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Assessing the implementation of BIM for enhancing green building certification evaluations

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ABSTRACT
Green building-related certifications ensure construction safety, quality, and sustainability by following approved conditions and specifications. This study provides a nuanced perspective on how Building Information Modeling (BIM) evolves into a dynamic tool for ongoing building performance management. Enhancing the BIM framework with innovative metrics can improve green building ratings and provide operational cost savings for developers and clients. This framework facilitates the development of standardized practices and best guidelines for integrating BIM with green building certifications, streamlining the process and making it more accessible to a broader range of projects. The study examined hypotheses using advanced statistical structural regression modeling (SEM) and implemented the bootstrapping methodology with 5000 random samples to ascertain the significance of the path coefficient. A mega project is being re-evaluated to illustrate the extent to which the implementation of BIM can enhance Green Building Index (GBI) scores. The findings indicate that BIM can enhance sustaining green certification criteria. Furthermore, a slight change in intermediary indicators within a 5% range under the rating system can impact the overall score by approximately 15–20%. Results indicate satisfactory BIM performance, with an R^2 value of 0.405, which is significant for utilizing BIM in GBI valuation across all hypothesized model path coefficients.

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KEYWORDS
Building information modeling (BIM); green buildings index (GBI); structure regression model; smart- (PLS-SEM) software; sustainable building practices

Introduction

BIM has emerged as a transformative technology in the architecture, engineering, and construction (AEC) industries. Its integration with green building certifications is a significant area of focus, as it enhances the sustainability of construction projects. The recently created BIM program offers data or information linked to green building evaluation, containing the project's attributes and operational efficiency (Vysotskiy, Makarov, Zolotova, & Tuchkevich, 2015; Porwal, et al., 2020; Ali, Elyamany, Ibrahim, Kineber, & Daoud, 2023). A combination of BIM with green building evaluation methods may be the optimum way to assess green buildings in the design phase. In Egypt, however, there isn't a set methodology for BIM-based green building evaluation implementations (Bin Zakaria et al., 2013; Abdel-Hamid & Abdelhaleem, 2021; Abdelhaleem, 2023; Ali et al., 2023). Therefore, it is crucial to consider sustainable building elements when formulating design options during the planning and pre-construction phases (Jalaei & Jrade, 2014). Comprehensive

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investigations into sustainability based on building nature, construction materials, and mechanical, electrical, and plumbing (MEP) schemes must be conducted by a specialized team for Green Buildings (Oduyemi, Okoroh, & Fajana, 2017). The two stages of the Green Building Accreditation procedure (design evaluation and verification appraisal) are where the true problems with using BIM in GBI evaluation arise (Kreider & Messner, 2013). BIM applications have difficulty evaluating each GBI credit due to the inadequate collaboration and integration of BIM apps (Hong Kong CIC, 2014). Additionally, engineering analysis, GBI coding, and sustainability evaluation rarely employ BIM (Zhang, Chen, Sun, & Hammad, 2015). Numerous buildings are unable to maintain their GBI certification after years of use. Exploring the use of BIM during the post-construction phase of green buildings can significantly enhance building performance by playing a crucial role in the operational phase. Integrating BIM data with building management systems, operators can efficiently monitor energy usage, track maintenance needs, and optimize overall performance. This integration leads to reduced operating costs and improved sustainability. BIM also facilitates lifecycle management, allowing building owners to plan for future renovations and sustainability retrofits. Consequently, investigating BIM tools in the post-construction phase adds depth to existing theoretical models, providing a holistic view of BIM's capabilities throughout the building lifecycle. The post-construction phase presents an opportunity to develop new metrics for measuring the sustainability of green building initiatives.

Green building evaluation models

Green building certification creates value through internationally recognized standards such as Leadership in Energy and Environmental Design (LEED) and the Building Research Establishment's Environmental Assessment Method (BREEAM). LEED-certified buildings were projected to save energy, water, maintenance, and overhead costs. The criteria for green building index rating are; sustainable site planning and management (SM), outdoor environment, as well as focusing on energy efficiency (EE), material and resources (MR), and water efficiency (WE). Additionally, it prioritizes indoor air quality (EQ), and innovative (IN) design and operational management throughout the building's entire lifecycle, from planning and design to construction, and maintenance (Ilhan & Yaman, 2016; Alireza Mohammadi, Igwe, Amador-Jimenez, & Nasiri, 2020, Abdelhaleem, 2023). Several sustainable building rating systems offer environmental sustainability criteria for building plans to fulfill the criterion for a green ranking scheme (Ilhan & Yaman, 2014). Implementing sustainable development practices in green buildings can reduce energy, water, and construction material consumption by 30–40%. These reductions occur gradually until reaching net-zero consumption. Implementing sustainability measures like water recycling and utilizing solar energy in residential units, can help achieve significant operational cost savings. Specifically, it utilizes BIM data (Alwan et al., 2015; Khoshfetrat et al., 2020) to input into an energy simulation program. Using BIM for sustainability analysis is essential for effectively combining these two systems (Luo & Wu, 2015; Rashidian, Drogemuller, & Omrani, 2024; Deli Liu, Zhou, & Li, 2025). There are four Green Star rating tools, each based on the desired certification level, and an assessment method that predicts the performance of buildings over their entire lifecycle from conception through operation. Rating systems for green buildings are also always evolving. The application for the GB project is referred to as the Design Assessment (DA). Following this, a Completion and Verification Assessment (CVA) is carried out one year after the construction. A significant finding was the inconsistency between the certification credits potentially obtainable through BIM and the actual credits achieved. This underscores the necessity for simulation models to deliver more accurate object representations (Ali et al., 2023).

