BIM Technology Sustainability Dynamics: A PEST Analysis of its Impact on the AECO Industry's External Macro-Environmental Factors

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Building Information Modeling (BIM) has been recognized as a revolutionary technique within the Architecture, Engineering, Construction, and Operations (AECO) sector. The present research investigates the influence of Building Information Modeling (BIM) implementation on the external macroenvironmental elements of the AECO sector via the use of a PEST analysis. The study utilizes a sophisticated structural equation modeling methodology, using data from a substantial industry survey to explore the intricate connections between the adoption of BIM and external influences. The research uncovers noteworthy favorable correlations between the adoption of BIM and the attainment of AECO. BIM in optimizing project budgets and timelines has been shown to provide significant economic advantages. Furthermore, the alignment of BIM with government goals has been seen to contribute to the attainment of political success. BIM in sustainable design methods has been shown to influence social results favorably. Furthermore, integrating BIM with emerging technologies is crucial to achieving technical success. This study offers significant contributions to professionals in the industry, policymakers, and academics by facilitating informed decision-making and advancing sustainable growth within the dynamic AECO industrial context.

Nevertheless, it is important to note that this study's scope is confined to Jeddah, Saudi Arabia. Therefore, it is advisable to conduct more research encompassing a wider geographical area and use a longitudinal methodology to investigate the long-term impacts of BIM in diverse places thoroughly.
Keywords: Architecture, Engineering, Construction, and Operations (AECO); BIM; external analysis; macro-environmental factors; PEST.

1. Introduction

In the Architecture, Engineering, Construction and Operations (AECO) sector, BIM is considered to be one of the transformational technologies. Indeed, recent survey data collected for 2021 show that over 70% of professionals in AEC have now applied BIM in operating projects, thus confirming diffusion throughout the industry [1]. With BIM remaining to be the game-changer in this industry, the call for understanding its impact on the sector of the macroenvironment of the AECO business is imperative [2]. Current industry reports state that implementation of BIM has reduced illustrations in construction by 20% and project costs by 15%, since project viability improved with fewer errors [3]. Further research has also determined that implementation of BIM results in reduction of unto 30% of such revision which is carried out in construction, constituting a significant gain in terms of cost and productivity [4].

The AECO industry works in a vital and every fluctuating environment that forms the influence of political, economic, social, and also technological. According to research projections are that United States government spending on infrastructures is set to grow at a rate of 5% annually over the next five years as more significant focus shifting on modernization and sustainable development [5]. Infrastructure development for politics drives the conditions of BIM adoption since the government agendas are set out to deliver better project outcomes and ensure maximal returns [6].

What is more, it is necessary to dwell on the effect of BIM in the industry with respect to the macroenvironmental factors to understand just how the industry is to react to regulatory changes and possible patronage from the government on BIM-enabled projects; BIM pops up as a tool that allows project budgets and schedules to be optimized and this has seen more and more AEC companies using it [7]. One report stated that BIM adoption has increased, in the last three years, by 30%, owed in large part to its ability to improve projects' cost management as well as project profitability [8]. At the same time that societies are demanding greater levels of sustainability and social responsibility, the ability of ES to support these lines of both design and construction practices is also being promoted. This is evidenced in one research study where BIM projects result in energy consumption and associated carbon emission being lowered by about 25% [9].

On the other hand, rapid technology changes continue to be very instrumental in shaping the future of the AECO industry. Connecting BIM with other emerging technologies, such as devices used in the Internet of Things and artificial intelligence, changes the real operation and maintenance of buildings [10]. One of the market studies on this matter predicted that the global market for BIM would be growing at a CAGR of 16.7% between 2021 and 2026, showing an industry affinity for digital transformation [11].

This paper reflects on how BIM adoption, and the external macroenvironmental factors shaping the AECO industry are interrelated. This study attempts to critically review the impact of the BIM implementations in the AECO sector in light of and in relation to the political, economic, social, and technological drivers through a PEST analysis. It is on this very note that the manuscript makes valuable input in driving the industry professionals, policymakers, and researchers toward informed decision-making, thus promoting sustainable development of the AECO industry with increasing dynamics.

