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Article

Vulnerability Assessment of the Prefabricated Building Supply Chain Based on Set Pair Analysis

Jinjin Li [1], Lan Luo [2] and Zhangsheng Liu [1,*]

[1] College of City Construction, Research Center of Management Science and Engineering, Jiangxi Normal University, Nanchang 330000, China; lijinjin@jxnu.edu.cn
[2] School of Public Policy and Administration, Nanchang University, Nanchang 330000, China; lanluo@ncu.edu.cn
* Correspondence: xiaoliu8033@jxnu.edu.cn

Abstract: In recent years, the disruption of the prefabricated building supply chain has led to increased construction period delays and cost overruns, limiting the development and popularization of prefabricated buildings in China. Therefore, this study established a vulnerability evaluation index system for the prefabricated building supply chain using the driving force–pressure–state–impact–response (DPSIR) framework. We employed the intuitionistic fuzzy analytic hierarchy process (IFAHP), the projection pursuit (PP) model, and variable weight theory to determine the indicator weights. The IFAHP was utilized to reduce the subjectivity in weight assignment and to obtain the degree of membership, non-membership, and hesitation of experts in evaluating the importance of indicators. The PP model was used to determine objective weights based on the structure of the evaluation data, and variable weight theory was applied to integrate subjective and objective weights according to management needs. We utilized Set Pair Analysis (SPA) to establish a vulnerability evaluation model for the building supply chain, treating evaluation data and evaluation levels as a set pair. By analyzing the degree of identity, difference, and opposition of the set pair, we assessed and predicted the vulnerability of the building supply chain. Taking the Taohua Shantytown project in Nanchang as a case study, the results showed that the primary index with the greatest influence on the vulnerability of the prefabricated building supply chain was the driving force, with a weight of 0.2692, followed by the secondary indices of market demand and policy support, with weights of 0.0753 and 0.0719, respectively. The project's average vulnerability rating was moderate (Level III), and it showed an improvement trend. During the project's implementation, the total cost overrun of the prefabricated building supply chain was controlled within 5% of the budget, the construction period delay did not exceed 7% of the plan, and the rate of production safety accidents was below the industry average. The results demonstrated that the vulnerability assessment method for the prefabricated building supply chain based on SPA comprehensively and objectively reflected the vulnerability of the supply chain. It is suggested to improve the transparency and flexibility of the supply chain, strengthen daily management within the supply chain, and enhance collaboration with supply chain partners to reduce vulnerability.

Keywords: prefabricated buildings; supply chain management; vulnerability assessment; DPSIR; intuitionistic fuzzy analytic hierarchy process; projection pursuit; set pair analysis

Academic Editor: Antonio Caggiano

Received: 13 November 2024
Revised: 20 February 2025
Accepted: 21 February 2025
Published: 24 February 2025

Citation: Li, J.; Luo, L.; Liu, Z. Vulnerability Assessment of the Prefabricated Building Supply Chain Based on Set Pair Analysis. *Buildings* **2025**, *15*, 722. https://doi.org/10.3390/buildings15050722

1. Introduction

Prefabricated building construction is a relatively new construction method. It is fast, efficient, and has a low carbon footprint due to prefabricated and standardized components [1]. Unlike traditional on-site operations, prefabricated building construction utilizes components fabricated in a factory using a standardized design. This method reduces environmental pollution at the construction site, improves construction quality, and reduces the waste of raw materials. As a result, prefabricated building construction is used widely in developing countries. For example, the proportion of prefabricated buildings in construction projects in China has increased rapidly from 6.5% in 2017 to 26.3% in 2022. The volume of newly constructed prefabricated buildings has also increased rapidly from 160 million square meters to 838 million square meters.

In the context of sustainable construction, the use of recycled materials in building materials has gained significant attention. High-ductility engineered geopolymer composites (EGCs) with recycled concrete and paste powder as green precursors have shown promising micro-properties and mechanical behavior [2]. These materials offer a sustainable alternative to traditional concrete, reducing the environmental impact of construction waste. Additionally, the role of recycled concrete aggregates in ductile engineered geopolymer composites is crucial, with the effects of the recycled concrete aggregate content and size being significant factors [3]. The incorporation of recycled aggregates not only contributes to sustainability but also influences the overall performance of the composites.

The traditional construction process occurs primarily at the construction site. Its supply chain management is centered on managing raw materials. Since there are few stakeholders, the possibility of supply chain disruption is low. Constructing prefabricated buildings is more complex, including the prefabrication of components in the factory, the transportation of materials from the factory to the construction site, and the installation at the construction site. This process involves multiple construction units and many prefabricated components that must be managed. Therefore, the supply chain is more complex for prefabricated buildings than for traditional construction. In addition, the potential for supply chain disruption is higher, and the consequences are more significant. For example, on 27 March 2023, a prefabricated building project in the Jinshan District of Shanghai had a safety accident due to improper transportation management and on-site safety management of prefabricated components. This incident interrupted the project supply chain and caused a long delay in the construction period. In May 2022, a construction project in the Honggutan District of Nanchang City was delayed for more than three months due to design and processing errors of prefabricated components. The direct economic loss exceeded millions. Therefore, it is necessary to analyze the vulnerability of the prefabricated building supply chain.

Due to the increasing proportion of prefabricated buildings in new construction projects, an increasing number of scholars have investigated prefabricated buildings. Wang [4] used fuzzy set qualitative comparative analysis to study the influence of five uncertainty factors in the prefabricated building supply chain on risk, including the environment, planning and control, supply and demand, manufacturing, and assembly and transportation. Masood [5] conducted an interview and questionnaire survey of project managers of prefabricated buildings in New Zealand. The author found that prefabricated building managers focused more on construction costs and engineering quality and less on the supply and delivery of prefabricated buildings. Du et al. [6] analyzed key factors affecting the carbon emissions of prefabricated building projects. Lu et al. [7] established a risk impact factor system for the prefabricated building supply chain and analyzed the factors using the decision-making trial and evaluation laboratory–interpretive structural modeling (DEMATEL-ISM) combined with the Pythagoras fuzzy set. A case study was used to verify the validity of the framework. Liu [8] used blockchain technology in the supply chain management of prefabricated buildings and conducted a simulation based on the asymmetric evolutionary game model. The results showed that blockchain technology enabled the government to increase the interest of stakeholders in using prefabricated buildings. Liu et al. [9] used prospect theory to establish an evolutionary game model of government supervision of the construction of prefabricated buildings. A dynamic equation was used to analyze the strategies. A literature survey on the Web of Science on 1 August 2024, indicated a lack of scientific and quantitative vulnerability assessment models and methods in managing the prefabricated building supply chain.

With the deepening of risk management research, many scholars have focused on identifying, mitigating, and improving the vulnerability of the supply chain. Wang [10] established an evaluation model to assess the supply elasticity of precast components, focusing on the evaluation criteria, enterprise elasticity, services, and green construction. Jiang et al. [11] analyzed the factors hindering the development of prefabricated buildings in China and found that risk was the main factor. Luo et al. [12] used social network analysis (SNA) to investigate the supply chain's vulnerability in prefabricated construction projects from multiple perspectives. Zhao et al. [13] used a structural equation model (SEM) and virtual frontier slack-based measure and data envelopment analysis (SBM-DEA) to establish a performance evaluation system for the prefabricated building supply chain. The results were used to guide enterprise supply chain management. Xun [14] developed a supply chain operation model based on the supply chain operations reference (SCOR) according to China's construction industry. This method improved the core competitiveness of prefabricated building construction enterprises. Liu [15] proposed an evolutionary game theory (EGT) model considering the government, construction units, and suppliers. The stakeholders in the supply chain improved the synergy level and decision-making efficiency. Yu [16] developed an intelligent multi-stakeholder management platform for prefabricated buildings to determine the level of green technology level and the supply chain profit for the prefabricated building supply chain for different cooperation strategies. The results were used to develop green cooperation strategies in the prefabricated building's supply chain. In summary, most scholars used multi-disciplinary research methods, such as SNA, grounded theory, SCOR, SEM, and fuzzy comprehensive evaluation, to analyze supply chain vulnerability.

A vulnerability evaluation of the prefabricated building supply chain is a multi-attribute evaluation. The weight calculation method is crucial for evaluating the relative importance of the influencing factors. Scholars have developed effective weight calculation methods, including subjective, objective, and combined weighting methods. The combined weighting method is superior to single weights and has been used for multi-attribute evaluations. Chen [17] used the intuitionistic fuzzy analytic hierarchy process (IFAHP) to obtain expert opinion, establish an intuitive fuzzy judgment matrix, and calculate the index weights to evaluate the government's credit risk for non-profit public–private partnerships (PPPs). Sahin et al. [18] proposed an improved game theory model based on the fuzzy analytic hierarchy process (IFAHP) to analyze two competitive shipyards. Wang et al. [19] proposed a game theory model to assess the participants' interactions in the wholesale electricity and DRX markets to improve the efficiency of the former. Ji et al. [20] classified and analyzed game theory methods for multi-objective decision optimization. Wu et al. [21] utilized the sparrow search algorithm to establish an improved projection tracking model. An objective evaluation of the location suitability of a large commercial complex was conducted, providing a scientific and objective decision-making approach for enterprises developing large commercial complexes to reduce site selection risks and improve investment efficiency. Yan et al. [22] proposed a comprehensive urban flood risk assessment method based on a two-dimensional coupled hydrodynamic model and an improved projection tracking method. This method significantly improved the accuracy and efficiency of urban flood disaster risk assessment.