BIM-based green building certification

BIM is a process of developing and utilizing digital models for project design, construction, and operation, according to a document that contractors regularly cite (Atul Pan et al., 2020; Hong Kong CIC, 2014). Additionally, BIM facilitates better collaboration among stakeholders, ensuring that sustainability goals are met throughout the project lifecycle (Alwan, et al., 2015; Siva Rama Krishna & Naga Satish Kumar, 2020) utilizing various techniques, including digitalization and building information modeling, to establish a dynamic environment for information exchange (Atul Porwal, Parsamehr, Szostopal, Ruparathna, & Hewage, 2020). BIM Technologies help customers better understand how construction works are moving through the majority of the different phases of development (Jalaei & Jrade, 2015; Abdel-Hamid & Abdelhaleem, 2021). BIM has been familiarized with sustainable houses by specialists to assess the influences of buildings on the ecosystem from a mixture of viewpoints, counting construction, and operation phases (Jrade & Jalaei, 2013). It has been demonstrated that using BIM for sustainability studies significantly saves time and money (Harding et al., 2014). Data may be extracted from BIM and analyzed to help create standards and recommendations (Kota, Haberl, Clayton, & Yan, 2014). However, there is no agreement on the meaning of BIM from different participants' perspectives. Cloud-based Sustainable Decision Support Systems (C-SDSS) were implemented by (Olawumi & Chan, 2021) to automate the evaluation of sustainability performance in buildings (Pan et al., 2024). Examine how BIM is utilized to guide clients and operational teams in accurately defining their information needs for projects (Al-Ashmori et al., 2020) highlighted the key benefits of BIM that drew the participants' interest and identified the main factors driving its implementation (Fonseca Arenas & Shafique, 2023). Utilize a systematic literature review approach to investigate the stakeholders in achieving Net Zero Carbon Buildings (NZCB). They emphasize the combination of BIM with prefabricated construction presents a significant opportunity for the progress and evolution of the construction sector. (Guo, Li, Zhang, & Wu, 2021) analyzed building performance and lifecycle to select suitable materials, emphasizing proximity and sustainability in new constructions. They assessed the data's suitability for factor analysis, utilizing Bartlett's Test of Sphericity (BTS) and the Kaiser-Meyer-Olkin (KMO) test. Although the study highlighted shortcomings in the 3D, 4D, and 5D dimensions, it also acknowledged that contextual factors can influence outcomes. According to (Cheng, Lu, Li, & Chen, 2022), a methodology for Building Information Modeling Life Cycle Assessment (BIM-LCA) has been developed to evaluate the embodied environmental impacts of buildings throughout their entire life cycle from production to disposal. While this expansion can be economically advantageous, it has also resulted in increased consumption of natural resources, a rise in waste generation, and higher greenhouse gas emissions. As discussed by (Olawumi & Chan, 2019), they argue that professionals' understanding of BIM software capabilities is crucial, while also identifying challenges that hinder the effective implementation of BIM technologies and Lean Construction (LC) principles. BIM is recognized as a key source of data generation and a tool for managing risks, offering the potential for improved accuracy in assessing design feasibility (Raouf & Al-Ghamdi, 2019), they argue that comparing studies on green BIM with those on non-green BIM can help identify areas within green BIM that could be improved. Maltese et al. (2017) aimed to minimize the environmental effects associated with construction activities by emphasizing the integration of BIM and Industrial Foundation Classes (IFC) to promote sustainability within the (AEC) industry. According to Atul Porwal et al. (2020), carbon accounting can be carried out using BIM applications and (LCA). This can be achieved by exporting the building's material schedule and utilizing BIM software plug-ins to compute operational energy usage and carbon emissions.

The future direction of BIM capabilities in green buildings

The goal of (Olanrewaju et al., 2022) is to investigate the synergies of (BIM) and Green Building Certification Systems (GBCS) to obtain more comprehensive knowledge about the extent of BIM implementation in sustainability areas of GBCS. According to their findings, energy has the most literature in the environmental sustainability dimension, while the social and economic dimensions have a 15% and 11% representation respectively. A systematic review by (Numa et al., 2024) explores the relationship between BIM tools and processes. Multi-objective optimization spanning orientation, envelope, and HVAC properties has resulted in a 21% decrease in energy use intensity (EUI) and an 8.5% decrease in lifecycle costs (Mohammed, 2020) utilized the potential of maturity and the collaborative features of a BIM model, the suggested framework seeks to develop an organizational strategy for coupling BIM to facilitate the realization of environmentally sustainable projects. (Yu Cao, Kamaruzzaman, & Mardhiyah Az, 2022) conducted a thorough systematic review focusing on the capabilities of (BIM) in green buildings. The three primary benefits of using BIM in green building project initiatives include superior project quality, more efficient lifecycle management, and enhanced collaboration among all stakeholders involved. A rules-based LEED evaluation method (RLEM) was created (Kang, 2020). The evaluation process can be enhanced regarding its variability and reusability while decreasing the rework rate associated with green building assessments. (Hattab, 2021) conducted a quantitative analysis of 523 journal articles to explore the three dimensions of sustainability that exhibit overlapping characteristics among their components. The effectiveness and trade-offs of using (BIM) in green buildings are complex and multifaceted, requiring further research. To address the identified research gap, this study makes a significant contribution by exploring the utilization of BIM in the post-construction phase of green building projects. This study aims to establish standardized metrics and a framework to address existing gaps in sustainability assessments of green buildings within (BIM), enabling all stakeholders to evaluate sustainability in BIM models. This framework will provide a standardized approach to energy modeling, environmental impact assessments, and sustainability compliance checks. This will facilitate a more streamlined path for achieving green building certifications like LEED and BREEAM. Such improvements can contribute to reducing the global carbon footprint and mitigating the effects of climate change. Furthermore, these advancements could lead to 20-30% budget savings for green buildings.

Research methodology

This study has achieved its objectives by creating a causal framework that recognized the linkage between BIM and green buildings through seven sustainability domains as features for their integration disciplines for enhancing green buildings throughout their life cycles. Additionally, it examined the trade-offs associated with BIM tools for enhancing green building ratings compared to existing methods. A research survey was carried out, concentrating on elements such as BIM tools, facility management, maintenance systems, and the application of renewable energy in projects, as well as their associated environmental effects. This involves evaluating how likely these causal relationships contributed to the development of GBIs, analyzing the parameters represented in the model, and determining the degree of alignment between the data and the model, utilizing an advanced statistical approach that addresses the specific gaps of the current studies and is used to test the study hypotheses on whether the adoption of BIM can contribute to the attainment of GBI certification for construction projects. The research model's findings are interpreted using Structural Equation Modeling (PLS-SEM), specifically investigating mediation effects among different concepts. This involves several steps: (1) Address specific research questions to assess the feasibility of a model. Extract the dataset containing all latent constructs of BIM practices, GBI certifications, environmental factors, and indicators comprising the SEM for (2) Model's hypotheses are represented by three statistical metrics; One hypothesis is the use of BIM in the evaluation process will improve the accuracy, which can be measured by comparing the results of the BIM-enhanced evaluation process with the results of the traditional evaluation process. Another hypothesis is that the use of BIM will result in a higher level of sustainability in the buildings being evaluated, which can be measured using metrics such as the green building certification score, the use of sustainable materials, and the implementation of sustainable design principles. A third hypothesis is that the use of BIM will lead to increased return on investment (ROI) of the evaluation process, which can be measured by comparing the benefits of the process with the costs associated with the process, using metrics such as the cost savings associated with the process and the increase in green building certification scores. (3) To demonstrate the model's effectiveness in predicting the values of the sample covariance matrix

Step 1: Factor Analysis Identification Model

- Identify the endogenous and exogenous variables
- Define the Latent variables.
- Pattern Matrix(Factor Loadings)

Step 2: Evaluation of the Measurement Model

- Dependability Evaluation
- Validity convergence
- Discriminant validity

Step 3: Parameters Estimates (Structural Model)

- Coefficient of determination (R^2)
- Path Coefficients
- Effect Size (F^2)

Step 4: Structural Model's Quality Indices

- Statistical Predictive Relevance

Step 5: Diagramming the SEM Model

Figure 1. SEM analysis of BIM-GBI achievement framework.

and how SEM adjusts for measurement error, it is necessary to estimate the factor model parameters and perform a regression analysis between the factors. (4) To assess the quality of fit of the model, it is essential to evaluate the model parameter estimation. This evaluation helps determine how well the model fits the data and provides insights into the accuracy and reliability of the estimated parameters. (5) Lastly, To investigate whether causal relationships are significant enough to be a more effective instrument for achieving GBI goals than alternative strategies for verifying GBI development scores, it is necessary to compare the effectiveness of BIM with other methods. Using the SmartPLS® software (Ringle et al., 2015), a bootstrapping technique with 5000 random samples was employed for the data analysis, adhering to this approach, structured in (Figure 1).

