	0	0	0	1	0	0
A3	0	0	1	1	1	1	0	0	0	0	0	0	0
A4	0	0	0	1	0	0	0	0	0	0	0	0	0
B1	0	0	0	1	1	1	0	0	0	0	0	0	0
B2	0	0	0	0	0	1	0	0	0	0	0	0	0
B3	0	0	0	0	0	0	1	0	0	0	0	0	0
C1	1	0	0	1	1	1	1	1	1	0	1	0	0
C2	1	0	0	1	0	0	1	0	1	0	0	0	0
C3	1	0	1	1	1	1	1	1	1	1	1	0	0

Table 2. *Cont.*

	A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	C4	D1	D2
C4	0	0	0	0	0	1	1	0	0	0	1	0	0
D1	1	0	1	1	1	1	1	1	1	0	1	1	0
D2	0	1	0	0	0	1	1	0	0	0	1	0	1

4.3. BN Model Analysis

4.3.1. Mapping Mechanism

This study adopts an analytical framework that integrates the improved ISM with the BN, in which the hierarchical structure derived from ISM is mapped onto the BN. Specifically, the deep-rooted factors are treated as root nodes, the intermediate and surface-level factors are treated as intermediate nodes, and the target factor is treated as the leaf node, so as to ensure that the constructed directed acyclic graph accurately reflects the dependency relationships among variables. The purpose of this mapping is to systematically reveal the complex interaction mechanisms among the causal factors affecting the safety resilience of the PBS. The corresponding mapping relationship is shown in Figure 4.

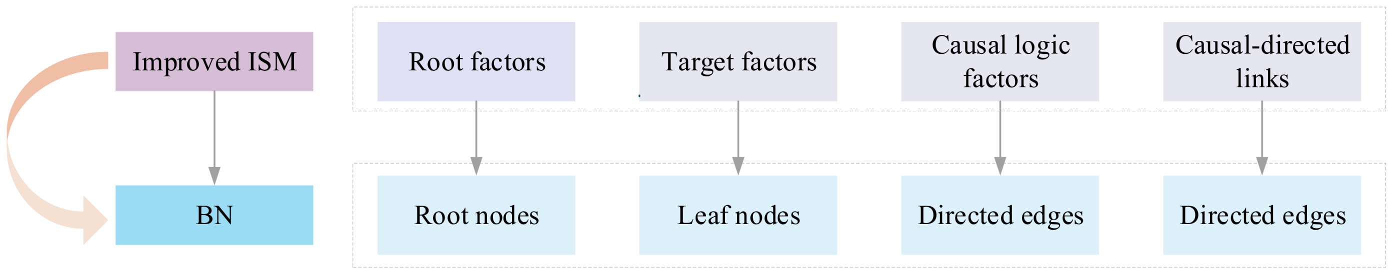

Figure 4. Improved ISM-BN mapping relationship diagram.

This approach enables the organic integration of structural analysis and probabilistic inference. On the one hand, the improved ISM clarifies, at the system level, the transmission paths and hierarchical relationships among the causal factors of safety resilience, thereby overcoming the limitation of traditional ISM that relies heavily on subjective expert judgment. On the other hand, the BN performs probabilistic inference on this structural basis, making it possible to evaluate the level of safety resilience and accurately identify key transmission paths. Therefore, the integration of the two methods combines the systematic nature of structural analysis with the rigor of probabilistic inference, providing a logically robust and quantitatively operable methodological tool for the study of safety resilience [38].

4.3.2. Parameter Estimation

(1) Calculation of prior probabilities for root nodes

In BN, the specification of prior probabilities for root nodes directly affects the reliability of network inference results. Since the deep-rooted factors of safety resilience in the PBS lack sufficient objective statistical samples, it is difficult to obtain stable prior probabilities using the frequency method. Therefore, this study adopts the triangular fuzzy number method to quantify expert evaluation information, so as to improve the accuracy and rationality of prior probability estimation [39].

Based on the results of the improved ISM analysis presented above, D1, C3, and D2, which are located at the bottom level of the hierarchical structure, were selected as the root nodes of the Bayesian Network. Five experts with extensive experience in PB safety management, construction organization, and risk analysis were invited to form an expert panel and to conduct fuzzy evaluations of the failure occurrence likelihood associated with each root node. The basic information of the experts is shown in Table 3. The expert evaluation process did not involve human medical experiments, intervention studies, or the collection of sensitive personal information. All experts participated voluntarily after being informed of the research purpose and data use. The evaluation results were used solely to estimate the prior probabilities of the root nodes, and the experts' identity information was anonymized.

Table 3. Basic information of the experts.

