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Barriers to Building Information Modeling from an Individual Perspective in the Chinese Construction Industry: An Extended Unified Theory of Acceptance and Use of Technology

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Abstract: Building information modeling (BIM) is a crucial information technology that promotes the transformation and upgrading of the construction industry. It has been widely used in various stages of construction projects, including design, construction, and operation. However, BIM technology still faces numerous obstacles in practice. From the perspective of construction practitioners, this study constructs a structural equation model to explore the obstacles encountered by construction practitioners in the process of applying BIM technology. Task–technology fit, effort expectancy, performance expectancy, user trust, and facilitating conditions can significantly improve practitioners' behavioral intention, with task–technology fit having the most significant impact on behavioral intention. Facilitating conditions and behavioral intention significantly affect usage behavior, while perceived cost does not significantly affect behavioral intention. The multiple-group analysis found that in the path of performance expectancy on behavioral intention, males have a significant effect while females do not; in the path of facilitating conditions on behavioral intention, higher education levels have a significant effect while lower education levels do not; in the path of facilitating conditions on behavioral behavior, lower usage time has a significant effect while higher usage time does not. Suggestions for promoting the application of BIM technology are proposed in this article to improve its utilization rate. This study provides more perspectives and ideas for future research on BIM diffusion.

Keywords: construction; building information modeling (BIM); application barriers; Unified Theory of Acceptance and Use of Technology (UTAUT)

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1. Introduction

With the rise of the Internet, information technology has been continuously integrated into social production and life, bringing tremendous changes to various industries. At the same time, the rapid development of information technology, represented by building information modeling (BIM), is profoundly influencing and changing the construction industry, injecting new vitality into the industry. BIM is usually understood as a technology and solution to enhance collaboration among design, engineering, and construction organizations [1]. It contributes significantly to owners, designers, contractors, and management teams collaborating, visualizing, and managing construction work to achieve better results [2]. These functions of BIM have yielded project benefits in design changes, reducing duplication, energy efficiency, shortening construction time, and quality management [3]. Therefore, the promotion of BIM research plays a significant role, bringing tremendous economic benefits and potentially leading to a digital transformation in the construction industry. BIM adoption rates have significantly increased in countries such as the United States [4], the United Kingdom [5], Singapore [6], and Chile [7]. Especially in Chile, considered a developing country, BIM usage has reached a high level [7]. However, BIM adoption rates have remained stagnant in China [8], also classified as a developing country. Despite the growing popularity of BIM technology in Asian countries such as China, South Korea, and Japan [9], the actual adoption rate in the Chinese construction industry falls short of expectations [10], even with the Chinese government's vigorous encouragement and promotion of BIM adoption. Thus, it becomes an urgent and practical issue to address how to increase the application rate of BIM in the Chinese construction sector.

Previous research has investigated the barriers to BIM adoption during its application process. However, these studies have focused solely on aggregate levels, such as industry, project, and organization. At the industry level, the lack of BIM standards and guidelines and inadequate government support have been identified as significant factors [11–13]. At the project level, resistance to change and high implementation costs have been considered primary obstacles [14,15]. On the organizational level, the lack of relevant knowledge and training has been recognized as one of the barriers influencing the promotion of BIM [15–17]. Although these studies have provided valuable insights into the obstacles encountered during BIM application, there are some limitations: Firstly, from the perspective of technology diffusion, there is a specific type of factor that has not been investigated: the perception of BIM by users, meaning that the researchers have overlooked the viewpoints of individuals at the personal level regarding BIM. Secondly, while existing research primarily summarizes the barriers to BIM adoption, few studies have explored the causal relationships between different factors. Thirdly, though Howard et al. examined BIM application barriers from an individual perspective [18], the subjects were mainly senior managers, excluding general managers and practitioners. Additionally, a survey of 375 organizations indicated that individual user resistance was the primary challenge in large-scale information technology implementations [19]. As BIM technology is essentially an information technology, it is also influenced by individual perceptions. Hence, it is necessary to investigate how individual users perceive BIM and how these perceptions affect its application in projects.

Therefore, to address the research above gaps, our study aimed to investigate the barriers construction practitioners face using BIM from an individual perspective. We sought to identify and rank the obstacles in the application process of BIM and reveal the causal relationships between different factors, with the ultimate goal of enhancing the adoption rate of BIM in the Chinese construction industry. To achieve this, we designed a questionnaire based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model and collected 408 valid responses from BIM users in the industry. Subsequently, we employed structural equation modeling (SEM) to analyze the proposed conceptual model empirically. This study investigates architectural practitioners' perspectives on using BIM individually. The research findings are expected to contribute to local policymakers, projects, and organizations effectively disseminating BIM technology among practitioners.

The remaining parts of this article are organized as follows. Section 2 provides an overview of research on the application of BIM, research on barriers to the application of BIM, and research on barriers to the application of BIM based on the UTAUT model. Section 3 introduces the conceptual framework and proposes several hypotheses regarding barriers to applying BIM. The research design, including data collection, variables, and methods, is presented in Section 4, while Sections 5 and 6 present the results and discussions, respectively. Finally, Section 7 summarizes the main research findings.