Analysis of gathered data

GBI members evaluate green building projects using the grading system, considering factors that could impact the Green Building certification process when utilizing BIM. They were chosen based on their backgrounds, knowledge of GBI, and participation in project evaluations. The information regarding the respondents is presented in (Table 1). The respondents demonstrate varying degrees of expertise and experience in both Building Information Modeling (BIM) and green building rating systems. Certain respondents possess expertise in both domains, whereas others specialize in only one. Additionally, the years of experience in each field differ among the respondents. Structured interviews were also conducted to explore their opinions through the analytical survey, while measures to overcome the barriers were also investigated. The study's target population is a wide range of construction industry professionals, including, contractors, subcontractors, and

Table 1. The proficiency levels of respondents along with their respective experience.

Years of experience in Building Information Modeling (BIM)	Frequency	Percentage	Years of experience in Green Building Rating Systems	Frequency	Percentage
1–5	21	62%	1–5	11	50%
6–10	9	26%	6–10	8	36%
11–15	4	12%	11–15	3	14%
Total	34	100%	Total	22	100%

construction managers. This Equation is used to determine the target population;

$$No. = Z^2pq/e^2 \tag{1}$$

(Z^2) is the normal curve's abscissa (1-equals the intended precision level, such as 95%), e is the intended confidence level, 'p' is the evaluated fraction of an attribute that each contributor presents, and 'q' is (1-p). With a 95% confidence level established, the result is (1.96) based on normality tables, p is assumed to be (0.08), and 'e' is considered to be (±5%). In the previous equation, substituting for 'Z, p, q, and e' results in a sample size of no = (102). After three months, 131 questionnaires in all were returned. All surveys were reviewed before the analysis was done. 131 participants, 28 (21%) construction managers, 25 (19%) contractors, and 78 (60%) GBI members, completed the survey. The data were organized using Excel and analyzed using SPSS. The response rate for this survey was 43%, exceeding the usual return rate in the construction industry, which typically falls between 20% and 30% (Mackenzie, Kilpatrick, & Akintoye, 2000). The survey questionnaire included key variables crucial for the research goals, focusing on BIM Practices that could impact GB certification score. The items in a questionnaire are retrieved through pilot testing to identify any issues for exploring the factors influencing the adoption of BIM for Green Buildings, ensuring that the questionnaire items are clear and relevant to the study. Measurement scales were employed for every latent variable to ensure the validity and reliability of the questionnaire. (PLS-SEM) technique assesses the research model, it focuses on examining correlations between latent variables using the simpler partial regression technique. (PLS-SEM) is considered suitable for exploratory models and situations where a priori hypotheses are less precise.

Development of the measurement model

The structural model encompasses the various components of PLS-SEM and the relationships that exist between them. To evaluate the covariance of observations data and ascertain the full relationships between variables, Structural equation modeling (SEM) combines two analysis techniques, it is a hybrid of factor and regression path analysis employing latent variables (Hair, Hult, Ringle, & Sarstedt, 2016). SEM is an appropriate method for testing and evaluating multivariate causal relationships between BIM usage and GBI, where it is a useful tool for researching complex constructs that are measured with error. The regression simultaneous equations approach for different dependent variables specifies between measured variables representing the hypothesized relationships between variables. The path (factor) analysis explores latent variables, justifying causal claims that construct causes multiple items, and checking what different indicators have in common for testing the confirmatory (measurement) factor analysis (CFA). The statistical technique called partial least squares analysis for structural equation modeling (SEM) consists of two parts: the measurement model and the structural model (Hair et al., 2016). The following actions are part of the evaluation analysis and validation: Structuring the model comes first, followed by evaluating the measurement model (Chen, 2015). This modeling approach was selected because it is reliable when assessing several components and can directly identify measurement errors (Hair et al., 2016). It is hardly surprising that researchers across various disciplines use SEM more often (Kline, 2015). It considers the connections between independent and dependent components concurrently using SEM (Urbach & Ahlemann, 2010). SEM enables the analysis of variables regarded as theoretical constructs, which have been developed to comprehend a research problem (Sarstedt, Ringle, Smith, Reams, & Hair, 2014). One of the factors in the study model is the relationship between the GBI process phases and the utilization of BIM. Thus, model development should ensure that the hypothesis and the testing of the various impacts of the connections are consistent to verify the validity of the model's theory.

Evaluation of the measurement model

To evaluate the distinctiveness of the indicators that cannot be accounted for by the factors, along with the robustness of the connections among latent variables (observable indicators). The framework outlined in this research consists of three primary factors and nine distinct indicators. This is achieved via a correlation analysis of the pattern matrix. Research hypothesis defined by, represents a logical connection between variables, articulated through various models that can be subjected to empirical testing. To delineate the measurement model, account for correlated errors, and identify the indicators associated with each factor, three Confirmatory Factor Analyses (CFA) are employed. They also determine whether the factors are correlated or uncorrelated. Meanwhile, the structural model investigates the hypotheses and the path link (constructs) between variables as shown in (Figure 2). It displays the structural regression with two endogenous variables and uses the Partial Least Square Path method to assess the causality of each indicator in the structural model's variance. The predictive relationship for the dependence of manifest variables on the constructs in the SEM is quantified according to the following statistical equations;

$$\eta_1 = \alpha_1 + \Upsilon_{11}\xi_1 + \zeta_1 \tag{2}$$

$$\eta_2 = \alpha_2 + \Upsilon_{21}\xi_1 + \beta_{21}\eta_1 + \zeta_2 \tag{3}$$

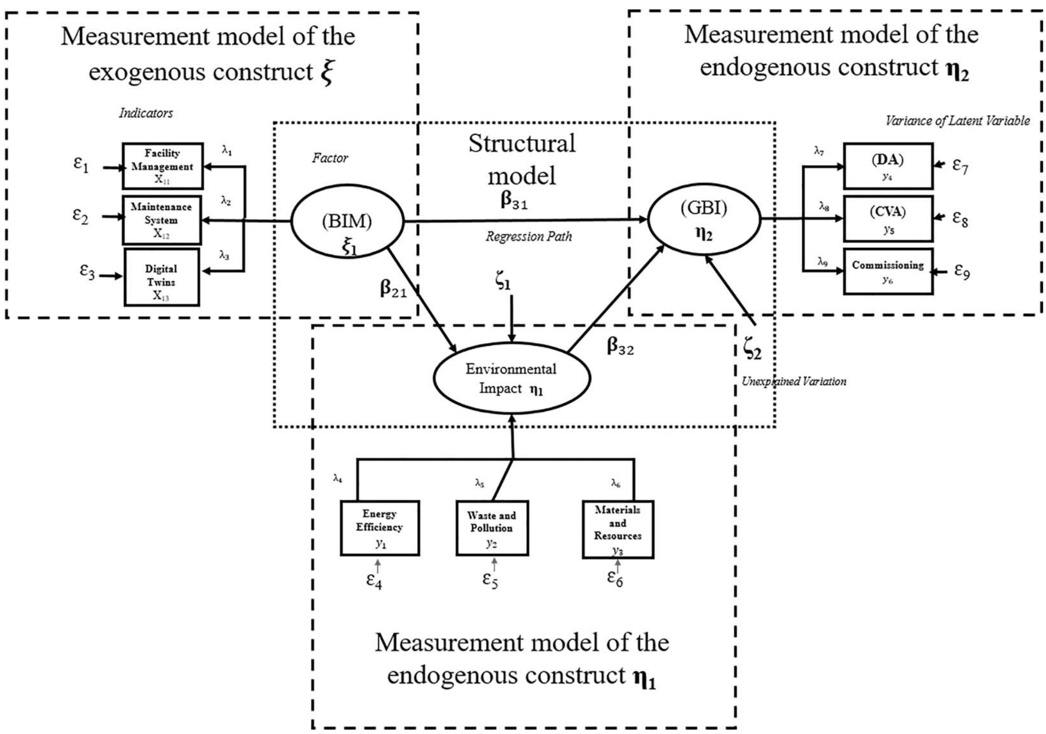

Figure 2. Path coefficients of latent variables in BIM-GBI (MODEL PARAMETERS).

