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Abstract: Over the course of the last twenty years, building information modeling (BIM) has emerged as a firmly established construction methodology integrating fundamental principles. The implementation of BIM methodologies possesses the capability to augment the attainment of quality, cost, and schedule objectives in construction endeavors. Notwithstanding the widespread adoption of BIM in the construction sector, the execution of BIM-related tasks frequently suffers from the absence of established methodologies. The objective of this study was to create a BIM application model through an examination of the correlation between BIM integration and the achievement of overall project success (OPS) in construction endeavors. In order to develop the BIM application model, feedback was solicited from a cohort of fourteen industry experts who assessed a range of BIM activities in light of prior research. The data that were gathered underwent exploratory factor analysis (EFA) in order to authenticate the results acquired from the expert interviews. Furthermore, construction professionals participated in structured surveys in order to evaluate the importance of said BIM practices. This study utilized partial least squares–structural equation modeling (PLS-SEM) to ascertain and authenticate the underlying framework and correlations between BIM implementation and OPS. The findings indicate a moderate correlation between the implementation of BIM and the success of a project wherein BIM is responsible for approximately 52% of the project's overall success. To optimize project outcomes, it is recommended that construction companies prioritize the implementation of BIM practices. This study highlights the correlation between the utilization of BIM and favorable project results, emphasizing the necessity for the construction sector to adopt BIM as a revolutionary instrument to attain enhanced project achievements.

Keywords: building information modeling (BIM); success of project; construction projects; partial least squares (PLS); structural equation modeling (SEM)

1. Introduction

In certain emerging nations, in order to meet national economic goals, significant changes have occurred in the building industry [1]. Regardless, the building sector in these nations could be more competitive, which is due to its inability to fulfill global standards for sustainable development. Typically, construction projects are confronted by various obstacles, including noncompletion, delays in schedule, expense overruns, low standards, and a high likelihood of failure to achieve the desired results [2]. Due to the restricted quantity of capital available in these markets, some projects might be postponed or canceled [3].

The construction sector needs to satisfy the needs of its governments, customers, and society and catch up to other sectors and their counterparts [4]. Given the disparities in economic and social aspects faced by this sector, construction is always afflicted with the same overlooked issues. Indeed, low salaries, large employment losses, and potential threats create a market with a high threat level [5]. Significant currency fluctuations (uncertainty), a shortage of knowledgeably made business decisions, and financing model constraints contribute to the risk [6]. In a larger sense, the primary causes of project delays have been highlighted [7]: construction financing challenges, client (owner) discrepancies about secure payment, design modifications, and a shortage of effective building supervision. BIM is critical in light of the abovementioned facts. BIM is a comprehensive process for creating and managing information about a built resource. BIM organizes and combines information from several disciplines to offer a digital picture of a resource's full life, from planning, design, and building to procedures [8]. This model has been verified as a tool whose use starts in the planning phase and concludes in the execution stage.

BIM seeks to decrease wasteful expenditures by integrating them into sustainable development [9]. According to Hadzaman, Takim, and Nawawi, BIM is an effective method used in most industrialized nations to address the abovementioned challenges [10]. In the current building business, BIM's benefits are gaining popularity [11]. It seeks to increase cost-effectiveness and efficiency to maximize production without sacrificing quality [12]. In developing nations, BIM adoption is quite low. According to Dowsett and Harty, while the demand for BIM is increasing in these nations, the reaction on the ground needs to be improved to alter the market dynamics of the building industry [13].

While BIM is widely used in many countries, its application in emerging nations is limited, as shown by Maqsoom et al., and the Malaysian building sector is no anomaly [14]. Despite the paucity of studies in the relevant literature, it has been shown that there needs to be more comprehensive research examining the degree of BIM understanding and implementation [15]. It has been noted that most construction players need more knowledge about BIM, and this lack of knowledge hinders the execution of BIM operations. Furthermore, despite the low awareness, past research demonstrates that practitioners need to gain more knowledge of the implementation idea (i.e., BIM) under consideration. Examples include BIM [13], building information modeling, and evaluation of the drivers of the logistics activities that enhance its results [16], with the three studies completed using SEM. Pham et al. investigated the adoption of risk management using descriptive statistics [17]. Utilizing the PLS (partial least squares) modeling method, the present study examines the mathematical connection between the implementation of BIM and overall project success (OPS). This study may support decision makers in the success of their engineering construction plans by avoiding needless expenses and enhancing quality due to appropriate BIM—building information modeling—utilization. The importance of this research is considerable for the building sector since BIM's significance needs to be understood.

Overall, the objective of this study is to examine the correlation between the adoption of BIM and the achievement of OPS in the context of construction projects. The implementation of BIM methodologies has demonstrated promising outcomes in enhancing the attainment of objectives related to quality, cost, and schedule in the construction sector. The absence of established methodologies for the implementation of BIM poses a significant obstacle. The present investigation endeavors to address this void by constructing a BIM application model that is grounded in expert assessments and methodical surveys. This research has significant implications for construction companies, as it provides guidance for the adoption and effective utilization of BIM practices. The manuscript commences with a comprehensive review of the relevant literature, followed by a detailed exposition of the methodology employed. The ensuing section presents the findings of the study, which are subsequently discussed in depth. Finally, the paper concludes with a set of recommendations that are intended to be of practical value to stakeholders of construction projects.

2. Literature Review

2.1. BIM Activity Measurements

BIM is a strategy for increasing the productivity of a project characterized by a program that is unique, advanced, difficult, or problematic [18]. This method is evaluated based on its structural and organizational characteristics, as well as its interdisciplinary analysis and functional testing [19]. BIM efforts ultimately increased safety, pricing, competitiveness, and good market image [13]. Historically, BIM research has been organized into the following stages: knowledge, functions, creativity, evaluation, normalization, and regulations. These steps are the primary stage to implementing the BIM [20]. The activities that take place throughout each of the six stages of arranging the BIM workshop are outlined in Table 1.

Table 1. BIM activities in construction.

BIM Stages	Assigned Code	Activities	References
Knowledge	BIM.SK1	BIM allows diverse teams to communicate and exchange information in real time more efficiently. This facilitates information sharing and improved decision making.	[18,21,22]
	BIM.SK2	BIM collects information about building components, materials, and systems that may be used to advise future developments.	[23–25]
	BIM.SK3	BIM models may be used to simulate various situations and evaluate the performance of various design alternatives.	[26]
	BIM.SK4	BIM may be used to provide training and instructional resources that aid in the development of the knowledge and abilities of construction professionals.	[13]
	BIM.SK5	BIM models may be used throughout the building process to gather and evaluate data.	[13]
Function	BIM.SF1	BIM may be used to develop comprehensive construction schedules that include design, engineering, and construction operations.	[13]
	BIM.SF2	BIM may be used to develop precise and thorough cost estimates that take into consideration the number and kind of materials needed, as well as labor expenses.	[2,26,27]
	BIM.SF3	BIM may be used to simulate building performance and evaluate the operation of various systems and components.	[4,5,28]
	BIM.SF4	BIM may be used to generate safety plans that detect possible construction hazards and dangers.	[1,29]
	BIM.SF5	Building information modeling (BIM) models may be used to assist the continuous management and repair of buildings and other infrastructure.	[6,30]
Evaluation	BIM.SE1	By simulating multiple scenarios and evaluating the effect of different design alternatives, BIM may be used to analyze the environmental impact of building projects.	[3,7,8]
	BIM.SE2	BIM may be used to quantify the embodied energy and carbon footprint of a building by combining information on building materials, systems, and components.	[31]
	BIM.SE3	When buildings and infrastructure have been created, BIM may be used to analyze their performance.	[32–34]
Creativity	BIM.SC1	BIM may be used to model construction scenarios and detect possible clashes or conflicts between various building systems.	[9,11]
	BIM.SC2	BIM may be used to construct three-dimensional models of buildings and infrastructure that can be used to see and simulate various design alternatives.	[10,12,35]
	BIM.SC3	Before building starts, BIM may help designers and builders explore creative concepts and identify possible obstacles.	[18]
Regulations	BIM.SR1	BIM enables the construction of an efficient and legally enforceable mechanism for conflict settlements.	[20,36,37]
	BIM.SR2	Adopting BIM necessitates not just a departure from traditional practices but also a change in one's approach to technical matters.	[38,39]
	BIM.SR3	Follow-up an action plan for BIM output	[13]
Normalization	BIM.SN1	BIM may be used to standardize building procedures, making it simpler for construction teams to collaborate and lowering the likelihood of mistakes or miscommunications.	[20]
	BIM.SN2	Standardization by BIM may lessen the possibility of project-impacting delays, cost overruns, and other difficulties.	[16,40]
	BIM.SN3	BIM's unified platform for exchanging information and collaborating on design and construction may guarantee that all parties are on the same page and working toward the same objectives.	[13]