Through integration of the most current industry data and statistical evidence, the study should reveal unique patterns, correlations, and opportunities where so far no thorough research has been made, thus adding a freshness of insights about how BIM adoption shows the way to success in achieving technical, economic, social, and political success in this fluid AECO industry environment. Furthermore, the paper addresses this lacuna by incorporating a detailed SEM using partial least squares (PLS) analysis, which looks at the linearity and nonlinearity of the relationships between BIM adoption and an external macroenvironmental factor in order to reveal hidden intricate casuistry. This approach will allow for full testing of direct and indirect relationships of BIM to the success of an AECO industry and hence reveal underlying mechanisms and causal pathways as have not been touched before. The study configuration comprises an analytical exercise based on a large-scale industry survey, which has data and a representative sample of the widest kinds of AECO professionals and organizations. Important variables have been picked up with the assistance of the survey that is related to BIM adoption, the outcome of the project, regulatory compliance, and BIM impact in an economic, social, and political way. The paper employs the PLS analysis technique to question the complex interconnections between these factors and, thereby, deliver strict statistical evidence that furthers the understanding of BIM in determining overall AECO industry performance. Figure 1 presents four major hypotheses of the research based on the PEST analysis.

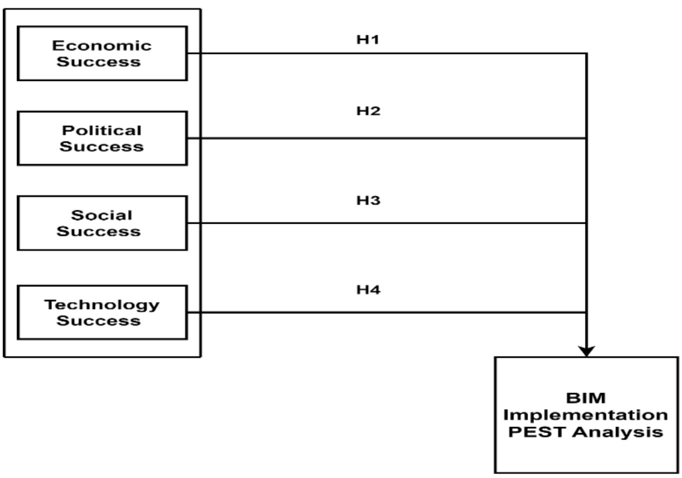

Figure 1 PEST-4 Hypothesis of the study

H1: Economic success has a significant relation with BIM implementation.

H2: Political success has a significant relation with BIM implementation.

H3: Social success has a significant relation with BIM implementation.

H4: Technology success has a significant relation with BIM implementation.

2. Identification of Factors through Literature

BIM has been identified as one of the transformative technologies in the AECO sector that has become key to improving technical success. The subsequent literature review is required in order to analyze key works showing how BIM improves technical efficiency, collaboration, and innovation during AECO project presentation [12].

BIM makes it possible to have strategic collaboration among the different stakeholders involved with an AECO project. According to waqar with respect to 3D visualization, the capability of BIM has been observed to enable good communication and comprehension among architects, engineers, contractors, and clients to ensure better collaboration and lesser miscommunication [13]. Real-time sharing of data through BIM enhances collaboration and coordination through the use of interdisciplinary information exchange [14].

The researchers have focused on design and analysis efficiency by regarding the impact of BIM. In this line, the study identified that BIM will eventually enable the designers to simulate and analyze design options, hence coming up with inhibited decisions and designs which meet the project goals [15]. Designers, through the use of BIM, are able to view their idea in virtual space; hence, they are in a position to see possible problems and make changes in advance of construction [16]. This iterative design process thereby minimizes chances of errors, costly modifications during construction, and hence enhances project outcomes [17].

The research declares that the conflict detection capabilities of BIM contribute to a great deal in risk mitigation on construction projects [18]. The capability of identifying and timely conflict resolution of various systems, that is, electrical and mechanical, at provided site saves time from costly rework and delays [19]. This allows detection of these conflicts and resolutions with the virtual model in order to avoid potential problems during actual construction through the Clash Detection feature of BIM [20]. BIM simplifies construction processes and therefore the technical success of the project by reducing rework and change order rates [21].

