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The Impact of BIM Technology on the Lifecycle Cost Control of Prefabricated Buildings: Evidence from China

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Abstract: Prefabricated construction has become a significant trend in the international building industry, yet its promotion in China faces cost challenges. This study explores the effect of building information modelling (BIM) technology on the various phases of prefabricated buildings, focusing on the entire lifecycle cost to reduce the overall cost. Key factors influencing the lifecycle as the whole cost control of prefabricated buildings are identified via the top 35 highly cited BIM papers; 15 experts were invited to evaluate the factors influencing the lifecycle cost control of prefabricated buildings, and 22 factors were identified to construct the surveys. The results of 364 valid questionnaires were analysed. Research indicates that BIM significantly impacts cost control across various stages of the lifecycle of prefabricated buildings. BIM's impact on cost control, ranked from highest to lowest, is as follows: construction and installation phase, production and transportation phase, operational maintenance phase, and design phase. By minimising costs at each stage, BIM enhances design efficiency, simulates production and logistics, reduces rework during construction, and, when integrated with artificial intelligence, BIM optimises operation and maintenance management. Leveraging BIM technology to its full potential effectively reduces the lifecycle costs of prefabricated buildings.

Keywords: prefabricated buildings; entire lifecycle cost; BIM; structural equation modelling; cost management

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1. Introduction

Modern society places greater emphasis on sustainable development, requiring various industries to upgrade and change their energy structures [1]. As a traditional energy-consuming sector, the construction industry consumes vast amounts of global energy annually and generates significant amounts of solid waste and greenhouse gases [2]. Prefabricated buildings, with advantages such as energy efficiency, high productivity, and environmental friendliness, are increasingly being adopted worldwide as a sustainable construction model to improve productivity and mitigate the negative environmental impacts of traditional construction activities [3]. Prefabricated buildings have become a development trend in the construction industry and an effective pathway toward green and eco-friendly practices [4].

Despite numerous advantages, the development of prefabricated buildings in China started late, with immature market conditions and technologies [5], leading to higher average costs for prefabricated building projects [6]. These factors have significantly constrained the growth of prefabricated buildings. Currently, cast-in-place remains the dominant construction method, and the overall proportion of prefabricated buildings is still relatively small [7], with significant regional disparities in development indirectly contributing to cost differences between prefabricated buildings and traditional constructions in different regions. Constraints related to transportation reduce on-site construction flexibility, and a lack of professional construction personnel directly or indirectly limits the widespread application of prefabricated components [8], further increasing costs [9]. Compared to traditional cast-in-place methods, higher costs of prefabricated buildings [10] have become a major obstacle to their development. There is an urgent need to standardise the management of prefabricated buildings, reduce entire lifecycle costs, and promote their widespread application.

Building information modelling (BIM) technology, based on digital modelling and information sharing, is widely applied and can effectively facilitate intelligent building management and operations [11]. BIM, through the rich data integration of building models, promotes industrialised construction [5], enhances the performance of prefabricated buildings, and offers significant potential for the industry's development [5]. It can reduce errors and rework in the design phase, improve project collaboration efficiency, optimise material procurement and inventory management, enhance construction efficiency, shorten construction timelines, and facilitate entire lifecycle cost control [12]. Giuseppe Piras et al. [13] conducted a case study on the Lazio Region Headquarters, a project leveraging BIM technology, artificial intelligence, machine learning, and the Internet of Things to implement spatial management strategies. Liu et al. [14] demonstrated the application of BIM technology to prefabricated buildings through a case study, highlighting its ability to provide an effective communication platform for all participants in the construction process. Rafael et al. [15] proposed a "Cloud BIM" model to enhance coordination among designers. Bortolini et al. [16] utilised the synergy between BIM 4D models and lean production principles to improve logistics planning and control in prefabricated buildings. Akanbi et al. [17] developed a BIM-based whole-life performance estimator (BWPE) to enhance the management of prefabricated components during the recycling phase. These studies underscore BIM's role in prefabricated building design, construction, logistics, and recycling stages. However, there is currently limited research on the entire lifecycle stages, and few studies address the regulatory role of BIM in cost control for prefabricated construction. As the stages within the lifecycle are interdependent, BIM can be used to plan comprehensively across the entire process. Although BIM offers numerous benefits, more professionals need to be skilled in BIM technology, resulting in additional costs associated with modelling. This shortage is one of the factors limiting the widespread adoption of BIM. Industrialisation is the future trend in the construction industry, and BIM is gradually being applied to prefabricated buildings. However, its impact on the entire lifecycle cost control for prefabricated buildings remains limited. Exploring the impact of BIM technology on the whole lifecycle costs of prefabricated buildings, integrating BIM with artificial intelligence, and fully leveraging BIM's moderating effect on construction cost control for prefabricated buildings is crucial for reducing costs, driving the development of intelligent building operations and promoting the widespread adoption of prefabricated buildings.

The study takes an entire lifecycle perspective on projects to consider the potentially complex interactions among factors influencing the cost of prefabricated buildings. Structural equation modelling (SEM) investigates the cost composition and influencing factors associated with prefabricated buildings. It comprehensively discusses the methods to fully utilise BIM technology in the context of cost control at various phases during prefabricated building construction, with the aim of further clarifying BIM's functional mechanisms and effectively reducing the entire lifecycle costs of prefabricated buildings.

This study examines BIM's impact on the lifecycle costs of prefabricated buildings. Section 2 covers the materials and methods, Section 3 shows the results, and Section 4 encompasses the discussion and the conclusions.

2. Materials and Methods

2.1. Variable Proposition and Model Construction

2.1.1. Selection and Determination of Variable Factors

EPC refers to a project management framework where engineering, procurement, construction, and trial operations are all handled by a single contractor [18]. This contractor assumes full responsibility for the project's quality, safety, timeline, and cost control. The entire lifecycle of prefabricated buildings mainly consists of four phases: the design phase, the production and transportation phase, the construction and installation phase, and the operation and maintenance phase. Each phase has varying degrees of influence on the cost of prefabricated buildings. The variables are first proposed to explore the moderating effect of BIM at different phases.

First, an initial selection of variable factors that may influence the lifecycle cost control of prefabricated buildings was conducted through a literature review. Using regional and international databases such as CNKI, VIP, Wanfang, CSCD, Elsevier SDOL, SpringerLink, SCI Expanded, ESI, EI Compendex Web, JCR, and ASCE, keywords such as "prefabricated buildings", "BIM technology", and "lifecycle cost control" were used to yield approximately 250 relevant articles. The collected literature was then organised, and focused filtering was conducted on investment risks in prefabricated residential projects. Priority was given to literature from SCI, EI, CSCD, CSSCI, and core Chinese journals, with a final selection of 35 papers based on their high citation frequency in recent years. The factors influencing the lifecycle cost control of prefabricated buildings were summarised from these sources.

Subsequently, a panel of experts convened to ensure the scientific accuracy of the variable selection process. The panel comprised 15 members: three from real estate development firms, three from prefabricated component suppliers, three from architectural design firms, three from construction firms, and an additional three scholars and experts from universities engaged in research on the cost of prefabricated buildings. These experts discussed and evaluated the variable factors influencing the lifecycle cost control of prefabricated buildings, ultimately identifying the most significant variables [19]. The basic information on the experts is shown in Table 1.

Table 1. Basic information on experts.