2. Literature Review

2.1. BIM Application

Given the significant impact of BIM on the construction industry, there has been a substantial amount of literature on the topic of BIM applications, focusing primarily on design, construction, and operation. BIM has many applications in the design phase, including 3D modeling and visualization, clash detection, and logistics management. For example, Providakis et al. used 3D modeling to predict settlement risk during tunnel excavation and applied it to water resources projects [20], where it facilitated project management [21]. Three-dimensional modeling and visualization can also be used for smart city planning [22]. Furthermore, BIM three-dimensional simulation in safety training on construction sites can increase training effectiveness [23]. Clash detection is a process that searches for and reports conflict between different parts of engineering projects and is often used in pipe facility analysis [24,25]. Magill et al. found that improving the logistics efficiency of integrated supply chains can optimize production [26] and play an essential role in improving safety on construction sites and reducing costs [27]. In the construction phase, BIM is also widely used. It can simulate the construction process [28], calculate the materials required on site, and manage materials [29]. Combining BIM with VR can also achieve visualized construction technology communication [30], realizing high-quality construction engineering [31].

Additionally, Liu et al. provided detailed construction schedule plans under resource constraints while reducing costs and ensuring construction safety [32]. In the operation and maintenance phase, BIM can be used for equipment management [33], maintenance plan development and execution, equipment failure detection, and analysis to improve equipment maintenance efficiency and reduce maintenance costs [34]. In summary, the application of BIM in the construction industry is widespread and has gradually become a trend, but it still faces some application barriers.

2.2. Barriers to BIM Application

Scholars have studied the barriers to applying BIM from different perspectives, including the industry, project, and organizational aspects. At the industry level, Manzoor et al. found that the lack of BIM standards and guidelines is a significant consideration for applying BIM [35]. Ahuja et al. believe that inadequate government support for adopting BIM is a crucial factor [12]. In addition, research has shown that the need for more skilled professionals and a limited implementation market can also hinder the application of BIM [13]. At the project level, Lee et al. suggest that potential data exchange issues and unforeseen errors obstruct the adoption and utilization of BIM in design, construction, and facility management [36].

Moreover, the benefits of implementing BIM in construction projects, such as improved scheduling, time and cost savings, facility management, and reduced rework, are key motivating factors for BIM use [10,37,38]. In addition to the benefits of BIM, project characteristics such as scale, team members' BIM expertise, and effective communication among them are also crucial for BIM success [39]. From an organizational perspective, implementing BIM can enable more effective communication and collaboration among internal and external stakeholders [40]. Therefore, implementing BIM relates to internal organizational characteristics such as qualified internal staff [41], inter-firm relationship network structure and organizational competitiveness [42,43], corporate culture, and innovation strategic technology [17]. At the same time, the attitude of top management towards BIM is also a critical factor in the company's use of BIM. In addition, the high initial investment, time, and cost required for BIM training and low investment returns also hinder the use of BIM [37,43], especially for small- and medium-sized construction enterprises [44]. It is important to note that the analysis of this study was conducted in the context of China, using the application status and barriers of BIM technology in the Chinese construction industry as an example. The intention is to provide valuable insights that may serve as a reference for similar countries and regions.

2.3. Barriers to BIM Application Based on the UTAUT Model

The UTAUT model integrates eight research models related to technology acceptance and usage, developed by Venkatesh et al. as an extension of the Technology Acceptance Model (TAM) [45,46]. Research has shown that the UTAUT model has high explanatory power for behavior and intention, up to 70% [47], and is more effective than previous models. Therefore, many scholars have used the UTAUT model to study the application of BIM technology. Howard et al. used the UTAUT model to investigate the views of UK construction professionals on the use of BIM and found that UK professionals believed that BIM was an unrewarding workflow [18]. Xue et al. combined the UTAUT model with the task–technology fit model to study the use of BIM by non-management employees [48]. Batarseh and Kamardeen added individual beliefs and expected variables to the UTAUT model to build a theoretical framework for personal adoption of BIM willingness [49]. Ademci and Gundes explored the driving factors and barriers to BIM implementation at the individual and organizational levels [50]. Murguia et al. analyzed the impact of industry culture cognitive elements on the willingness of participants to adopt BIM using the UTAUT model [51]. Addy et al. conducted empirical research on the promotion factors of surveyors' adoption of BIM using the UTAUT model. They found that workload and facilitating conditions significantly positively impacted BIM adoption [52].

BIM has been widely adopted in various aspects, such as design, construction, and operation. However, as the depth of application increases, so do the barriers encountered. Existing research on BIM application barriers mainly revolves around the industry, project, and organizational levels, identifying factors such as the lack of standards and guidelines, insufficient government support, data exchange issues, company culture, and organizational competitiveness as primary obstacles [35,36,43]. However, most of these studies merely summarize the application barriers and lack an in-depth examination of the causal relationships between various factors. Furthermore, in BIM application barrier studies based on the UTAUT model, researchers such as Howard et al. and Murguia et al. have incorporated attitude and industry culture as variables [18,51]. However, they lack integration with other technology acceptance models. Additionally, the scope of participants in these studies is limited, focusing either on high-level management or solely general construction practitioners (non-managers). Apart from that of Howard et al., there is a scarcity of studies exploring the barriers to applying BIM from an individual perspective. Therefore, it is imperative to focus on construction practitioners using BIM as research subjects, including senior management, general management, and general construction practitioners, to comprehensively investigate the obstacles encountered while promoting and applying BIM from a personal standpoint.

