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Risk Assessment Model for Prefabricated Construction Projects Using Multi-Factor Evaluation

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Abstract

This study develops a multi-factor risk assessment model for prefabricated construction projects, covering production capacity, transportation limits, on-site conditions, and worker skills. A scoring system was tested on 21 projects across three provinces. Results show that transportation delays and inaccurate component scheduling were the most significant risk contributors. The model provides a structured framework for predicting project uncertainty and improving planning reliability during the early design stage.

Keywords

prefabrication risk, project evaluation, supply chain constraints, component scheduling, construction management

1. Introduction

Prefabricated construction has been widely promoted as an effective approach to shortening project schedules, reducing material waste, and improving on-site safety compared with traditional cast-in-place construction [1]. Despite these advantages, recent studies show that prefabricated projects continue to face substantial uncertainty across the full supply chain, including fluctuations in factory output, constraints on transport routes, variable lifting conditions, and differences in crew experience [2,3]. These risks are often more complex than those found in conventional construction because production, transportation, and installation occur at different locations and require tight coordination among multiple teams [4]. As the prefabrication market expands in many countries, recurring issues such as unstable manufacturing capacity, long dispatch distances, and limited site access remain widely reported. Research on risk in prefabricated construction has grown significantly in recent years. Several studies have developed risk indicator systems focusing on safety, production phases, or project-level management, covering workers, equipment, managerial practices, and environmental factors [5]. Other contributions adopt network-based analytical methods to identify critical risk nodes and the interactions among them [6]. These network-oriented studies emphasize that risks are often interconnected and propagate through supply-chain relationships rather than occurring in isolation, highlighting the importance of understanding

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stakeholder coordination and information flow across the prefabricated construction lifecycle [7]. Additional works propose intelligent safety-evaluation methods using machine learning or optimization techniques, yet these models typically target a single phase or rely on limited case samples, which restricts their generalizability [8].

Supply-chain-focused research further highlights that production and logistics risks are particularly influential in prefabricated construction. Existing studies have developed index systems addressing manufacturing delays, transportation uncertainties, and site-installation bottlenecks [9,10]. Other research shows that transport disruptions and inaccurate component scheduling often exert stronger impacts on overall project outcomes than pure logistics constraints, especially when oversized modules must pass through narrow or complex road networks [11]. The importance of coordination and information flow is also well recognized: when factory production, freight scheduling, and on-site lifting operations are not synchronized, crews experience idle time, repeated resequencing, and elevated safety pressures [12]. Although these findings provide valuable insights, most existing models evaluate production, transport, and site conditions separately. Few studies combine these risks into a unified framework that can be used during early planning to guide project-level decisions. Transportation-related risks remain a recurring concern in the literature. Prior studies indicate that route restrictions, special handling requirements, and the risk of damage during long-distance delivery can increase both project duration and cost [13,14]. Industry reports similarly identify logistics and temporary storage limitations as major barriers to the wider adoption of prefabrication in dense urban contexts [15,16]. Component scheduling is another decisive factor: inaccurate sequencing contributes to on-site congestion, excessive temporary storage, inefficient crane utilization, and project-wide slowdowns [10,12]. Multi-criteria evaluation techniques—including fuzzy comprehensive evaluation, TOPSIS, and AHP-based weighting—have been widely used to structure these complex indicators in prefabricated construction risk studies [17]. Although these methods help formalize decision-making, many models rely on small datasets, broad indicator lists, or limited validation across projects, which reduces their practical applicability during early design stages. Overall, existing research reveals three key limitations. First, many digital and analytical risk-assessment frameworks emphasize conceptual structures or factory-level perspectives but lack validation using real project data with measurable outcomes [18]. Second, a large portion of sequencing studies depends on BIM-based or simulation-only tools without real-time operational feedback, limiting their usefulness for on-site decision-making [19]. Third, few models integrate production capacity, transport restrictions, site constraints, and worker-skill

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factors into a unified scoring system that reflects the interdependencies among risks across the prefabricated supply chain. These gaps underline the need for practical, multi-factor tools that support early project planning while accounting for the systemic nature of risks in prefabricated construction.

This study develops a multi-factor risk assessment model designed specifically for early-stage planning of prefabricated construction projects. The model consolidates risks related to production capacity, transport limits, site conditions, and worker skills into a structured scoring system that remains simple enough for routine project use while still capturing key supply-chain constraints. It is tested on 21 projects from three provinces, enabling cross-context comparison rather than reliance on a single case. Based on these evaluations, we identify the relative contribution of the major risk categories and show that transport delays and inaccurate component scheduling are consistently the strongest sources of overall project risk. The aim of this study is to provide a practical decision-support tool that helps project teams identify critical sources of uncertainty during early planning and improve the reliability and predictability of prefabricated construction projects.