Many multi-attribute evaluation methods have been proposed. The most commonly used classical research methods are the fuzzy comprehensive evaluation method, gray clustering, and the technique for order of preference by similarity to an ideal solution (TOPSIS). Set pair analysis (SPA) is a new multi-attribute evaluation method proposed by the Chinese professor Zhao Keqin in 1989. It is especially suitable for dealing with uncertainty in system analysis, decision evaluation, risk assessment, and similar topics. Yuan et al. [23] established a water resource conflict risk assessment model for transboundary basins based on SPA. They selected the Mekong Basin for verification and analysis and proposed risk prevention measures for water cooperation based on the research results. Bi [24] developed a risk assessment model for oil and gas pipelines based on SPA. The research results provided information for pipeline safety management. Lin [25] used SPA to evaluate the development potential of urban underground locations, providing new development ideas. Yan [26] created an evaluation model based on SPA to assess the carrying capacity of scenic spots. They verified the effectiveness and feasibility of the method with examples. Ge et al. [27] established a risk assessment model for the spontaneous combustion of residual coal in coal mine areas based on the combination empowerment model and SPA. The result provided new insights into the prevention, control, and management of residual coal. Yang et al. [28] developed an evaluation model to assess open-pit slope stability based on SPA and verified the feasibility of the model using a case study.

In summary, Chinese and international scholars have made substantial achievements in this field. However, further improvements are required regarding research objects and methods. (1) Regarding research objects, most studies on the supply chain's vulnerability in prefabricated buildings have focused on supply chain management or risk management but have not consider the engineering of prefabricated buildings. These studies primarily analyzed the performance and cost. This strategy does not reveal the complexity of the vulnerability of the prefabricated building supply chain. (2) Regarding research methods, most scholars have used combined weighting, which retains the advantages of subjective and objective weighting and is superior to using single weights. Numerous multi-attribute evaluation methods have been proposed, but these methods cannot deal with the fuzzy uncertainty of the vulnerability in the prefabricated building supply chain. SPA is a multi-attribute evaluation method that has been successfully used to assess many complex systems.

Therefore, we conduct a vulnerability assessment of the prefabricated building supply chain in China and identify the influencing factors. We establish a quantitative vulnerability assessment model and use the Taohua Shantytown project in Nanchang, China, as a case study. The potential literature contributions of this paper are as follows: (1) We construct a novel index system for evaluating the vulnerability of the supply chain of prefabricated buildings. The driving force–pressure–state–impact–response (DPSIR) framework is used to determine the relationships between the influencing factors. This approach considers the engineering background. The index system is constructed based on the existing literature and a questionnaire survey, providing a theoretical basis for the scientific evaluation of the vulnerability assessment of the prefabricated construction supply chain. (2) We innovatively construct a quantitative vulnerability assessment model for the prefabricated building supply chain. The model uses the IFAHP to determine the degree of membership, non-membership, and hesitation of experts in evaluating indicator importance. The projection pursuit (PP) model is used to determine objective weights based on the structure of the evaluation data. Variable weight theory is used to integrate subjective and objective weights. SPA is applied to determine the degree of identity, difference, and opposition of the vulnerability assessment data and evaluation levels of the prefabricated building supply chain. The vulnerability of the prefabricated building supply chain is evaluated using a science-based approach, providing accurate results.

The remainder of this article is organized as follows: Section 2 describes the vulnerability assessment index system for the prefabricated building supply chain. Section 3 presents the vulnerability assessment model. Section 4 focuses on the case study of the Shantytown project in Nanchang City, China. Section 5 concludes the paper. The technical route of this paper is shown in Figure 1 below.

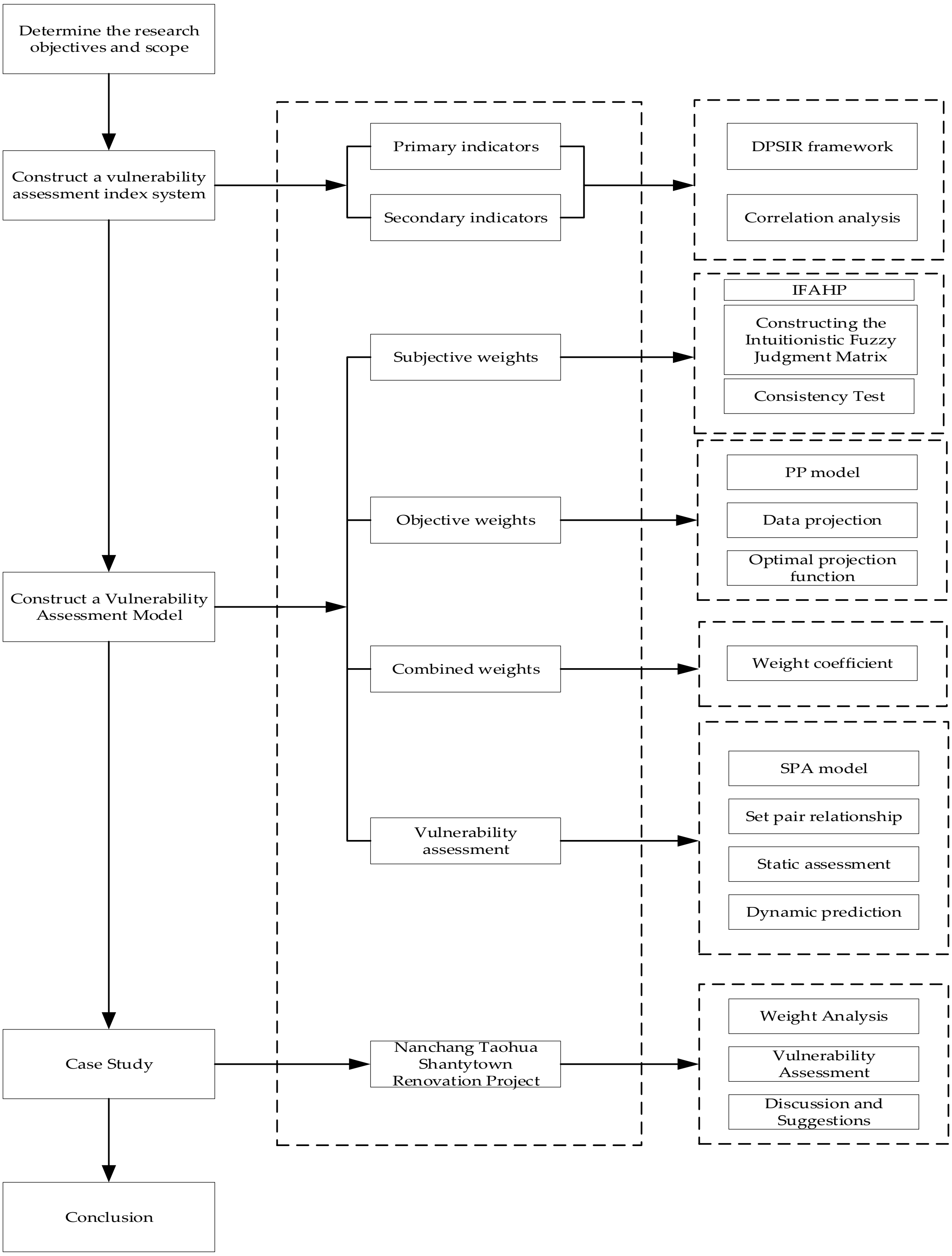

Figure 1. Technology roadmap.

2. Vulnerability Evaluation Index System of Prefabricated Building Supply Chain Based on DPSIR

The prefabricated building supply chain is a cooperative network of enterprises dealing with prefabricated building project design, production, transportation, storage, and assembly at the construction site. The flow of the prefabricated components is crucial in this supply chain. Management is a collaboration between the stakeholders.

The prefabricated building supply chain ecosystem is a complex business network that includes a multitude of participants such as design units, prefabricated component factories, transportation companies, construction units, suppliers, and related regulatory agencies. These participants are interconnected through information flows, logistics, and capital flows, collaborating to complete prefabricated building projects. For instance, design units provide architectural design schemes; prefabricated component factories produce components based on design specifications; transportation companies are responsible for transporting the components from the factory to the construction site; construction units carry out on-site assembly; suppliers provide various raw materials, and regulatory agencies ensure that the entire process complies with relevant laws and standards. This ecosystem is closely related to external factors such as the macroeconomic environment of the construction industry, policies and regulations, technological development, and market demand. The macroeconomic environment influences the scale of investment and market demand for construction projects; policies and regulations provide guidelines and direction for the operation of the supply chain, such as regulations on the proportion of prefabricated buildings and environmental protection requirements; technological development drives innovation in the production of prefabricated components, transportation methods, and construction techniques; market demand directly determines the market size and development potential of prefabricated buildings.

Vulnerability is the lack of resilience of a system, ecosystem, or individual when faced with stress and threats. In this paper, the vulnerability of the prefabricated building supply chain is defined as the degree of difficulty in maintaining the normal operation of the supply chain affected by internal and external adverse factors in the design, production, logistics, and construction of prefabricated buildings. In contrast to risk, which emphasizes external adverse factors, the vulnerability of the prefabricated building supply chain focuses on the system's characteristics. Unlike resilience, which considers the system's characteristics, the vulnerability of the prefabricated building supply chain takes into account the influence of external adverse factors.

The DPSIR model [22] is a comprehensive and innovative research framework suitable for the vulnerability analysis of the prefabricated building supply chain. It conducts a systematic and interactive analysis of external and internal factors. We use this model to identify the primary indices and weak links during management and conduct a literature review to identify the secondary indices.