No.	Affiliation	Position Category
1	Real estate developer	Management personnel
2	Real estate developer	Management personnel
3	Real estate developer	Management personnel
4	Prefabricated component supplier	Technical personnel
5	Prefabricated component supplier	Technical personnel
6	Prefabricated component supplier	Management personnel
7	Architectural design firm	Technical personnel
8	Architectural design firm	Technical personnel
9	Architectural design firm	Management personnel
10	Construction company	Technical personnel
11	Construction company	Technical personnel
12	Construction company	Management personnel
13	Ordinary higher education institution	Research personnel
14	Ordinary higher education institution	Research personnel
15	Ordinary higher education institution	Research personnel

After discussions with the expert panel, the final primary indicators were determined, including the design, production, transportation, construction, installation, operation, maintenance, BIM technology, and cost control of prefabricated buildings. A total of 23 secondary indicator measurement items were identified, as shown in Table 2.

Table 2. System for lifecycle cost management of prefabricated buildings based on BIM.

Latent Variable	Identifier Number	Measurement Index	Indicator Source
A: design	A2	Research on and development of new building materials and PC components	[20–25]
	A3	Split design degree of PC component	[20–22,25]
	A5	Integration degree of design–construction	[20–22,26]
	A6	The degree of design standardisation	[20–22,27]
	A9	Integration level of the prefabrication industry chain	[28,29]
C: production and transportation	C2	Versatility of production equipment	[20–22,27]
	C3	Transportation solutions	[21,28,30–32]
	C4	The rate of damage during transportation	[32–34]
D: installation and construction	D1	Management and technical level of the on-site workers	[22,35]
	D3	The level of collaboration among various trades	[20,22,27]
	D4	Degree of installation mechanisation	[22,27]
	D7	Secondary handling of PC components	[36,37]
F: operation and maintenance	F1	Rational development of a green operation plan by artificial intelligence (AI)	[22,24,35,38]
	F2	Tracks and maintenance of the buildings and facilities via BIM database	[39–41]
	F3	Demolition and recycling utilisation rate	[27,38]
G: BIM	G3	BIM 5D technology	[39,40,42]
	G4	Integration of BIM and RFID technology	[43–46]
	G5	Combination of BIM and cloud computing technology	[39,40]
	G6	Information platform construction for BIM lifecycle cost control	[39–41]
H: cost of prefabricated buildings	H1	The EPC contractor's capability to control costs and estimate the investment required for prefabricated projects	[47–54]
	H2	Cost control effectiveness for construction	[20,38,51]
	H3	Cost-driven stakeholder collaboration mechanism	[47,51–54]

In the above table, PC components refer to prefabricated concrete elements [55]. Prefabricated buildings are manufactured in factories through standardised and mechanised processes. The secondary variable factors at each stage can influence the costs at that particular stage. Similarly, the secondary variables related to BIM may affect how much BIM influences the regulation of prefabricated buildings. Effective cost control at each stage is essential to the overall lifecycle cost. The cost of prefabricated buildings is a limiting factor concerning their widespread adoption, and the ability to control costs to some extent determines whether prefabricated buildings can be promoted and implemented on a large scale.

2.1.2. Questionnaire Development and Data Collection

Based on the variables proposed in Table 2, the questionnaire used a five-point Likert scale to quantify the indicators. Respondents quantified the impact of each variable on the entire lifecycle of prefabricated buildings by assigning values between 1 and 5, where higher values corresponded to a greater level of impact [56]. Considering online surveys' efficiency and convenience, this study used the Wenjuanxing platform for distribution. Since the research focuses on prefabricated buildings in China, the target audience for the survey was the Chinese population. The questionnaire was distributed to respondents via online platforms. The respondents included construction personnel, designers, government construction department personnel, etc. A total of 364 valid questionnaires were collected. The statistical assessment of the respondents' age structure, educational background, and years of experience is shown in Figure 1.

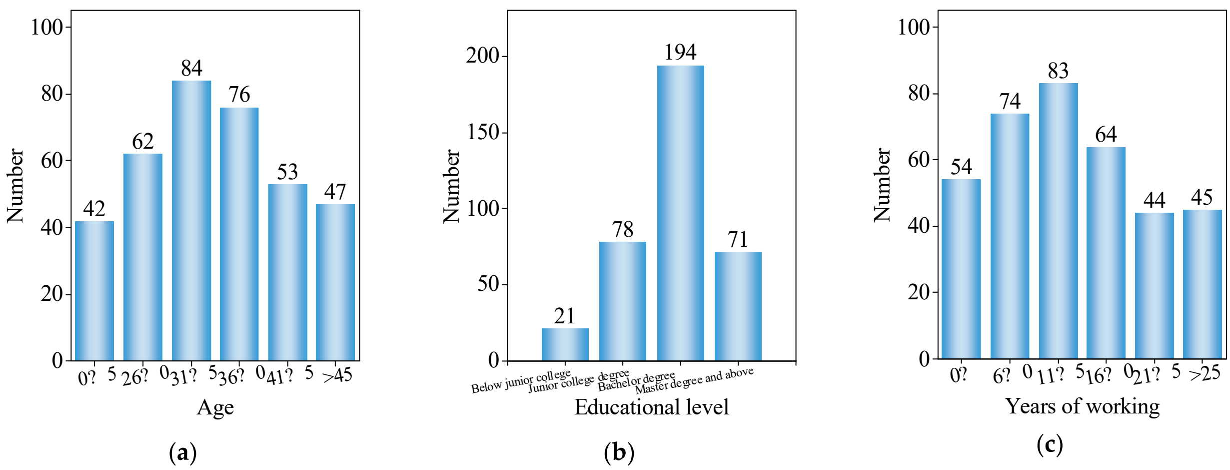

Figure 1. Respondent demographics: (**a**) Age, (**b**) Education level, (**c**) Years of working.

Figure 1 shows that most respondents were between 31 and 35 years old, predominantly held a bachelor's degree, and had 11 to 15 years of work experience. This profile is consistent with typical civil engineering professionals, supporting the reliability of the questionnaire data. A data table was compiled showing the extent of the impact of each variable on the entire lifecycle cost control of prefabricated buildings.

2.1.3. The Analysis of the Reliability and Validity of the Questionnaire

Reliability is an important indicator for measuring data consistency. Before conducting data analysis, it is essential to test the reliability first. The study used the Cronbach's alpha coefficient to measure the internal consistency of the survey questionnaire [57].

Validity is an important indicator for measuring data effectiveness. Based on factor analysis, various indicators such as the Kaiser–Meyer–Olkin (KMO) value, commonalities, variance explained, and factor loadings can be calculated to confirm data validity. The factor analysis can only be conducted if the KMO value reaches 0.7 or above and the significance level of the Bartlett's sphericity test meets the two-tailed test criteria. These conditions indicate that the questionnaire data are suitable for factor analysis [58]. We used SPSSAU for data testing.

2.2. Hypotheses and Model Establishment

2.2.1. Reliability and Validity Testing of the Measurement Model

Before validating the measurement model, it is necessary to test its reliability. The standardised factor loadings (SFL), composite reliability (CR), and average variance extracted (AVE) of the variables were calculated using the software SPSSAU24.0. These metrics help explain and reflect the measurement model's internal consistency and reliability.

Discriminant validity is an essential concept in the measurement model, used to assess whether a measurement tool can distinguish between different concepts or constructs [59]. When the square root value of the AVE for any latent variable is higher than the absolute value of the correlation between those variables and other latent variables, it indicates good discriminant validity among the latent variables. The reliability and validity of the model were tested.