3. Conceptual Framework

This study was conducted in China to investigate the application of BIM technology in the Chinese construction industry. The primary objectives were to identify barriers encountered during the BIM application process, rank their impact, and analyze the relationships between these barriers to mitigate their effects and enhance the adoption of BIM in the Chinese construction sector. To address this issue, relevant theories related to technology acceptance need to be employed and integrated into a more comprehensive model that considers variables closely related to human society and specific BIM engineering processes [53]. Consequently, this study builds upon the UTAUT model, incorporating the actual situation of the Chinese construction industry to examine the extent of BIM adoption. A novel BIM technology acceptance model is proposed in this paper, as illustrated in Figure 1.

The model was developed by adjusting the UTAUT model, which retains three key factors: effort expectancy, performance expectancy, and facilitating conditions. In the UTAUT, performance expectancy and effort expectancy are regarded as antecedents of behavioral intention and have been widely applied in different studies, particularly in information acceptance [54,55]. Taib et al. and Isaac et al. found that performance expectancy and effort expectancy have a positive impact on behavioral intention [56,57]. Facilitating conditions also influence behavioral intention, with Ronaghi and Forouharfar indicating that the more favorable conditions there are, the stronger the usage intention [54]. Additionally, psychology and behavioral science research show that behavioral intention affects usage behavior, which is explained and predicted by behavioral intention [58].

Furthermore, the model includes task–technology fit as an antecedent of performance expectancy and behavioral intention. Task–technology fit is critical for individual BIM users, especially for construction industry practitioners, because if the task and BIM match, they can receive more rewards, as confirmed by Goodhue and Thompson [59]. Task–technology fit is also highly correlated with behavioral intention [60]. Finally, the model adds two variables: perceived cost and user trust. The perceived cost variable is derived from the perceived risk theory, which holds that perceived risks and costs influence users' acceptance of technology and products [61]. BIM technology-related software is different from ordinary office software, with strong professionalism, requiring a certain amount of time and financial cost during the learning process, as Yang et al. demonstrated [62]. The user trust variable is based on consumer trust theory [63]. Building software is designed to replace traditional manual methods and requires high precision; users may need clarification on the accuracy of automated calculation results, leading to a reluctance to use. Nordhoff et al. found that people are more willing to use tools only if they trust them. Therefore, behavioral intention is related to the user's trust level [64].

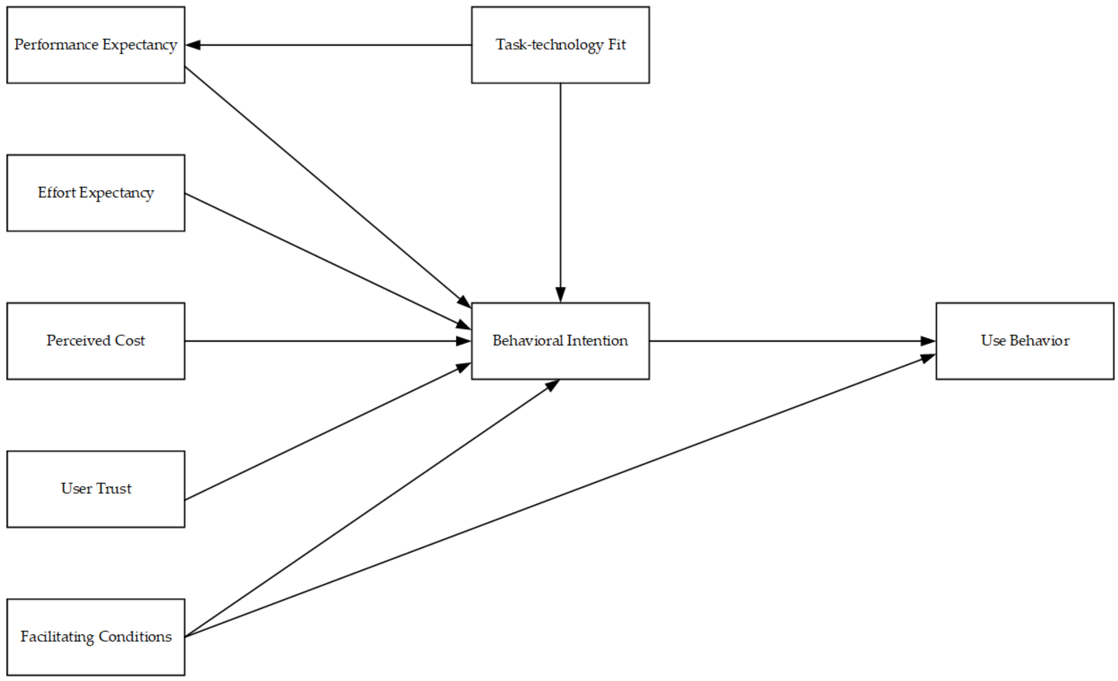

Figure 1. Proposed BIM acceptance model.