The DPSIR model is used to analyze the following factors:

(1) Driving force: It refers to the factors influencing the vulnerability of the prefabricated building supply chain. Due to these factors, the prefabricated building supply chain evolves dynamically, deviating from expectations and resulting in adverse effects. Factors affecting the prefabricated construction supply chain include policy changes in the construction industry, changes in prefabricated construction market demand, and the emergence of new technologies in the construction industry. Therefore, we included the following search terms to identify the secondary indicators: market demand for prefabricated buildings, technological progress in the construction industry, policies related to prefabricated buildings, macroeconomics of the construction industry, and development trend of prefabricated buildings;

(2) Pressure: Pressure describes the direct effect of driving forces on the prefabricated building supply chain. The pressure manifests in the fluctuations in raw material and labor prices. Therefore, we included the following search terms to identify the secondary indicators: raw material cost of prefabricated buildings, failures of prefabricated construction, management challenges of the prefabricated building supply chain, and project delivery time in prefabricated construction projects;

(3) State: The state reflects the current operation and stability of the prefabricated building supply chain, including the logistics efficiency and inventory management of prefabricated components and partnerships between different units in the supply chain. Indicators related to daily risk management and emergency management are classified as state indicators. Therefore, we included the following search terms to identify state-related secondary indicators: management of the prefabricated building supply chain, inventory management of the prefabricated building supply chain, risk management of the prefabricated building supply chain, and multi-party supply chain coordination;

(4) Impact: Impact refers to the effect of the vulnerability of the prefabricated building supply chain on project management objectives. Considering the research purpose of this paper, only the adverse effects are analyzed. According to the management objectives, the influencing factors can be divided into cost, construction period, construction safety, construction quality, social impact, and environmental impact. These are closely related to supply chain management. Therefore, we included the following search terms to identify secondary indicators related to the impact: cost overruns of prefabricated buildings, delay in prefabricated construction projects, quality accidents in prefabricated construction, safety accidents in prefabricated construction, customer satisfaction with prefabricated construction;

(5) Response: Response refers to the measures and strategies used by the managers of the prefabricated building supply chain to cope with potential adverse effects. The aim of the response is to mitigate the impact of vulnerability and improve the stability and resilience of the supply chain. Response indicators include technology and management; for example, managers develop new assembly design and processing and construction technologies to cope with adverse effects. They also optimize supply chain management and emergency strategies and establish innovative cooperation models. Therefore, we included the following search terms to identify secondary indicators related to the response: supply chain emergency management strategy, technology innovation in prefabricated buildings, management optimization of the prefabricated building supply chain, and model innovation in prefabricated buildings.

The search of the literature (journal papers and highly cited conference papers) ranged from 2014 to 20 August 2024. We used keywords from previous papers and searched the title and abstract. We obtained 80 English language publications, which were reduced to 30 after initial reading. The vulnerability evaluation index system is presented in Table 1.

Table 1. The vulnerability evaluation index system of the prefabricated building supply chain.

Primary Index	Secondary Index	Reference
Driving force: D	Market demand: D_1	[1,8]
	Policy support: D_2	[1,5,10]
	Environmental protection requirements: D_3	[1,6]
	Safety construction requirements: D_4	[1,7,8]
Pressure: P	Building materials and labor price fluctuations: P_1	[4,8]
	Talent availability: P_2	[1,5,6]
	Public acceptance of prefabricated buildings: P_3	[29]

Table 1. *Cont.*

Primary Index	Secondary Index	Reference
State: S	Component processing flexibility: S_1	[5–8]
	Redundancy rate of major components: S_2	[1,4]
	Number of potential suppliers: S_3	[1,4,5]
	Supplier reputation: S_4	[1,6]
	Transport capacity: S_5	[1,7,8]
Impact: I	Prefabricated building quality pass rate: I_1	[4,8]
	Safety measures during construction of prefabricated buildings: I_2	[1,5,6]
	Customer satisfaction: I_3	[1,4,5]
	Cost overruns: I_4	[1,6]
Response: R	Flexible construction capability: R_1	[1,7,8]
	Suitability of emergency plan: R_2	[2,13]
	Effectiveness of emergency measures: R_3	[1,5,10]
	Information communication: R_4	[29]

(1) D_1 (market demand) refers to the demand for prefabricated buildings in the construction market in a certain period. It reflects the market activity and development potential of the prefabricated construction industry.

(2) D_2 (policy support) refers to the support of governments at all levels, such as the National Development and Reform Commission and the Housing and Construction Bureau, for the development of the prefabricated construction industry.

(3) D_3 (environmental protection requirements) refers to the provisions and requirements of the national and local government or relevant environmental protection agencies to provide environmental protection measures during construction.

(4) D_4 (safety construction requirements) refers to the provisions and requirements of the national and local government or relevant industry regulatory agencies to provide safety measures during construction.

(5) P_1 (building material and labor price fluctuations) refers to the price fluctuations of building materials and labor costs in a certain period due to changes in market supply and demand, industry policy regulation, changes in labor market conditions, and other factors.

(6) P_2 (talent availability) refers to the quantity and quality of human resources with suitable management skills and experience that can be recruited by enterprises in the prefabricated construction supply chain.

(7) P_3 (public acceptance of prefabricated buildings) refers to the public's (e.g., the buyers, evictees, and users of public buildings) acceptance and willingness to adopt prefabricated building technology and products.

(8) S_1 (component processing flexibility) is the adaptability and response speed of component manufacturing and processing links in the prefabricated building supply chain to design changes, customer demand changes, technological updates, or other internal and external factors.

(9) S_2 (redundancy rate of major components) refers to designing and producing additional prefabricated components to protect against potential production defects, transportation losses, or wear and tear during construction.

(10) S_3 (number of potential suppliers) is the total number of potential suppliers that provide a component or service to the prefabricated construction market. This indicator reflects the degree of diversification of the supply chain.

(11) S_4 (supplier reputation) is the reputation of the prefabricated building component supplier, i.e., the supplier's reliability, delivery timeliness, and cooperation sincerity.

(12) S_5 (transport capacity) is the transport efficiency of prefabricated components, which includes the availability of transport vehicles and cargo carrying capacity.

(13) I_1 (prefabricated building quality pass rate) refers to the proportion of construction components that meet or exceed the requirements of national and industry quality specifications during the construction of prefabricated buildings. It reflects the quality of design, processing, and construction of prefabricated components.

(14) I_2 (safety measures during construction of prefabricated buildings) refers to the implementation of safety measures and the incidence of accidents during construction in the planning, design, production, transportation, installation, and other aspects of prefabricated building projects.

(15) I_3 (customer satisfaction) is the customer's satisfaction with the management of a prefabricated building project.

(16) I_4 (cost overruns) is the amount of costs that exceed the budgeted cost.

(17) R_1 (flexible construction capacity) is the response speed and adjustment ability of prefabricated building construction links to market demand changes, design adjustments, technical updates, and other factors.

(18) R_2 (suitability of an emergency plan) is the rationality and completeness of the emergency plan of each unit in the prefabricated building supply chain.

(19) R_3 (effectiveness of emergency measures) refers to the effectiveness of emergency measures taken by units in the prefabricated building supply chain when external shocks occur, indicating to what extent the measures can alleviate the interference and impact of the external shocks on the supply chain.

(20) R_4 (information communication) refers to the efficiency, accuracy, and timeliness of engineering information exchange among participants (including design units, prefabricated part factories, transportation and storage units, and construction units) in the prefabricated building supply chain.

In order to deeply explore the correlation among the indicators in the prefabricated building supply chain vulnerability assessment index system, this study uses Pearson's correlation coefficient to conduct a comprehensive analysis [3]. The Pearson correlation coefficient measures the degree of linear correlation between variables and ranges from -1 to 1. Close to 1 indicates a strong positive correlation; close to -1 indicates a strong negative correlation, and close to 0 indicates a weak linear correlation. The statistical analysis software SPSS 25.0 was used in the calculation process. After calculation, the absolute values of the indicators are all less than 0.7, which shows that the correlation between the indicators in Table 1 is weak. This proves the independence of the indicators selected in this paper [4].

3. Vulnerability Assessment Model of Prefabricated Building Supply Chain

3.1. Data Collection and Evaluation Levels

(1) D_1, D_2, D_3, and D_4 are qualitative indicators. The questionnaire survey method was used to consult experts in China's prefabricated construction industry and use their in-depth understanding to assess and predict the market demand, clarify the policy support, and understand current requirements for the green and safe construction of prefabricated buildings in China.

(2) P_1 is a quantitative index. It is calculated as follows:

$$P_1 = \frac{w_1^* \sum_{i=1}^{n} a_{1i}^* + w_2^* \sum_{j=1}^{m} a_{2i}^* + w_3^* \sum_{k=1}^{p} a_{3k}^*}{w_1 \sum_{i=1}^{n} a_{1i} + w_2 \sum_{j=1}^{m} a_{2j} + w_3 \sum_{k=1}^{p} a_{3k}}, \quad (1)$$

where w_1, w_2, and w_3 are the weights of concrete, steel, and labor in the base period and n, m, and k are the number of enterprises surveyed in these areas, respectively. a_{1i}, a_{2j}, and a_{3k} are the prices of concrete, steel, and labor of enterprises i, j, and k, respectively. * indicates the reporting period for these indicators in Table 1.

P_2 and P_3 are qualitative indices. A questionnaire survey was used to consult experts in China's prefabricated construction industry to obtain index data.

(3) S_1 is a qualitative index. The questionnaire survey was used to obtain expert opinion. S_2 is a quantitative index, which is calculated as follows:

$$S_2 = \frac{\sum_{i=1}^{n} d_i^*}{\sum_{i=1}^{n} d_i}, \tag{2}$$

where n represents the number of major components and d_i and d_i^* represent the planned consumption and redundancy of component i, respectively. d_i and d_i^* are measured in tons.