2.2. OPS Measurement

The successful completion of the project had evolved into a universal need within the building and construction sector. For this reason, it is essential for all parties involved in the project, including consumers, designers, and consultants, to have a solid grasp of what constitutes a successful endeavor. Alomari, Gambatese, and Anderson developed a hierarchical model that validated the importance of cost, quality, and timeliness as primary goals for productive building projects [24]. The hierarchical prototype explains the intervention of a star or success factor measurement, which is the principal objective of a productive construction project [41,42]. The essential aim of a finished building project, along with the life cycle times, excellence, and cost as key objectives in building projects, are the time, cost, and quality of the ultimate hierarchical point, respectively. According to Giel, Issa, Olbina, Tirunagari, and Kone, the factors that impact the accomplishment of a construction project are shown in Table 2 [43,44].

Table 2. Project success factors.

Cost	Time	Quality
Enhance the project's profitability	delivering the job on schedule	Improve conformity to specification
Increase the financial flow of the project	Delivering on time reduces variation order implementation time.	Availability of means to meet a certain quality standard
Reduce costs of order variations	Increase resource availability as expected across the project duration	delivering projects following the quality of raw materials and equipment

2.3. The Connection between BIM Application and OPS

In the earlier period, scholars evaluated the efficiency of construction project management in facilitating the accomplishment of construction projects. However, recognizing the project's victory was contingent on the practical approach to assessing the project. BIM is the tool that contributes to the project's success. It was determined that BIM had achieved a degree of maturity where the content and format of the workshop findings were adequate [45]. According to Ibrahim, Esa, and Kamal, the dynamic nature of projects in recent years necessitates new and novel concepts that rely on the collaborative efforts of project participants to increase the project's value [46]. BIM may decide and manage forthcoming issues for these project innovations to prevent disputes and strengthen their concepts [47].

Regarding overall performance and project completion, the influence of BIM on workers and enterprises varies from the prior research. In other words, BIM may have a systemic impact on the effectiveness of businesses by identifying the ideal value [48].

Prior research has examined the correlation between BIM and the efficacy of construction endeavors. Numerous scholarly investigations have examined the potential advantages of implementing BIM, including enhanced collaboration, improved project coordination, and decreased instances of errors and rework [2,3,39,49]. The studies mentioned above have yielded encouraging findings, indicating that BIM has the potential to exert a positive influence on project outcomes [6,25,49].

The significance of researching the relationship between BIM implementation and OPS stems from the study's contribution to the existing body of information on the issue in a newly uncharted situation. In addition, to the finest of our knowledge, such empirical research is one of the first conducted inside the construction environment. The research also sheds light on the effect of BIM operations across the various stages on the OPS in the construction sector. As stated by Lim and Latief, one method to explain the relevance of a study's contribution is to throw additional theoretical insight into the phenomena under examination, such as BIM, in a new national setting, such as BIM [50]. Nevertheless, the current research distinguishes itself through its unique methodological approach. The present study employs an SEM methodology to comprehensively analyze the association between BIM and the achievement of project success. SEM enables the comprehensive analysis of intricate associations among multiple variables concurrently, thereby facilitating a more comprehensive and nuanced comprehension of the impact of BIM on the success of construction projects. This study seeks to utilize SEM to examine the complex relationships among different factors related to BIM and the achievement of project success [2,3]. This approach effectively responds to the necessity for a more thorough examination. It substantially contributes to the current body of knowledge in the realm of construction project management and BIM implementation. Figure 1 depicts the conceptual model demonstrating the investigation's proposed route (H1).

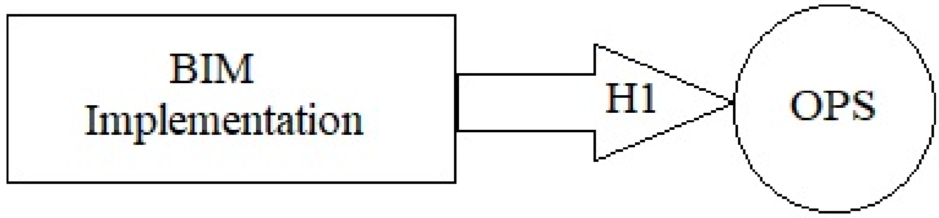

Figure 1. Impact of BIM activity adoption on OPS.

3. Approach to Research

According to past studies, there are few research approaches for BIM tolerance and regulatory emphasis at the macro level [19,31]. As a result, this research included two-stage questionnaires. The first step is a pilot study, a standard procedure for validating a measurement instrument before its use in primary research [44]. The second step of testing the theoretical hypothesis is the primary research—the first question aimed to fulfill the objective of evaluating the significant factors for structure model development. At the same time, the second main questionnaire fulfilled the development of a structure model between BIM implementation and OPS.

The theoretical modeling begins with the creation of some research strategy. The theoretical modeling is the overview of a research topic investigation used for developing intermediary theories evaluated with actual data. The conceptual modeling approach consists of three steps: (1) identifying the components of the model, (2) classifying these constructs, and (3) describing the relations between these constructs [43]. Figure 1 depicts the model outcomes that followed this procedure. Figure 2 illustrates the study design for this study. To characterize the model's constructions, 14 professionals in the building industry were interviewed to verify these activities and categorize them according to Table 1. These professionals currently work as project managers in construction projects in Malaysia and have experience of at least ten years in their field. Also, it was essential to interview only project managers with experience working in project environments supported by BIM. The interviews were conducted from 15–25 January 2023.

3.1. Pilot Study

Pilot research was conducted using exploratory factor analysis (EFA) to investigate the previously described categories by delivering the first questionnaire to construction experts. According to Ahsan et al. [51], the research samples for the EFA examination should range between 150 and 300. Nonetheless, Asadi et al. [52] claimed little agreement among academics over the sample size for factor analysis, although they encouraged using a larger sample. Pham et al. and Abdel-Hamid and Abdelhaleem stated that factor examination is acceptable for 20–50 variables; meanwhile, individual factors cannot be accurately defined if the number of variables exceeds this threshold [17,53]. Nonetheless, research revealed that fewer variables might be employed if the sample size is large [24]. The sample size utilized for this investigation was 200 as an illustrative sample within acceptable limits [25]. Respondents were involved based on their working experience in Malaysia's construction industry, especially deploying BIM in routing project management.

The respondents' data were obtained from official online resources in the construction sector. The pilot study was conducted from 1–20 February 2023.