Based on the literature review and analysis of the relevant variables mentioned above, the following hypotheses are proposed:

H1. *Task–technology fit positively correlates with one individual's performance expectancy to use BIM.*

H2. *Task–technology fit positively correlates with one individual's behavioral intention to use BIM.*

H3. *Performance expectancy can strengthen individuals' behavioral intention to use BIM.*

H4. *Effort expectancy positively influences the individual's behavioral intention to use BIM.*

H5. *Perceived cost positively affects individuals' behavioral intention to use BIM.*

H6. *User trust positively affects individuals' behavioral intention to use BIM.*

H7. *Facilitating conditions positively affect individuals' behavioral intention to use BIM.*

H8. *Facilitating conditions have a positive effect on one individual's usage of BIM.*

H9. *Behavioral intention can increase one individual's usage of BIM.*

4. Data Collection and Analysis Method

4.1. Questionnaire Design

Based on the review of previous studies on BIM adoption barriers by Venkatesh et al. and related research, a questionnaire was designed for this study. Most of the questions in the questionnaire were derived from the relevant literature, as shown in Table 1. The questionnaire was used to investigate the BIM adoption behavior and its influencing factors among construction professionals.

The questionnaire consisted of two parts. The first part collected background information of the respondents, while the second part included latent variables and their observed variables. In studies using the UTAUT model, Likert scales are commonly used to obtain data on IT system users' perceptions [65]. Therefore, we designed the questionnaire as a Likert five-point scale, which is an attitude assessment method. Respondents can rate the observed variables based on their feelings, with scores ranging from "strongly agree" (5 points), "agree" (4 points), "neutral" (3 points), "disagree" (2 points), to "strongly disagree" (1 point).

Table 1. Items and their sources.

Variable	Description	Source
Task–technology fit (TTF)	Related BIM is mature enough to meet my daily work needs.	[66]
	The work processed by the BIM used is well matched.	[67]
	There are sufficient types of BIM families to meet my work requirements.	[68]
	BIM can achieve integration between different software.	[48]
Effort expectancy (EE)	I think learning to use BIM is easy.	[45]
	I think it is not necessary to spend too much effort to become proficient in using BIM.	[69]
	I think BIM has poor applicability and interoperability.	[70]
	I think there is insufficient integration between BIM and traditional 2D construction drawings.	[48]
Performance expectancy (PE)	I think using BIM is very helpful for my work.	[45]
	I think using BIM can help me complete work tasks faster.	[71]
	I think using BIM can improve my work efficiency.	[52]
	If I use BIM, I will increase my chances of increasing my income.	[54]
Perceived cost (PC)	I need to spend a lot of money to purchase BIM software.	[72]
	I think the price of using BIM software is too high, and I may have financial barriers.	[62]
	If BIM software prices are reduced, I would be more willing to continue purchasing.	[72]
	I think learning to use BIM software incurs high time costs.	[73]
User trust (UT)	I believe that BIM is safe.	[64]
	I believe that BIM is reliable.	[74]
	I believe that the results of using BIM software applications are accurate.	[75]
	I think spending time learning to use BIM software is worth it.	[64]
Facilitating conditions (FC)	The company provides funding support for BIM software and hardware facilities costs.	[76]
	The supplier can provide good support.	[77]
	The government recommends implementing BIM.	[78]
	The government has issued many policies to promote the development of BIM.	[71]
	I have sufficient resources and knowledge to use BIM in my work.	[79]
Behavioral intention (BI)	I am willing to use BIM.	[18]
	I am willing to recommend BIM to others.	[45]
	I hope to continue using BIM in the future.	[48]
Use behavior (UB)	In my work, I will frequently use BIM.	[74]
	I will recommend BIM to people around me.	[45]
	I will continue using BIM in the future.	[54]

4.2. Data Collection

This study focuses on construction practitioners using BIM as research subjects. Two methods were employed to collect data. Firstly, a questionnaire was collected through the Credamo platform, a specialized integrated data platform for research and modeling. Credamo provides large-scale surveys, data collection, and modeling analysis services for research institutions, enterprises, and individuals. Additionally, Credamo offers consultation services to meet challenging research needs, such as longitudinal tracking surveys, paired sample surveys (e.g., leader–subordinate relationships), and E-Prime experiments. So far, Credamo has served over 3000 academic institutions globally, covering various disciplines, including management, psychology, medicine, sociology, etc. The data collected through Credamo is considered to be professional and reliable.

As the data collected through Credamo was insufficient, we utilized the second data collection method. The survey questionnaire was emailed to construction industry professionals who use BIM. A "snowball sampling" strategy was employed to gather more feedback, inviting respondents to forward the questionnaire to their colleagues. This strategy was chosen to increase the relative response rate. Through both methods, a total of 546 responses were collected. Out of these, 138 were incomplete or had ambiguous answers and were invalid, resulting in a final sample size of 408 valid responses, with an effective response rate of 74.7%.