Expert ID	Type of Organization	Education	Years of Experience
E1	University	PhD	18
E2	University	Master's degree	16
E3	Construction	Bachelor's degree	15
E4	Component manufacturing enterprise	Master's degree	10
E5	Consulting/Supervision unit	Master's degree	13

Subsequently, a defuzzification process was employed to transform the experts' linguistic judgments into precise probability values. In this way, the fuzziness and uncertainty arising from subjective judgments were reduced while expert knowledge was incorporated, thereby enhancing the scientific validity and operability of model parameterization. Expert ratings were expressed using five-level linguistic variables, and the triangular fuzzy numbers corresponding to each level are defined in Table 4.

Table 4. Grade standard and definition of triangular fuzzy numbers.

Risk Likelihood Level	Description	Triangular Fuzzy Number ($\times 10^{-1}$)
I	Severe damage or high risk pressure	(0.0, 0.1, 0.3)
II	Large impact or relatively high risk pressure	(0.2, 0.3, 0.5)
III	Small impact or moderate risk pressure	(0.4, 0.5, 0.6)
IV	Slight impact or low risk pressure	(0.5, 0.7, 0.8)
V	No impact or no risk pressure	(0.7, 0.9, 1.0)

On this basis, the mean area method and the idea of the dependency uncertain ordered weighted averaging operator (DUOWA) were employed to integrate expert judgments with uncertain weights [40]. This method does not artificially assign fixed weights. Instead, it dynamically determines the weights of expert evaluations by calculating the similarity between individual expert evaluation results and the group comprehensive evaluation, thereby reducing the influence of individual biased judgments on the prior probabilities of root nodes and improving the stability and credibility of the expert evaluation results. The specific calculation steps are as follows:

(1) Set the fuzzy evaluation values of experts as $P_{\mathrm{t}} = (a_t, b_t, c_t)$, and calculate the arithmetic mean of fuzzy evaluations $\widetilde{P}_v = (a_v, b_v, c_v)$ using Equation (10).

$$a_v = \frac{1}{n}\sum_{t=1}^{n} a_t, b_v = \frac{1}{n}\sum_{t=1}^{n} b_t, c_v = \frac{1}{n}\sum_{t=1}^{n} c_t, t = 1, 2, 3, \cdots, n \tag{10}$$

(2) $d\left(P_r, \widetilde{P}_v\right)$ and $s\left(P_r, \widetilde{P}_v\right)$ represent the distance measure and similarity between P_t and $\widetilde{P}_v$, respectively. The calculation formulas are as follows:

$$d\left(P_t, \widetilde{P}_v\right) = \frac{1}{3}(|a_t - a_v| + |b_t - b_v| + |c_t - c_v|) \tag{11}$$

$$s\left(P_t, \widetilde{P}_v\right) = 1 - \frac{d\left(P_t, \widetilde{P}_v\right)}{\sum_{t=1}^{n} d\left(P_t, \widetilde{P}_v\right)} \tag{12}$$

(3) Calculate the similarity weight coefficient W_t.

$$W_t = \frac{s\left(P_t, \widetilde{P}_v\right)}{\sum_{t=1}^{n} s\left(P_t, \widetilde{P}_v\right)} \tag{13}$$

(4) Synthesize the fuzzy evaluation values of experts and calculate the defuzzified exact value P of the prior probability of the root node.

$$P = \sum_{t=1}^{n} W_t \times P_t \tag{14}$$

According to the above method, the prior probabilities of each root node are calculated, and the results are shown in Table 5.

Table 5. Expert evaluation of root nodes.

Root Node	E1	E2	E3	E4	E5	Prior Probability
D1	4	2	3	4	3	53.3%
C3	3	2	1	3	4	42.5%
D2	3	4	3	2	5	57.3%

As shown in Table 2, D2 has the highest prior probability among the three root nodes (57.3%), followed by D1 (53.3%), whereas C3 exhibits a comparatively lower prior probability (42.5%).

(2) Calculation of conditional probabilities for non-root nodes

After determining the prior probabilities of the root nodes, the collected 136 samples of PB safety accident cases were further imported into Netica for probabilistic learning and inference analysis [41]. It should be noted that the CPTs of the non-root nodes constructed in this study were mainly derived from the causal information recorded in publicly available accident investigation reports. Therefore, the results reflect the conditional probability relationships embedded in publicly accessible historical accident samples. Since some accident reports may have incomplete records of hazard evolution processes, early risk signals, and near-miss events, the CPTs may underestimate the effects of certain latent factors or early-stage disturbances [42]. To mitigate this influence, the sample screening process prioritized accident cases with relatively complete information, clear causal descriptions, and strong relevance to the prefabricated construction process. According to the modeling requirements, the states of both the root nodes and intermediate nodes were uniformly classified into two categories, namely, Normal (N) and Failure (F), and the Bayesian Network model for the safety resilience of the PBS was constructed accordingly. The resulting network fault analysis diagram can intuitively reflect the dependency relationships among the risk factors and their influence on the overall safety state of the system.