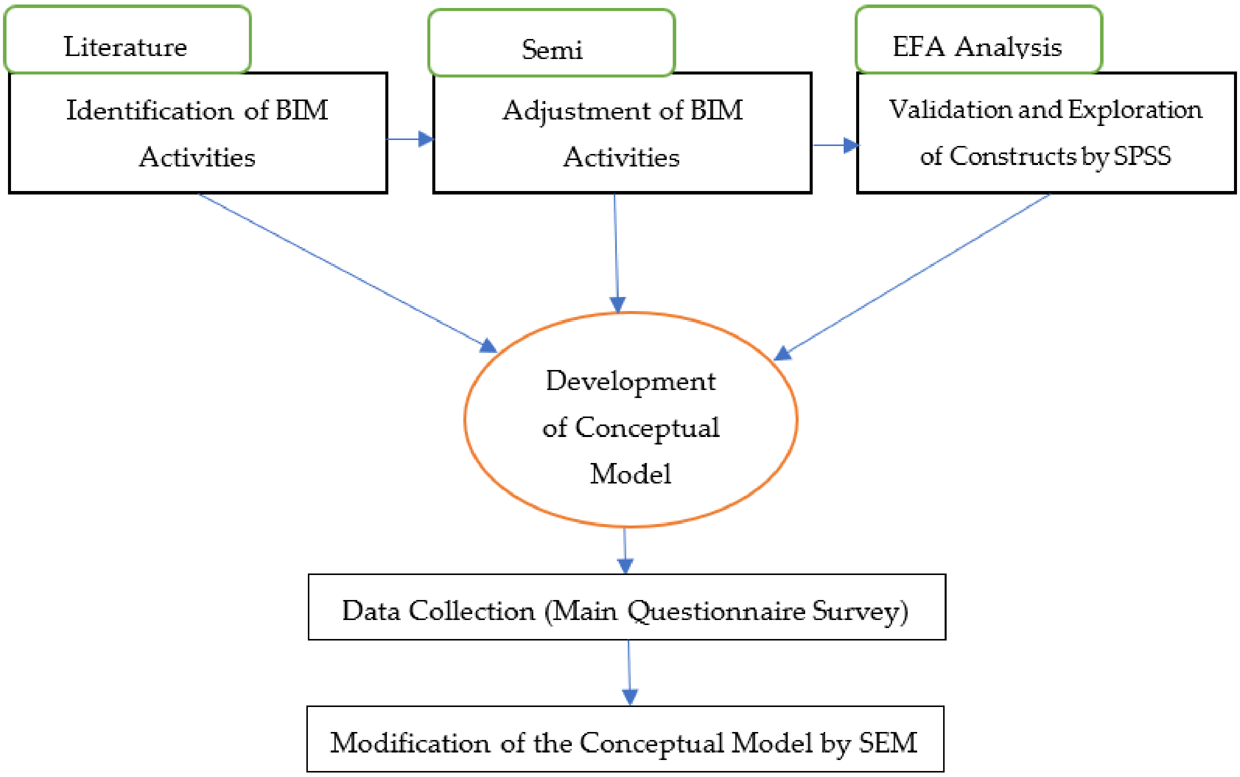

Figure 2. Research approach design.

3.2. Main Questionnaire

An efficient sectional survey was developed based on cumulative findings of the research-relevant material investigation. Permitting preliminary interviews and the Exploratory Factor Analysis (EFA) assessment (Questionnaire Form 1), adjustments and then categorizations were made to the activity classes. The study was conducted in Malaysia, namely in Perak. To measure the effect of BIM activities and OPS questions, many prospective participants in the construction industry were asked to complete Questionnaire 2. This questionnaire was constructed with four major sections: the respondent's demographic profile, BIM activities (Table 1), overall project success variables (cost, period, and excellence), and open-ended queries to identify additional activities considered critical by respondents. The respondent characteristics were kept the same for the participants, and the recruitment in the survey was also performed similarly to the pilot survey. The primary questionnaire survey was conducted from 22 February–15 March 2023.

3.3. Analytical Approach

To examine how BIM affects construction project success, four models adaptive by the literature body were assessed and compared by top options generated by applying BIM to create a simulation model for productive construction development: MLR (Multiple linear regression), SD (system dynamics), SEM (structural equation modeling), and ANN (artificial neural network) methods. The association between non-observed variables has prevented the adoption of the regression equation. This severely limits the application of the regression equation [26].

The system dynamics could not be used, since there was no temporal link in the data (i.e., the information was not time-related). The fundamental goal of the study was to look at how BIM may be used to apply OPS, and the ANN is indeed a device used for making predictions. The SEM method may be used to characterize the connection among as many unobservable and observable factors as the range of the research permits. SEM is an efficient tool for handling changing mistakes, according to Mostafa et al. [2]. This study used SEM to develop a model to establish the connection between BIM (activities) and OPS. Da Silva et al. [27] noted that although hypothesis testing procedures have been universally accepted, SEM has become a well-established non-experimental scientific method. The use of articles from the Information Management (MI) Quarterly has been shown to be an effective method over time, as Ibrahim et al. [28] also agreed.

Moreover, SEM is a popular and extensively utilized source of information in the social sciences. The research used the SEM approach proposed by Tariq et al. [4] because of its prominent application in the building industry. The PLS model, incorporating both formative and reflective elements, was also used to analyze the activities in BIM phases and their effect on OPS to establish the cause-and-effect relationship between them. When employing PLS, the measuring model outlines the link between the construct (BIM application) and seen indicators, as stated by Alaloul et al. [5].

Further, Covariance-Based Structural Equation Modeling (CB-SEM) and PLS-SEM are two statistical techniques commonly employed in structural equation modeling [26]. The CB-SEM technique involves estimating model parameters by minimizing the difference between the observed covariance matrices and the covariance matrices that the model implies. PLS-SEM is a statistical technique that prioritizes estimating latent variables and their interrelationships by maximizing explained variance. PLS-SEM is considered a more appropriate statistical technique for research studies with smaller sample sizes, non-normally distributed data, and when the focus is on latent variables [2]. The researcher likely opted for PLS-SEM as the analytical tool in this investigation owing to its adaptability in managing limited sample sizes, non-parametric data distributions, and the prioritization of latent variables, which correspond with the research aims and data attributes.

4. Results

4.1. Demographic Details

Figure 3 indicates demographic details. Three essential groups were chosen for the questionnaire, contractors, consultants, and clients, with architects, surveyors, civil, electrical, mechanical engineers, and other subcategories of these professions/occupations. The percentage of replies based on work span was stated as follows: the maximum assessment response was 30.0% with 15 to 20 years of experience, while 25.4% had between 10 and 15 years of experience. A total of 12.1% of employees had fewer than five years of practice or experience. These findings indicate that respondents had the required expertise and expertise to review the BIM elements, creating a high degree of trust in their contribution and the validity of the findings. Figure 3 indicates that most participants (54.1%) were civil engineers, followed by quantity engineers (18.2%). Totals of 23%, 44.5%, and 15% of respondents had B.Sc. (bachelor's in sciences), MS (master's in sciences), and Ph.D. degrees, respectively.

Due to the novelty of BIM in Malaysia, to access the required sub-population, stratified sampling was utilized [23]. This method was offered to assist the writers in gathering the most trustworthy and accurate data possible, given that this survey focuses on BIM. Respondents received BIM activities based on their information and expertise utilizing a 5-point Likert scale (5—strongly agree, 4—agree, 3—neutral, 2—disagree, 1—strongly disagree), which has been used in several prior BIM studies [54]. This gave participants various replies depending on their expertise with construction schemes. The study's purpose was to determine the sample size. For a standard distribution curve, an illustrative examination, such as the mean, mode, and median, would need more than thirty examples.

Nonetheless, Harris decided that a minimum sample size of 200 would ensure the validity of SEM [55]. It was claimed that a particular requirement of a model of the complex route should have a sample size of 200 or above, although Sánchez and Serrano recommended that the sample size should be greater than 100, preferably more than 200 [56]. Because of the SEM methodology used in this study, 230 among 340 construction experts were contacted separately, and participation in the analysis of SEM was accepted. It is important to note that the size of the sample utilized for this research is larger than those used in the earlier BIM studies by Dinis et al. (231 respondents); Bughio et al. (2018) (330 respondents); and Manzoor, Othman, and Kang et al. (sample size of 285) [13,20].