Materials and Methods

2.1 Study Area and Sample Description

This study used data from 21 prefabricated construction projects located in three provinces in eastern and central China. The projects include residential buildings, public facilities, and small mixed-use structures. Each project relied on factory-made components such as wall panels, slabs, beams, and stairs. Transport distances ranged from short local deliveries to long hauls of more than 150 km. Data were collected through site visits, interviews with project managers, and review of production and delivery records. All sampling was done during normal working conditions. The projects cover a wide range of on-site environments, from dense urban sites with limited access to more open suburban locations.

2.2 Experimental Design and Control Setup

A comparative design was used to examine how different risk sources affect overall project risk. For each project, the proposed risk model was applied and compared with the assessment prepared by the project team during early planning. The assessment made by the project team served as the control, reflecting common practice based on experience. The experimental condition used the structured scoring system developed in this study. The system groups risks into four categories: production capacity, transport limits, site conditions, and worker skills. Both assessments relied on the same project information. This setup makes

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it possible to see which risks are highlighted or overlooked when a more systematic method is applied.

2.3 Measurement Methods and Quality Control

Risk-related data were gathered from several sources. Factory data included daily production rates, equipment status, and available overtime capacity. Transport data included road limits, travel time, delivery logs, and records of delays. Site data covered lifting areas, storage space, access routes, and the number of weather-related stoppages. Worker data included the number of trained operators and their experience with prefabricated assembly. All information was checked by two researchers working independently. When differences were found, the entries were confirmed with the project team or verified using delivery logs or written records. Projects with missing essential information were removed to maintain data reliability.

2.4 Data Processing and Model Equations

All indicators were normalized to allow comparison across projects. Risks were grouped into the four categories, and a weighted score was calculated for each category. The total project risk score RRR was calculated as:

$$R=\sum_{i=1}^{n} w_i\, s_i,$$

where s_i is the normalized value of indicator i and w_i is its weight. Each category-level score C_j was calculated as:

$$C_j=\frac{1}{m_j}\sum_{k=1}^{m_j} s_{jk},$$

where m_j is the number of indicators in category j and s_{jk} is the score of each indicator in that category. All calculations were done in Python. Indicator weights were obtained by averaging expert inputs to keep the system clear and easy to use. The results were then compared across the 21 projects to identify which risk sources appeared most often.

2.5 Validation and Sensitivity Analysis

A sensitivity analysis was performed to test the stability of the model. Indicator weights were adjusted within a ±15% range, and changes in the total risk score were recorded. This helped identify which indicators had the strongest effect on the final results. The model outputs were also compared with actual events recorded in each project. Projects that experienced

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transport delays or major scheduling problems showed higher scores in those categories, which supports the accuracy of the scoring method.

3. Results and Discussion

3.1 Overall Risk Patterns Across the Projects

The multi-factor model produced a clear risk profile for each of the 21 prefabricated projects. Most projects fell into the medium-risk range, while a few showed notably higher scores due to long transport routes or tight installation schedules. Projects with stable suppliers and short delivery distances tended to have lower scores. In contrast, projects that relied on scattered factories or faced strict milestone dates showed higher overall risk. Transportation limits and scheduling issues contributed more to total risk than worker skills or site conditions. A similar pattern has been reported in earlier studies that link supply-chain constraints with project uncertainty [20]. Figure 1 summarizes the category-level scores and highlights the strong influence of transport and scheduling factors.

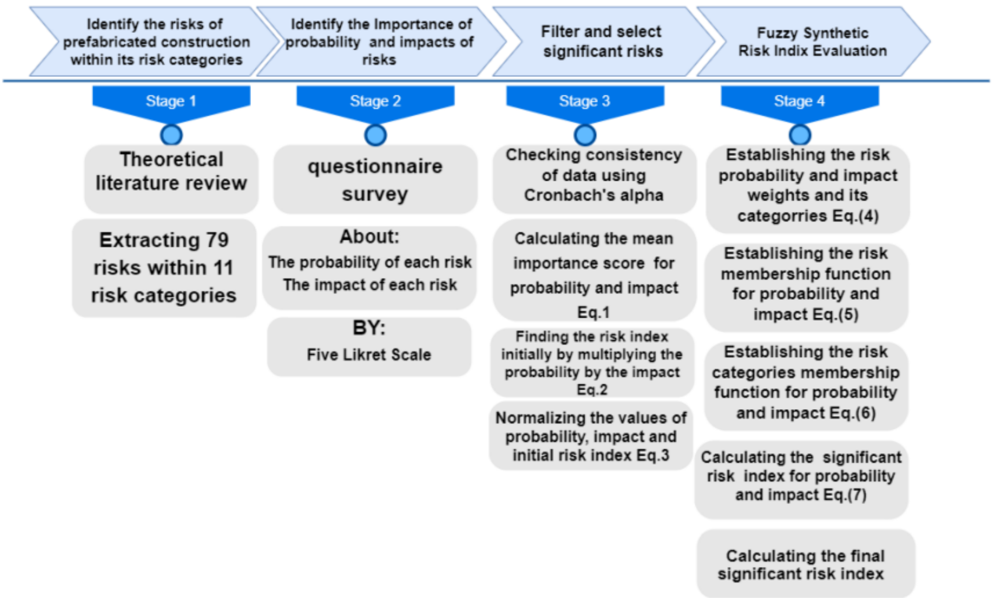

Fig. 1.Risk scores for the four categories across the 21 projects, showing the strong effect of transport and scheduling factors.