4.3. Analysis Method

Under the guidance of the conceptual framework, we employed SEM to explore the causal mechanism between effort expectancy, performance expectancy, perceived cost, user trust, facilitating conditions, task–technology fit, behavioral intention, and use behavior among building professionals when using BIM. SEM is a comprehensive statistical method for explaining the relationship between multiple variables and is commonly used in factor analysis [80]. SEM provides a better method for researchers to analyze complex theoretical models [81]. In the past 20 years, SEM has become increasingly popular in behavioral studies because SEM can address the issue of unobserved variables, handle multiple dependent variables, and allow both independent and dependent variables to include measurement errors [82]. In summary, SEM is an effective method that can be used to test causal relationships between variables and help us gain a better understanding of the obstacles that building professionals encounter when using BIM.

5. Results

5.1. Descriptive Statistics

The demographic characteristics of the sample are presented in Table 2. In terms of gender, the sample was balanced with females (50.98%) and males (49.02%). The majority of participants had a bachelor's degree (52.45%). Additionally, 48.53% of respondents had 5–10 years of work experience in the construction industry, while 30.39% had over ten years of experience, indicating that the survey participants had extensive work experience and were knowledgeable about the construction industry. Regarding BIM usage duration, 72.55% of respondents reported using BIM for over two years. Most respondents were from developers, design institutes, and contractors, accounting for 87.25% of the sample. In terms of job position, technical personnel accounted for the largest proportion (57.87%).

Table 2. Description of socio-demographic characteristics.

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	200	49.02%
	Female	208	50.98%
Education	Junior college and below	31	7.60%
	Bachelor	214	52.45%
	Master	149	36.52%
	Doctor	14	3.43%
Work experience (years)	0–5	86	21.08%
	6–10	198	48.53%
	11–15	83	20.34%
	>15	41	10.05%

Table 2. *Cont.*

Characteristic	Category	Frequency	Percentage (%)
Workplace	Developer	112	27.45%
	Design institute	143	32.05%
	Contractor	101	24.75%
	Consultancy firm	16	3.92%
	Research institution	34	8.33%
	Others	2	0.49%
Job position	Technical personnel	236	57.84%
	General management	84	20.59%
	Senior management	60	14.71%
	Others	28	6.86%
Usage time (years)	0–1	37	9.07%
	1–2	75	18.38%
	2–4	139	34.07%
	4–6	127	31.13%
	>6	30	7.35%

5.2. Reliability and Validity Tests

5.2.1. Reliability Tests

Cronbach's α coefficient was used to measure the internal consistency of the questionnaire and conduct a reliability test. Table 3 shows that Cronbach's α coefficients of all variables are above 0.7 [83], indicating a high degree of reliability of the questionnaire.

Table 3. Reliability and convergent validity.

Construct	Code	Factor Loading	Cronbach's α	AVE	CR
Task–technology fit (TTF)	TTF1	0.768	0.820	0.536	0.822
	TTF2	0.697			
	TTF3	0.734			
	TTF4	0.727			
Effort expectancy (EE)	PE1	0.765	0.821	0.537	0.822
	PE2	0.760			
	PE3	0.705			
	PE4	0.698			
Performance expectancy (PE)	EE1	0.823	0.823	0.547	0.827
	EE2	0.699			
	EE3	0.766			
	EE4	0.658			
Perceived cost (PC)	PC1	0.796	0.835	0.564	0.838
	PC2	0.760			
	PC3	0.744			
	PC4	0.701			
User trust (UT)	UT1	0.757	0.832	0.556	0.833
	UT2	0.760			
	UT3	0.713			
	UT4	0.751			
Facilitating conditions (FC)	FC1	0.771	0.847	0.529	0.849
	FC2	0.745			
	FC3	0.720			
	FC4	0.649			
	FC5	0.746			
Behavioral intention (BI)	UI1	0.837	0.816	0.611	0.825
	UI2	0.766			
	UI3	0.739			
Use behavior (UB)	UB1	0.779	0.789	0.560	0.729
	UB2	0.737			
	UB3	0.727			

5.2.2. Validity Tests

Before conducting validity testing, we performed Kaiser–Meyer–Olkin (KMO) and Bartlett's tests to evaluate the suitability of the survey data for factor analysis. The KMO value was 0.919, which was greater than 0.9, and the Sig value of the sample data chi-square statistic was 0.000, which was less than the significant level of 0.05, suggesting sufficient correlations among the measurement items, and it was suitable for factor analysis. Then, we conducted a confirmatory factor analysis to test the validity, and the results are shown in Table 3. The factor loadings of each latent variable were between 0.658 and 0.81, all greater than 0.5. The composite reliability (CR) ranged from 0.729 to 0.849, all greater than 0.7 [84]. The average variance extracted (AVE) ranged from 0.529 to 0.611, all greater than the critical value of 0.5, indicating that the questionnaire had good convergent validity.

In Table 4, the discriminant validity values, that is, the square root values of AVE for each construct are shown to be larger than the squared correlation estimate, thus providing good evidence of discriminant validity.

Table 4. Discriminant validity.