S_3 is the number of local prefabricated building suppliers that meet the requirements. It is a quantitative indicator. We used the general principles of enterprise quality credit evaluation issued by the National Standards Committee to obtain S_4. The credit rating of prefabricated building suppliers was divided into five categories: A, B, C, D, and E, and the credit rating was obtained using expert opinion.

(4) The following five indicators were obtained from on-site investigations with different contents. S_5 is the transport capacity (such as the delivery time, transportation cost, and loss rate during transportation); I_1 is the quality pass rate after completing construction; I_2 refers to the safety measures; I_4 is the cost overrun; R_1 is flexible construction capability.

(5) I_3, R_2, R_3, R_4: Customer satisfaction (I_3) and the three response indices (R_2, R_3, and R_4) were obtained from a questionnaire survey. The indicator weights were derived by consulting experts.

The 20 indicators have different measurement units. Therefore, we used linear normalization:

$$\begin{cases} x_{ij}^* = \dfrac{x_{ij} - \min\limits_{1\le i\le k}(x_{ij})}{\max\limits_{1\le i\le k}(x_{ij}) - \min\limits_{1\le i\le k}(x_{ij})} & \text{Benefit index} \\ x_{ij}^* = \dfrac{\max\limits_{1\le i\le k}(x_{ij}) - x_{ij}}{\max\limits_{1\le i\le k}(x_{ij}) - \min\limits_{1\le i\le k}(x_{ij})} & \text{Cost index} \end{cases}, \tag{3}$$

where x_{ij} and x_{ij}^* refer to the evaluation data of the index before and after normalization, respectively.

We categorized the vulnerability of the prefabricated building supply chain into five levels (Table 2).

Table 2. Vulnerability levels of the prefabricated building supply chain.

Level	Description
Very low (I)	The supply chain of prefabricated buildings exhibits very high stability and shock resistance and very low vulnerability. Project managers do not have to implement additional vulnerability management measures.
Low (II)	The supply chain of prefabricated buildings shows high stability and shock resistance and low vulnerability. Project managers should review existing vulnerability management measures.
Medium (III)	The stability and impact resistance of the supply chain of prefabricated buildings are average, and the vulnerability is medium. Project managers should review existing vulnerability management measures, identify key influencing factors, and implement targeted vulnerability management measures.

Table 2. *Cont.*

Level	Description
High (IV)	The stability and impact resistance of the supply chain of prefabricated buildings are low, and the vulnerability is high. Project managers should immediately develop comprehensive vulnerability management measures to reduce the vulnerability of the project.
Very high (V)	The stability and impact resistance of the supply chain of prefabricated buildings are very low, and the vulnerability is very high. Project managers need to re-assess comprehensive vulnerability management strategies and recommend that construction should be stopped until vulnerabilities have significantly improved.

3.2. Calculation of Combined Weights

(1) Subjective weight assignment based on IFAHP

IFAHP is a weight calculation method that combines AHP and intuitive fuzzy set theory. It considers the degree of membership, non-membership, and hesitation of experts and is suitable for dealing with the uncertainty and fuzziness of decision information [30]. The main steps are as follows:

Step 1: construct the intuitionistic fuzzy judgment matrix.

The judgment matrix is constructed using intuitionistic fuzzy numbers, which are listed in Table 3.

Table 3. The evaluation scale of the vulnerability index based on intuitionistic fuzzy set.

Evaluation Result	Intuitive Fuzzy Number
Indicator *i* is extremely important compared to indicator *j*	(0.90,0.10,0.00)
Indicator *i* is much more important than indicator *j*	(0.80,0.15,0.05)
Indicator *i* is significantly more important than indicator *j*	(0.70,0.20,0.10)
Indicator *i* is slightly more important than indicator *j*	(0.60,0.25,0.15)
Indicator *i* is equally important than indicator *j*	(0.50,0.30,0.20)
Indicator *i* is slightly more important than indicator *j*	(0.40,0.45,0.15)
Indicator *i* is significantly more important than indicator *j*	(0.30,0.60,0.10)
Indicator *i* is much more important than indicator *j*	(0.20,0.75,0.05)
Indicator *i* is extremely important compared to indicator *j*	(0.10,0.90,0.00)

Experts were invited to evaluate the importance of the vulnerability assessment indicators at the same level. The scoring rules are listed in Table 3. The intuitionistic fuzzy matrix $\boldsymbol{A}$ of the indicators at different levels is obtained:

$$\boldsymbol{A} = \left(a_{ij}\right)_{n\times n}, \tag{4}$$

where $a_{ij} = (\mu_{ij}, v_{ij}, \pi_{ij})$; μ_{ij} represents the expert's positive judgment on the degree of importance; v_{ij} represents the expert's negative judgment on the degree of importance, and π_{ij} represents the expert's due judgment on the degree of importance.

Step 2: perform a consistency check.

We establish a consistent intuitionistic judgment matrix $\overline{Z} = (\overline{z}_{ij})_{m\times n}$ = $(\overline{\mu}_{ij}, \overline{v}_{ij})_{m\times n}$. when $j > i+1$, the method is as follows:

$$\begin{cases} \overline{\mu}_{ij} = \dfrac{\sqrt[j-i-1]{\prod_{t=i+1}^{j-1}\mu_{it}\mu_{tj}}}{\sqrt[j-i-1]{\prod_{t=i+1}^{j-1}\mu_{it}\mu_{tj}}\ \sqrt[j-i-1]{\prod_{t=i+1}^{j-1}(1-\mu_{it})(1-\mu_{tj})}} \\ \overline{v}_{ij} = \dfrac{\sqrt[j-i-1]{\prod_{t=i+1}^{j-1}v_{it}v_{tj}}}{\sqrt[j-i-1]{\prod_{t=i+1}^{j-1}v_{it}v_{tj}}\ \sqrt[j-i-1]{\prod_{t=i+1}^{j-1}(1-v_{it})(1-v_{tj})}} \end{cases}. \tag{5}$$

The distance d between the two matrices is calculated as follows:

$$d(\overline{Z}, Z) = \frac{1}{2(n-1)(n-2)} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\left| \overline{\mu}_{ij} - \mu_{ij} \right| + \left| \overline{v}_{ij} - v_{ij} \right| + \left| \overline{\pi}_{ij} - \pi_{ij} \right| \right). \quad (6)$$

If the distance measure d between Z and $\overline{Z}$ satisfies $d(Z, \overline{Z}) < \tau$, the consistency test is passed. τ is the threshold of the consistency indicator. It is 0.1.

If the consistency test fails, we modify the matrix Z:

$$\begin{cases} \widetilde{\mu}_{ij} = \frac{(\mu_{ij})^{1-\sigma}(\overline{\mu}_{ij})^{\sigma}}{(\mu_{ij})^{1-\sigma}(\overline{\mu}_{ij})^{\sigma} + (1-\mu_{ij})^{1-\sigma}(1-\overline{\mu}_{ij})^{\sigma}} \\ \widetilde{v}_{ij} = \frac{(v_{ij})^{1-\sigma}(\overline{v}_{ij})^{\sigma}}{(v_{ij})^{1-\sigma}(\overline{v}_{ij})^{\sigma} + (1-v_{ij})^{1-\sigma}(1-\overline{v}_{ij})^{\sigma}} \end{cases}, \quad (7)$$

where σ begins with 1 and ends with 0, and the interval is -0.01. The iteration continues until the test is passed.

Step 3: We calculate the relative and absolute weights of the indicators in each level.

The intuitive fuzzy matrix formula can be expressed as

$$\begin{cases} v_i = \frac{\sum_{j=1}^{n} \overline{\mu}_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} (1-\overline{v}_{ij})} \\ \pi_i = 1 - \frac{\sum_{j=1}^{n} (1-\overline{v}_{ij})}{\sum_{i=1}^{n} \sum_{j=1}^{n} \overline{\mu}_{ij}} \end{cases}. \quad (8)$$

We calculate the relative weight of the ith indicator w_i:

$$w_i = \frac{\frac{1-v_i}{1+\pi_i}}{\sum_{j=1}^{n} \frac{1-v_i}{1+\pi_i}}. \quad (9)$$

The absolute weight of the secondary indicator is obtained by multiplying the relative weight of the primary indicator.

(2) Objective weight assignment based on the PP model

The objective of the PP model is to project high-dimensional data in a certain direction into low-dimensional data, interpret the objective weight vector of the indicators as the projection direction, and transform low-dimensional spatial data into final evaluation results [29]. The main steps are as follows:

Step 1: perform data collection and preprocessing.

The PP model uses evaluation data. Equation (3) is used for preprocessing. The evaluation data set $\left[x_{ij}^{*}\right]_{n \times 20}$ is obtained, where x_{ij}^{*} represents the score of the j secondary index of the i research object after normalization, n is the number of research objects, and 20 is the number of secondary indices.

Step 2: we project the data set $\left[x_{ij}^{*}\right]_{n \times 20}$ into a direction in space $\vec{\alpha}$ to obtain the projection value $y(i)$ of the low-dimensional space:

$$y(i) = \sum_{j=1}^{m} \alpha(j) x_{ij}, \quad (10)$$

where $\sum_{j=1}^{m} \alpha^2(j) = 1$ and $0 < \alpha(j) < 1$.