4.3.3. Result Analysis

After the prior probabilities of the root nodes and the conditional probability tables (CPTs) were imported into Netica, forward inference was first performed on the established Bayesian Network for the safety resilience of the PBS. The results are shown in Figure 5. The probability of the target node R being in the failure state is 72.1%, which is significantly higher than that of the normal state (N = 27.9%). This indicates that, under the conditions represented by the existing accident samples, the overall safety resilience of the PBS is relatively fragile, meaning that the system is more likely to experience degradation of safety functions, accumulation and amplification of risks, and weakening of operational stability when subjected to external disturbances or internal disorder.

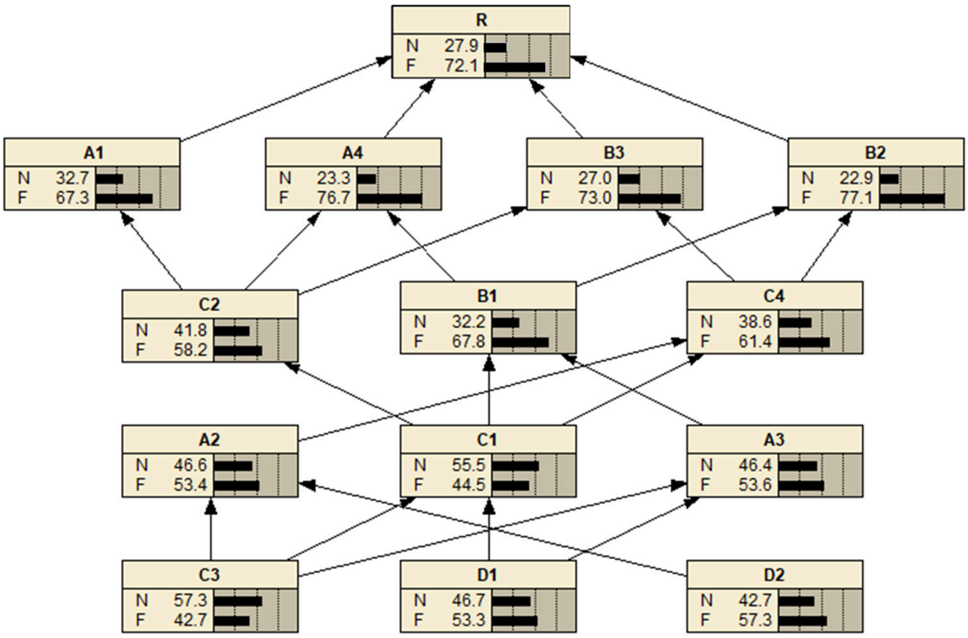

Figure 5. Bayesian Network model for safety resilience analysis.

Meanwhile, the forward inference results also show that several surface-level factors, namely the temporary structure factor (B2), equipment factor (A4), critical process technology factor (B3), and prefabricated component factor (A1), exhibit relatively high failure probabilities. This suggests that these factors are the direct manifestation nodes of low system safety resilience. Located at the end of the risk transmission chain, they are more likely to absorb the combined effects of deep-rooted governance factors and intermediate transmission factors. Therefore, these surface-level high-risk nodes not only represent the external manifestation of system vulnerability, but also serve as important entry points for the subsequent identification of key sensitive factors and critical transmission paths. This finding is also consistent with engineering practice, and provides a basis for the subsequent sensitivity analysis and the identification of key transmission paths.

Subsequently, posterior probability analysis was conducted. Considering that research on the safety resilience of the PBS needs to identify the key triggers leading to system failure, the leaf node R was set to the failure state (F = 100%), and backward diagnosis was performed to calculate the posterior probabilities of each causal factor, as shown in Figure 6. A comparison between the prior and posterior probabilities is presented in Figure 7.

To further identify the key nodes exerting the greatest influence on the safety resilience of the PBS, sensitivity analysis was conducted on the leaf node R based on the established Bayesian Network, and the results are presented in Table 6. The results show that the five factors with the highest ROV values are the equipment factor (A4), critical process technology factor (B3), prefabricated component factor (A1), temporary structure factor (B2), and worker factor (C2), indicating that changes in these factors are most likely to cause fluctuations in the state of the target node and therefore constitute the primary sensitive factors affecting the safety resilience of the PBS.