2.2.2. Model Establishment

Structural equation modelling is a statistical framework that analyses the relationships among latent variables through the covariance matrix of observed variables. In constructing the factors influencing the model, this study follows Davis [60] and Venkatesh et al.'s approaches [61]. The research categorises latent variables into exogenous and endogenous constructs. Endogenous variables are those influenced by any variable within the model, while exogenous variables, unaffected by others, directly impact other variables.

When the model's fit meets the criteria, a larger path coefficient indicates a greater degree of influence [62]. Based on the characteristics of latent and observed variables, five dimensions—BIM technology, design, PC component production and transportation, construction installation, and operation and maintenance—were classified as exogenous latent variables. The 22 secondary indicators listed in Table 2 were designated as endogenous observed variables. An endogenous latent variable representing the cost of prefabricated constructions was introduced to establish a structural equation model for studying cost control factors throughout the lifecycle of prefabricated buildings within a BIM-based EPC framework.

As part of the path analysis, we first established a structural model of the influencing factors for lifecycle cost control of prefabricated buildings based on BIM technology, grounded in the theoretical model's path hypotheses. We then defined the relationships among the potential variables according to the theoretical framework. Subsequently, by incorporating effective sample data from questionnaires, we solved the constructed model, which involved model fitting. Ultimately, we derived the standardised coefficients for each variable in the model, allowing us to estimate the path coefficients and conduct significance tests [63].

Figure 2 illustrates the theoretical model developed to examine the cost control factors of BIM technology throughout the entire lifecycle of assembled buildings.

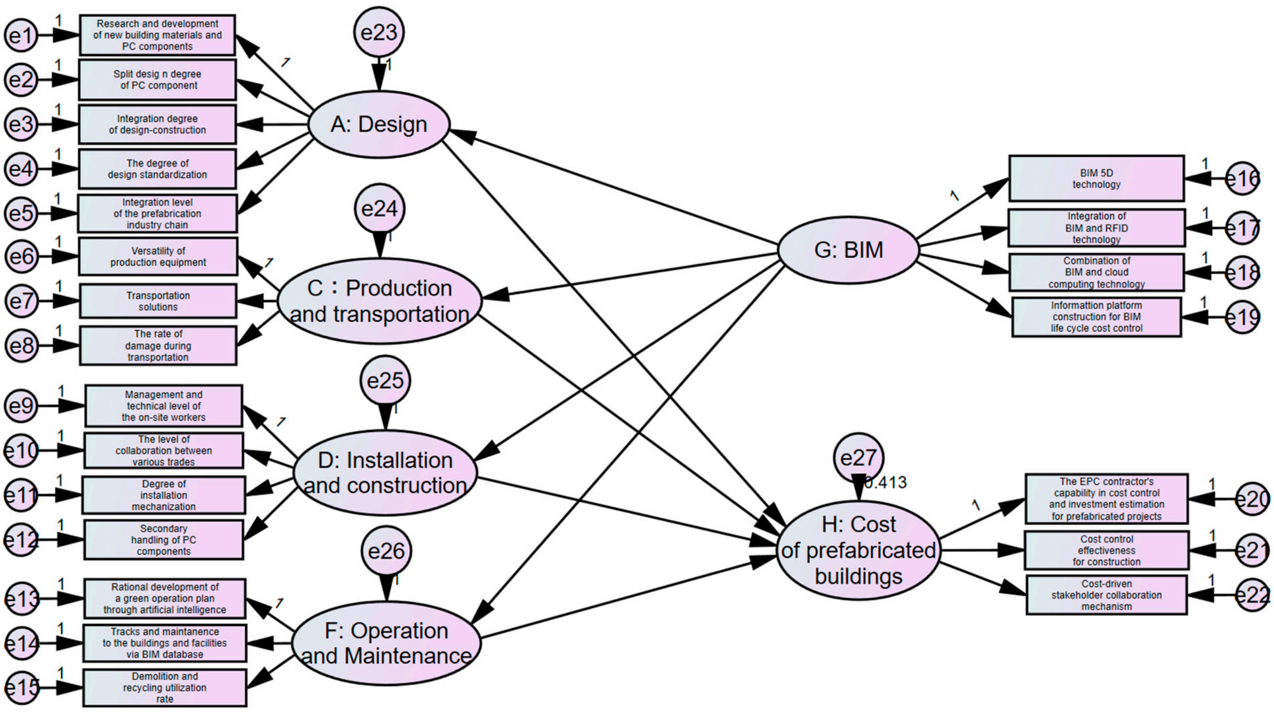

Figure 2. Structural equation modeling.

Here, we propose the following five hypotheses:

Hypothesis 1. *The BIM information technology has a positive impact on the design costs of prefabricated buildings.*

Hypothesis 2. *BIM information technology has a positive impact on the production costs of PC components in prefabricated buildings.*

Hypothesis 3. *BIM information technology positively impacts the construction and installation costs of prefabricated buildings.*

Hypothesis 4. *BIM information technology positively impacts the operation and maintenance costs of prefabricated buildings.*

Hypothesis 5. *BIM information technology positively impacts the entire lifecycle cost of prefabricated buildings.*

3. Results

The lifecycle stages of prefabricated buildings include the design stage, the production and transportation stage, the installation and construction stage, and the operation and maintenance stage. The relationships among these four stages and their abbreviations are illustrated in Figure 3.

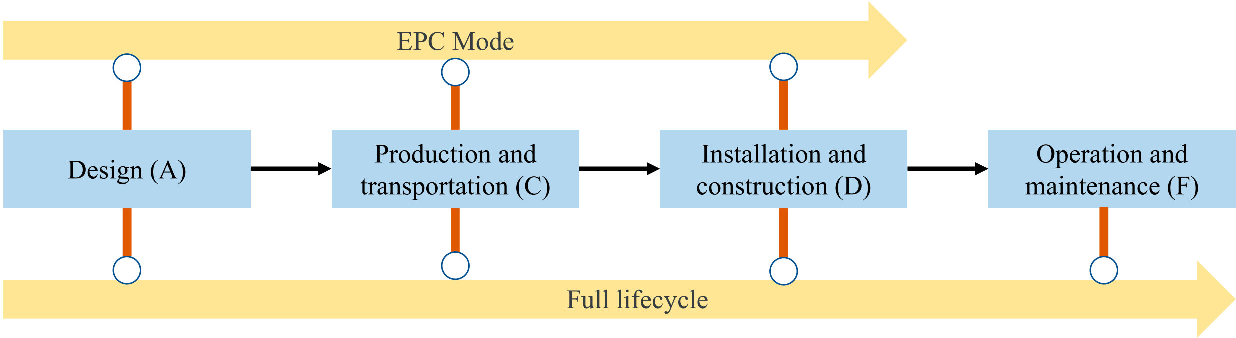

Figure 3. Relationship diagram including each stage of the building lifecycle.

3.1. Results of the Reliability and Validity Analysis of the Questionnaire

3.1.1. Results of the Questionnaire Data Reliability Analysis

After testing, the Cronbach's alpha reliability coefficients for the six first-order variable indicators in the model of factors influencing the lifecycle cost control of prefabricated buildings were shown in Figure 4.