Step 3: construct the optimal projection function of the PP model:

$$\begin{cases} \max Q(\alpha) = S_y \left| D_y \right| \\ S_y = \frac{\sum_{i=1}^{n} |y(i) - E(y)|}{\sqrt{n-1}} \\ D_y = \sum_{i=1}^{n} \sum_{j=1}^{m} (R - r_{ij}) u(R - r_{ij}) \end{cases}, \quad (11)$$

where S_y represents the standard deviation of the projection values, D_y denotes the local density of the projection values, E stands for the average value of the projection values, and r_{ij} is the distance between the projected points; $u\left(R - r_{ij}\right)$ represents the unit step function; R is the radius of the observation window.

A meta-heuristic optimization algorithm is used for convergence, and the optimal projection vector $\overrightarrow{\boldsymbol{\alpha}}^*$ is obtained, i.e., the objective weight $\left\{\omega_j\right\}$ of the index.

Meta-heuristic optimization algorithms assume that the problem can be effectively modeled and that an optimal solution exists within a finite search space. They also presume that the algorithm's parameters are set appropriately to ensure convergence to a satisfactory solution. But these algorithms are limited by their reliance on random sampling, which can lead to suboptimal solutions or getting trapped in local optima. Additionally, they may require significant computational resources and do not guarantee finding the global optimum, especially in dynamic or large-scale problems.

(3) Combinatorial weight assignment based on the variable weight theory

Combining weights using the variable weight theory is widely used in decision analysis, evaluation models, and multi-criteria decision-making [30]. The main steps are as follows:

Step 1: determine the weight coefficient of the subjective and objective weights.

The weight coefficients of the subjective and objective weights are δ and γ, respectively, reflecting the managers' preference for the subjective and objective weights of the indicators. A larger δ means that managers are more inclined to use subjective weights; when $\delta = 0.5$, they believe that subjective and objective weights are equally important. $\delta + \gamma = 1$.

Step 2: calculate the weight of the constant combination.

The constant combined weight W_i^c of the ith indicator is a combination of subjective and objective weights:

$$W_i^c = \delta W_i^s + \gamma W_i^o, \tag{12}$$

where W_i^s and W_i^o are the subjective and objective weights of the ith index, respectively.

Step 3: calculate variable weights.

Variable weight theory is used to calculate the combination weights ω_i:

$$\omega_i = \frac{W_i^c\left(x_i^*\right)^{\alpha_i - 1}}{\sum_{i=1}^{n} W_i^c\left(x_i^*\right)^{\alpha_i - 1}}, \tag{13}$$

where α_i is the variable weight coefficient of the ith index, representing the importance of the index.

3.3. Vulnerability Assessment Model Based on SPA

(1) Static assessment of vulnerability based on SPA

SPA is a novel method to analyze system uncertainty. It uses a set pair (a pair of connected sets) to reveal the relationship between certainty and uncertainty in the system using holistic and relational analysis [28]. The steps are as follows:

Step 1: Abstract the evaluation data and the evaluation level into two sets to create the set pair relationship. The most commonly used SPA method is the five-member-set logarithm:

$$\mu = \sum_{i=1}^{n} \omega_i a_i + \sum_{i=1}^{n} \omega_i b_i i_1 + \cdots + \sum_{i=1}^{n} \omega_i c_i j. \tag{14}$$

Step 2: The key to quantifying the set pair relationship is to solve the connection degree μ_l. The connectedness of the benefit indicator μ_l is

$$\mu_l = \begin{cases} 1 + 0i_1 + 0i_2 + \cdots + 0i_{k-2} + 0j & x_l \geq s_1 \\ \frac{2x_l - s_1 - s_2}{s_1 - s_2} + \frac{2s_1 - 2x_l}{s_1 - s_2} i_1 & \frac{s_1 + s_2}{2} \leq x_l < s_1 \\ \frac{2x_l - s_2 - s_3}{s_1 - s_3} i_1 + \frac{s_1 + s_2 - 2x_l}{s_1 - s_3} i_2 & \frac{s_2 + s_3}{2} \leq x_l < \frac{s_1 + s_2}{2} \\ \vdots & \vdots \\ \frac{2x_l - 2s_{K-1}}{s_{K-2} - s_{K-1}} i_{K-2} + \frac{s_{K-2} + s_{K-1} - 2x_l}{s_{K-2} - s_{K-1}} j & s_{K-1} \leq x_l < \frac{s_{K-2} + s_{K-1}}{2} \\ 0 + 0i_1 + 0i_2 + \cdots + 0i_{k-2} + 1j & x_l < s_{K-1} \end{cases}, \tag{15}$$

where s denotes the upper and lower limits of the evaluation level.

The connectedness of the cost indicator μ_l is

$$\mu_l = \begin{cases} 1 + 0i_1 + 0i_2 + \cdots + 0i_{k-2} + 0j & x_l \leq s_1 \\ \frac{s_1 + s_2 - 2x_l}{s_2 - s_1} + \frac{2x_l - s_1}{s_2 - s_1} i_1 & s_1 < x_l \leq \frac{s_1 + s_2}{2} \\ \frac{s_2 + s_3 - 2x_l}{s_3 - s_1} i_1 + \frac{2x_l - s_1 - s_2}{s_3 - s_1} i_2 & \frac{s_1 + s_2}{2} < x_l \leq \frac{s_2 + s_3}{2} \\ \vdots & \vdots \\ \frac{s_{K-1} - 2x_l}{s_{K-1} - s_{K-2}} i_{K-2} + \frac{2x_l - s_{K-2} - s_{K-1}}{s_{K-1} - s_{K-2}} j & \frac{s_{K-2} + s_{K-1}}{2} < x_l \leq s_{K-1} \\ 0 + 0i_1 + 0i_2 + \cdots + 0i_{k-2} + 1j & x_l > s_{K-1} \end{cases}. \tag{16}$$

Step 3: in SPA, confidence is used to determine the evaluation level.

$$h_k = (f_1 + f_2 + \cdots + f_k) > \lambda, \tag{17}$$

where $f_1 = \sum_{i=1}^{n} \omega_i a_i$, $f_2 = \sum_{i=1}^{n} \omega_i b_{i,1}$, $f_3 = \sum_{i=1}^{n} \omega_i b_{i,2}$, $f_{k-1} = \sum_{i=1}^{n} \omega_i b_{i,K-2}$, and $f_k = \sum_{i=1}^{n} \omega_i c_i$; λ is the confidence level.

(2) Dynamic prediction of vulnerability based on SPA

The SPA model contains substantial evaluation information. The most mature method to perform an evolutionary analysis of multiple relationships is to solve the multi-order derivatives of the connection degree and conduct a state analysis of the multi-order derivatives to determine the evolution of the vulnerability.

The derivatives of the degree of connection are

$$\begin{cases} \partial\mu = \partial a + \partial b + \partial c + \partial d = \frac{a}{a+b} + \frac{b}{b+c} + \frac{c}{c+d} + \frac{d}{d+e} \\ \partial^2\mu = \partial^2 a + \partial^2 b + \partial^2 c = \frac{\partial a}{\partial a + \partial b} + \frac{\partial b}{\partial b + \partial c} + \frac{\partial c}{\partial c + \partial d} \\ \partial^3\mu = \partial^3 a + \partial^3 b = \frac{\partial^2 a}{\partial^2 a + \partial^2 b} + \frac{\partial^2 b}{\partial^2 b + \partial^2 c} \\ \partial^4\mu = \partial^4 a = \frac{\partial^3 a}{\partial^3 a + \partial^3 b} \end{cases}. \tag{18}$$

State analysis aims to determine the vulnerability trend by comparing the coefficients for the same and different levels. We use the state analysis of the first-order partial derivative as an example. Its potential function is $Shi = \left(\frac{a}{a+b}\right) / \left(\frac{c}{c+d}\right)$. When the value of this function is greater than 1, the vulnerability indicator is homogeneous; thus, the vulnerability is low. In contrast, when the value is less than 1, the vulnerability index is in the opposite state; thus, the vulnerability is high. When the value is 1, the vulnerability is stable.

The collected questionnaire results were imported into the SPSS 25.0 software, and Cronbach's Alpha coefficient, the most commonly used reliability analysis tool at present, was selected for reliability analysis. The results show that Cronbach's Alpha coefficients are all greater than 0.7, indicating that the experts participating in the questionnaire have a high consistency on this item; that is, the reliability of the questionnaire results is good. In addition, the validity test tool of the SPSS software is used to learn that the KMO of this questionnaire survey is 0.817 > 0.8. Therefore, the data obtained from this questionnaire have a high content validity. We can move on to the next step.

4. Case Study

4.1. Project Overview

We conducted a case study of the Peach Blossom Shantytown project in Nanchang City. It includes five high-rise residential buildings (1#, 2#, 3#, 4#, and 5#), three commercial buildings (6#, 7#, and 8#) and service rooms, and two underground garages. The residential building has a prefabricated frame shear wall structure with 24–26 floors. The tallest building is 80.10 m high, and the skirt building has a 3–6-story frame structure. The total construction area is 13.7 m^2. The above-ground construction area is 103,000 m^2, and the underground construction area is 34,000 m^2. The prefabricated proportion of the project is 45%. Most prefabricated components are used in the vertical components and stairs. The prefabricated insulation layer was included in the PC component. The prefabricated external wall did not have an insulation layer, and only the non-assembled external wall floor had a thermal insulation layer.

4.2. Weights of Evaluation Indicators

Due to the length limitation of this paper, we only describe the subjective weight calculation of the five primary indicators. The importance values from the experts are input into Equation (5) to establish the intuitive judgment matrix $\overline{Z}$. Equation (6) is used to calculate the distance $d(\overline{Z}, Z)$ = 0.2421 > 0.1 between the Z matrix and the $\overline{Z}$ matrix, indicating inconsistency between the matrices. The matrix Z is modified using Equation (7) and passes the consistency test when $\sigma = 0.86$. The subjective weight of the primary indicators is obtained by inputting the data of the modified matrix Z into Equations (8) and (9). Similarly, the subjective weights of all secondary indicators are obtained.