For that, exact quantity takeoffs and cost estimation are required. BIM has an automated quantity departure feature that helps in providing detailed information about material quantities. As a result of this, the cost estimates can be more accurate [22]. The study has identified that because of this data-driven approach, cost management and budgeting have become better; hence, project teams make more intelligent decisions on resource optimization. BIM enables construction simulation, and through that project team is able to visualize as well as optimize construction sequences [23]. This is evidenced by various research to enable successful project planning, logistics management, and resources allocation. Meanwhile, through the modelling of the real construction process in advance, it will allow the project teams to avoid bottlenecks in developing optimized workflows for greater efficiency in the technical delivery of projects. As such, "BIM also influences building facility management and its maintenance stages," [21]. The contribution of BIM in the research to efficient facility management was expressed with the provision of exhaustive data about the building. This data-driven strategy will provide for the building's optimal operational life and technical success by monitoring and tracking assets and performance and optimizing its maintenance.

BIM integrated with emerging technologies like Virtual and Augmented Reality enhances technical efficacy in the AECO industry. With regard to capability enhancement, the VR/AR functionalities within BIM enhance visualization and design review by knowing decisions through the course of a project's different phases, the study has observed [24]. The project teams will thus be able to work more promptly, creatively, and productively using the new advanced technologies.

BIM has become indispensable to improve project outcomes, utilize resources optimally, and innovate in the AECO industry [25]. From the literature review, these studies provide good input on multifarious advantages of BIM implementation that inspire further research on BIM, addressing the importance of the role of BIM towards technical advancement in the AECO industry. The impacts of BIM on the technical performance of AECO projects are beyond only the "project phases" level. In this regard, the potential of BIM to facilitate collaboration, effective design with accurate analysis, has been further equated to more benefits for a project team and the organization itself. According to one study, an AEC company providing BIM as an integrated part of its workflow reported its benefits in terms of project delivery time and reduced project cost.

More importantly, it has been highlighted that the collaborative nature of BIM increases the overall quality of AECO projects [26]. At the same time, real-time data sharing and coordination among the different disciplines identify errors and clashes at an early stage. This quality construction also enhances the overall results of projects. This aspect is considered to be crucial for mega, complex projects that have many stakeholders and design elements [27].

BIM's contribution to technical success in the AECO industry is indivisible from its ability both to support sustainability initiatives and enhance collaboration and design efficiency. The need to solve environmental issues and meet statutory regulations has meant that sustainable design is a prominent industry feature. With the integration of tools that allow for environmental analysis, BIM helps architects and engineers determine what environmental impact their design choices will have [28]. This attribute aligns with societal values for sustainability; hence, BIM is a necessary tool to help carry out environmentally sensitive designs in keeping with the dynamic needs of communities.

Furthermore, conflict detection and the capability for risk mitigation with enhanced functionalities in BIM provide even better assurance over the structural integrity and safety of AECO projects. Possible conflicts between building systems identified during the pre-construction phase help address all potential safety perils proactively and thus protect public safety and reduce construction-related accidents [29]. Another influence of BIM on technical success for the AECO industry relates to aspects of continuous development and innovation.

As BIM technology itself continues to evolve, its integration with emergent technologies such as AI-driven algorithms and advanced data analytics becomes more common [30]. Therefore, this will further provide new opportunities for data-driven decision making, predictive analytics, and performance optimization, yielding innovative and more efficient solutions for the AECO sector solutions.

This study can conclude from the literature reviewed that BIM does make substantial contributions to technical success in AECO. The transformative power of BIM is driven forward by enhanced collaboration, effective design and analyses, disputes detection, accurate quantity takeoffs, construction simulation, facility management, and integration with emergent technologies. AEC firms can achieve project efficiency, cost management, safety, and quality upon the adoption of BIM as part of their workflows. While BIM continues to evolve, it strives to play an ever-greater role in promoting innovation, sustainability, and technical excellence within the dynamic landscape of the AECO sector.