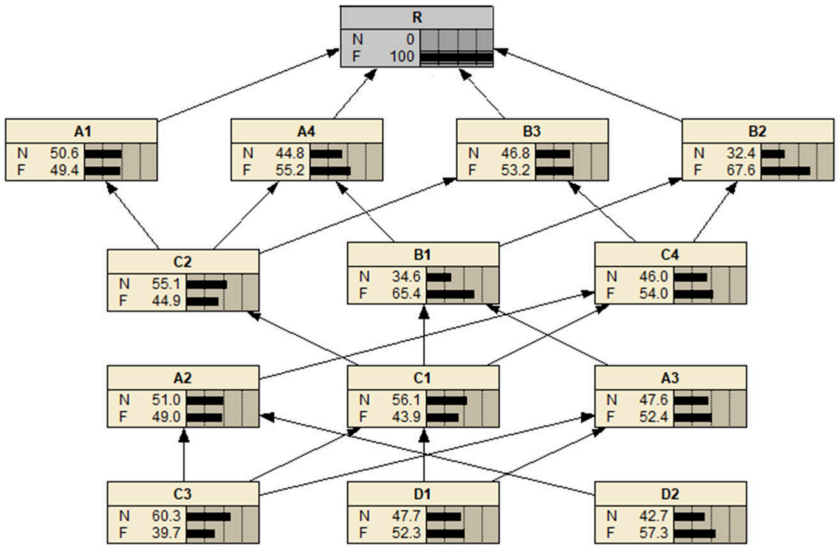

Figure 6. Posterior probability analysis of causal factors.

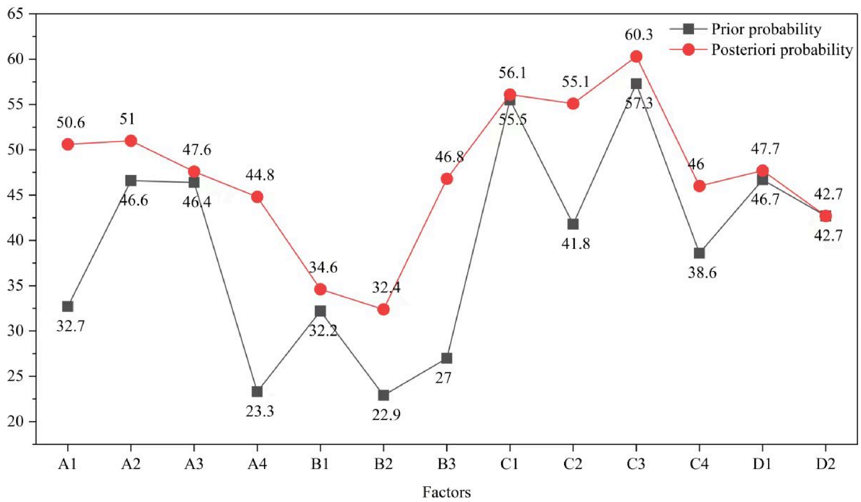

Figure 7. Comparison between prior and posterior probabilities of causal factors.

Among them, the equipment factor (A4) has the highest ROV value, reaching 0.9227, indicating that changes in its state are most likely to trigger fluctuations in the target node and that it is the most prominent sensitive source affecting system safety resilience. PB projects rely heavily on hoisting machinery, transport equipment, and auxiliary installation devices. During component lifting, transfer, positioning, and installation, equipment performance, operating condition, and operational accuracy directly determine whether the construction system can remain stable. Once equipment failure or operational abnormality occurs, the risk can rapidly propagate to hoisting operations, component installation, and overall construction organization, thereby directly weakening project system safety resilience. Therefore, strict equipment entry inspection procedures should be implemented, special inspections should be conducted for hoisting machinery, transport equipment, and key auxiliary devices, and regular maintenance and repair mechanisms should be established to ensure that core equipment remains in a safe and controllable condition. It should be further noted that equipment factors are more closely associated with downstream execution nodes at the construction site level, and the state of equipment is jointly influenced by on-site management factors (C1) and main safety responsibility factors (C3). Therefore, equipment factors not only reflect the direct effect of equipment failure on the system safety state, but also indicate that inadequate upstream responsibility implementation and weak on-site management may be amplified through the equipment link and eventually transformed into accident risks.

Table 6. ROV results for each node.

Factors	Prior Probability	Posterior Probability	ROV	Rank
A4	23.3	44.8	0.9227	1
B3	27.0	46.8	0.7333	2
A1	32.7	50.6	0.5474	3
B2	22.9	32.4	0.4148	4
C2	41.8	55.1	0.3182	5
C4	38.6	46.0	0.1917	6
A2	46.6	51.0	0.0944	7
B1	32.2	34.6	0.0745	8
C3	57.3	60.3	0.0524	9
A3	46.4	47.6	0.0259	10
D1	46.7	47.7	0.0214	11
C1	55.5	56.1	0.0108	12
D2	42.7	42.7	0.0000	13

The critical process technology factor (B3) has an ROV value of 0.7333, second only to the equipment factor, indicating that it also has a significant influence on system safety resilience. PB construction differs from traditional cast-in-place operations in that it is essentially a technology-integrated process centered on component lifting, node connection, positioning correction, temporary fixation, and key installation procedures. The control level of critical processes directly determines installation quality, joint force reliability, and the stability of the construction process. Once these critical process links are poorly controlled, local technical deviations can rapidly evolve into systemic risks. Therefore, attention should be focused on core procedures such as hoisting, node connection, and key installation operations. Special construction schemes should be prepared, technical disclosure should be strengthened, advanced construction technologies and refined control methods should be promoted, and a whole-process technical hazard inspection mechanism should be established to promptly identify and correct deviations in the implementation of critical processes.