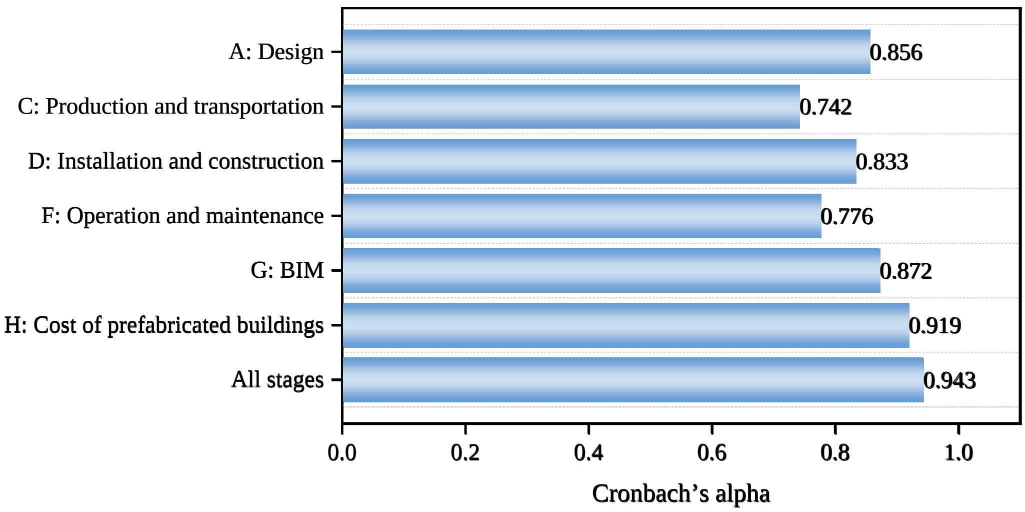

Figure 4. Results from the reliability coefficient analysis.

The value of the Cronbach's alpha coefficient represents the reliability of the questionnaire. Specifically, a Cronbach's alpha value > 0.8 indicates very high reliability, a Cronbach's alpha value between 0.7 and 0.8 indicates good reliability, a Cronbach's alpha value between 0.6 and 0.7 indicates acceptable reliability, and a Cronbach's alpha value < 0.6 indicates poor reliability [57].

An analysis of Figure 4 reveals that the reliability coefficients for phases A, D, F, and H were all greater than 0.8, while phase C had the lowest reliability coefficient, i.e., 0.742, which is still above 0.7, indicating good reliability. The overall reliability coefficient for all phases was 0.943. Based on this comprehensive analysis, the reliability coefficients for the variables in the questionnaire are considered to be high, indicating that the reliability of the questionnaire is strong, providing researchers with more dependable analytical results that accurately reflect the relationships among the various variables [64]. Upon validation, the data were deemed suitable for further analysis.

3.1.2. Results of the Questionnaire Validity Analysis

Based on the analysis, the validity test results for our data were obtained. The results show that the questionnaire's KMO value was 0.932. The approximate chi-square value for Bartlett's test of sphericity was 5285.83, with 276 degrees of freedom (df) and a p-value significance of 0. The results indicate that the variables in the questionnaire data were correlated and that the data concentration was good.

Figure 5 illustrates the factor loadings and Figure 6 shows the cumulative variance after performing an orthogonal rotation of the data.

Figure 5 shows that the factor loadings of the variables within the same measurement dimension were relatively high, with the minimum being 0.602 for the factor loading of F3 on F, which is greater than the factor loadings of other indicators on different dimensions. This indicates a high level of correlation among these variables within the dimension. From Figure 6, it can be seen that the cumulative explained variance of the test indicators reached 69.33% > 50%. This suggests that the six common factors extracted effectively explained the information contained in the questionnaire.

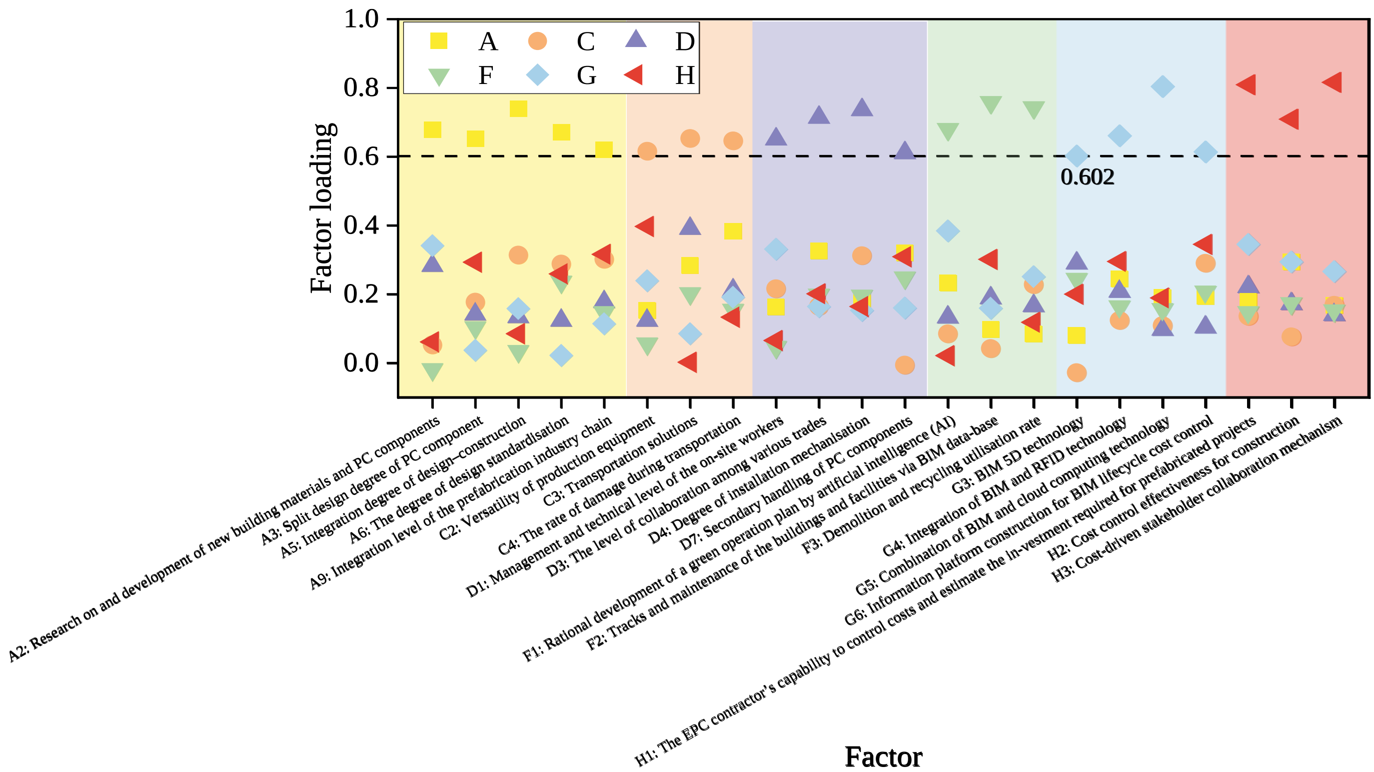

Figure 5. Factor loadings.