	TTF	EE	PC	UT	PE	BI	UB	FC
Task–technology fit (TTF)	0.732							
Effort expectancy (EE)	0.314	0.739						
Perceived cost (PC)	−0.534	−0.532	0.751					
User trust (UT)	0.321	0.345	−0.554	0.746				
Performance expectancy (PE)	0.429	0.337	−0.544	0.361	0.733			
Behavioral intention (BI)	0.495	0.524	−0.620	0.538	0.532	0.782		
Use behavior (UB)	0.518	0.493	−0.664	0.538	0.547	0.629	0.748	
Facilitating conditions (FC)	0.347	0.292	−0.544	0.474	0.424	0.570	0.548	0.728

Note: The first values of each column are the square roots of AVE values, and other values are the correlations among constructs.

5.3. *Model Goodness-of-Fit Tests*

After ensuring the reliability and validity of the measures, we established a structural equation model using the theoretical framework proposed in Figure 1 and analyzed the model using Amos24.0 software. The fit indices of the model are presented in Table 5, with a chi-square to degrees of freedom ratio (χ^2/df) of 1.742, which is less than the recommended threshold of 3. The goodness of fit index (GFI), incremental fit index (IFI), and comparative fit index (CFI) were all greater than 0.9, indicating an acceptable model fit. The root mean square error of approximation (RMSEA) was 0.042, which is less than the criterion of 0.05, indicating a good fit. Therefore, the proposed model was deemed appropriate.

Table 5. Model goodness of fit.

Indicators	χ^2/df	RMSEA	GFI	IFI	CFI
Recommended value	<3	<0.05	>0.9	>0.9	>0.9
Actual value	1.724	0.042	0.902	0.947	0.947

5.4. *Path Analysis*

The standardized path coefficients and their significance levels are presented in Table 6. The *p*-values of the paths corresponding to H1, H2, H3, H4, H6, H7, H8, and H9 were all less than 0.05, indicating that these hypotheses were supported. However, the *p*-value of the path corresponding to H5 was greater than 0.05, indicating that the hypothesis that perceived costs significantly influence usage intention was rejected.

Table 6. Standardized coefficients.

Estimation Path	Coefficient	S.E.	Hypothesis	Results
TTF→PE	0.541 ***	0.078	H1	Supported
TTF→BI	0.163 *	0.068	H2	Supported
PE→BI	0.181 **	0.045	H3	Supported
EE→BI	0.251 ***	0.064	H4	Supported
PC→BI	−0.127	0.082	H5	Partially supported
UT→BI	0.210 **	0.056	H6	Supported
FC→BI	0.212 ***	0.056	H7	Supported
FC→UB	0.231 ***	0.078	H8	Supported
BI→UB	0.569 ***	0.091	H9	Supported

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

In a nutshell, the factors affecting the adoption of BIM are illustrated in Figure 2. Behavioral intention was influenced by task–technology fit, performance expectancy, effort expectancy, user trust, and facilitating conditions, in descending order of importance: task–technology fit > effort expectancy > facilitating conditions > user trust > performance expectancy. Meanwhile, usage behavior was influenced by facilitating conditions and behavioral intention, with the relative importance in descending order: behavioral intention > facilitating conditions.

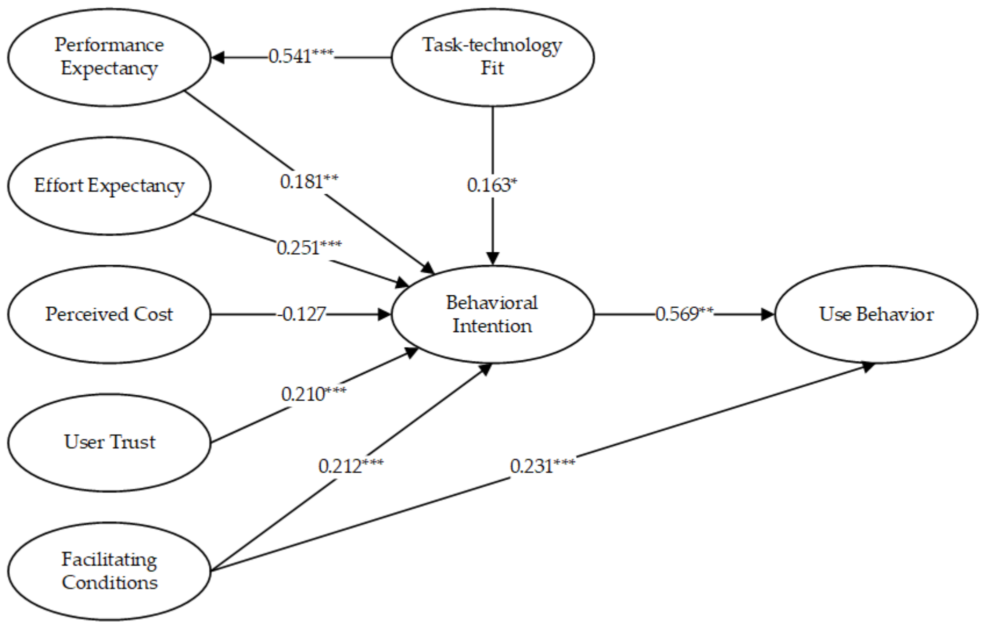

Figure 2. Path diagram of BIM application barriers.