Equations (10) and (11) are used to construct the objective function of the PP model. A particle swarm optimization algorithm is used to determine the optimal solution of the objective function. The objective weights (and the absolute weights) of the secondary indicators are obtained by inputting the elements into the optimal projection vector. The objective weights of the primary indexes are obtained by summing the objective weights of the secondary indices.

The project manager of the Nanchang Taohua Shantytown has no preference regarding subjective or objective weights. Thus, the weight coefficient of subjective and objective weights is 0.5. We enter the subjective and objective indicator weights into Equation (12) to obtain the combined indicator weights W_i^c. We input the indicator data and weights into Equation (13) to obtain the variable indicator weights (Table 4). The calculated values are $\alpha = 0.25$ and $\alpha = 0.75$, indicating no key indicator and a key indicator, respectively.

Table 4. Combined weights.

Index	Constant Combination		Variable Weight Combination Weights			
			α=0.25		α=0.75	
	Weight	Sort	Weight	Sort	Weight	Sort
D	0.2692	1	0.2172	3	0.2680	1
P	0.1378	5	0.1286	5	0.1376	5
S	0.2135	2	0.2180	2	0.2155	2
I	0.1861	4	0.2240	1	0.1852	4
R	0.1934	3	0.2121	4	0.1937	3
D_1	0.0724	3	0.0607	2	0.073	2
D_2	0.0736	2	0.0506	1	0.0743	1
D_3	0.0512	11	0.0560	13	0.0485	13
D_4	0.0720	5	0.0499	3	0.0721	3

Table 4. *Cont.*

Index	Constant Combination		Variable Weight Combination Weights			
			α=0.25		α=0.75	
	Weight	Sort	Weight	Sort	Weight	Sort
P_1	0.0480	12	0.0435	11	0.0499	11
P_2	0.0657	7	0.0470	7	0.0658	7
P_3	0.0241	17	0.0381	19	0.0219	19
S_1	0.0602	8	0.0570	9	0.0597	9
S_2	0.0320	15	0.0369	15	0.0337	15
S_3	0.0360	14	0.0395	14	0.0349	14
S_4	0.0161	20	0.0237	20	0.0165	20
S_5	0.0692	6	0.0610	5	0.0707	5
I_1	0.0230	18	0.0392	18	0.0219	18
I_2	0.0601	9	0.0733	8	0.0599	8
I_3	0.0753	1	0.0720	4	0.0719	4
I_4	0.0277	16	0.0395	16	0.0315	16
R_1	0.0457	13	0.0317	12	0.0495	12
R_2	0.0551	10	0.0498	10	0.0516	10
R_3	0.0205	19	0.0542	17	0.0247	17
R_4	0.0720	4	0.0765	6	0.0679	6

Analysis of weights:

(1) The driving force has the highest weight and is the most influential primary indicator. The driving force causes adverse consequences such as the interruption of the prefabricated building supply chain, influencing the evolution direction of P, S, I, and R. External economic factors, technological progress, policy changes, and market demand affect the vulnerability of the prefabricated building supply chain. These factors influence the environment and complexity of the supply chain. Therefore, it is reasonable that the driving force is the most important primary indicator of the vulnerability of the prefabricated building supply chain.

(2) The level of policy support is the most important secondary index. Policy support significantly affects enterprises in the prefabricated building supply chain. Financial subsidies and tax relief can reduce the construction costs and improve the profits of enterprises. Advantages in the bidding market can significantly enhance the competitiveness of enterprises in the construction market. Stable government support policies reduce the uncertainty of the prefabricated construction supply chain. Conversely, unclear or frequent changes in supporting policies can significantly increase the uncertainty and vulnerability of the prefabricated construction supply chain.

(3) The index weight of market demand is 0.073. It is the second most important secondary index. Market demand reflects the market activity and development potential of the prefabricated construction industry. The higher the market demand, the more incentive supply chain stakeholders have to optimize resource allocation and promote technological innovation and capacity expansion. A higher market demand is also more conducive to the long-term development of the prefabricated construction industry.

4.3. Evaluation Levels

(1) Static evaluation

The weights of the last five relationships of the secondary and primary indices and the target layer are listed in Table 5.

Table 5. Results of static vulnerability assessment based on SPA.

Index	The Number of Weighted Quintuple Connections	Result
Target layer	$0.1857 + 0.3439i_{\mu1} + 0.2946i_{\mu2} + 0.1484i_{\mu3} + 0.0273j_{\mu}$	III
D	$0.1440 + 0.3319i_{\mu1} + 0.3069i_{\mu2} + 0.1829i_{\mu3} + 0.0343j_{\mu}$	III
P	$0.1568 + 0.3095i_{\mu1} + 0.2538i_{\mu2} + 0.1969i_{\mu3} + 0.0829j_{\mu}$	III
S	$0.1581 + 0.3125i_{\mu1} + 0.3564i_{\mu2} + 0.1140i_{\mu3} + 0.0590j_{\mu}$	III
I	$0.1750 + 0.2585i_{\mu1} + 0.2376i_{\mu2} + 0.1013i_{\mu3} + 0.2276j_{\mu}$	III
R	$0.1912 + 0.3001i_{\mu1} + 0.2368i_{\mu2} + 0.1539i_{\mu3} + 0.1181j_{\mu}$	III
D_1	$0.1228 + 0.3661i_{\mu1} + 0.3339i_{\mu2} + 0.1702i_{\mu3} + 0.0070j_{\mu}$	III
D_2	$0.1496 + 0.3099i_{\mu1} + 0.3667i_{\mu2} + 0.1554i_{\mu3} + 0.0185j_{\mu}$	III
D_3	$0.1156 + 0.3520i_{\mu1} + 0.2891i_{\mu2} + 0.1170i_{\mu3} + 0.1263j_{\mu}$	III
D_4	$0.1862 + 0.3365i_{\mu1} + 0.2679i_{\mu2} + 0.1769i_{\mu3} + 0.0325j_{\mu}$	III
P_1	$0.1700 + 0.3119i_{\mu1} + 0.3294i_{\mu2} + 0.1554i_{\mu3} + 0.0333j_{\mu}$	III
P_2	$0.1108 + 0.3379i_{\mu1} + 0.2032i_{\mu2} + 0.1977i_{\mu3} + 0.1503j_{\mu}$	III
P_3	$0.1283 + 0.3571i_{\mu1} + 0.3399i_{\mu2} + 0.1641i_{\mu3} + 0.0105j_{\mu}$	III
S_1	$0.1266 + 0.3518i_{\mu1} + 0.2333i_{\mu2} + 0.1923i_{\mu3} + 0.0960j_{\mu}$	III
S_2	$0.1746 + 0.3926i_{\mu1} + 0.2450i_{\mu2} + 0.1167i_{\mu3} + 0.0711j_{\mu}$	III
S_3	$0.1975 + 0.3907i_{\mu1} + 0.2206i_{\mu2} + 0.1332i_{\mu3} + 0.0581j_{\mu}$	III
S_4	$0.1085 + 0.3196i_{\mu1} + 0.3298i_{\mu2} + 0.1884i_{\mu3} + 0.0537j_{\mu}$	III
S_5	$0.1695 + 0.2857i_{\mu1} + 0.3761i_{\mu2} + 0.1023i_{\mu3} + 0.0664j_{\mu}$	III
I_1	$0.1177 + 0.3567i_{\mu1} + 0.2153i_{\mu2} + 0.1947i_{\mu3} + 0.1157j_{\mu}$	III
I_2	$0.1394 + 0.3927i_{\mu1} + 0.2969i_{\mu2} + 0.1217i_{\mu3} + 0.0494j_{\mu}$	III
I_3	$0.1602 + 0.2594i_{\mu1} + 0.3709i_{\mu2} + 0.1087i_{\mu3} + 0.1007j_{\mu}$	III
I_4	$0.1770 + 0.2836i_{\mu1} + 0.2813i_{\mu2} + 0.1448i_{\mu3} + 0.1133j_{\mu}$	III
R_1	$0.1229 + 0.2177i_{\mu1} + 0.3687i_{\mu2} + 0.2531i_{\mu3} + 0.0376j_{\mu}$	III
R_2	$0.1747 + 0.3252i_{\mu1} + 0.3535i_{\mu2} + 0.1225i_{\mu3} + 0.0241j_{\mu}$	III
R_3	$0.1205 + 0.2751i_{\mu1} + 0.3278i_{\mu2} + 0.1644i_{\mu3} + 0.1122j_{\mu}$	III
R_4	$0.1067 + 0.3931i_{\mu1} + 0.3448i_{\mu2} + 0.1300i_{\mu3} + 0.0254j_{\mu}$	III

According to the confidence $\lambda = 0.6$, the vulnerability level of the empirical research object is III ($0.1857 + 0.3439 + 0.2946 > 0.6$).

(2) Dynamic evaluation

The first-, second-, third-, and fourth-order partial derivatives of the second- and first-order indices and the target layer are listed in Tables 6–9.

Table 6. First-order partial derivative.