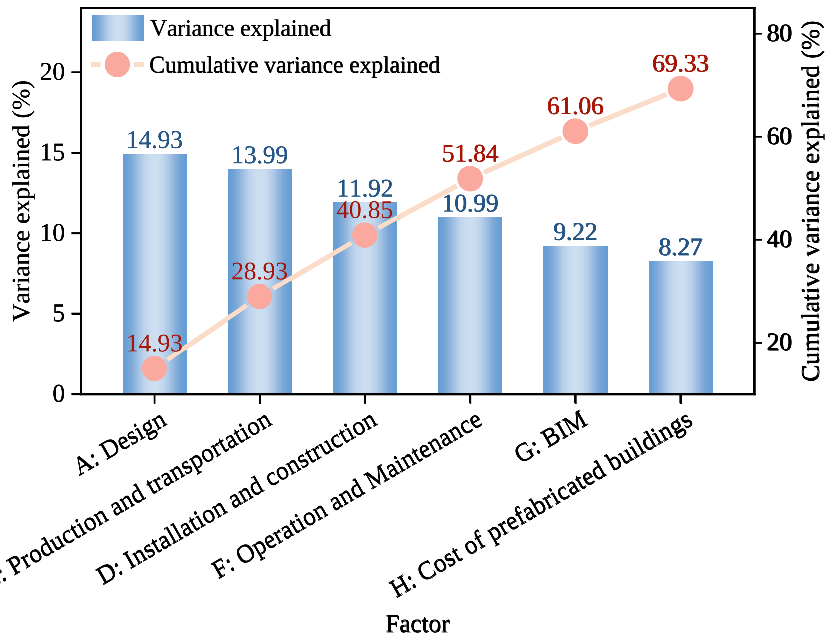

Figure 6. Variance explanation.

3.2. Results of the Reliability and Validity Testing of the Measurement Model

3.2.1. Results of the Reliability Testing of the Measurement Model

In the validation analysis of the measurement model, composite reliability (CR) and average variance extracted (AVE) were used to explain and reflect the internal consistency reliability of the measurement model. A higher CR value indicates a higher degree of internal consistency among the measurement indicators of a latent variable. p represents the significance probability value. When $p < 0.001$, it is indicated as "***". the absolute value of the standardized path coefficient (standardized factor loading) is greater than 0.5, AVE > 0.5, and CR > 0.7, indicating that the measurement model has good internal consistency [65]. The specific values from the model are presented in Table 3.

Table 3. Factor loadings, CR, and AVE metrics for the measurement model.

Latent Variable	Observed Variable	Standardized Loadings (Std. Estimate)	Composite Reliability (CR)	Average Variance Extracted (AVE)
A: design	A2: research and development of new building materials and PC components	0.762 ***	0.857	0.501
	A3: split design degree of PC components	0.754 ***		
	A5: integration degree of design–construction	0.682 ***		
	A6: the degree of design standardization	0.674 ***		
	A9: integration level of the prefabrication industry chain	0.766 ***		
C: PC component production	C2: versatility of production equipment	0.644	0.749	0.500
	C3: transportation solutions	0.705 ***		
	C4: the rate of damage during transportation	0.768 ***		
D: installation and construction	D1: management and technical level of the on-site workers	0.636	0.841	0.572
	D3: the level of collaboration among various trades	0.838 ***		
	D4: degree of installation mechanization	0.811 ***		
	D7: secondary handling of PC components	0.723 ***		

Table 3. *Cont.*

Latent Variable	Observed Variable	Standardized Loadings (Std. Estimate)	Composite Reliability (CR)	Average Variance Extracted (AVE)
F: operation and maintenance	F1: rational development of a green operation plan by artificial intelligence (AI)	0.731	0.779	0.54
	F2: tracks and maintenance of the buildings and facilities via a BIM database	0.726 ***		
	F3: demolition and recycling utilization rate	0.747 ***		
G: BIM	G3: BIM 5D technology	0.637	0.874	0.583
	G4: integration of BIM and RFID technology	0.784 ***		
	G5: combination of BIM and cloud computing technology	0.783 ***		
	G6: information platform construction for BIM lifecycle cost control	0.781 ***		
H: cost of prefabricated buildings	H1: the EPC contractor's capability to control costs and estimate the investment required for prefabricated projects	0.99	0.925	0.806
	H2: cost control effectiveness for construction	0.779 ***		
	H3: cost-driven stakeholder collaboration mechanism	0.911 ***		

Note: *** indicates that the significance level is very significant.

The standardized factor loadings (SFL) of the variables obtained following analyses are shown in Figure 7, while the composite reliability (CR) and average variance extracted (AVE) are presented in Figure 8.

The measurement model must meet the criteria of SFL $\geq$ 0.5, CR value $\geq$ 0.7, and AVE $\geq$ 0.5 to satisfy the reliability requirements. From Figure 7, it can be observed that the variable with the minimum SFL value was D1, whose value was 0.636 > 0.5. As shown in Figure 8, the variable with the minimum AVE value was C, whose value was 0.5 $\geq$ 0.5. The variable with the minimum CR value was C, whose value was 0.749 > 0.7. These results indicate that the measurement model had good internal consistency.

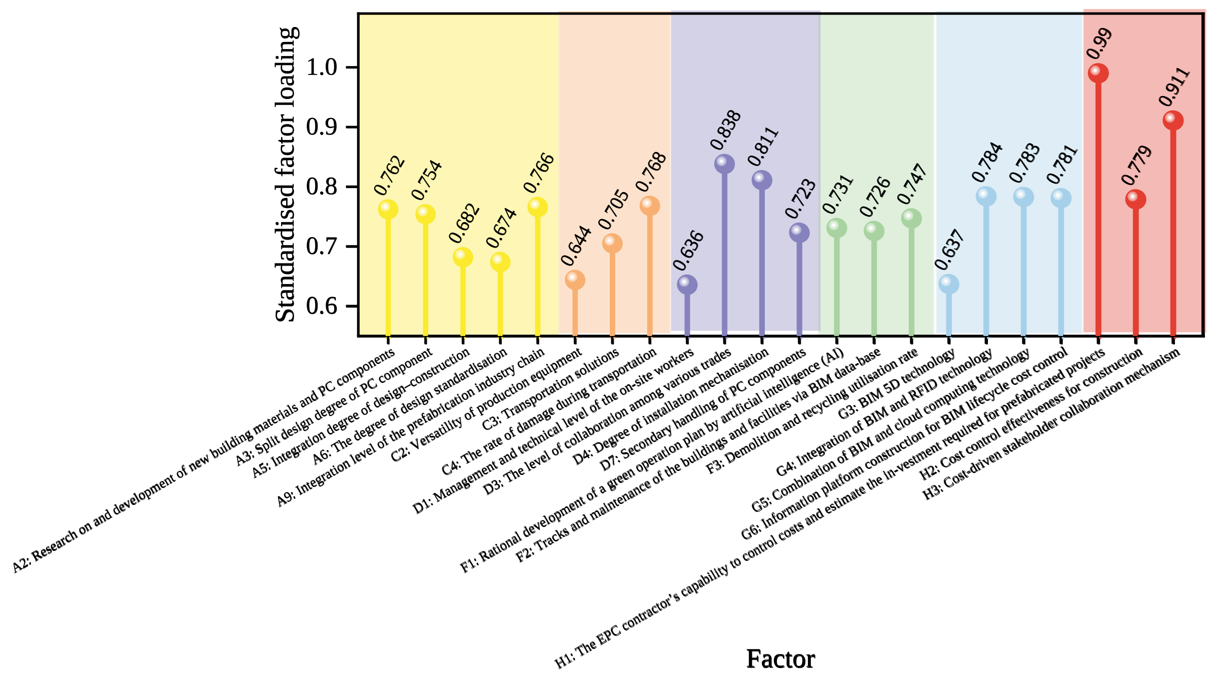

Figure 7. Standardised factor loadings (SFL) of the measurement model.