The first equation describes how the exogenous variable predicts the first endogenous variable, and the second describes how the exogenous variable and the first endogenous variable predict the second endogenous variable. The study examined the relationships among the hypothesized latent variables. Analyzing the variance/covariance matrix between the observed variables is regarded as reliable (Wong & Fan, 2013). The procedure entailed employing Chi-square testing to compute the data correlation matrix, which revealed the estimated path coefficients. This was followed by deriving the implied correlation matrix and determining the parameters needed to produce it. Adoption of these measures guarantees that the latent variables in the structural model will demonstrate a substantial correlation with one another. The Commissioning Process (CP), Design Assessment (DA), and Completion and Verification Assessment (CVA) can all benefit greatly from the created SEM model's justification.

Estimation of the structural model parameters

The model parameters' correlation of all indicators is determined by tracing the paths of the 3-factor models, each with 3 indicators, the variances of all variables in the SEM, and covariances of pairs of variables are specified as follows;

$$Cor(a_i, a_j) = \lambda_{ai}\lambda_{aj}, \tag{4}$$

where λ represents factor loading or standardized estimates,

$$Cor(a_i, b_i) = \lambda_{ai}\Phi\lambda_{bi}, \tag{5}$$

where Φ_{AB} represents covariance factor correlation,

$$Cor(a_i, a_i) = \lambda_{ai^2} + Var(e_{ai}), \tag{6}$$

where e_{a1} represents error variances of indicators.

The model needs to maintain a correlation that matches the observed data. The model parameters are identified as nine-factor loadings, eleven variances of the error terms, and three latent regression slopes to be estimated to fit the SEM, as shown in (Table 2), which depicts the implied correlations matrix ($\sum$) of the model. The residual correlations in the sample covariance matrix (S) are displayed in (Table 3). The objective was to modify the model to produce a residual correlation matrix with values as close to zero as possible, indicating a well-fitting model. The error or residual indicator term is derived from the least squares fitting function. This matrix demonstrates that all variances are equal to 1, while the covariances among the residuals, indicating independence, are equal to 0. This is compared to the observed correlations matrix using unweighted least squares estimators, which provide the maximum likelihood estimators for the proposed model. The model's accuracy was evaluated by comparing the corresponding population observed (covariance) matrix with the chi-square statistic (p-value) derived from the residual distribution. Since the p-value in this instance is 0.25, which is insignificant, the model adequately describes the data, and the null hypothesis cannot be ruled out, yielding the empirical correlation matrix. Although the predicted residuals' distribution is largely normal, misspecification may have occurred, as seen by the tail on the right. This is a diagnostic of the model's predictive and influential components for the correlation in the suggested model.

To estimate factor Φ_{AB}, compute correlations implied by the model. Three parameters determine a single correlation of 0.1, whereas the model has no bearing on the remaining variances. It is said that there is little association or that the indicators are untrustworthy. The scale settings of A, B, a, and b determine how the model inferred covariance matrix and the actual covariance matrix compare, yielding the values for the Phi and Lambdas. When factor A and factor B have equal variances on all factors, regression shows the effect of one unit change in the independent variables (A, B) on the dependent variables ($a_1, \ldots, a_n$ and $b_1, \ldots, b_n$). This leads to the establishment of standardized factor loadings, which represent the standardized regression coefficients of the indicators

Table 2. Model-implied covariance (statistical correlation) matrix ($\sum$) of estimators.

Indicators	Facility Management (FM)	Maintenance System (MS)	Digital Twins (DT)	Energy Efficiency (EE)	Waste and Pollution (WP)	Materials and Resources (MR)	Design Assessment (DA)	Completion and Verification Assessment (CVA)	Commissioning Process (CP)
Facility Management	$\lambda_1^2+\theta_1=1$	0	0	0	0	0	0	0	0
Maintenance System	$\lambda_1\lambda_2$	$\lambda_2^2+\theta_2=1$	0	0	0	0	0	0	0
Digital Twins	$\lambda_1\lambda_3$	$\lambda_2\lambda_3$	$\lambda_3^2+\theta_3=1$	0	0	0	0	0	0
Energy Efficiency	$\lambda_1\lambda_4\Phi_{21}$	$\lambda_2\lambda_4\Phi_{21}$	$\lambda_3\lambda_4\Phi_{21}$	$\lambda_4^2+\theta_4=1$	0	0	0	0	0
Waste and Pollution	$\lambda_1\lambda_5\Phi_{21}$	$\lambda_2\lambda_5\Phi_{21}$	$\lambda_3\lambda_5\Phi_{21}$	$\lambda_4\lambda_5$	$\lambda_5^2+\theta_5=1$	0	0	0	0
Materials and Resources	$\lambda_1\lambda_6\Phi_{21}$	$\lambda_2\lambda_6\Phi_{21}$	$\lambda_3\lambda_6\Phi_{21}$	$\lambda_4\lambda_6$	$\lambda_5\lambda_6$	$\lambda_6^2+\theta_6=1$	0	0	0
Design Assessment	$\lambda_1\lambda_7\Phi_{31}$	$\lambda_2\lambda_7\Phi_{31}$	$\lambda_3\lambda_7\Phi_{31}$	$\lambda_4\lambda_7\Phi_{32}$	$\lambda_5\lambda_7\Phi_{32}$	$\lambda_6\lambda_7\Phi_{32}$	$\lambda_7^2+\theta_7=1$	0	0
Completion and Verification Assessment	$\lambda_1\lambda_8\Phi_{31}$	$\lambda_2\lambda_8\Phi_{31}$	$\lambda_3\lambda_8\Phi_{31}$	$\lambda_4\lambda_8\Phi_{32}$	$\lambda_5\lambda_8\Phi_{32}$	$\lambda_6\lambda_8\Phi_{32}$	$\lambda_7\lambda_8$	$\lambda_8^2+\theta_8=1$	0
Commissioning Process	$\lambda_1\lambda_9\Phi_{31}$	$\lambda_2\lambda_9\Phi_{31}$	$\lambda_3\lambda_9\Phi_{31}$	$\lambda_4\lambda_9\Phi_{32}$	$\lambda_5\lambda_9\Phi_{32}$	$\lambda_6\lambda_9\Phi_{32}$	$\lambda_7\lambda_9$	$\lambda_8\lambda_9$	$\lambda_9^2+\theta_9=1$

Table 3. The residual error variances matrix (S).