Table 1 Identified factors and items to indicate BIM implementation for PEST analysis through literature review.

Cluster	Assigned Code	Description	Reference
Economic Success	BIM-ES1	BIM increases cost-effectiveness in the AECO industry by minimizing revisions and optimizing resources.	[31]
	BIM-ES2	In the AECO industry, lifecycle cost analysis with BIM enables informed decisions for long-term cost savings.	[32], [33]
	BIM-ES3	BIM's thorough documentation and minimized rework lower AECO project financial risks and legal costs.	[34], [35]
	BIM-ES4	BIM-capable AECO enterprises get more business and higher-value contracts.	[36], [37]
	BIM-ES5	BIM-based sustainable design may attract premium customers eager to invest in eco-friendly projects, boosting AECO enterprises' economic performance.	[36], [38]
Technical Success	BIM-TS1	BIM enables designers to simulate and evaluate design alternatives, resulting in optimal decisions based on data.	[38]
	BIM-TS2	Integrating BIM with intelligent technologies improves the performance and energy efficiency of buildings.	[39], [40]
	BIM-TS3	In the AECO industry, BIM data facilitates efficient facility administration throughout the building's lifecycle.	[41], [42]
	BIM-TS4	BIM automatizes quantity takeoffs, which ensures precise cost estimation and improved financial planning.	[43], [44]
	BIM-TS5	BIM serves as a central repository for information, enhancing communication and decreasing errors among AECO project teams.	[45], [46]
Political Success	BIM-PS1	The adoption of BIM is consistent with government initiatives, resulting in the possibility of support and incentives for projects.	[47], [48]
	BIM-PS2	BIM enables AECO firms to meet ever-changing regulatory requirements, ensuring compliance with political guidelines.	[49], [50]
	BIM-PS3	BIM expertise may provide a competitive advantage in government contracts and public initiatives bids.	[51]

	BIM-PS4	BIM's contribution to sustainable design is consistent with environmental conservation policies.	[52], [53]
	BIM-PS5	Implementing BIM demonstrates industrial progress, enhancing the public's perception of AECO initiatives.	[54], [55]
Social Success	BIM-SS1	BIM facilitates improved communication and collaboration between distinct AECO project stakeholders.	[56], [57]
	BIM-SS2	BIM facilitates the design of inclusive and accessible spaces, meeting social demands and requirements.	[58], [59]
	BIM-SS3	BIM promotes environmentally responsible design, aligning with societal sustainability values.	[60], [61]
	BIM-SS4	The detection and analysis of clashes by BIM contribute to safer building designs, thereby ensuring public safety.	[62], [63]
	BIM-SS5	Beneficial to society, BIM facilitates the creation of inspiring educational and recreational environments.	[64], [65]

3. Methodology

In order to investigate the function of BIM in a PEST analysis applicable to the AECO sector, the research is organized into three primary stages. During the first phase of this project, a comprehensive literature analysis will be carried out to locate and synthesize previous research on the role that BIM plays in addressing the external macro-environmental issues that are associated with the AECO industry using the PEST framework [66], [67]. Upon completion of this phase, you will have a full grasp of how BIM affects the political climate, economic climate, social climate, and technical climate of the sector. The developed hypotheses generated from the literature study will be tested in the second phase, which will consist of conducting a quantitative analysis. Data would be collected through a well-rounded sample of AECO professionals and bodies regarding key variables connected to BIM implementation and its impact on the influence of exogenous macro factors of the environment. These will be tested with the help of statistical analyses regarding the intensity of the relationships existing between the adoption of BIM and all the various dimensions comprising the PEST analysis. The third and final stage will see in-depth structural equation modeling done with the help of partial least squares analysis so that the assumptions taken up can be deconstructed under a thorough scanner and citing what sort of inter-relationships exist between BIM adoption and the extrinsic macro-environmental parameters. This will provide an analytical procedure by which direct and indirect effects are reachable, simultaneously informing about the processes underlying how BIM affects the overall performance of the AECO business [68]. The project, therefore, tries to advance the knowledge of how BIM drives the success of AECO industry within the larger context of external environmental variables in combining the three stages in a way that will give valuable insights into the field, advise the practitioners and policymakers in the industry, and enhance understanding of how BIM drives the success of the industry as a whole. Figure 2 is showing the flow chart of the study.