5.5. Multiple-Group Analysis

To test whether the proposed model had cross-group stability, this study conducted a multiple-group path analysis on demographic variables (i.e., gender, education level, experience, and usage time). The demographic variables did not impact the model if there were no significant differences. If significant differences were found, it would indicate that the demographic variables had a moderating effect. First, we grouped participants based on gender, education level, experience, and usage time. Then, assuming the measurement model was true, we examined the structural model. The *p*-values of the structural coefficients were 0.159, 0.585, 0.763, and 0.273 for gender, education level, experience, and usage time, respectively, all of which were greater than 0.05, indicating that there were no significant differences in the structural coefficients across the groups.

However, the above description only reflects the overall phenomenon, which may obscure the inter-group effects of specific factor loads. Therefore, we used parameter pairing to test individual paths, and some striking findings emerged in the critical ratios for differences between parameters (measurement weights). Please refer to Table 7 for specific results. In the gender grouping, we found that gender played a role in the path from performance expectancy to behavioral intention. The standardized path coefficients from performance expectancy to behavioral intention in the male and female group models were 0.306 and 0.062, respectively. The absolute value of the critical ratio difference between parameters was 2.37 > 1.96, indicating that at the 0.05 significance level, gender had a moderating effect on the path from performance expectancy to behavioral intention, and performance expectancy had a more significant impact on male behavioral intention than female usage intention.

Table 7. Multiple-group analysis.

	Gender			**Education**			**Usage Time**		
Paths	Male	Female	CRDP	Low-Education	High-Education	CRDP	Low-Time	High-Time	CRDP
TTF→PE	0.564 ***	0.511 ***	−0.137	0.525 ***	0.597 ***	−0.742	0.511 ***	0.589 ***	1.073
TTF→BI	0.098	0.212 *	0.868	0.187 *	0.187	−0.135	0.155	0.179	0.134
EE→BI	0.287 ***	0.267 **	−0.5	0.274 ***	0.185 *	−0.714	0.313 ***	0.096	−1.831
PC→BI	−0.097	−0.145	−0.244	−0.095	−0.176	−0.473	−0.075	−0.249 *	−1.132
UT→BI	0.293 ***	0.103	−1.829	0.286 ***	0.093	−1.741	0.233 **	0.207 **	−0.116
FC→BI	0.165 *	0.294 **	0.714	0.123	0.367 ***	2.015	0.137	0.348 ***	1.547
PE→BI	0.306 **	0.053	−2.37	0.172 *	0.147	0.024	0.17 *	0.154	−0.32
FC→UB	0.157	0.273 **	0.612	0.252 **	0.137	−0.756	0.293 ***	0.016	−2.02
BI→UB	0.556 ***	0.617 ***	0.621	0.550 ***	0.656 ***	0.987	0.55 ***	0.728 ***	1.19

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; CRDP indicates critical ratio difference between parameters.

Education played a role in the path from facilitating conditions to behavioral intention in the education grouping, with standardized path coefficients of 0.123 and 0.376 for the low-education and high-education group models, respectively. The critical ratio difference between parameters was 2.015 > 1.96, indicating that at the 0.05 significance level, education had a moderating effect on the path from facilitating conditions to behavioral intention, and facilitating conditions had a more significant impact on the behavioral intention of the high education group than the low education group.

However, we did not find any path whose critical ratio value was greater than 1.96 in the experience grouping, so we concluded that experience did not have a moderating effect on the model. In contrast, usage time played a role in the path from facilitating conditions to usage behavior, with standardized path coefficients of 0.293 and 0.016 for the low and high usage time group models, respectively. The absolute value of the critical ratio difference between parameters was 2.020 > 1.96, indicating that at the 0.05 significance level, usage time had a moderating effect on the path from facilitating conditions to usage behavior, and facilitating conditions had a greater impact on the usage behavioral of the low usage time group than the high usage time group.

6. Discussions

As shown in Table 6, all hypotheses except H7 were supported. The significant positive correlation between performance expectancy and behavioral intention is consistent with the basic principle of the UTAUT model. It confirms the findings of Murguia et al. that users who perceive BIM as helpful for improving productivity and completing work more effectively will have greater motivation to adopt BIM [51]. However, this result contradicts the findings of Howard et al., who found that performance expectancy did not significantly influence individual users' adoption of BIM in the UK and that BIM adoption was imposed by organizations and projects rather than a personal choice, therefore perceived as an additional uncompensated task by practitioners [18]. In addition, significant differences were found between males and females in the path from performance expectancy to behavioral intention in multi-group analysis, with males being significant on this path while females were not, indicating that providing more performance rewards to males will increase their usage intention.

Effort expectancy significantly impacted behavioral intention, indicating that users who perceive BIM as easy to use are more willing to use it in projects. In the UK, Ghana, and

China, effort expectation is also essential for behavioral intention [18,48,52]. Facilitating conditions significantly influence both behavioral intention and usage behavior, consistent with the findings of Sargent et al. and Venkatesh et al. [45,85]. In addition, the respondents' educational level also affects the path, with facilitating conditions having a greater impact on the usage intention of high-educated groups than on low-educated groups. High-educated employees have better learning abilities and are more sensitive to facilitating conditions. Yuan and Yang found that support is an essential factor in adopting BIM in all companies [86]. Facilitating conditions needs support from the government, suppliers, and companies to promote the application of BIM. At the same time, the sample's BIM usage time moderates the path from facilitating conditions to usage behavior, with employees with more BIM usage time being less sensitive to facilitating conditions than those with less usage time. Providing sufficient facilitating conditions will generate strong behavioral intentions among new employees in the early stages.