	FM	MS	DT	EE	WP	MR	DA	CVA	CP
FM	0								
MS	0	0							
DT	0	0	0						
EE	0	0	0.02	0					
WP	0	0	0.002	−0.01	0				
MR	0	0.012	0	−0.05	0	0			
DA	0.03	0.01	0	0	0	0	0		
CVA	0.015	−0.02	0	0	0.01	0	0.02	0	
CP	0.02	0.01	0.01	−0.03	0	0	−0.03	0.01	0

associated with the factors. In this study, the scale setting strategy is fixing the first indicator loading approach, as the variance of latent variable A is set to be equal to the latent score variance of a_1. The concepts of correlation and regression are only capable of capturing linear relationships. Out of the four graphs presented, the top-left one is suitable for conducting correlational analysis as the other three graphs illustrate data that cannot be captured through these formulas. (Figure 3) shows how strongly the BIM-GBI evaluation variables are correlated. The correlation coefficient formula is computed using the following equation:

$$\rho X, Y = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E(X)^2}.\sqrt{E(Y^2) - E(Y)^2}} \tag{7}$$

Evaluation of the precision of the structural model

The next stage concerns the significance and relevance that should be assessed for testing hypotheses related to the model's variables using path coefficients, providing insights into the relationships proposed in the model. The modeling technique employed in this work was chosen because it can discriminate between measurement errors and was useful in examining a wide range of components (Mohmed, Lokman, Ahmad, & Abdalrhman, 2019). Model development, the first stage monitored by analyzing the structural model with a dimension and a basic mode, was carried out using the Smart PLS program (Ringle et al., 2015). In the second phase of structural equation modeling, it is essential

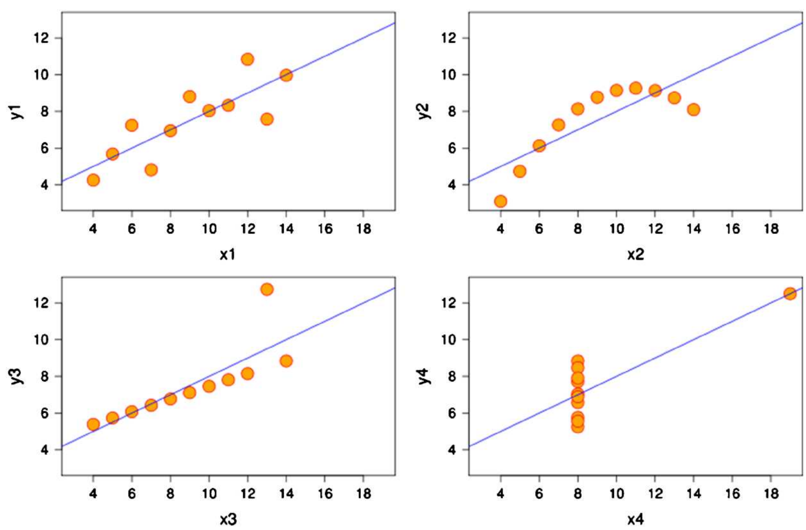

Figure 3. Bidirectional relationship of factors for BIM related-GBI assessment.

to assess the reliability of the measurement model and to examine convergent validity. Every construct should have a Cronbach's alpha of at least 0.5, and every estimated indicator reliability in the model should have an average variance larger than 0.50. The following equation displays the composite reliability index;

$$\rho c = \frac{\left(\sum \lambda_i\right)^2}{\left(\sum \lambda_i\right)^2 + \sum Var(\theta_i)} \tag{8}$$

i.e. the factor's variance divided by the composite model's overall variance. Additionally, assuming the internal consistency can be verified using Cronbach's alpha coefficient. Convergent validity refers to whether the correlation is high enough for the indicators that are considered to measure the same thing. The discriminant validity refers to whether indicators that measure different things do not correlate too strongly with each construct indicator. The estimated model parameter values confirm the statistical significance of the model. However, there are concerns about the right tail of the bootstrap distribution. This is shown by testing with a 5% risk of error, if the discriminant validity (HTMT) value is much lower than the associated threshold values (0.85 and 0.90). Every number in the 95% column is below these thresholds, indicating that every HTMT value is considerably lower than 0.85 and 0.90, respectively. More importantly, all HTMT values are found to be significantly lower than this value (i.e. the upper bound of the confidence intervals is smaller than 0.85), even if a more cautious threshold of 0.85 is applied to all latent construct combinations (i.e. including BIM tools and environmental impact in addition to GBI). For instance, the 95% confidence interval of the HTMT for GBI and BIM tools has lower and upper bounds of 0.556 and 0.369, respectively. More importantly, even when a more cautious threshold of 0.85 is applied to all latent construct combinations (i.e. including BIM tools and environmental impact in addition to GBI), all HTMT values are found to be significantly lower than this value (i.e. the upper bound of the confidence intervals is smaller than 0.85). For example, the lower and upper bounds of the 95% confidence interval of the HTMT for the GBI and BIM tools are 0.556 and 0.369, respectively. The HTMT value of 0.465 for BIM tools and GBI is much lower than the more cautious threshold value of 0.85 because the upper bound of 0.556 is lower than 0.85. The results of the bootstrap confidence interval for the HTMT criterion demonstrate the discriminant validity of the latent constructs. All model evaluation criteria have been satisfied, supporting the validity and reliability of the measures. The modeling technique utilized in this research demonstrated its effectiveness in detecting measurement errors and accurately evaluating different components. Concerning the implications of using BIM for green building certification evaluations within the construction sector, the results from the PLS-SEM analysis are statistically significant. The findings presented in (Table 4) support the findings of the PLS-SEM model. This reinforces the conclusions, indicating that the PLS-SEM analysis provides valuable insights into the specific criteria assessed in the questionnaire survey (Gotz, Liehr-Gobbers, & Krafft, 2010).

Structural model's quality indices

After establishing the model's dimension, the next step entails building the fundamental model. The coefficient of determination (R^2) and effect size (F^2) are the key ideas for assessing the structural model. Two important parameters must be taken into account when evaluating the predictive power of structural models: the Cohen effect size (F^2) and the Pearson coefficient of determination (R^2) (Sarstedt et al., 2014; Ringle et al., 2015; Dilshad & Latif, 2013). Each structural model's influence was evaluated using a standardized effect size metric based on Cohen's (F^2), this measures the degree to which an independent variable significantly influences a dependent variable and entails comprehending the variance explained by the model and the practical implications of the path coefficients. Using Puschel's scale, the effect size (F^2) magnitude is classified as weak (0.02), moderate (0.15), or strong (0.35). Meanwhile, the coefficient of determination (R^2) indicates the percentage of

Table 4. Validation and reliability of model parameters.

Latent Variables-Endogenous Construct	Observable Indicators	Convergent Validity			Internal Consistency Reliability			Discriminant Validity
		Loadings	Indicator Reliability	AVE	Cronbach's Alpha	Reliability ρ_A	Composite Reliability ρ_C	HTMT
		>0.7	>0.5	>0.5	>0.7	>0.7	>0.7	Significantly lower than 0.85
BIM	FM	0.858	0.736	0.681	0.776	0.832	0.865	Yes
	MS	0.798	0.637					
	DT	0.818	0.669					
EI	EE	0.883	0.694	0.748	0.831	0.839	0.899	Yes
	WP	0.917	0.841					
	MR	0.843	0.711					
GBI	DA	0.879	0.773	0.747	0.831	0.836	0.899	Yes
	CVA	0.870	0.757					
	CP	0.843	0.711					

the supported latent variable's variation that can be explained. The F-squared serves as a valuable measure for evaluating the extent to which a construct significantly influences the R^2 values of a model. It also assesses the variance of endogenous variables and quantifies the degree to which a forecaster influences a construct. In the last step, the model's structural validity is evaluated using the predictive relevance indicator, or Q^2, which measures the model's capacity for outcome prediction (Ringle et al., 2015). As advised by (Hair et al., 2016), the study used (Q^2) values to validate the model dimension in determining the connection between BIM and GBI evaluations. Cross-validity redundancy (Q^2) values were found to be more than zero, suggesting that the study's endogenous components had predictive relevance. Essentially, any (Q^2) number larger than zero demonstrates the analytical significance of the model. The quality indices of the model are presented in (Table 5) to assess the alignment of the measurement model results with the study hypotheses. The interrelation between the Building Information Modeling (BIM) and Green Building Index (GBI) frameworks, along with their associated environmental (EI) predictor constructs, is supported by the AVE and F2 values. With an R^2 value of 0.405, the necessity for alignment between BIM usage and GBI criteria indicators is validated for about 41% of the explained variance.