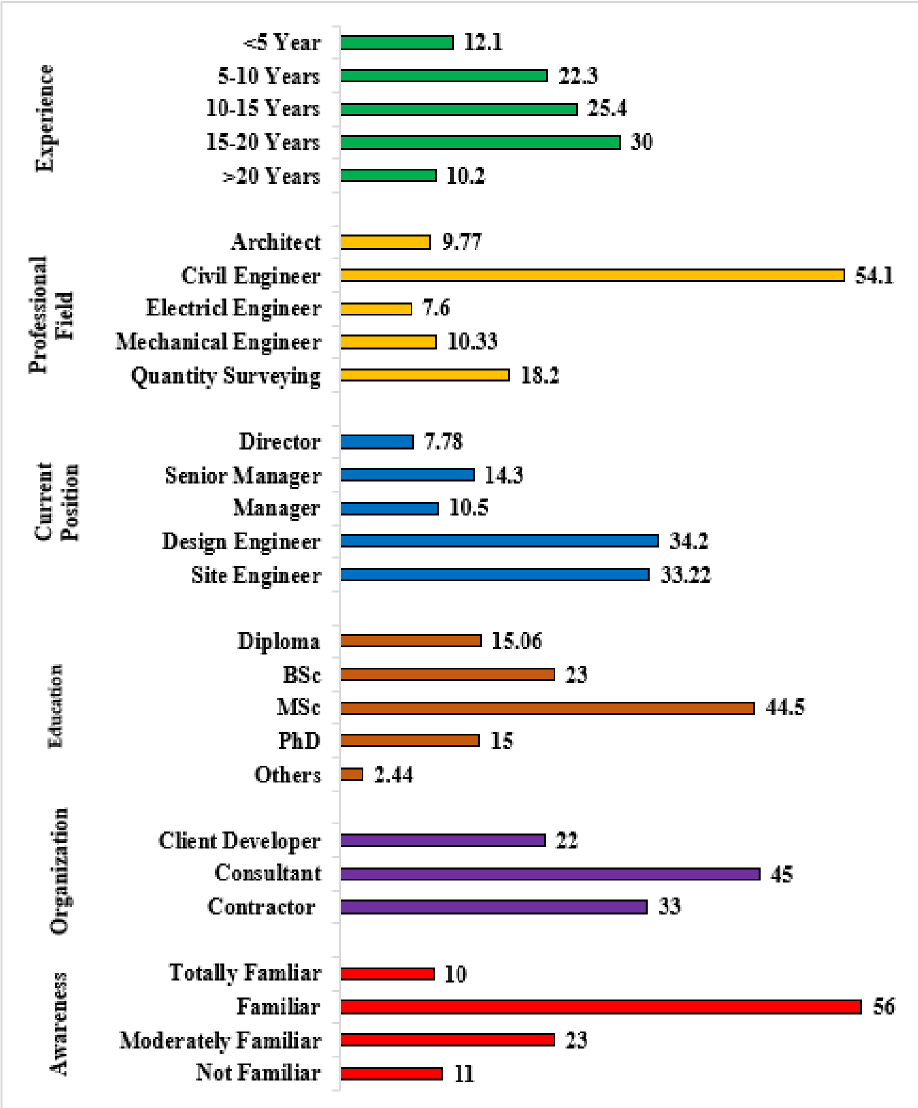

Figure 3. Demographic profile.

They constituted an estimated 68% response rate. For this kind of inquiry, this rate of return is considered adequate. Because of the customized strategy and the extended duration (160 days) given for gathering data, which began in the mid of May 2021, the response rate was very high. There were 217 valid responses (13 were deemed incomplete and discarded). It is essential to highlight that the degree of knowledge among Malaysian construction experts is more significant (60.8%) than in a previous survey (54%). This disparity may be attributable to their lower sample size (40 respondents) than the present survey's (217 respondents), which provides a high confidence level [57]. It is more possible, particularly in sectors with a significant concentration of construction professionals, to gather the views of qualified practitioners from the general community.

4.2. Descrciptive Statistics

The presented table (Table 3) displays descriptive statistics of ratings provided by 200 respondents on diverse variables associated with BIM implementation. The mean values denote the arithmetic mean of the scores for each variable, whereas the standard deviation signifies the degree of variability or dispersion around the mean [18,54]. The variance is a statistical metric that accurately indicates the extent to which scores are dispersed. Skewness values indicate the symmetry of a distribution, whereby negative values denote left-skewness and positive values denote right-skewness. Using descriptive statistics provides valuable insights into the respondents' ratings, the degree of variability, and the distribution characteristics of the variables [2,57]. This approach concisely summarizes the data's central tendency, dispersion, and skewness.

Table 3. Descriptive statistics.

Variable	N	Mean	Std. Deviation	Variance	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
BIM.SK1	200	3.611	0.6158	0.379	−0.328	0.172
BIM.SK2	200	3.504	0.5762	0.332	−0.223	0.172
BIM.SK3	200	3.586	0.6664	0.444	−0.114	0.172
BIM.SK4	200	3.541	0.6311	0.398	−0.105	0.172
BIM.SK5	200	3.559	0.5871	0.345	0.041	0.172
BIM.SF1	200	3.493	0.6595	0.435	0.122	0.172
BIM.SF2	200	3.494	0.6558	0.430	0.073	0.172
BIM.SF3	200	3.473	0.7075	0.501	−0.003	0.172
BIM.SF4	200	3.444	0.6981	0.487	0.117	0.172
BIM.SF5	200	3.482	0.6926	0.480	0.060	0.172
BIM.SE1	200	3.5590	0.63000	0.397	−0.103	0.172
BIM.SE2	200	3.633	0.6866	0.471	0.117	0.172
BIM.SE3	200	3.494	0.7156	0.512	0.353	0.172
BIM.SC1	200	3.474	0.7152	0.511	0.397	0.172
BIM.SC2	200	3.457	0.7061	0.499	0.414	0.172
BIM.SC3	200	3.438	0.7216	0.521	0.413	0.172
BIM.SR1	200	3.420	0.7566	0.572	0.492	0.172
BIM.SR2	200	3.490	0.7634	0.583	0.347	0.172
BIM.SR3	200	3.433	0.7139	0.510	0.341	0.172
BIM.SN1	200	3.371	0.7646	0.585	0.493	0.172
BIM.SN2	200	3.478	0.8252	0.681	0.221	0.172
BIM.SN3	200	3.5170	0.74598	0.556	0.115	0.172

4.3. Normality

The tabulated data present the outcomes of the Shapiro–Wilk normality examination performed on the BIM-implementation-associated variables. The Shapiro–Wilk test is a statistical tool used to evaluate the degree of deviation of data from a normal distribution. The degrees of freedom are represented by the variable "df", while the *p*-value is displayed in the "Sig." column [58]. The findings suggest significant deviations from normality as all variables, including BIM.SK1 to BIM.SN3, exhibit *p*-values below 0.05, as indicated in Table 4. Consequently, the distribution of data of these variables is non-normal [58]. The statement mentioned above suggests that it is crucial to consider the non-normality of variables during their analysis and employ suitable statistical methodologies capable of accommodating non-normal data.

Table 4. Normality test results.

	Shapiro–Wilk		
	Statistic	**df**	**Sig.**
BIM.SK1	0.975	200	0.001
BIM.SK2	0.983	200	0.015
BIM.SK3	0.984	200	0.020
BIM.SK4	0.981	200	0.009
BIM.SK5	0.983	200	0.015
BIM.SF1	0.977	200	0.002
BIM.SF2	0.982	200	0.012
BIM.SF3	0.979	200	0.004
BIM.SF4	0.977	200	0.003
BIM.SF5	0.981	200	0.010
BIM.SE1	0.980	200	0.006
BIM.SE2	0.976	200	0.002
BIM.SE3	0.967	200	0.000
BIM.SC1	0.964	200	0.000
BIM.SC2	0.965	200	0.000
BIM.SC3	0.964	200	0.000
BIM.SR1	0.950	200	0.000
BIM.SR2	0.963	200	0.000
BIM.SR3	0.971	200	0.000
BIM.SN1	0.953	200	0.000
BIM.SN2	0.961	200	0.000
BIM.SN3	0.971	200	0.000

4.4. Identification and Classification of the Model's Constructs

Using an EFA, a factor structure of 22 points is pertinent for BIM tasks and is indeed studied, as indicated in Table 5. Several proven factorability characteristics were employed in the construction of the relationship. The Kaiser–Meyer–Olkin (KMO) test is frequently used to examine whether or not the incomplete connections among variables are minimal (Sharma, 1996). According to Chegu Badrinath and Hsieh, the KMO index for practical factor analysis spans from 0 to 1, with a lower limit of 0.6 [29]. The correlation matrix can also be determined to be an identity matrix using Bartlett's sphericity test [59,60].

Almarri, Aljarman, and Boussabaine proposed that the sphericity assessment by Bartlett must be significant ($p < 0.05$) for the factor assessment to be deemed suitable [1]. Initial findings indicate that the KMO sample sufficiency measure was 0.819, which was more than the recommended value of 0.6, and that Bartlett's test sphericity test was significant ($\times 2$ (210) = 1255.831, $p < 0.05$). In addition, the diagonals of the matrix, which is of anti-image relation, were more extensive than 0.5, validating the addition of every factor in the analysis [61,62]. This primarily tells us the estimations for each variable's variation when all contributing factors are considered, and Fair values (0.3) indicate variables that do not adequately match the factor solution. All initial communities in the current investigation were over the threshold.