Index	First Order Partial Derivative	Result
Target layer	$0.3507 + 0.5386i_{\mu1} + 0.6651i_{\mu2} + 0.8445i_{\mu3}$	Counterpotential
D	$0.3026 + 0.5196i_{\mu1} + 0.6266i_{\mu2} + 0.8422i_{\mu3}$	Counterpotential
P	$0.3363 + 0.5495i_{\mu1} + 0.5631i_{\mu2} + 0.7036i_{\mu3}$	Counterpotential
S	$0.3360 + 0.4672i_{\mu1} + 0.7577i_{\mu2} + 0.6591i_{\mu3}$	Counterpotential
I	$0.5211 + 0.4012i_{\mu1} + 0.4037i_{\mu2} + 0.3079i_{\mu3}$	Counterpotential
R	$0.3891 + 0.5590i_{\mu1} + 0.6061i_{\mu2} + 0.5657i_{\mu3}$	Counterpotential
D_1	$0.2512 + 0.5230i_{\mu1} + 0.6623i_{\mu2} + 0.9607i_{\mu3}$	Counterpotential
D_2	$0.3255 + 0.4581i_{\mu1} + 0.7024i_{\mu2} + 0.8938i_{\mu3}$	Counterpotential
D_3	$0.2473 + 0.5490i_{\mu1} + 0.7119i_{\mu2} + 0.4810i_{\mu3}$	Counterpotential
D_4	$0.3562 + 0.5568i_{\mu1} + 0.6022i_{\mu2} + 0.8449i_{\mu3}$	Counterpotential

Table 6. *Cont.*

Index	First Order Partial Derivative	Result
P_1	$0.3527 + 0.4864i_{\mu1} + 0.6794i_{\mu2} + 0.8236i_{\mu3}$	Counterpotential
P_2	$0.2469 + 0.6245i_{\mu1} + 0.5068i_{\mu2} + 0.5682i_{\mu3}$	Counterpotential
P_3	$0.2643 + 0.5123i_{\mu1} + 0.6744i_{\mu2} + 0.9398i_{\mu3}$	Counterpotential
S_1	$0.2646 + 0.6012i_{\mu1} + 0.5482i_{\mu2} + 0.6671i_{\mu3}$	Counterpotential
S_2	$0.3078 + 0.6158i_{\mu1} + 0.6774i_{\mu2} + 0.6214i_{\mu3}$	Counterpotential
S_3	$0.3357 + 0.6392i_{\mu1} + 0.6235i_{\mu2} + 0.6963i_{\mu3}$	Counterpotential
S_4	$0.2534 + 0.4921i_{\mu1} + 0.6365i_{\mu2} + 0.7781i_{\mu3}$	Counterpotential
S_5	$0.3725 + 0.4317i_{\mu1} + 0.7862i_{\mu2} + 0.6064i_{\mu3}$	Counterpotential
I_1	$0.2480 + 0.6237i_{\mu1} + 0.5251i_{\mu2} + 0.6273i_{\mu3}$	Counterpotential
I_2	$0.2621 + 0.5695i_{\mu1} + 0.7093i_{\mu2} + 0.7113i_{\mu3}$	Counterpotential
I_3	$0.3817 + 0.4115i_{\mu1} + 0.7733i_{\mu2} + 0.5191i_{\mu3}$	Counterpotential
I_4	$0.3844 + 0.5020i_{\mu1} + 0.6602i_{\mu2} + 0.5612i_{\mu3}$	Counterpotential
R_1	$0.3609 + 0.3712i_{\mu1} + 0.5930i_{\mu2} + 0.8706i_{\mu3}$	Counterpotential
R_2	$0.3494 + 0.4792i_{\mu1} + 0.7427i_{\mu2} + 0.8359i_{\mu3}$	Counterpotential
R_3	$0.3046 + 0.4563i_{\mu1} + 0.6659i_{\mu2} + 0.5944i_{\mu3}$	Counterpotential
R_4	$0.2135 + 0.5327i_{\mu1} + 0.7262i_{\mu2} + 0.8368i_{\mu3}$	Counterpotential

Table 7. Second-order partial derivative.

Index	Second Order Partial Derivative	Result
Target layer	$0.3943 + 0.4475i_{\mu1} + 0.4406i_{\mu2}$	Counterpotential
D	$0.3680 + 0.4533i_{\mu1} + 0.4266i_{\mu2}$	Counterpotential
P	$0.3797 + 0.4939i_{\mu1} + 0.4445i_{\mu2}$	Counterpotential
S	$0.4183 + 0.3814i_{\mu1} + 0.5348i_{\mu2}$	Counterpotential
I	$0.4366 + 0.4263i_{\mu1} + 0.6949i_{\mu2}$	Counterpotential
R	$0.4104 + 0.4798i_{\mu1} + 0.5172i_{\mu2}$	Counterpotential
D_1	$0.3244 + 0.4413i_{\mu1} + 0.4081i_{\mu2}$	Counterpotential
D_2	$0.4154 + 0.3947i_{\mu1} + 0.4400i_{\mu2}$	Counterpotential
D_3	$0.3106 + 0.4354i_{\mu1} + 0.5968i_{\mu2}$	Counterpotential
D_4	$0.3901 + 0.4804i_{\mu1} + 0.4162i_{\mu2}$	Counterpotential
P_1	$0.4203 + 0.4172i_{\mu1} + 0.4520i_{\mu2}$	Counterpotential
P_2	$0.2834 + 0.5520i_{\mu1} + 0.4715i_{\mu2}$	Counterpotential
P_3	$0.3404 + 0.4317i_{\mu1} + 0.4178i_{\mu2}$	Counterpotential
S_1	$0.3056 + 0.5231i_{\mu1} + 0.4511i_{\mu2}$	Counterpotential
S_2	$0.3333 + 0.4762i_{\mu1} + 0.5215i_{\mu2}$	Counterpotential
S_3	$0.3444 + 0.5062i_{\mu1} + 0.4724i_{\mu2}$	Counterpotential
S_4	$0.3399 + 0.4360i_{\mu1} + 0.4500i_{\mu2}$	Counterpotential
S_5	$0.4632 + 0.3544i_{\mu1} + 0.5646i_{\mu2}$	Counterpotential
I_1	$0.2845 + 0.5429i_{\mu1} + 0.4556i_{\mu2}$	Counterpotential
I_2	$0.3152 + 0.4453i_{\mu1} + 0.4993i_{\mu2}$	Counterpotential
I_3	$0.4812 + 0.3473i_{\mu1} + 0.5983i_{\mu2}$	Counterpotential
I_4	$0.4336 + 0.4320i_{\mu1} + 0.5405i_{\mu2}$	Counterpotential
R_1	$0.4930 + 0.3850i_{\mu1} + 0.4052i_{\mu2}$	Copotential
R_2	$0.4217 + 0.3922i_{\mu1} + 0.4705i_{\mu2}$	Counterpotential
R_3	$0.4004 + 0.4066i_{\mu1} + 0.5284i_{\mu2}$	Counterpotential
R_4	$0.2861 + 0.4232i_{\mu1} + 0.4646i_{\mu2}$	Counterpotential

Table 8. Third-order partial derivative.

Index	Third Order Partial Derivative	Result	Index	Third Order Partial Derivative	Result
Target layer	$0.4684 + 0.5039i_{\mu 1}$	Counterpotential	S_1	$0.3688 + 0.5369i_{\mu 1}$	Counterpotential
D	$0.4481 + 0.5152i_{\mu 1}$	Counterpotential	S_2	$0.4117 + 0.4773i_{\mu 1}$	Counterpotential
P	$0.4346 + 0.5263i_{\mu 1}$	Counterpotential	S_3	$0.4049 + 0.5173i_{\mu 1}$	Counterpotential
S	$0.5231 + 0.4163i_{\mu 1}$	Copotential	S_4	$0.4380 + 0.4921i_{\mu 1}$	Counterpotential
I	$0.5059 + 0.3802i_{\mu 1}$	Copotential	S_5	$0.5665 + 0.3857i_{\mu 1}$	Copotential
R	$0.4611 + 0.4812i_{\mu 1}$	Counterpotential	I_1	$0.3439 + 0.5437i_{\mu 1}$	Counterpotential
D_1	$0.4237 + 0.5195i_{\mu 1}$	Counterpotential	I_2	$0.4144 + 0.4714i_{\mu 1}$	Counterpotential
D_2	$0.5128 + 0.4729i_{\mu 1}$	Copotential	I_3	$0.5808 + 0.3673i_{\mu 1}$	Copotential
D_3	$0.4163 + 0.4218i_{\mu 1}$	Counterpotential	I_4	$0.5010 + 0.4442i_{\mu 1}$	Copotential
D_4	$0.4481 + 0.5358i_{\mu 1}$	Counterpotential	R_1	$0.5615 + 0.4872i_{\mu 1}$	Copotential
P_1	$0.5018 + 0.4800i_{\mu 1}$	Copotential	R_2	$0.5181 + 0.4546i_{\mu 1}$	Copotential
P_2	$0.3392 + 0.5393i_{\mu 1}$	Counterpotential	R_3	$0.4962 + 0.4349i_{\mu 1}$	Copotential
P_3	$0.4408 + 0.5082i_{\mu 1}$	Counterpotential	R_4	$0.4034 + 0.4767i_{\mu 1}$	Counterpotential

Table 9. Fourth-order partial derivative.