Discussion of the findings

An analysis of the methodologies utilized in the existing literature indicates that (Hattab, 2021) employs quantitative analyses of a substantial number of journal articles, while other researchers, including (Olanrewaju et al. 2022), focus on qualitative studies regarding the applications of BIM. Acknowledging these diverse methodological frameworks facilitates a more refined understanding of the findings, thereby mitigating potential biases that arise from an indiscriminate treatment of all studies. The results from these investigations underscore various aspects of sustainability (Olanrewaju et al., 2022) point out that the majority of literature is concentrated on energy,

Table 5. The modification indices of the endogenous constructs.

Items	Pearson coefficient (R^2)	Level of Explanatory Power	Effect size Value (F^2)	Strength of the Association	Predictive relevance (Q^2)
Building Information Modeling Practices (BIM)	0.405	Substantial	0.368	Strong	0.113
Compilation and verification assessment (CVA)	0.273	Moderate	0.245	Moderate	0.187
Design assessment (DA)	0.288	Substantial	0.398	Strong	0.126
Commissioning Process (CP)	0.341	Substantial	0.130	Small	0.298

whereas (Numa et al., 2024) present practical numerical evidence illustrating BIM's influence on environmental sustainability. This distinction suggests that, although energy efficiency is a prevalent topic, the scope and depth of analysis can differ markedly. Numerous studies indicate a positive relationship between BIM and environmental efficiency; however, the degree of data representation may vary, highlighting areas that warrant further investigation. The foundational work established by (Kang, 2020) and (Hattab, 2021) for future inquiries into less explored dimensions, such as post-construction sustainability, highlights the progression of this field of study. The study's findings are consistent with earlier research, particularly those investigating the convergence of (BIM) and Artificial Intelligence (AI). They also reflect similarities in analyzing how advanced technology improves building performance (Alireza Mohammadi et al., 2020; Fonseca Arenas & Shafique, 2023). Recent studies address general applications of BIM during design and construction, the research into its utilization during the post-construction phase distinguishes itself by addressing a relatively underexplored area. The BIM-enhanced evaluation process demonstrated a high level of accuracy, with precision, recall, and F1 score values of 0.85, 0.92, and 0.89, respectively. Additionally, the study found that the BIM-enhanced evaluation process resulted in a 20% reduction in environmental impact, which is consistent with other research that found similar reductions in carbon emissions for green building certification evaluations (Olawumi & Chan, 2021; Al-Ashmori et al., 2020; Atul Porwal et al., 2020). Moreover (Guo et al., 2021) employed the 3rd, 4th, and 5th dimensions of BIM, contrasting with the current study's focus on the 7th dimension of BIM. While BIM offers numerous advantages, it can be hindered by technological barriers, potentially restricting its broader efficiency. Utilizing the 7th dimension of BIM, the evaluation process can incorporate more advanced and comprehensive aspects of building information, enhancing the overall evaluation quality. Research findings indicate that using BIM during the post-construction can significantly improve operational efficiency. By leveraging BIM for real-time monitoring and data integration, facilities managers can make informed decisions that enhance energy efficiency, reduce waste, and implement effective predictive maintenance procedures. This practical approach leads to lower operational costs and extends the lifespan of buildings. Additionally, it minimizes downtime, enhances occupant comfort, and promotes sustainability by lowering the need for emergency repairs, which often have a higher environmental impact.

The implications of results

The results promote sustainability, cost efficiency, regulatory compliance, and continuous performance monitoring. By adopting BIM, organizations can enhance their buildings' quality, efficiency, and sustainability, leading to long-term benefits for both the environment and the bottom line. The study looked at how to certify a mixed-use building as a green building, using a mid-sized building that is being designed and constructed sustainably. By systematically evaluating performance data through BIM, stakeholders can identify inefficiencies and make iterative improvements. This cycle of feedback and improvement supports long-term sustainability goals and enhances the building's green certification. The study has the potential to facilitate the creation of novel metrics tailored to assess a building's performance after it has been occupied. Such metrics would enhance theoretical models for evaluating the effectiveness of green building efforts. Higher GBI levels are correlated with more BIM usage, as shown in (Figure 4a), which indicates a positive association between BIM and GBI in all circumstances. The research highlights the variation of the constructs and illustrates their interconnection. The return on investment (ROI) indicator, stemming from the efficiency of resources, materials, and energy (Figure 4b), has the potential to significantly reduce environmental impacts by 18% and 13%, respectively. Nevertheless, their effect on the mean variance for the environmental impact construct is relatively minor. By accurately modeling the structural design and material usage, potential cost savings are identified, helping to avoid unnecessary expenses and resulting in a more economical construction process. The presented model ensures that the building complies with green building codes and standards. Furthermore, the incorporation of intelligent building technologies, including digital twins, alongside BIM facilitates the real-time