3.2 Influence of Transport and Scheduling on Overall Risk

Transport-related indicators had the strongest effect on total risk. Projects that required long-distance delivery or passed through congested urban areas recorded higher scores and more frequent disruption events. Scheduling issues also played a major role. When factory output did not match the planned installation sequence, crews faced unplanned storage, resequencing, and repeated lifting adjustments. These findings match earlier research

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showing that logistics constraints and poor coordination are primary sources of delay in prefabricated and modular projects [21]. In the current dataset, the combination of long transport routes and inaccurate component sequencing was the main driver of high-risk cases.

3.3 Relationship Between Risk Scores and Observed Field Outcomes

To test whether the model reflects real project performance, risk scores were compared with field records. Projects with high transport and scheduling scores also reported more delay days and more frequent changes to daily lifting plans. These projects often stored large components temporarily in limited yard space, which slowed crane operations and created additional handling work. In contrast, low-risk projects had smoother installation flow and fewer interruptions. This relationship supports previous findings that steady logistics and accurate sequencing reduce time loss in prefabricated assembly [22]. Figure 2 presents the normalized importance of each risk category, showing that transport and scheduling remain the most influential factors across the sample.

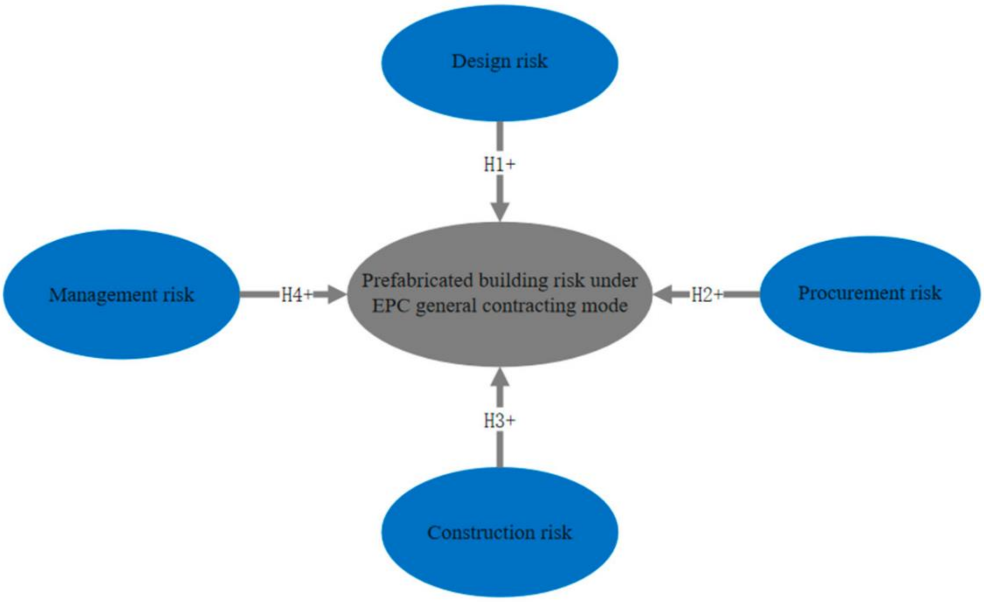

Fig. 2.Normalized importance of the four risk categories, with transport and scheduling having the highest influence.

3.4 Comparison with Earlier Studies and Practical Implications

Compared with existing risk assessment frameworks, which often involve large indicator sets or rely on expert scoring alone, the present model places emphasis on factors that directly influence day-to-day planning. Previous studies using fuzzy evaluation or structural equation modeling highlighted the importance of logistics and management risks, but many required large survey samples and were not tailored to project-specific analysis [23]. The current model provides a simpler structure that can be applied early in design using basic project data.

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The results show that early checks on transport routes, delivery timing, and lifting windows can help reduce major sources of uncertainty before construction begins. This suggests that risk assessment in prefabricated projects should shift from broad checklists to project-specific profiles that guide adjustments to production planning and delivery arrangements.

4. Conclusion

This study introduced a simple multi-factor model to assess risk in prefabricated construction projects and applied it to 21 projects from three provinces. The results showed that transport delays and inaccurate component scheduling were the main factors behind high-risk scores, while production limits, site conditions, and worker skills had smaller but still noticeable effects. The model groups risks into four clear categories and uses straightforward scoring, making it suitable for early project planning when limited information is available. The findings suggest that careful planning of delivery routes, arrival timing, and lifting sequences can reduce major sources of uncertainty and help stabilize workflow during installation. However, the analysis is based on a moderate sample size and does not include full real-time data for on-site operations. Future studies should test the model on more project types, include sensor-based data, and integrate safety indicators so that project teams can evaluate efficiency and risk at the same time. A more complete digital system that links production, transport, and on-site work may offer further improvements in the prediction and management of risk in prefabricated construction.

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