Table 5. EFA.

	Constituent						
	1	**2**	**3**	**4**	**5**	**6**	**Cronbach Alpha**
BIM.SK2	0.799						
BIM.SK5	0.791						
BIM.SK4	0.785						0.860
BIM.SK3	0.779						
BIM.SK1 *							
BIM.SF3		0.770					
BIM.SF5		0.754					
BIM.SF4		0.713					
BIM.SF1		0.693					0.802
BIM.SF2		0.637					
BIM.SE1			0.890				
BIM.SE3			0.872				0.882
BIM.SE2			0.858				
BIM.SC3				0.871			
BIM.SC2				0.849			0.806
BIM.SC1				0.693			
BIM.SR1					0.832		
BIM.SR2					0.827		0.748
BIM.SR3					0.749		
BIM.SN2						0.917	
BIM.SN1						0.887	0.828
BIM.SN3 *							
Eigen Value	3.157	2.873	2.542	2.372	2.066	1.762	
% Variance	13.728	12.489	11.052	10.313	8.983	7.660	

* Items excluded due to loading less than 0.6 or cross-loadings. Extraction method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization.

Each loading factor was more significant than 0.6. The results of the EFA for all 22 questions yielded six factors with eigenvalues greater than 1. The six eigenvalues and components explained 64.165% of the total variance. Notably, the final component had three items (BIM.SN3) that belonged to the normalization phase and were omitted from the primary research. Similarly, the second component had five items among these five items (BIM.SK1) that belonged to the knowledge mode and were omitted from the research.

Consequently, on BIM-relevant theory, Table 6 outlines six potential extraction components. The reliability statistics for the EFA-extracted factors were determined [63]. The activities of each factor (group) phase were calculated based on the variable with the most excellent loading in Table 6's structure matrix. It demonstrates that the surety assessment was satisfactory. For freshly established metrics, a Cronbach's alpha value larger than 0.6 is satisfactory, while the average value is 0.7, and values greater than 0.8 are very reliable. As each of the preceding Cronbach's alpha values was more than 0.7, they were all acceptable. According to Olugboyega et al., all objects' average set correlations were more than 0.3, suggesting stable internal variables [6].

Table 6. Check for validity and reliability in the construct.

BIM Stages	Assigned Code	Loadings	Cronbach Alpha	Composite Reliability	AVE
Knowledge	BIM.SK2	0.867	0.853	0.901	0.695
	BIM.SK3	0.803	-	-	-
	BIM.SK4	0.807	-	-	-
	BIM.SK5	0.855	-	-	-
Function	BIM.SF1	0.790	0.802	0.862	0.558
	BIM.SF2	0.751	-	-	-
	BIM.SF3	0.695	-	-	-
	BIM.SF4	0.707	-	-	-
	BIM.SF5	0.781	-	-	-
Evaluation	BIM.SE1	0.919	0.873	0.922	0.798
	BIM.SE2	0.914	-	-	-
	BIM.SE3	0.845	-	-	-
Creativity	BIM.SC1	0.816	0.806	0.885	0.720
	BIM.SC2	0.868	-	-	-
	BIM.SC3	0.861	-	-	-
Regulations	BIM.SR1	0.737	0.736	0.848	0.651
	BIM.SR2	0.840	-	-	-
	BIM.SR3	0.841	-	-	-
Normalization	BIM.SN1	0.921	0.844	0.927	0.865
	BIM.SN2	0.939	-	-	-

4.5. First-Order Measurement Model

The SEM presented in Figure 4 signifies the study's conceptual model in Figure 1. From Tables 1 and 2, each BIM and OPS build of the model was described as well classified based on prior research. Ranjbar et al.'s analysis of model measurement involves the (1) estimations and consistency of the first indicator, (2) combined dependability, (3) extracted average variance (AVE), and (4) discriminant validity [30]. For our study, the PLS method adheres to Yaakob, Ali, and Radzuan's recommendations for the weighting scheme, data measure, maximum iterations, abort criteria, and starting weights [7]. The scale should only eliminate indicators with outside loadings between 0.40 and 0.65 if doing so significantly increases composite reliability and AVE [8]. It was determined that external load variables smaller than 0.65 did not meet this condition, and, as advised, additional research was deemed unnecessary [3]. This is the threshold at which about half of the indicator's variation is described by its component, and the variance explained exceeds the variance of error [64]. The external loadings with all variables in the basic measurement model can be seen in Table 6 and Figure 4. Therefore, all outside loads for items connected to the stages of knowledge, function, regulations, normalization, creativity, and evaluation had loading factors more than 0.65 based on the original measurement model, indicating their substantial effect on the associated constructs.

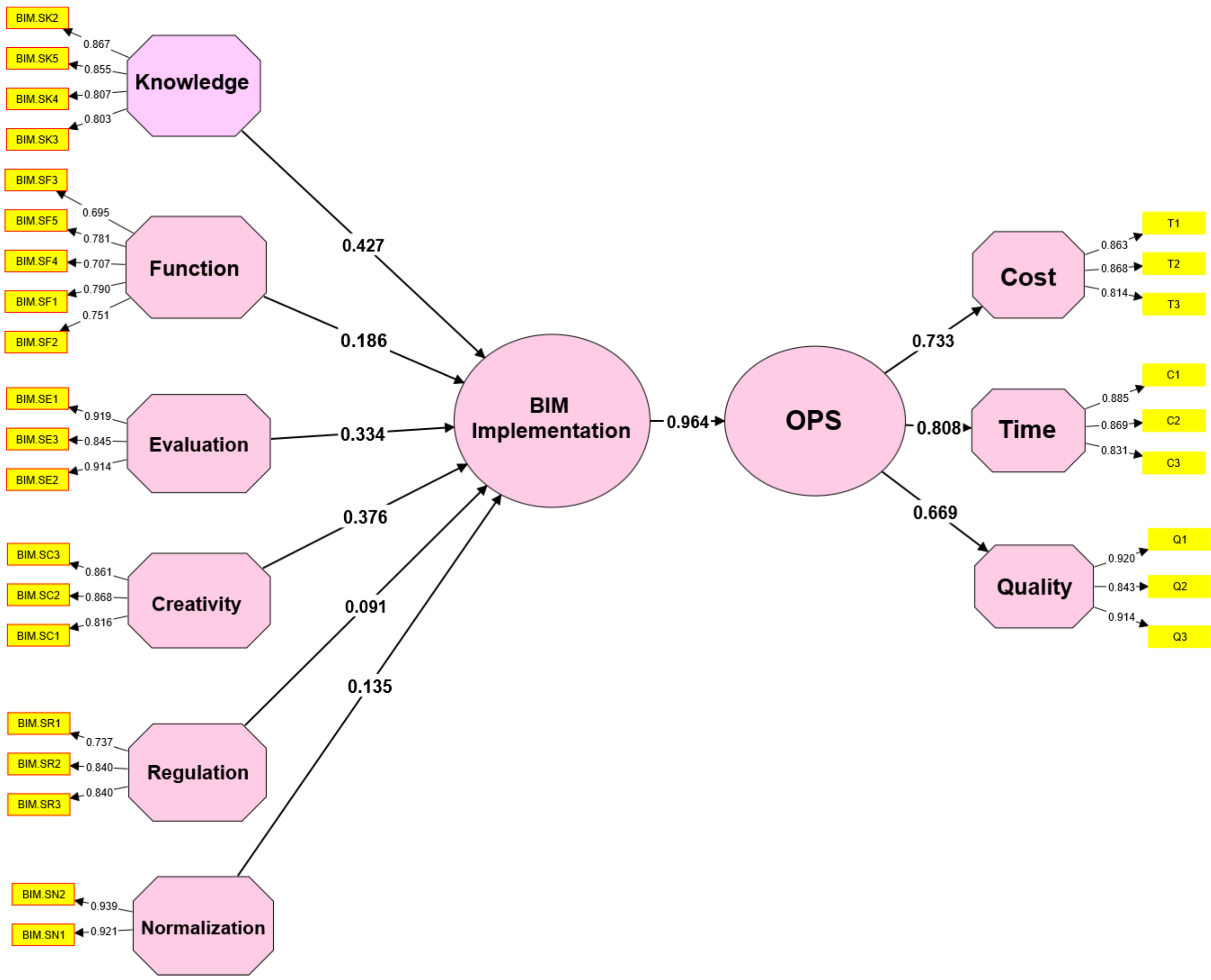

Figure 4. Structure model along with the coefficient of the path (outer loading results are shown on arrows).