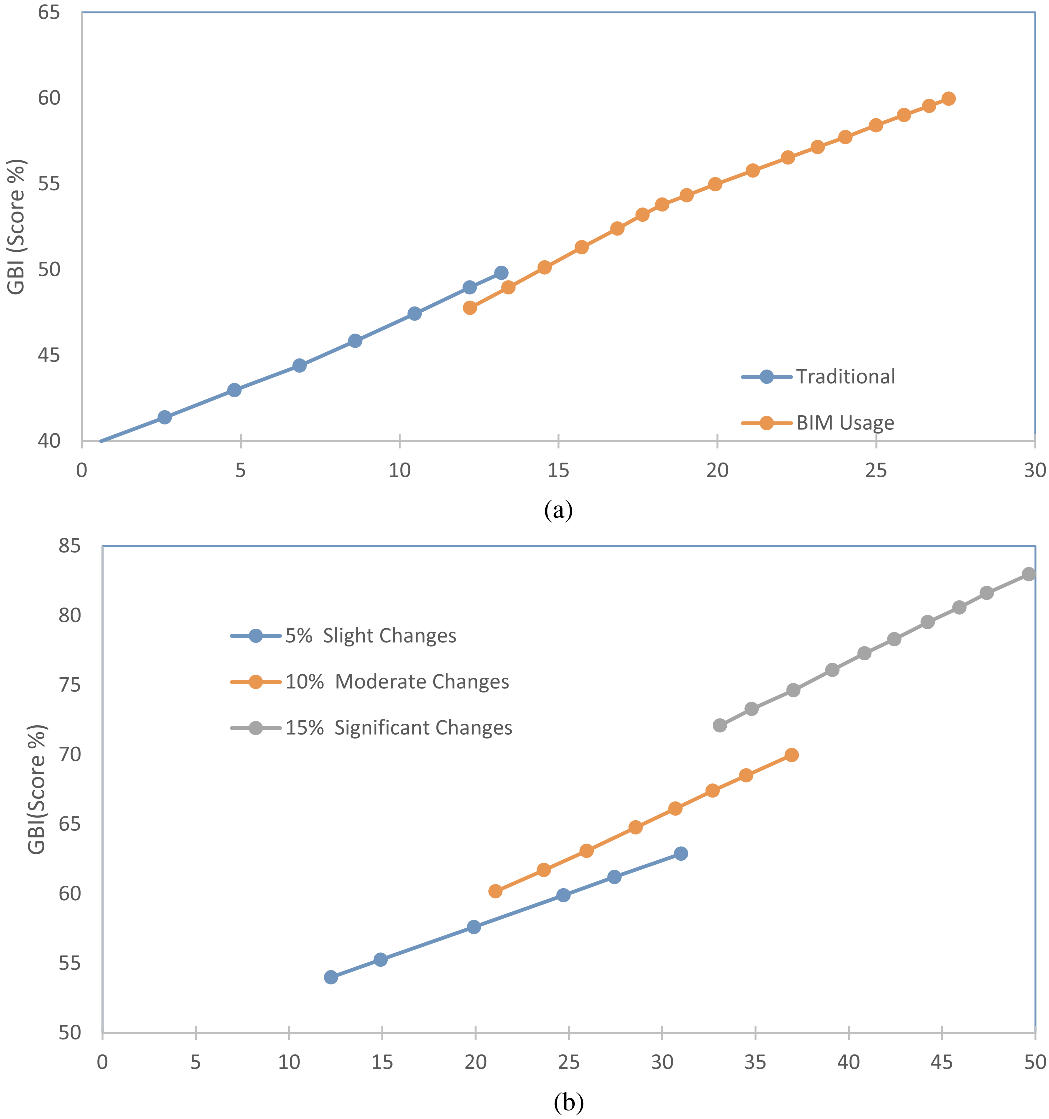

Figure 4. a. The impact of BIM on the green building rating system. b. The impact of green building rating system on ROI indicators.

assessment of the building's operational efficiency. This enables facility managers to make immediate adjustments to maintain optimal conditions. As a result, continuous evaluation and optimization of sustainability features are possible, ensuring that the building remains environmentally friendly throughout its lifecycle. These findings show practical improvements in sustainability, leading to higher green building certification scores.

Conclusions

The study contributes to the existing body of knowledge by providing a comprehensive framework for evaluating the sustainability of buildings using BIM and smart building technologies. By leveraging this model, project teams can enhance the overall sustainability of their buildings, resulting in continuous evaluation and optimization of sustainability features are possible, ensuring that the building remains environmentally friendly throughout its lifecycle. These findings show practical improvements in sustainability, leading to higher green building certification scores. The study's results emphasize the importance of accurately modeling the structural design and material usage to identify potential cost savings. Incorporating intelligent building technologies, including digital twins, alongside BIM facilitates real-time observation of the building's performance. This capability enables facility managers to make timely adjustments to maintain optimal conditions. Organizations can successfully reduce environmental impact by up to 20% by understanding the contribution of each indicator to the model constructions, which is a noteworthy accomplishment according to the grading system. By leveraging the study's findings, the project team can enhance the building project's sustainability, cost efficiency, regulatory compliance, and continuous performance monitoring. Additional investigation is required to overcome the limitations in the study, it is advisable to reassess and fine-tune the model to pinpoint the critical stages necessary for developing tailored causal models for various categories of construction projects. This process may include adjusting the model's elements to integrate (LCAs), introducing new indicators, or establishing alternative thresholds for (GBI) criteria. Additionally, investigating the effectiveness of renewable energy sources in reducing environmental impact could provide valuable insights.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Ethics approval statements

The Ethics Review Committee of the Faculty of Engineering at the University has approved the study's survey (approval number: SREC-00125).

Data availability statement

Data supporting this study are included in the article.

References

Abdel-Hamid, M., & Abdelhaleem, H. (2021). Project cost control using five dimensions building information modeling. *International Journal of Construction Management*. doi:10.1080/15623599.2021.1880313

Abdelhaleem, H. (2023). International green building systems and egyptian green pyramid system: A comparative study. *International Journal of Construction Management*. doi:10.1080/15623599.2023.2210786

Al-Ashmori, Y. Y., Othman, I., Rahmawati, Y., Mugahed Amran, Y. H., Abo Sabah, S. H., Darda'u Rafindadi, A., & Mikic, M. (2020). BIM benefits and its influence on the BIM implementation in Malaysia. *Ain Shams Engineering Journal*, *11*(4), 1013–1019. doi:10.1016/j.asej.2020.02.002

Ali, A. H., Elyamany, A., Ibrahim, A. H., Kineber, A. F., & Daoud, A. O. (2023). Modeling the relationship between modular construction adoption and critical success factors for residential projects in developing countries. *International Journal of Construction Management*, *0*(0), 1–12.

Alwan, Z., Greenwood, D., & Gledson, B. (2015). Rapid LEED evaluation performed with BIM-based sustainability analysis on a virtual construction project. *Construction Innovation*, *15*(2), 134–150.

Bin Zakaria, Z., Bin Zakaria, Z., Mohamed Ali, N., Tarmizi Haron, a., Marshall-Ponting, a. J., & Abd Hamid, Z. (2013). Exploring the adoption of Building Information Modelling (BIM) in the Malaysian construction industry: A qualitative approach. *International Journal of Research in Engineering and Technology*, *2*(8), 384–383. doi:10.15623/ijret.2013.0208060

Cao, Y., Kamaruzzaman, S. N., & Mardhiyah Az, N. (2022). Green building construction: A systematic review of BIM utilization. *Buildings*, *12*(8), doi:10.3390/buildings12081205

Chen, L. Y. (2015). Determinants of software-as-a-service adoption and intention to use for enterprise applications. *International Journal of Innovation and Applied Studies*, *10*(1), 138.

Cheng, B., Lu, K., Li, J., & Chen, H. (2021). Comprehensive assessment of embodied environmental impacts of buildings using normalized environmental impact factors. *Journal of Cleaner Production*, *334*, 130083. doi:10.1016/j.jclepro.2021.130083

Dilshad, R. M., & Latif, M. I. (2013). Focus group interview as a tool for qualitative research: An analysis. *Pakistan J. Soc. Sci*, *33*(1), 191–198.

Fonseca Arenas, N., & Shafique, M. (2023). Recent progress on BIM-based sustainable buildings: State of the art review. *Developments in the Built Environment*, *15*. doi:10.1016/j.dibe.2023.100176

Gotz, O., Liehr-Gobbers, K., & Krafft, M. (2010). *Evaluation of structural equation models using the partial least squares (PLS) approach, Handbook of partial least squares* (pp. 691–711). Springer.

Guo, K., Li, Q., Zhang, L., & Wu, X. (2021). BIM-based green building evaluation and optimization: A case study. *Journal of Cleaner Production*, *320*(9), doi:10.1016/j.jclepro.2021.128824

Hair, J. F. Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications. ISBN: 1452217440.

Harding, J., et al. (2014). Do building information modeling applications benefit design teams achieving BREEAM accreditation? *Journal of Construction Engineering*, *1*(8).

Hattab, M. A. (2021). The dynamic evolution of synergies between BIM and sustainability: A text mining and network theory approach. *Journal of Building Engineering*, doi:10.1016/j.jobe.2021.10215

Hong Kong CIC. (2014). *CIC building information modelling standards* (pp. 0–103).