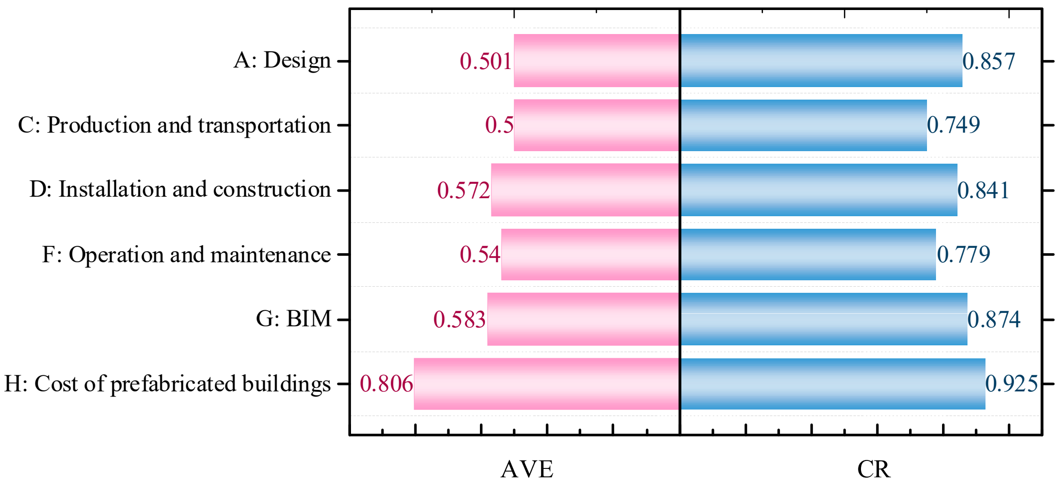

Figure 8. Average variance extracted (AVE) and composite reliability (CR) of the measurement model.

3.2.2. Results of the Validity Testing of the Measurement Model

The validity of the measurement model based on the data is shown in Figure 9.

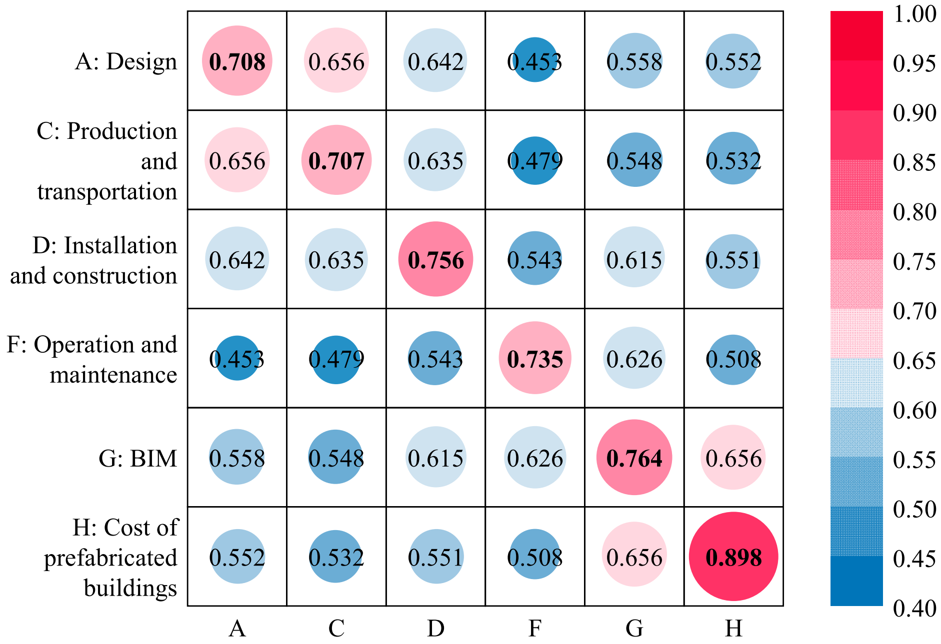

Figure 9. Absolute values of correlation coefficients for the primary variables.

Figure 9 shows that the square root value of the AVE for the six latent variables ranged from 0.707 to 0.898, while the correlations between different variables ranged from 0.453 to 0.656. Comparing these values, the square root value of the AVE for each latent variable was higher than the absolute value of its correlation with other latent variables, demonstrating good discriminant validity among the latent variables.

3.3. Structural Equation Modeling Results

Using the path analysis function of AMOS, 364 valid data points in the SAV format from the SPSS questionnaires were imported to solve the constructed model, a process which involved fitting the model. After running the model and the program, clicking "view text" generated a report. The "Estimates" section provides the standardized coefficients for each variable in the model, allowing for the estimation of path coefficients and significance testing [66]. The results are shown in Table 4.

Table 4. Results of running the structural equation model.

X	→	Y	Unstandardized Regression Coefficient	SE	z (CR Value)	*p*	Standardized Regression Coefficient	Significance
A: design	→	H: cost of prefabricated buildings	0.266	0.101	2.642	0.008	0.188	Significant
C: production and transportation	→	H: cost of prefabricated buildings	0.254	0.127	2	0.045	0.174	Significant
D: installation and construction	→	H: cost of prefabricated buildings	0.459	0.140	3.268	0.001	0.294	Significant
F: operation and maintenance	→	H: cost of prefabricated buildings	0.324	0.112	2.895	0.004	0.232	Significant
G: BIM	→	A: design	0.859	0.091	9.385	0	0.767	Significant
G: BIM	→	C: production and transportation	0.894	0.098	9.119	0	0.823	Significant
G: BIM	→	D: installation and construction	0.866	0.092	9.414	0	0.854	Significant
G: BIM	→	F: operation and maintenance	0.890	0.092	9.645	0	0.785	Significant
A: design	→	A2: research and development of new building materials and PC components	1.202	0.095	12.709	0	0.766	Significant
A: design	→	A3: split design degree of PC components	1.181	0.093	12.629	0	0.76	Significant
A: design	→	A5: integration degree of design–construction	0.998	0.088	11.303	0	0.669	Significant
A: design	→	A6: the degree of design standardization	1.000	-	-	-	0.679	Significant
A: design	→	A9: integration level of the prefabrication industry chain	1.191	0.094	12.699	0	0.766	Significant
C: production and transportation	→	C2: versatility of production equipment	1.000	-	-	-	0.644	Significant
C: production and transportation	→	C3: transportation solutions	1.027	0.100	10.247	0	0.673	Significant
C: production and transportation	→	C4: the rate of damage during transportation	1.249	0.112	11.168	0	0.772	Significant
D: installation and construction	→	D1: management and technical level of the on-site workers	1.000	-	-	-	0.641	Significant
D: installation and construction	→	D3: the level of collaboration among various trades	1.256	0.106	11.8	0	0.788	Significant
D: installation and construction	→	D4: degree of installation mechanization	1.139	0.100	11.365	0	0.75	Significant
D: installation and construction	→	D7: secondary handling of PC components	1.190	0.104	11.391	0	0.734	Significant
F: operation and maintenance	→	F1: rational development of a green operation plan by artificial intelligence (AI)	1.000	-	-	-	0.726	Significant
F: operation and maintenance	→	F2: tracks and maintenance of the buildings and facilities via a BIM database	1.105	0.092	12.07	0	0.726	Significant
F: operation and maintenance	→	F3: demolition and recycling utilization rate	1.219	0.099	12.265	0	0.741	Significant

Table 4. *Cont.*

X	→	Y	Unstandardized Regression Coefficient	SE	z (CR Value)	*p*	Standardized Regression Coefficient	Significance
G: BIM	→	G3: BIM 5D technology	1.000	-	-	-	0.621	Significant
G: BIM	→	G4: integration of BIM and RFID technology	1.250	0.106	11.806	0	0.769	Significant
G: BIM	→	G5: combination of BIM and cloud computing technology	1.209	0.110	11.026	0	0.701	Significant
G: BIM	→	G6: information platform construction for BIM lifecycle cost control	1.313	0.113	11.601	0	0.751	Significant
H: cost of prefabricated buildings	→	H1: the EPC contractor's capability to control costs and estimate the investment required for prefabricated projects	1.000	-	-	-	0.901	Significant
H: cost of prefabricated buildings	→	H2: cost control effectiveness for construction	0.927	0.051	18.158	0	0.854	Significant
H: cost of prefabricated buildings	→	H3: cost-driven stakeholder collaboration mechanism	0.908	0.028	32.068	0	0.812	Significant

Note: → indicates regression or measurement relationships.