Chan, Olawumi, and Ho evaluated the internal reliability for composite reliability (C.R.) using Cronbach's alpha, which measures sensitivity concerning the number of constituents [31]. According to Evans et al., values over 0.65 are suitable for any study, as well as above 0.50, particularly for exploratory research [32]. The models fall accordingly to the C.R. > 0.70 criterion and are so accepted, as shown in Table 6. AVE works as a typical metric for assessing the convergent validity of model structures, with values over 0.50 indicating an excellent convergent value [34]. According to Table 4, all constructions pass this criterion.

When the idea differs from other conceptions based on observable criteria, discriminant validity has been demonstrated. As a result, the construct is distinct. It captures events poorly described by other constructs in the model, as seen by the construct's discriminatory validity, according to Mahamadu, Mahdjoubi, and Booth [33]. There are three ways to measure discriminant validity: the Nguyen et al. criteria, the HTMT or Heterotrait–Monotrait ratio of the correlations criterion, and the cross-loading criterion [9]. To measure the discriminative validity, the square root of the AVE of each construct may be compared to correlations from one construct with any other construct [57,63]. The square root of the AVE should be greater than the relationship among latent variables, according to the concepts of Wang et al. [11].

Table 7 demonstrates that the outcome validates the discriminant validity of the measurement model. Nonetheless, several academics have rejected Fornell and Larcker's

(1981) definition of discriminative validity. Consequently, Hadzaman, Takim, and Nawawi suggested an alternative way of evaluating discriminative validity (i.e., the HTMT ratio criterion) [10].

Table 7. (Fornell–Larcker) discriminant validity and the relationship between latent variables.

Construct	Cost	Creativity	Evaluation	Function	Knowledge	Normalization	Quality	Regulation
Cost								
Creativity	0.459							
Evaluation	0.375	0.298						
Function	0.486	0.281	0.243					
Knowledge	0.160	0.447	0.373	0.5				
Normalization	0.258	0.176	0.221	0.268	0.258			
Quality	0.375	0.298	0.146	0.243	0.373	0.221		
Regulation	0.233	0.248	0.090	0.271	0.210	0.163	0.090	
Time	0.459	0.241	0.298	0.281	0.447	0.176	0.298	0.248

The HTMT method, which analyzes the relation among two constructs provided they are reliably calculated, is a unique approach for analyzing the discriminant-variance-based SEM validity. The HTMT was well employed in this work to analyze the validity of discriminants.

HTMT values should be less than 0.85 and 0.90, indicating that the two conceptions are distinct [6]. The HTMT value should be less than 0.90 if the model's constructs are conceptually remarkably similar and less than 0.85 if the model's constructs are conceptually dissimilar. Table 8 displays the HTMT values for all investigated constructions. Therefore, the notions have shown sufficient discriminating validity.

Table 8. Analysis score on the HTMT.

Construct	Cost	Creativity	Evaluation	Function	Knowledge	Normalization	Quality	Regulation	Time
Cost	0.862								
Creativity	0.378	0.849							
Evaluation	0.326	0.251	0.893						
Function	0.407	0.23	0.192	0.746					
Knowledge	0.979	0.376	0.33	0.423	0.833				
Normalization	0.218	0.147	0.188	0.229	0.222	0.93			
Quality	0.327	0.251	1	0.192	0.33	0.188	0.893		
Regulation	0.182	0.198	0.074	0.174	0.171	0.134	0.074	0.807	
Time	0.378	1	0.251	0.23	0.375	0.147	0.251	0.198	0.849

This research also used the cross-loading criteria to establish discriminatory validity. This approach aims to identify that the indicator loading of certain constructs latent in nature must be greater than the indicator's loading for alternative constructs latent in nature for each row [65,66]. Their constructions' loading indicators must be more valuable than the alternative construct. Table 9 reveals that the allocated latent construct indicator load is more significant from their cross-loadings on varying constructs. Each construct exhibits a significant degree of one-dimensionality, as seen by the outcome [67].

Table 9. Cross-loadings (discriminant validity).

	Creativity	Evaluation	Function	Knowledge	Normalization	Regulation	Cost	Quality	Time
BIM.SC1	0.816	0.237	0.244	0.382	0.108	0.196	0.814	0.237	0.379
BIM.SC2	0.868	0.233	0.194	0.291	0.161	0.132	0.867	0.233	0.299
BIM.SC3	0.861	0.162	0.14	0.275	0.103	0.175	0.860	0.162	0.279
BIM.SE1	0.242	0.919	0.165	0.353	0.14	0.073	0.242	0.92	0.348
BIM.SE2	0.194	0.914	0.196	0.341	0.172	0.08	0.194	0.914	0.337
BIM.SE3	0.239	0.845	0.153	0.174	0.197	0.042	0.239	0.843	0.174
BIM.SF1	0.253	0.203	0.79	0.315	0.18	0.128	0.252	0.203	0.301
BIM.SF2	0.142	0.238	0.751	0.274	0.283	0.122	0.141	0.238	0.265
BIM.SF3	0.145	0.019	0.695	0.205	0.034	0.149	0.144	0.018	0.192
BIM.SF4	0.197	0.055	0.707	0.313	0.144	0.157	0.197	0.056	0.295
BIM.SF5	0.116	0.15	0.781	0.439	0.169	0.107	0.116	0.15	0.43
BIM.SK2	0.327	0.334	0.372	0.867	0.182	0.22	0.326	0.335	0.815
BIM.SK3	0.27	0.254	0.361	0.803	0.175	0.093	0.269	0.255	0.664
BIM.SK4	0.297	0.234	0.312	0.807	0.124	0.093	0.297	0.234	0.801
BIM.SK5	0.353	0.271	0.365	0.855	0.252	0.151	0.352	0.271	0.819
BIM.SN1	0.119	0.172	0.174	0.188	0.921	0.125	0.118	0.171	0.188
BIM.SN2	0.152	0.177	0.248	0.224	0.939	0.124	0.152	0.177	0.216
BIM.SR1	0.083	−0.011	0.063	0.166	0.062	0.737	0.083	0.011	0.198
BIM.SR2	0.174	0.077	0.24	0.177	0.13	0.84	0.174	0.077	0.176
BIM.SR3	0.207	0.078	0.186	0.071	0.12	0.84	0.207	0.078	0.074
C1	0.327	0.334	0.372	0.800	0.182	0.22	0.814	0.092	0.275
C2	0.353	0.271	0.365	0.755	0.252	0.151	0.868	0.271	0.218
C3	0.297	0.234	0.312	0.607	0.124	0.093	0.863	0.234	0.131
Q1	0.242	0.401	0.165	0.353	0.14	−0.073	0.242	0.914	0.348
Q2	0.239	0.341	0.153	0.174	0.197	−0.042	0.239	0.843	0.174
Q3	0.194	0.200	0.196	0.141	0.172	−0.08	0.194	0.203	0.037
T1	0.861	0.162	0.14	0.275	0.103	0.175	0.279	0.162	0.885
T2	0.768	0.233	0.194	0.291	0.161	0.132	0.299	0.233	0.869
T3	0.716	0.237	0.244	0.382	0.108	0.196	0.379	0.237	0.831

4.6. Second-Order Measurement Model

Since the primary variables (dependent and independent factors) were second-order latent factors, the bootstrap method evaluated the significance of every first-order latent variable. One aspect of implementing BIM was formative, while the project's success was reflective [41,42]. Typically, elevated relations are seen among indicators of measurement models' anticipation of what still needs to be carried out [68,69]. In addition, according to Li, Wang, and Alashwal, the significant correlation between formative factors shows potential collinearity [35]. We investigated the collinearity between the construct's formative constituents by measuring the value of VIF (variable inflation factor). For this investigation, we examined collinearity difficulties while interacting with reflective-formative second-order construct types using internal VIF values [67,70]. Six subscales of BIM activities of the first order, covering the normalization stage, the regulatory stage, the creative stage, the knowledge stage, the evaluation stage, and the function stage, exhibited a high-value co-efficient of the path (exterior weight), as indicated in Table 10. Figure 5, along with

Table 8, reveals that knowledge stage had the highest outer loading (β = 0.427, $p < 0.001$), after the creativity stage (β = 0.376, $p < 0.001$), evaluation stage (β = 0.334, $p < 0.001$), the function stage (β = 0.186, $p < 0.001$), the normalization stage (β = 0.135, $p < 0.001$), and the regulation stage (β = 0.091, $p < 0.001$). All VIF values were less than 3.5, showing that these subdomains separately contributed to a higher-order construct.