The prefabricated component factor (A1) has an ROV value of 0.5474, indicating that, as the core physical carrier of PB projects, it has an important influence on system safety resilience. Component quality, dimensional accuracy, connection compatibility, ex-factory integrity, and post-transport condition directly determine whether subsequent hoisting and assembly can be carried out smoothly. Once there are production defects, transportation damages, or on-site adaptation deviations in the components, it will not only affect the installation efficiency but also may induce risks such as node instability, component falling, and structural deformation, thus shaking the safety foundation of the project system. Therefore, full-process quality control should be implemented around the three key links of component production, transportation, and on-site acceptance. By screening qualified production enterprises, optimizing transportation protection measures, and strictly conducting on-site verification and acceptance, unqualified components should be prevented from entering the construction site to reduce the core risks of the system at the source.

The temporary structure factor (B2) has an ROV value of 0.4148 and also exhibits high sensitivity, indicating that temporary support systems, temporary fixing devices, and transitional load-bearing structures are essential to maintaining safety and stability during the construction stage of PB. Because the overall structural system remains incomplete after component hoisting and before permanent connections are formed, temporary structures play a critical role in maintaining component stability, ensuring installation accuracy, and controlling stage-specific force transfer. Their reliability therefore directly determines the overall safety level during construction. Accordingly, temporary structures should be specially designed by qualified professionals in accordance with specific site conditions, and they should be erected and accepted strictly in line with the approved scheme. During construction, regular inspections should be strengthened, especially after adverse weather such as strong winds and heavy rainfall, and any identified problems should be promptly reinforced and rectified to ensure that temporary structures remain in a safe and stable condition at all times.

The worker factor (C2) has an ROV value of 0.3182 and remains a key causal factor affecting system safety resilience. On-site personnel are the direct executors connecting equipment, processes, components, and management measures, and they play a decisive role in hoisting command, component installation, joint construction, and on-site coordination. Insufficient safety awareness, inadequate technical competence, or poor compliance with operational standards can directly lead to equipment mis operation, process loss of control, and installation deviations, thereby further amplifying system risks. Therefore, strict qualification review should be implemented before workers enter the site; tiered safety education and skills training should be carried out for different positions. A performance appraisal mechanism linked to safety performance should be established. By strengthening on-site inspections and correcting violations, work behaviors should be continuously standardized, and the personnel's adaptability and response capabilities to complex construction scenarios should be improved.

Overall, the above high-sensitivity factors are all concentrated at the project implementation level of PB. They not only directly affect critical on-site operations, but also exhibit significant coupling across different stages and tasks. Therefore, they have the most prominent influence on the safety resilience of the project system.

By integrating the results of posterior probability inference and sensitivity analysis, the key transmission paths affecting the safety resilience of the PBS were further identified.

The first key path is: primary safety responsibility factor (C3) → site management factor (C1) → worker factor (C2) → prefabricated component factor (A1). This path reflects the hierarchical transmission mechanism of safety resilience in the PB supply chain, characterized by the progressive linkage among organizational governance, management practices, human behavior, and physical resources. Safety production responsibility factors (C3), on-site management factors (C1), and worker factors (C2) all belong to the adaptive resilience dimension, respectively reflecting the system's adaptive capacity in terms of responsibility implementation, on-site regulation, and personnel behavioral response. In contrast, prefabricated component factors (A1) belong to the predictive resilience dimension, reflecting the system's capacity to identify and anticipate potential problems in advance, such as component quality defects, hoisting deviations, connection hazards, and installation risks. Specifically, as a deep-rooted factor, the primary safety responsibility factor determines the basic level of the project's safety responsibility system, institutional supply, resource input, and regulatory enforcement, and exerts a source-level influence on the standardization, completeness, and constraint intensity of site management. The site management factor further shapes workers' safety awareness, operational compliance, and risk identification ability through construction organization, operational coordination, safety disclosure, process supervision, and correction of violations. The worker factor, acting as a key intermediary connecting management requirements with on-site physical risks, directly affects critical processes related to prefabricated components, including hoisting, positioning, connection, fixation, and protection, thereby influencing installation quality, transportation integrity, and load-bearing stability.

This path is particularly explanatory because PB projects are characterized by large-scale components, frequent hoisting operations, refined node connections, and intensive multi-party coordination. Under such conditions, any upstream governance deficiency may be continuously transmitted along the management–behavior chain to downstream physical risks. In this sense, risks associated with prefabricated components do not arise solely from the quality of the components themselves, but also from the cumulative effects of insufficient fulfillment of safety responsibilities, weak site management, and inappropriate worker behavior. Therefore, this path suggests that improving the safety resilience of PBS should not be limited to component quality inspection or local operational correction; rather, it should start with the effective implementation of primary safety responsibilities and be supported by stronger site management and worker behavior governance, so as to fundamentally prevent risks from accumulating and amplifying at the physical entity level. This finding further indicates that top-level safety governance exerts sustained and amplified influences on multiple downstream subsystems, and thus constitutes the primary entry point for enhancing the safety resilience of PBS.