Behavioral intention significantly positively affects usage behavior. Psychologists generally believe that behavioral thoughts govern human behavior, so explaining why willingness to use affects usage behavior is relatively easy. This view has been confirmed in related studies in China, Korea, and the UK [18,86,87]. All the hypotheses regarding the original variables of the UTAUT model have been valid as described above. Next, we continue to discuss the extended variables of the UTAUT model.

We found that task–technology fit significantly impacts performance expectancy. Task–technology fit describes the ability of BIM to complete tasks at each stage of a project and is a competitive feature of BIM [48]. Therefore, task–technology fit plays a crucial role in performance expectancy. This result confirms the findings of Tulubas Gokuc and Arditi, who pointed out that BIM can meet the most critical needs of design professionals, including enhancing visualization and design efficiency [88]. Meanwhile, behavioral intention is mainly influenced by task–technology fit. Potential BIM adopters always consider the fit of their work and decide to apply it when the fit is good.

Regarding the path of user trust and behavioral intention, we found that few scholars in the construction field have focused on the relationship between user trust and behavioral intention. Therefore, in this study, we explored the relationship between the two, and the results showed that user trust significantly affects behavioral intention. This finding is consistent with the research of Nordhoff et al., which indicates that people are only more willing to use tools if they trust them [64].

In addition, the relationship between perceived cost and usage intention was insignificant. One possible explanation for this finding is that with the increasing popularity of BIM in China, increasingly more companies are purchasing BIM-related software for their employees to learn for free. Employees can also acquire BIM-related knowledge from various other channels.

7. Conclusions

Improving the application rate of BIM is not only an essential measure for the construction industry to respond to digitization but also plays a vital role in enhancing the competitiveness of China's construction industry in the international arena. In recent years, the determinants and mechanisms of increasing the use of BIM have attracted increasing attention from the academic community, policymakers, and the media. Unlike previous scholars who mainly focused on the research of application barriers of BIM in industries, projects, or organizations, this study believes that it is necessary to evaluate the obstacles to the diffusion of BIM technology from the perspective of practitioners. Through a review of relevant literature, we designed a questionnaire. Then, taking advantage of the questionnaire survey, we developed an analytical framework to capture individuals' perceptions of the barriers to applying BIM. We used SEM to explore the impact of task–technology fit, effort expectancy, performance expectancy, user trust, perceived cost, and facilitating conditions on employees' application of BIM.

In this empirical analysis, we found that task–technology fit is the most significant barrier affecting BIM usage by practitioners, emphasizing the importance of aligning BIM technology with work tasks to increase users' willingness to adopt it. Therefore, we recommend ensuring that practitioners' actual work requirements match the capabilities of BIM software. Effort expectancy, as the second most significant barrier factor, also dramatically affects the diffusion of BIM. Improving interoperability between different BIM tools can reduce practitioners' effort expectancy and facilitate the integration of BIM into daily work processes [89].

Facilitating conditions also play a crucial role as a barrier to BIM adoption, impacting users' intention and behavior. At the enterprise level, top management support and resource allocation to BIM teams and providing assistance and support to new employees can promote BIM adoption. Governments should also promote BIM by specifying its use in government-funded projects and enhancing its implementation in private and public projects through policy supplements. Professional organizations in the construction industry can contribute by developing guidelines for data processing procedures to guide practitioners in incorporating BIM technology effectively. User trust is another significant factor influencing behavioral intention. To encourage BIM adoption, developers should improve software security, accuracy, and user experience to build trust among potential users.

Furthermore, the performance of SEM varies among different social-demographic groups, particularly in the obstacle factor of facilitating conditions. Multi-group analysis showed that highly educated fresh graduates are more likely to be favorable candidates for enterprises seeking to recruit employees for BIM-related tasks. Gender differences also influence performance expectancy on usage behavior, with males exhibiting a more vital need for performance. In light of this finding, enterprises should consider providing appropriate performance rewards to BIM practitioners, especially male employees, to address performance expectancy barriers. In conclusion, this study highlights critical barriers to BIM adoption from an individual perspective. It provides valuable insights for practitioners, enterprises, and policymakers in the construction industry, specifically focusing on the context of BIM usage in China.

This study provided empirical evidence from an individual perspective on barriers to BIM adoption, contributing to the growing literature and current relevant theory on the subject. The research findings revealed the factors influencing barriers to BIM adoption and identified potential solutions for improving BIM adoption rates. However, there are some limitations in this study. On the one hand, there are many different types of practitioners in the construction industry, and most of the survey samples in this paper represent only one part of the industry chain. In future research, researchers could select specific samples according to specific links in a more targeted manner. On the other hand, although this paper expanded the UTAUT model, some barriers were still not included in the actual process. Therefore, in future research, researchers can continue to explore possible barriers more carefully and comprehensively based on practical circumstances.

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