Table 10. Utilizing bootstrap for testing second-order models in the constructive phase.

Path	β	S.E.	*t*-Values	*p*-Values	VIF
Creativity → BIM Implementation	0.376	0.027	13.892	<0.001	1.23
Evaluation → BIM Implementation	0.334	0.034	9.741	<0.001	1.203
Function → BIM Implementation	0.186	0.017	11.264	<0.001	1.268
Knowledge → BIM Implementation	0.427	0.025	16.858	<0.001	1.451
Normalization → BIM Implementation	0.135	0.023	5.79	<0.001	1.104
Regulation → BIM Implementation	0.091	0.031	2.979	<0.001	1.107

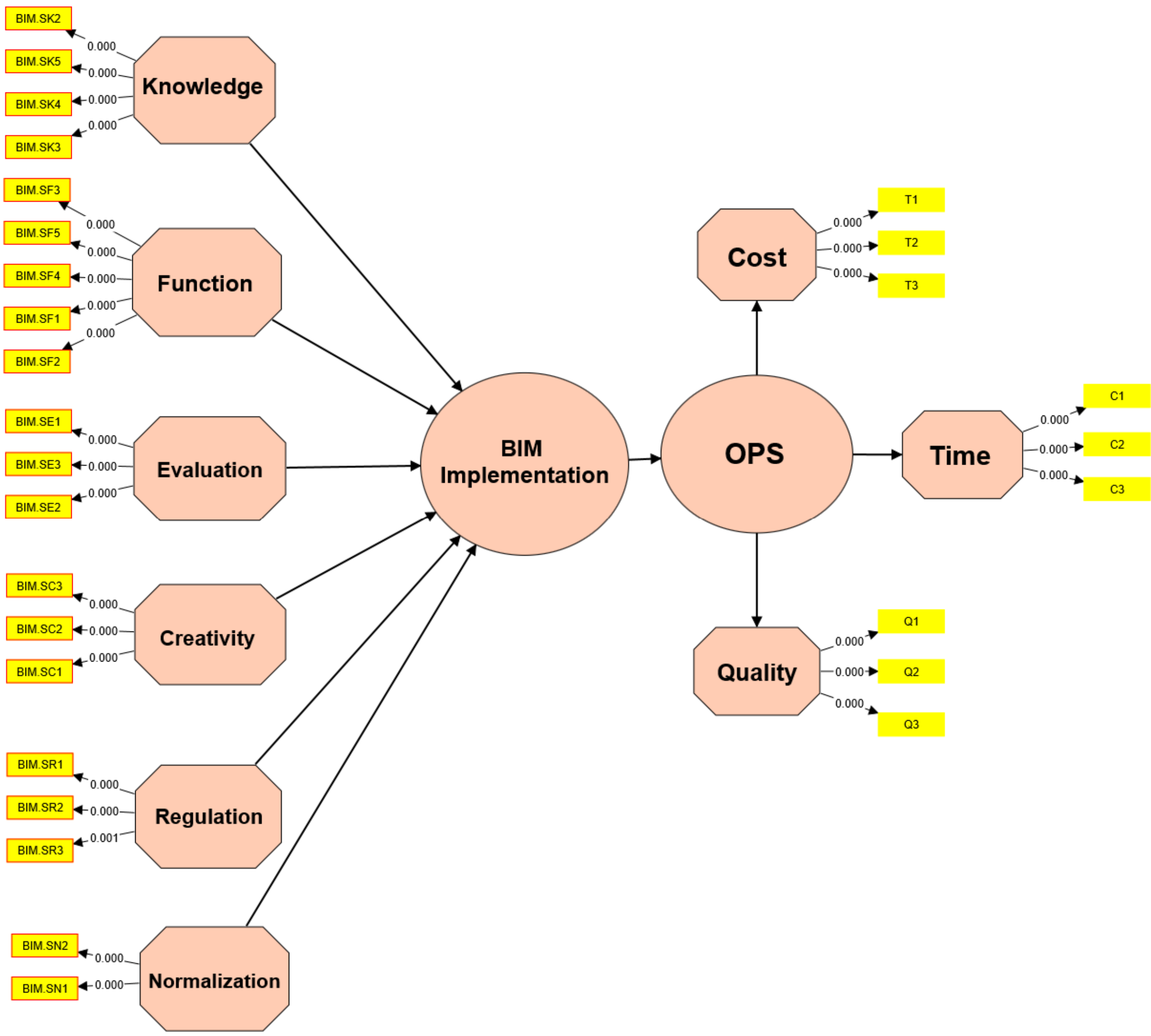

Figure 5. Bootstrapping analysis (path coefficients and then *p*-values are shown on the interior model).

In this model, the success of the project was seen in the second-order construct, and outcomes for project success categorized into three subscales, including quality, money, and schedule, pointed to these subscales as contributing significantly to project success as second-order variables latent in nature. Valued path coefficients were well over 0.65 and were crucial, as shown in Table 11.

Table 11. Utilizing bootstrap for testing second-order models in the reflective phase.

Path	β	S.E.	*t*-Values	*p*-Values
OPS → Cost	0.733	0.042	17.395	<0.001
OPS → Quality	0.669	0.063	10.573	<0.001
OPS → Time	0.808	0.026	31.022	<0.001

4.7. Path Analysis of Structure Model

A method for linear regression is path analysis. It is a method of preference in social management and science. Likewise, Durdyev et al. stated that path analysis is the primary method for simultaneously investigating all complicated interactions [20]. Principally, a structural equation model is used throughout the SEM analysis step. The structural model could be utilized for evaluating the relation in study components. After fitting the model, a structural equation model is the second major step in SEM analysis [67]. The structural model may be utilized by finding the links among variables. The structural model explains links deeply between variables [71,72]. According to Ayman, Alwan, and McIntyre, the statistics illustrate the link between exogenous and independent factors and endogenous or dependent variables [37]. The structural model's evaluation is predicated mainly on the overall model fit, followed by the postulated parameter estimations' magnitude, direction, and significance. The last step is validating the planned study connection based on the research assumptions stated in Figure 1. SEM was used to examine the study hypothesis. The influence of BIM deployment on success factors was analyzed using PLS-SEM following this model's study framework. Figure 5 depicts the corresponding research hypothesis model.

Ihe importance of the model's hypothesis was assessed in the traditional methodology framework. Again, a random sampling of the primary dataset comprises the bootstrapping procedure to create a fresh sample that is identical in size to the primary samples. Manzoor et al. verified the dependability of the dataset and their significance levels and, therefore, the inaccuracy of the derived route coefficients [58]. As illustrated in Figure 5, the importance of the route is represented by standardized path coefficients (β) and *p*-values. The results of the bootstrapping procedure are shown in Figure 5 along with Table 12 as *p*-values of each path [64]. Utilizing the data, BIM efforts' influence on the projects' performance was statistically seeable. Mahamadu et al. found that BIM activities' impact on success is favorable and statistically seen ($\beta = 0.9$, $p < 0.001$) [12].

Table 12. Hypotheses and relative strategic paths.