The second key path is: primary safety responsibility factor (C3) $\rightarrow$ safety information factor (A2) $\rightarrow$ emergency response factor (C4) $\rightarrow$ critical process technology factor (B3). This path reveals the dynamic evolutionary mechanism of safety resilience in the PB supply chain, characterized by the interaction among governance, information, response, and technology. Safety production responsibility factors (C3) and emergency response factors (C4) mainly reflect adaptive resilience, representing the system's dynamic adaptive capacity in responsibility implementation, organizational regulation, and sudden risk response. Safety information factors (A2) belong to predictive resilience, reflecting the system's capacity to collect, transmit, identify, and provide early warnings based on risk information. Key process technology factors (B3) reflect absorptive resilience, indicating the system's capacity to withstand disturbances and maintain a safe state by relying on key process control, technical support, and construction process stability. Along this path, the primary safety responsibility factor first determines whether the project has a sound information management system, a risk reporting mechanism, and a cross-party communication platform, thereby affecting the efficiency of safety information collection, sharing, transmission, and feedback. High-quality safety information not only enhances the system's capacity for risk identification and early warning, but also provides a basis for the rapid assessment of abnormal on-site conditions and emergency decision-making. Supported by such information, the emergency response factor enables timely handling of sudden risks. Its effectiveness directly determines whether on-site risks can be rapidly isolated, whether loss-of-control situations can be contained in time, and whether the construction system can recover to a stable operating state as quickly as possible. Ultimately, the critical process technology factor, as the surface-level carrier node of this path, depends on the continuous support of upstream governance, information, and response mechanisms. Once these links fail, deviations, instability, or interruption are more likely to occur in critical construction processes, thereby directly undermining the safety resilience of the PBS.

In the prefabricated construction process, critical procedures such as component hoisting, joint grouting, temporary support conversion, precise positioning, and connection exhibit strong sequential dependence and coordination requirements, making them highly sensitive to the accuracy of information and the timeliness of response. In particular, when disturbances such as equipment failure, component deviation, sudden weather changes, or operational conflicts occur, delayed safety information transmission, slow emergency response activation, or improper on-site handling can easily lead to loss of control in critical processes and further amplify construction risks. Therefore, improving the safety resilience of PBS depends not only on technical improvements themselves, but also on an information-driven and response-oriented governance model. By establishing efficient information transmission mechanisms, improving emergency linkage systems, and enhancing the dynamic support capacity of critical processes, the system's ability to recover rapidly and adapt continuously under disturbances can be effectively strengthened.

5. Discussion

Different from traditional risk management research, this paper starts from the perspective of resilience. It not only identifies key risk factors but also reveals the hierarchical transmission mechanism among factors and the formation logic of system vulnerability, which provides new theoretical support and methodological tools for the safety management of PB.

(1) Influencing factors.

The improved ISM—BN framework constructed in this paper provides quantitative verification for the formation mechanism of the safety resilience of the PBS, indicating that the system safety resilience is not triggered independently by a single factor. Instead, it is the result of the combined action of five key causal factors, namely equipment factors (A4), key process technology factors (B3), prefabricated component factors (A1), temporary structure factors (B2), and operator factors (C2), as well as two key conduction paths. The results of this study are in good agreement with the existing literature. Luo et al. [43] pointed out that most accidents are not caused by a single factor but by the interaction of multiple risk factors. Song et al. [1] indicated that operator factors (C2) and temporary structure factors (B2) are important key factors affecting the safety of PB. This study further confirms these two types of factors.

(2) Hierarchical classification.

One of the core contributions of this study lies in revealing the hierarchical structure in the formation of the safety resilience of the PBS. The improved ISM analysis shows that the deep-level factors (C3, D1, D2) at the bottom of the hierarchical structure determine the institutional basis, resource allocation conditions, and operating environment of project safety governance, and are the fundamental support for the system safety resilience; the middle-layer factors (C1, C2, A2, A3, C4, etc.) undertake the functions of risk conduction, amplification, and conversion, and are important bridges for the evolution of deep-level factors to the on-site implementation layer; the surface-layer factors (A1, A4, B2, B3, etc.) are concentrated as direct risk nodes and are the most easily exposed links of system vulnerability.