Arrows represent regression or measurement relationships. From the output analysis, all path relationships were found to have significant standardized coefficients, indicating that the path relationships in the theoretical model were validated.

A summary of the estimation and significance testing results for the model's path coefficients is presented in Figure 10.

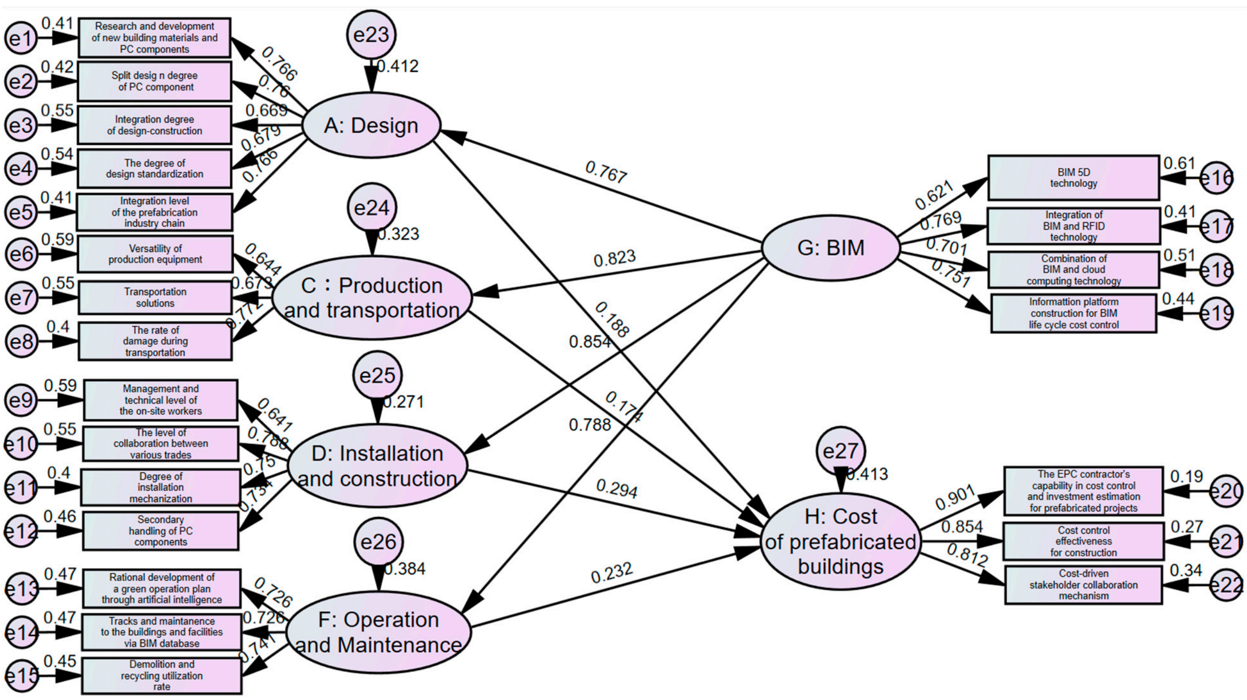

Figure 10. Results of structural model analysis.

To test the validity of the proposed relationships among the six variables in this study, a path analysis was conducted using the elements of the five hypotheses. The hypotheses were evaluated based on the path coefficients, with all corresponding *p*-values being less than 0.05. This indicates that none of the hypotheses were rejected, confirming that the proposed model fitted the sample data. As shown in Table 4 and Figure 10, all five hypotheses were supported by the standardized path coefficients and significance results. The details are as follows:

Hypothesis 6. *BIM information technology (path coefficient* $\beta = 0.767$*,* $p < 0.001$*) positively impacts the design cost of assembled buildings.*

Hypothesis 7. *BIM information technology (path coefficient* $\beta = 0.823$*,* $p < 0.001$*) has a positive effect on the component production cost of assembled buildings.*

Hypothesis 8. *BIM information technology (path coefficient* $\beta = 0.854$*,* $p < 0.001$*) positively influences the installation and construction cost of assembled buildings.*

Hypothesis 9. *BIM information technology (path coefficient* $\beta = 0.785$*,* $p < 0.001$*) positively affects the operation and maintenance cost of assembled buildings.*

Hypothesis 10. *Given that BIM information technology has a significant positive effect on all four stages of the assembled building lifecycle, it positively influences the total lifecycle cost of these buildings.*

To evaluate the degree of impact of BIM technology on the design, PC component production, installation and construction, and operation and maintenance stages, the latent variable G was categorised into three levels based on path coefficients: Level 1 (0.85–1.0, significant impact), level 2 (0.8–0.85, moderate impact), and level 3 (0.75–0.8, minor impact) [67]. As shown in Table 4, the latent variable BIM technology had a significant positive effect on the design, PC component production, installation and construction, and operation and maintenance stages, with standardised path coefficients of 0.767, 0.823, 0.854, and 0.785, respectively. This indicates that the implementation of BIM information technology can reduce the construction costs of prefabricated buildings. Among the four main stages of the lifecycle of prefabricated buildings, the installation and construction and the operation and maintenance stages had the most significant impact on costs, followed by the design and the PC component production stages. The impact of BIM technology was greatest in the construction and installation stages, followed by the PC component production, operation and maintenance, and design stages, respectively.

3.4. Strategies and Recommendations for Reducing the Whole Lifecycle Costs of Prefabricated Buildings Using BIM Technology

In the design stage, integrating BIM with cloud computing technology and constructing a BIM entire lifecycle cost control information platform would allow designers from various disciplines to implement their design concepts. Through collision simulations, this integration could reduce design errors in prefabricated buildings and minimise cost increases caused by design changes [68].

In the production and transportation stage, traditional technologies need more standardisation in the production process of prefabricated buildings. This can lead to component damage and rework during transportation, resulting in increased costs. The perfect integration of BIM and RFID technology would help achieve the ideal goals of zero inventory and zero defects during the construction process. Based on the actual rate of progress, information should be continuously fed back to the production management subsystem to adjust the component production and transportation plans timely. This would help reduce waiting times, material shortages, and rework, thereby lowering the production and transportation costs of prefabricated buildings [69].

In the construction and installation stage, BIM's automatic quantity calculation function can be used to estimate the current quantity of work for each procedure. This allows for the rational allocation of personnel, machinery, and materials on the project. When changes occur in the project, the Revit(BIM)2021 can adjust the division of tasks and the schedule, optimising processes to avoid idleness and rush work. Using BIM for technical handovers allows (i) information to be conveyed more intuitively and comprehensively to the on-site workers, preventing losses caused by improper operations, (ii) simulation analysis of construction to be performed, and (iii) supply materials to be provided as needed to reduce inventory and lower the costs. Integrating BIM with cost software would enable the monitoring of project costs in real time and would prevent cost overruns. By using BIM technology, personal subjective judgments during construction can be minimized. By using BIM data to guide the construction process, financial resources can be efficiently utilized, thereby reducing waste throughout the project [70].