Path	β	S.E.	*t*-Values	*p*-Values
BIM Implementation → OPS	0.9	0.006	48.3	<0.001

4.8. Explanatory Control of the Structural Model

The findings indicate that the measuring model has good individual item reliability and computable and discriminant validity. The overall explanatory power of said structural model may be measured by assessing the variance of the dependent variable that the model can explain. The PLS technique permitted multiple squared (R^2) correlations for relying on variables within the model. The PLS algorithm indicated that R^2 is comparable to a standard regression [36]. R^2 reflects the total amount of variation. The independent factors within the dependent variable have explained this. Thus, a higher R^2 value improves the prediction power of a structural model. According to Table 13, the R^2 values were computed in this study by utilizing the smart-PLS method. This model's primary dependent variable, project success, had an adjusted R^2 of 0.92, indicating that the exogenous latent variable can predict 92.0% of success of the project. According to Samimpay and Saghatforoush, the results indicate that the size defined in the BIM application is highly predictive. The change in R^2 when a self-dependent construct is omitted through the model determines if excluded construct has a significant influence on the relying constructs [39]. Its metric is known as f^2 or impact size. The computation of the efficient size is indicated in Equation (1) [38]:

$$f^2 = (R^2 \text{ include} - R^2 \text{ exclude})/(1 - R^2 \text{ exclude}) \quad (1)$$

Table 13. R^2 values.

Endogenous Latent Variable	R^2	Adjusted R^2	Explained Size
Project Success	0.916	0.92	Highly Predictive

Guidelines for evaluating effect size are f^2 0.02, f^2 0.15, and f^2 0.35, signifying modest, medium, and high impact sizes of the exogenous construct, respectively. Based on the conclusion of f^2, which indicated that the size of an exogenous construct affects the project's outcome, the impact size of BIM activities is vast (f^2 = 1.433).

4.9. Predictive Significance of the Structural Model

A critical component of a structural model is its ability to evaluate the model's predictive validity. The blindfold method confirmed the cross-validated redundancy estimates for each dependent variable [73]. The results indicate that the Q^2 scores (0.91) for project success had a predictive value greater than zero, indicating that the independent construct had predictive importance for the dependent construct considered in this research. Table 14 shows that Q^2 is greater than 0. Hence, it is reasonable to conclude that the model has a high prediction accuracy.

Table 14. Predictive relevance results.

Endogenous Latent Variable	SSO	SSE	Q^2 (=1 − SSO/SSE)
Project Success	1944.000	1172.371	0.397

4.10. Importance of Performance Matrix Analysis

According to Dowsett and Harty, PLS-SEM proves the relative significance of an autonomous variable in a route model in explaining the dependent variable [13]. IPMA expands the findings of PLS-SEM by considering the working of every variable. The outcomes may be derived from two aspects crucial for management actions: significance and performance [14]. Utilizing the structural model's overall impacts (importance) as well as the mean value for variable scales latent in nature, it is possible to identify crucial areas for enhancing management operations (or the model's particular emphasis). In this research, IPMA served as the dependent variable for BIM activities. The significance and performance of the exogenous variable (BIM implementation) are shown in Table 15.

Table 15. Indicating importance—total effects for BIM activities.

Predictor	Importance	Performance
BIM Implementation	1.834	51.263

5. Discussion

Implementing BIM between professionals and their significant operations may significantly enhance the success of initiatives. Improved SEM models and the statistical values derived from their investigations provide a solid foundation for comprehending relationships between the models presented. As a result of such an analysis and modification procedure, several intriguing facts emerge.

5.1. Identification Level of Building Projects Success

According to Yaakob, Ali, and Radzuan, construction time is the total number of days that must be accomplished from the commencement of ground operations until the project is finished, expressed in months, weeks, or even years [7]. The statistics showed that the time component had the highest outside loading score, at 0.808. The findings are consistent with [22], which demonstrated that the time measured inside the client benefit system contributes to the success of a project and that BIM may shorten the duration of projects. For instance, introducing BIM in a motorway in Croatia might reduce the project duration by around 12 months. These numbers represent 6% of the entire budget and 17% of the timeline [18]. The project also depends on the factor of time. It is beneficial when determining how long a construction project will take to complete, how long it will take to execute variation orders, whether resources will be available for the project's life or duration, and how long it will take to obtain authority approval [73]. According to Barqawi, Chong, and Jonescu, quality may be a collection of characteristics needed for services provided by parties involved in building projects and the basis for determining fitness and customer satisfaction [70].

With an outside loading of 0.73, the quality factor is rated as the second most crucial element, although it is still modest. Shahid et al. demonstrated that it is still crucial to the project's success and is one of the conventional yet subjective metrics of project success. This conclusion is reinforced by Girginkaya Akdag, and Maqsood, who explored the application of BIM as a problem-solving tool for the aquatic building sector [20]. The research results show that BIM can be logically explained by boosting the quality in determining essential functionality for diverse maritime building assignments. According to Acquah, Eyiah, and Oteng, cost is one of the fundamental ideas for the execution of construction projects; it is often determined during the preconstruction phase and may rely on the client's financial constraints [19]. The cost factor was rated last, with an outside loading of 0.669. All indications are examined, and the majority of responders concurred that financial flow is essential for the success of a project and that BIM may impact cash flow and lower project costs via careful planning. This conclusion, which was corroborated by Iqbal et al., indicated that if BIM is appropriately used during the initial phase, capital costs for construction projects might be reduced by 10–20% [15]. However, Iqbak et al. asserted that cost is essential considering the capital cost of construction and that all projects will have continuous operational costs that will be considered during the project planning phase, which largely determines the project's success in the end [74].

5.2. Impact of BIM on Project Success

The study identified that general factors quality, productivity, and product functions are less in construction than in other industries. In addition, it examines BIM's impact on building success to enhance the efficiency of construction projects. The correlation between the dependent and independent variables was performed to determine the impact of BIM on the project's success. The data indicate that the deployment of BIM adds 52% to the project's success. The BIM implementation has an essential link with the OPS (overall project success) when the value is more than 0.96, which is significant when the firm or organization adds one unit of BIM, which boosts project success by 0.96 owing to cost, time, and quality aspects. Several of the BIM implementation's outputs would assist project managers in meeting the client's cost, quality, and schedule criteria, according to the results. The earlier mentioned studies demonstrate that by evaluating the building information modeling efficacy, the success of the project will be impacted by how effectively the project is managed, which is specified in terms of cost, time, and quality. All findings on the success of this study were better than expected. The goal of this section has been achieved, and it is consistent with earlier research that has shown that construction projects should prioritize time, quality, and money because these aspects ultimately determine the project's success [16]. BIM is widely utilized in the building sector as a supplementary tool to handle challenges such as limited resources and stringent planning [40].

6. Conclusions

In many nations, BIM largely relies on the building industry, and its use is minimal in emerging economies. Like several other emerging nations, anomalies in building quality and discrepancies have been observed in Malaysia, particularly in large projects. To minimize this problem, BIM tasks are essential to implement. PLS-SEM was used to verify the correlations between BIM adoption and OPS constructs. In the created structural model, based on information gathered from 217 building project specialists, a straight path and nine indirect channels have been confirmed as vital.

Furthermore, the connection between the variables was confirmed via routes between components and activity items that are both direct and indirect. According to the results, implementing BIM may reduce unnecessary time and efficiently boost quality, and the time and quality factor are crucial success factors for the project. The analysis revealed that knowledge mode has the most significant external weight on the BIM application at 0.427. Regarding the influence of BIM implementation, the creativity and evaluation phases follow next with an outside weight of 0.376 and 0.334, respectively. The regulation, normalization, and function stages tend to have the most negligible impact on BIM implementation compared to other factors, with outer weights of 0.09, 0.13, and 0.186, respectively.

Consequently, senior management will be able to organize their BIM resources and group members based on the impact of BIM phases, and their commitment to achieving outstanding project performance will be enhanced. In addition to completing the project quickly and improving its quality, the results reveal that BIM impacts the project's success in terms of time, cost, and excellence. However, BIM may affect project outcomes, and it has been shown that BIM implementation can contribute to project success.

The following sections highlight the academic and practical significance of these findings:

- The prior study needs to consider BIM deployment activities and techniques more. Most empirical research on BIM in emerging countries did not investigate the activities and procedures that comprise BIM practice.
- By studying the association between BIM implementation and OPS, the current research has contributed to filling this knowledge gap.
- This study improves the understanding of BIM methodologies and activities, contributing to the knowledge of construction engineering management.
- This study offers a platform for future studies by objectively demonstrating that the mechanism of BIM has a substantial and favorable effect on OPS. It may also contribute to the corpus of information, leading to more research on the building project.

This study has significant implications for professionals that want to use BIM to ensure their projects succeed, such as building project owners and contractors. Adopting and performing the actions, this study may assist all parties in focusing on the project's purpose in terms of cost, period, and quality, hence impacting the project's degree of success.

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