Ilhan, B., & Yaman, H. (2016). Green building assessment tool (GBAT) for integrated BIM-based design decisions. *Automation in Construction*, *70*, 26–37. doi:10.1016/j.autcon.2016.05.001

Jalaei, F., & Jrade, A. (2014). Integrating Building Information Modeling (BIM) and energy analysis tools with green building certification system to conceptually design sustainable buildings. *Journal of Information Technology in Construction*, *19*, 494–519.

Jalaei, F., & Jrade, A. (2015). Integrating building information modeling (BIM) and LEED system at the conceptual design stage of sustainable buildings. *Sustainable Cities and Society*, *18*, 95–107. doi:10.1016/j.scs.2015.06.007

Jrade, A., & Jalaei, F. (2013). Integrating building information modeling with sustainability to design building projects at the conceptual stage. *Building Simulation*, *6*(4), 429–444. doi:10.1007/s12273-013-0120-0

Kang, T. (2020). Rule-based LEED evaluation method considering BIM linkage and variability. *KSCE Journal of Civil Engineering*, doi:10.1007/s12205-020-1026-x

Khoshfetrat, R., Sarvari, H., Chan, D. W. M., & Rakhshanifar, M. (2020). Critical risk factors for implementing building information modelling (BIM): a Delphi-based survey. *International Journal of Construction Management*, *22*(1), 11. doi:10.1080/15623599.2020.1788759.

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Kota, S., Haberl, J. S., Clayton, M. J., & Yan, W. (2014). Building information modeling (BIM)-based daylighting simulation and analysis. *Energy and Buildings*, *81*, 391–403. doi:10.1016/j.enbuild.2014.06.043

Kreider, R. G., & Messner, J. I. (2013). *The uses of BIM: Classifying and selecting BIM uses. Version 0.9*. University Park, PA, USA: The Pennsylvania State University. http://bim.psu.edu.

Liu, D., Zhou, X., & Li, Y. (2025). Balancing performance and cost of LLMs in multi-agent framework for BIM data retrieval. *Architectural Engineering and Design Management*, doi:10.1080/17452007.2025.2456768

Luo, Y., & Wu, W. (2015). Sustainable design with BIM facilitation in project-based learning. *Procedia Engineering*, *118*, 819–826. doi:10.1016/j.proeng.2015.08.519

Mackenzie, S., Kilpatrick, A. R., & Akintoye, A. (2000). UK construction skills shortage response strategies and an analysis of industry perceptions. *Construction Management and Economics*, *18*(7), 853–862. doi:10.1080/014461900433131

Maltese, S., Tagliabue, L. C., Cecconi, F. R., Pasini, D., Manfren, M., & Ciribini, A. L. (2017). Sustainability assessment through green BIM for environmental, social and economic efficiency. *Procedia Engineering*, *180*, 520–530. doi:10.1016/j.proeng.2017.04.211

Mohammadi, A., Igwe, C., Amador-Jimenez, L., & Nasiri, F. (2020). Applying lean construction principles in road maintenance planning and scheduling. *International Journal of Construction Management*. doi:10.1080/15623599.2020.1788758

Mohammed, A. B. (2020). Collaboration and BIM model maturity to produce green buildings as an organizational strategy. *HBRC Journal*, *16*(1), 243–268. doi:10.1080/16874048.2020.1807815

Mohmed, S., Lokman, H., Ahmad, S., & Abdalrhman, M. (2019). Measuring the feasibility of using BIM application to facilitate GBI assessment process. *Journal of Building Engineering*, *25*, 100821. doi:10.1016/j.jobe.2019.100821

Numa, M., Saadat, U., & Farooq, M. U. (2024). BIM and sustainable design: A review of strategies and tools for green building practices. *Journal of Engineering Research and Sciences*, *3*(2), 1–7. doi:10.55708/js0302001

Oduyemi, O., Okoroh, M. I., & Fajana, O. S. (2017). The application and barriers of BIM in sustainable building design. *Journal of Facilities Management*, *15*(1), 15–34. doi:10.1108/JFM-03-2016-0008

Olanrewaju, O. I., Enegbuma, W. I., Donn, M., & Chileshe, N. (2022). Building information modeling and green building certification systems: A systematic literature review and gap spotting. *Sustainable Cities and Society*, *81*. doi:10.1016/j.scs.2022.103865

Olawumi, T. O., & Chan, D. W. M. (2019). Critical success factors for implementing building information modeling and sustainability practices in construction projects: A Delphi survey. *Sustainable Development*, *27*, 587–602. doi:10.1002/sd.1925

Olawumi, T. O., & Chan, D. W. M. (2021). Green-building information modeling (Green-BIM) assessment framework for evaluating sustainability performance of building projects: A case of Nigeria. *Architectural Engineering and Design Management*, *17*(5-6), 458–477. doi:10.1080/17452007.2020.1852910

Pan, X., Khan, A. M., Eldin, S. M., Aslam, F., Ur Rehman, S. K., & Jameel, M. (2024). BIM adoption in sustainability, energy modeling and implementing using ISO 19650: A review. *Ain Shams Engineering Journal*, *15*(1), 102252.

Porwal, A., Parsamehr, M., Szostopal, D., Ruparathna, R., & Hewage, K. (2020). The integration of building information modeling (BIM) and system dynamic modeling to minimize construction waste generation from change orders. *International Journal of Construction Management*. doi:10.1080/15623599.2020.1854930

Raouf, A. M. I., & Al-Ghamdi, S. G. (2018). Building information modeling and green buildings: Challenges and opportunities. *Architectural Engineering and Design Management*, *15*, 1–28. doi:10.1080/17452007.2018.1502655

Rashidian, S., Drogemuller, R., & Omrani, S. (2024). An integrated building information modelling, integrated project delivery and lean construction maturity model Rk for BIM data retrieval. *Architectural Engineering and Design Management*, *20*(6), 1454–1470. doi:10.1080/17452007.2024.2383718

Ringle, C. M., Da Silva, D., & Bido, D. d. S. (2015). Structural equation modeling with the Smartpls. doi:10.5585/remark.v13i2.2717

Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy*, *5*(1), 105–115. doi:10.1016/j.jfbs.2014.01.002

Siva Rama Krishna U., & Naga Satish Kumar Ch. (2020). A case study on the maintenance of bituminous concrete pavement considering life cycle cost analysis and carbon footprint estimation. *International Journal of Construction Management*, *22*(5), 1–9. doi:10.1080/15623599.2020.1742629

Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *JITTA - Journal of Information Technology Theory and Application*, *11*(2), 5.

Ur Rehman, H. S., Raza, M. A., Masood, R., Khan, M. A., Alamgir, S., & Javed, M. A. (2022). A multi-facet BIM-based approach for Green Building design of new multi-family residential building using LEED system. *International Journal of Construction Management*, DOI:10.1080/15623599.2022.2033419

Vysotskiy, A., Makarov, S., Zolotova, J., & Tuchkevich, E. (2015). Features of BIM implementation using Autodesk software. *Procedia Engineering*, *117*(1), 1148–1157.

Wong, K.-D., & Fan, Q. (2013). Building information modeling (BIM) for sustainable building design. *Facil. Struct. Surv*, *31*(6), 138–157.

Zhang, C., Chen, J., Sun, X., & Hammad, A. (2015). Lifecycle evaluation of building sustainability using BIM and RTLS. *Proceedings of Winter Simulation Conference*, 3236–3247.