The discovery of this hierarchical relationship has important theoretical significance and practical value. From a theoretical perspective, it goes beyond the limitations of traditional safety research that attributes accidents to single operational errors or local equipment failures, and reveals the systematic and multi-level coupling characteristics of the safety resilience of PB. From a practical perspective, it shows that the safety problems of PB should not be limited to the governance of surface phenomena such as hoisting errors, node deviations, or component defects, but should further trace the governance defects, management imbalances, and conduction mechanisms behind them [44]. PB projects span multiple stages such as design, production, transportation, hoisting, assembly, and temporary support. The links are closely connected and highly dependent. Governance and management problems in the upstream links often accumulate through intermediate factors and are concentrated as safety risks in the construction implementation stage [32]. Therefore, the improvement of the safety resilience of the PBS should not only rely on local control measures but should construct a hierarchical and classified governance path around deep-level governance capabilities, intermediate conduction nodes, and surface high-risk factors.

(3) Policy and management implications for safety governance.

This study also reveals a long-standing but inadequately quantified issue in the safety management of PB. Although China has introduced a series of relatively comprehensive safety management standards and regulations, this study finds that the factor of the main responsibility for work safety (C3) at the bottom of the hierarchical structure, as a root-cause driving condition, through sensitivity analysis and path diagnosis, shows that the state changes of these two factors will significantly affect the overall safety resilience of the system along two key paths. It should be noted that the disconnect between safety policies and front-line implementation is not unique to the PB sector, but represents a common responsibility transmission challenge in construction safety management. This finding indicates that there is still an obvious disconnect between safety policies at the institutional level and on-site actual implementation. Especially in situations where multi-subject collaboration, subcontract management, and the transmission of work safety responsibilities are ineffective, a high-level supply of safety systems often fails to be effectively translated into compliant operation behaviors at the front line and a stable safety state of the system. As mentioned in the study by Zhang et al. [24], management deficiencies at a higher level are prone to translate into procedural violations and unsafe behaviors at the operational level. Therefore, improving the safety resilience of PB not only requires the improvement of top-level institutional design, but also the establishment of a traceable and quantifiable responsibility transmission mechanism to promote the transformation of safety management from static compliance inspection to a dynamic, closed-loop, and data-driven resilience governance model.

Furthermore, the findings of this study provide implications for safety policy formulation and cross-regional application in PB. From the perspective of safety policy, safety supervision of PB should not remain limited to post-accident accountability or risk control in a single link. Instead, a whole-process safety resilience governance mechanism should be established. Existing studies have pointed out that risk management in PB involves continuous processes such as risk identification, risk prediction, risk assessment, and risk response, and that whole-process and closed-loop risk management is of great significance for improving the safety of PB supply chains [45]. On the one hand, responsibility coordination among owners, contractors, component manufacturers, supervision units, and regulatory authorities should be strengthened, so that safety production responsibilities can be effectively transmitted to key stages such as design, production, transportation, hoisting, assembly, and temporary support. On the other hand, for highly sensitive risk nodes such as equipment factors, key process technology factors, prefabricated component factors, temporary structure factors, and worker factors, special inspections, dynamic monitoring, quality traceability, and emergency response systems should be improved. Relevant studies also show that safety risk monitoring systems for prefabricated building construction based on BIM and ontology technology can promote safety knowledge sharing, automatic risk identification, and risk response, thereby improving safety risk management performance [21]. Therefore, safety governance in PB should gradually shift from experience-based supervision to data-driven, risk-warning-oriented, and resilience-enhancement-oriented governance.

(4) Regional applicability and generalizability

From the perspective of regional applicability, although this study is based on accident cases of PB in China, the analytical logic formed by the improved ISM-BN framework has a certain degree of generalizability and can provide methodological reference for safety resilience assessment of PB in other regions or countries. For example, Jeong et al. [46] identified safety risk factors based on PB accident cases in the U.S. OSHA database and pointed out that the results could provide a basis for developing safety management guidelines for prefabricated construction. This indicates that identifying key safety risk factors based on accident cases has cross-regional research value. In particular, in regions where PB are rapidly promoted, construction processes are complex, and multi-actor collaboration is highly required. This framework can help identify the structural relationships and probabilistic sensitivities among risk factors, thereby supporting the prioritization of safety governance and the optimization of resource allocation. However, it should be noted that different countries and regions differ in regulatory systems, construction organization modes, labor structures, levels of industrialization, and accident reporting systems. Therefore, the specific indicator system, probability parameters, and risk transmission paths identified in this study still need to be adaptively adjusted according to local engineering practices.

6. Conclusions

This study focuses on the safety resilience of PBS. Based on 136 PB safety accident reports that occurred in China between 2016 and 2025, the improved ISM—BN method is comprehensively used to systematically analyze the hierarchical relationships, key factors, and action paths affecting the safety resilience of PBS. The following conclusions are drawn:

(1) An indicator system for the safety resilience of PBS was identified and constructed. Through the collation, coding, and statistical analysis of accident reports, 13 key causal factors were extracted and classified into four categories: predictive resilience, resistance resilience, adaptive resilience, and recovery resilience. From a systematic perspective, it was revealed that the safety resilience of PB is not directly determined by a single factor but is a comprehensive result formed by the combined action of multiple types of factors.