Index	Fourth Degree Partial Derivative	Result	Index	Fourth Degree Partial Derivative	Result
Target layer	0.4818	Counterpotential	S_1	0.4072	Counterpotential
D	0.4652	Counterpotential	S_2	0.4631	Counterpotential
P	0.4523	Counterpotential	S_3	0.4391	Counterpotential
S	0.5568	Copotential	S_4	0.4709	Counterpotential
I	0.5709	Copotential	S_5	0.5949	Copotential
R	0.4893	Counterpotential	I_1	0.3874	Counterpotential
D_1	0.4492	Counterpotential	I_2	0.4678	Counterpotential
D_2	0.5202	Copotential	I_3	0.6126	Copotential
D_3	0.4967	Counterpotential	I_4	0.5300	Copotential
D_4	0.4554	Counterpotential	R_1	0.5354	Copotential
P_1	0.5111	Copotential	R_2	0.5327	Copotential
P_2	0.3861	Counterpotential	R_3	0.5329	Copotential
P_3	0.4645	Counterpotential	R_4	0.4584	Counterpotential

Analysis of evaluation results:

(1) As shown in Table 5, the vulnerability level of the prefabricated building supply chain is III (medium). Thus, project managers should review existing vulnerability management measures, identify key influencing factors, and implement targeted vulnerability management measures. The prefabricated building supply chain of the Taohua Shantytown project in Nanchang City is sensitive to external disturbances, and the adjustment ability and resilience are high. However, targeted vulnerability management measures are required.

(2) Regarding engineering practice, despite many adverse external influences during the construction of the Taohua Shantytown project in Nanchang City, almost no impact occurred on the prefabricated supply chain. The project was completed on schedule; the total cost did not exceed the budget, and no production safety accidents occurred during the construction period. After the delivery, the construction units and the relocation

and resettlement groups were satisfied with the project. Thus, the evaluation results are in line with actual conditions, demonstrating the validity of the proposed vulnerability assessment method.

(3) The results in Table 5 indicate that the vulnerability levels obtained from the primary and secondary indicators are III, making it difficult to identify the dominant influencing factors. Therefore, we conducted a dynamic evaluation. As shown in Tables 6–9, the target layer and most of the primary and secondary indicators show a reverse trend; that is, the vulnerability level of the project shows a downward trend. In the first-order deflection, the primary index I exhibits a homogeneous relationship; thus, the vulnerability is decreasing. This index is related to the vulnerability of the project management, indicating that achieving this goal is becoming more difficult as the project continues.

4.4. Discussion

This section aims to contextualize the findings of our study within the broader landscape of international research on the vulnerability of prefabricated building supply chains. By comparing our results with similar studies, we highlight the originality of our work and its contributions to science, society, and the economy.

(1) Comparison with International Studies

Our study's findings reveal a nuanced understanding of the vulnerability of the prefabricated building supply chain, particularly in the context of the Taohua Shantytown project in Nanchang. When compared to previous research, we find that our approach offers a more detailed and refined analysis of vulnerability factors. For instance, while Wang et al. [4] identified broad categories of risk factors affecting supply chains, our study delves deeper into specific indices, such as market demand and policy support, providing a more granular view of the vulnerabilities faced by the prefabricated building sector.

In terms of methodology, our use of the Set Pair Analysis (SPA) framework distinguishes our research from traditional evaluation methods. For example, while classic methods such as the analytic hierarchy process (AHP) and fuzzy comprehensive evaluation have been widely used [2,3], they often overlook the dynamic interactions between various factors. In contrast, our SPA-based model captures the complexities of these interactions, allowing for a more comprehensive assessment of vulnerability. The results of our SPA model indicate that the primary index influencing vulnerability is the driving force, with a weight of 0.2692, which aligns with the findings of Masood et al. [5] but provides a more detailed breakdown of secondary indices.

(2) Originality of the Study

The originality of our study lies in its focus on the specific vulnerabilities of the prefabricated building supply chain in China, a rapidly growing sector that has not been thoroughly examined in the existing literature. By integrating the driving force–pressure–state–impact–response (DPSIR) framework with the SPA methodology, we have developed a robust evaluation index system that reflects the unique challenges faced by this industry.

Our findings indicate that the primary index influencing vulnerability is the driving force, with market demand and policy support emerging as the most critical secondary indices. This insight underscores the necessity for targeted policy interventions and market strategies to enhance the resilience of the prefabricated building supply chain.

(3) Contributions to Science, Society, and the Economy

From a scientific perspective, this study enriches the existing body of knowledge on supply chain vulnerability by providing a detailed evaluation framework that can be adapted to other sectors facing similar challenges. The methodology developed herein can serve as a template for future research aimed at assessing vulnerabilities in various industrial contexts.

Socially, our findings advocate for improved collaboration among stakeholders in the prefabricated building ecosystem, emphasizing the importance of public acceptance and regulatory support. By addressing the vulnerabilities identified in our study, policymakers and industry leaders can work together to foster a more sustainable and resilient construction environment.

Economically, enhancing the resilience of the prefabricated building supply chain has significant implications for cost savings and efficiency improvements. By minimizing delays and cost overruns, our research contributes to the economic viability of prefabricated buildings, promoting their adoption and integration into mainstream construction practices.

(4) In-Depth Discussion of Findings

The results of our vulnerability assessment reveal that while the prefabricated building supply chain in the Taohua Shantytown project has a moderate vulnerability rating, there is an observable trend towards improvement. This finding suggests that proactive management strategies, such as enhancing supply chain transparency and flexibility, are effective in mitigating vulnerabilities.

Moreover, the identification of market demand and policy support as key factors highlights the need for the continuous monitoring of external influences that can impact the supply chain. As the construction industry evolves, adapting to changing market conditions and regulatory landscapes will be essential for maintaining supply chain resilience.

4.5. Countermeasures and Suggestions

Our results indicate that policy support and market demand are the dominant secondary indicators, and the "impact" index suggests a decreasing trend. Therefore, based on the supply chain management results of this case study, we propose the following management strategies to improve supply chain vulnerability.

(1) Strengthen policy guidance and support for prefabricated buildings

The government should provide financial subsidies and tax breaks for projects using prefabricated buildings to reduce the cost of enterprises and enhance their research and development motivation. It should strengthen legislation related to prefabricated buildings; formulate targeted laws, regulations, and industry standards; provide legal protection for developing supply chains; and optimize existing regulations to meet the needs of the prefabricated building industry. The government should focus on promoting prefabricated building demonstration projects, enhancing public and industry awareness, improving project management through successful cases, and using financial incentives to accelerate the popularity of prefabricated buildings.

(2) Stimulate market demand and broaden application scenarios

The high weight of the secondary index "market demand" shows that policy support from the government is required to improve the market's demand for prefabricated buildings in China. In addition, enterprises in the supply chain of prefabricated buildings should make efforts to demonstrate the advantages of prefabricated buildings, eliminate public doubt, and improve people's acceptance by holding exhibitions and conferences and using new media (such as short videos). Enterprises should consider using prefabricated buildings in education, real estate, temporary hospitals, tourism, and commercial real estate to meet the needs of different industries and expand market coverage. Enterprises need to broaden financing channels; cooperate with financial institutions; and provide special loans, financial leasing, and other services to reduce the financing cost of prefabricated construction projects and ensure the smooth progress of projects.

(3) Build a multi-party cooperative supply chain ecosystem

The countermeasures and suggestions are key strategies to promote the development of China's prefabricated construction industry. New technologies, such as cloud computing and blockchain, should be adopted to improve information delivery, communication, and management efficiency related to the prefabricated building supply chain to achieve transparent sharing and reduce the risk of disruption. Competition between enterprises should be reduced to establish cooperative relationships, share resources, and improve the stability and flexibility of the supply chain.

5. Conclusions

This study has made several significant contributions to the field of prefabricated building supply chain vulnerability assessment. The following lists outline our main findings and conclusions:

(1) Index System Establishment: We successfully constructed a novel index system for evaluating the vulnerability of the prefabricated building supply chain. This system, developed using the DPSIR framework, provides a theoretical basis for scientifically evaluating the vulnerability of prefabricated construction supply chains;

(2) Quantitative Assessment Model: We innovatively developed a quantitative vulnerability assessment model that integrates the intuitionistic fuzzy analytic hierarchy Process (IFAHP), the projection pursuit (PP) model, and variable weight theory. This model offers a scientific approach for evaluating the vulnerability of prefabricated building supply chains;

(3) Weights of Primary and Secondary Indices: Our analysis revealed that the driving force index, with a weight of 0.2692, has the most significant influence on the vulnerability of the prefabricated building supply chain. Within this, market demand and policy support were identified as the most influential secondary indices, with weights of 0.0753 and 0.0719, respectively;

(4) Case Study Results: The case study of the Taohua Shantytown project in Nanchang indicated that the project's average vulnerability rating was moderate (Level III), showing an improvement trend. This aligns with the actual performance of the project, validating our assessment method;

(5) Management Recommendations: Based on our findings, we recommend improving the transparency and flexibility of the supply chain, strengthening daily management, and enhancing collaboration with supply chain partners to reduce vulnerability;

(6) Limitations and Future Research: We acknowledge the limitations of our study, particularly in defining a more accurate vulnerability measure and developing a wider applicability evaluation index. We suggest that future research focus on including more quantitative indicators and exploring alternative methods for determining vulnerability assessment levels.

Author Contributions: Conceptualization, J.L. and Z.L.; methodology, J.L. and Z.L.; software, J.L.; validation, J.L., Z.L. and L.L.; formal analysis, J.L. and L.L.; investigation, J.L. and Z.L.; resources, J.L. and L.L.; data curation, J.L.; writing—original draft preparation, J.L. and Z.L.; writing—review and editing, J.L. and L.L.; visualization, J.L. and L.L.; supervision, J.L. and Z.L.; project administration, J.L.; funding acquisition, Z.L. All authors have read and agreed to the published version of the manuscript.

Funding: This manuscript was funded by National Natural Science Project (71863020); Jiangxi Province Culture, Art and Science Planning General Project (YG2022098).

Data Availability Statement: The data needed for case study can be obtained from the correspondent for scientific research.

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

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