In the operation and maintenance stage, the civil engineering industry has transitioned from a construction-focused phase to a new one that emphasizes construction and health management, including maintenance, inspection, care, and repair. The field of civil engineering should also transition from traditional construction methods to digital and intelligent construction approaches [71]. BIM technology has significant advantages over traditional methods used in the operation and maintenance phase of prefabricated buildings' lifecycle. These advantages are primarily reflected in data completeness, information visualization, decision support, and collaborative management. With BIM models, issues can be quickly pinpointed, such as the location of damage to a prefabricated component or equipment failure. This method saves time significantly compared to traditional manual inspection, reduces misjudgments, and allows for efficient problem identification. Additionally, using the comprehensive data from BIM, building operators can perform preventive maintenance based on historical data and equipment operational status, reducing the occurrence of unexpected failures and emergency repair costs [72]. By integrating BIM with artificial intelligence [73], intelligent monitoring, data analysis, and predictive maintenance of prefabricated buildings can be enhanced. This combination optimizes resource allocation, extends building service life, reduces maintenance costs, and improves management efficiency.

Additionally, the integration of BIM with artificial intelligence can significantly drive the development of prefabricated buildings toward automation and intelligence. Artificial intelligence [74,75] uses deep learning algorithms to predict the lifecycle cost of buildings. First, by collecting a large amount of cost data from existing building projects, it will categorize such data into input features such as building area, floor height, structural type, enclosure type, building age, and construction year. Clearly it also needs to define the targets to be predicted, including initial costs, operation and maintenance costs, environmental impact costs, and end-of-life costs. The time dimension (year or month) should be incorporated to create time series data, which would then be preprocessed. Next, the preprocessed data should be input into prediction models, commonly including models based on LSTM (long short-term memory) [76] and transformer [77]. Through the backpropagation algorithm, the model continuously adjusts its parameters during training to reduce the error between the predicted values and the actual values. Additionally, to avoid model overfitting, validation set data should be used to monitor training in real-time and adjust hyperparameters based on performance. Finally, the deployed model, with strong generalization capabilities, can be applied to lifecycle cost prediction for building projects.

3.5. Case Study on BIM for Lifecycle Cost Control in Prefabricated Buildings

A demonstration project of prefabricated affordable housing in the Sichuan Province was used as a case study. The building in question had 32 floors, a floor height of 2.9 m, and a total building area of 14,793 square meters. The prefabrication rate was 24.32%, while the assembly rate reached 57.45%. BIM technology was employed throughout the construction process, with Figure 11 showcasing the BIM model used to control the entire building process.

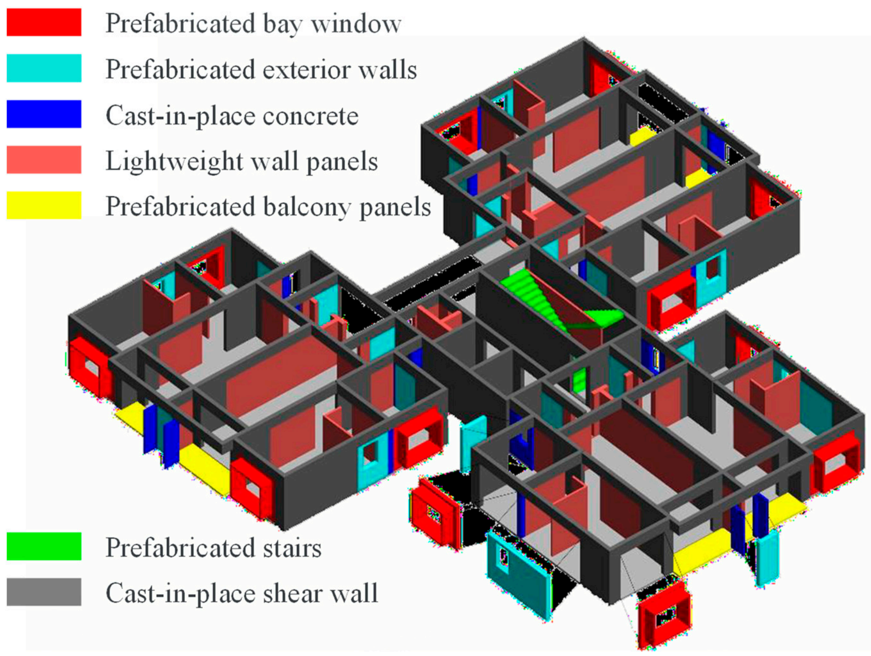

Figure 11. Demonstration project of prefabricated affordable housing.

This project integrated BIM technology with prefabricated construction and had the following technical features. (1) BIM technology, enabling decision-makers to plan effectively and stakeholders such as contractors, supervisors, and owners to clearly understand the project's status. The building's data were also stored long-term, facilitating the management of the construction at a later stage. Utilizing BIM technology from a holistic lifecycle perspective enables more forward-thinking design considerations. (2) BIM was used to design standardized component modules, which were then manufactured in factories, enabling standardized modules with diverse combinations. BIM technology offers a clearer representation of component dimensions and weights, enabling the development of more rational transportation plans tailored to these specifications. (3) Pre-construction simulations, helping avoid errors during construction, thereby reducing rework needs and lowering installation costs. (4) The powerful information capabilities of BIM, enabling the presentation of detailed information for each component, including the manufacturer and identification number, facilitating more convenient operational maintenance in the future.

Designers can easily achieve integrated architectural, structural, and mechanical designs using BIM technology, from solution development to construction drawings, factory production, transportation, and on-site assembly, while considering future deconstruction, thus achieving integrated designs and control across the building's entire lifecycle.

By linking the cost data from each stage of the prefabricated building's lifecycle, a comparison between the lifecycle costs of prefabricated and cast-in-place buildings can be made. According to the project data, using BIM for lifecycle management can save 45% of materials, 36% of water, and 30% of energy, while reducing the construction period duration by 31%. Compared to traditional cast-in-place buildings, the use of BIM technology for management and execution in the context of prefabricated buildings can result in a cost saving of 79,200 yuan per standard floor structure, demonstrating significant cost efficiency.

4. Discussion and Conclusions

This study provides a reference for the cost control of prefabricated buildings throughout their entire lifecycle under the general contracting management model using BIM technology. The research focuses on the key factors influencing the cost control of prefabricated buildings and the impact of BIM technology on cost control. The main conclusions are as follows:

(1) Latent variable BIM technology has a significant positive effect on the design, PC component production, installation and construction, and operation and maintenance phases, with the greatest impact observed during the construction and installation phase. Secondly, in the production and transportation phases, the impact is relatively minor in the design phase.

(2) In the design phase, BIM technology enables a lifecycle perspective, facilitating more forward-looking design considerations. In the production and transportation phases, it allows for standardized modules, diverse combinations, and optimized transport plans. During the construction and installation phase, BIM enables the performance of pre-construction simulations to prevent errors and minimize rework needs. In the operational and maintenance phase, it provides detailed information on each component, streamlining post-construction management. Overall, BIM technology effectively reduces the total lifecycle cost of prefabricated buildings.

(3) BIM technology influences each stage of the lifecycle of prefabricated constructions, providing significant potential for cost control. In the future, prefabricated buildings can utilize BIM and artificial intelligence to lower costs, facilitating a broader adoption and supporting sustainable development in construction.

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