(2) The traditional ISM was improved based on GRA, and an adjacency matrix and a reachability matrix with more data support were constructed. Thirteen influencing factors were divided into four levels. The results show that there is an obvious hierarchical structure among the influencing factors of the safety resilience of the PBS. Among them, the deep-layer factors are the root driving conditions for the safety resilience of the system, the middle-layer factors play the role of risk transmission and amplification, and the surface-layer factors directly represent the safety state of the system.

(3) A BN model for the safety resilience of the PBS was constructed. Through reverse diagnosis and sensitivity analysis, five key nodes (equipment factors, key process technology factors, prefabricated component factors, temporary structure factors, and operator factors) and two key conduction paths (factors of the main body of work safety → on-site management factors → operator factors → prefabricated component factors and factors of the main body of work safety → safety information factors → emergency response factors → key process technology factors) were identified, providing clear management focuses for the precise improvement of the system's safety resilience.

Although this paper has achieved certain research results, there are still some limitations. First, the accident samples mainly come from public accident investigation reports, and there may be incompleteness in the details of causes and process information in some cases. Second, although the prior probabilities of root nodes are estimated by the triangular fuzzy number method combined with expert judgment, there is still some subjectivity inevitably. Third, the structural relationships and probabilistic characteristics constructed in this study are relatively static, as they are based on historical accident samples, and therefore do not fully capture the dynamic evolution of safety resilience in PB projects under real-time construction conditions. In addition, this study mainly focuses on the application of the improved ISM-BN model to identify the influencing mechanism of safety resilience in PBS, and has not yet conducted a systematic comparison with other risk-coupling analysis methods. Future research can further combine on-site monitoring data and project management data and introduce dynamic research methods to conduct in-depth analysis of the time-series change mechanism of the safety resilience of PBS, so as to further improve the applicability and explanatory power of the model. Meanwhile, comparative studies involving multiple methods could be conducted to further verify the applicability and advantages of the improved ISM-BN model in terms of risk path clarity, key node identification capability, and model interpretability, so as to enhance its generalizability and decision-support capacity.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PB	Prefabricated buildings
PBS	Prefabricated buildings system
ISM	Interpretive Structural Modeling
BN	Bayesian Network
GRA	Grey Relational Analysis
SEM	Structural Equation Modeling
DAG	Directed Acyclic Graph
CPT	Conditional Probability Table

Appendix A

Table A1. Adjacency matrix A.

	A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	C4	D1	D2
A1	0	0	0	0	0	0	0	0	0	0	0	0	0
A2	0	0	0	0	0	0	0	0	0	0	1	0	0
A3	0	0	0	0	1	0	0	0	0	0	0	0	0
A4	0	0	0	0	0	0	0	0	0	0	0	0	0

Table A1. *Cont.*

	A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	C4	D1	D2
B1	0	0	0	1	0	1	0	0	0	0	0	0	0
B2	0	0	0	0	0	0	0	0	0	0	0	0	0
B3	0	0	0	0	0	0	0	0	0	0	0	0	0
C1	0	0	0	0	1	0	0	0	1	0	1	0	0
C2	1	0	0	1	0	0	1	0	0	0	0	0	0
C3	0	0	1	0	0	0	0	1	0	0	0	0	0
C4	0	0	0	0	0	1	1	0	0	0	0	0	0
D1	0	0	1	0	0	0	0	1	0	0	0	0	0
D2	0	1	0	0	0	0	0	0	0	0	0	0	0

Table A2. Reachability sets, antecedent sets, and intersection sets of the factors.

	Reachability Sets $R(a_i)$	Antecedent Sets $Q(a_i)$	Intersection Sets $C(a_i)$
A1	A1	A1, C2, C1, C3, D1	A1
A4	A4	A4, C2, B1, C1, A3, C3, D1	A4
B3	B3	B3, C2, C4, A2, C1, C3, D1, D2	B3
B2	B2	B2, B1, C4, A2, C1, A3, C3, D1, D2	B2
C2	C2, A1, A4, B3	C2, C1, C3, D1	C2
B1	B1, A4, B2	B1, C1, A3, C3, D1	B1
C4	C4, B3, B2	C4, A2, C1, C3, D1, D2	C4
A2	A2, C4, B3, B2	A2, D2	A2
C1	C1, C2, B1, C4, A1, A4, B3, B2	C1, C3, D1	C1
A3	A3, B1, A4, B2	A3, C3, D1	A3
C3	C3, C1, A3, C2, B1, C4, A1, A4, B3, B2	C3	C3
D1	D1, C1, A3, C2, B1, C4, A1, A4, B3, B2	D1	D1
D2	D2, A2, C4, B3, B2	D2	D2

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