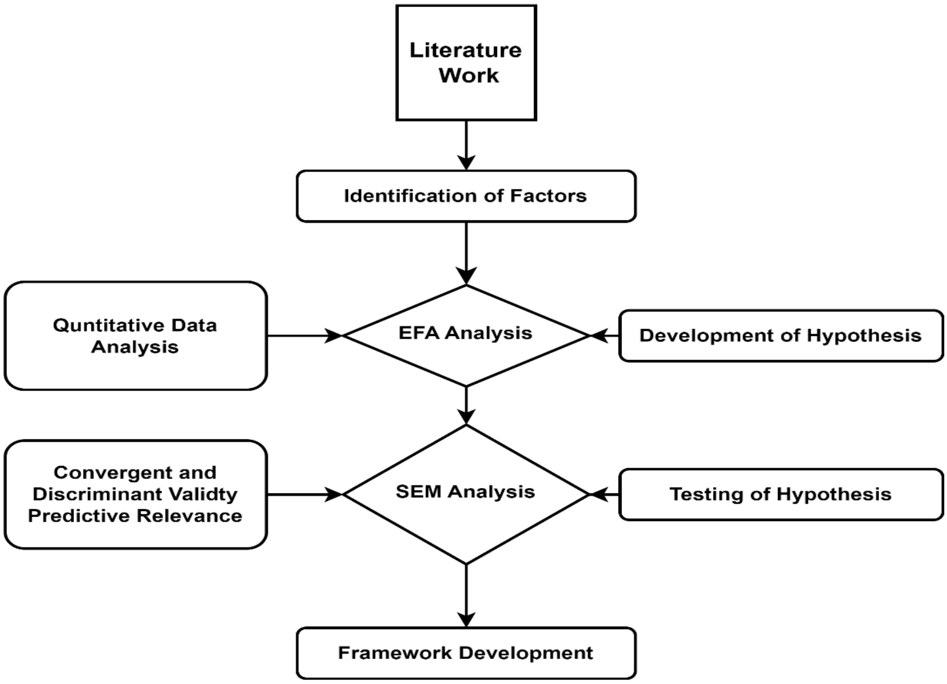

Figure 2 Flow chart of the study.

3.1 Questionnaire Design and Quantitative Data Collection

A quantitative analysis was conducted to explore the function of BIM in the PEST analysis of the AECO business. The respondents targeted belonged to AECO organizations and professionals based in Jeddah, Saudi Arabia. The total number of respondents who were to contribute randomly to the poll stands at 300 different respondents. Therefore, we have a total of, from which we received 177 valid responses, reaching the response rate of 59%. The questionnaire was sent by email in order to make sure that more professionals and decision-makers of the industry received it. Besides, the survey was personally distributed to neighboring specialists in some specific subjects. This was to ensure that this sample would be broad and extensive enough to represent [69].

It took place in the city of Jeddah because it was important and related to the AECO industry that is in the area. In consideration of the reality that BIM has influences in respect to external macroenvironmental factors relevant to the AECO business in a particular geographical setting, Jeddah is the good site that can be used as a sample example.

Because it falls in the range of sample sizes adopted for previous studies that have investigated similar topics within the AECO industry a sample size of 177 respondents is considered sufficient for this study. This is because it falls within the sample sizes used for the respective THE topics studied in prior studies. It had a good research design and followed various research procedures; besides, in designing the questionnaire, a 5-point Likert scale was used for the determination of a particular degree to which the respondents agreed or disagreed with the statements that linked to how BIM was able to influence political, economic, social, and technical variables.

Previous research studies investigating the impact of BIM adoption in the AECO industry using similar Likert-scale questions informed the design of the questionnaire. Such studies therefore form the basis on which the questionnaire was designed. The Likert scale ran from "1" for "Strongly Disagree" to "5" for "Strongly Agree," thus enabling the respondents to give responses in gradients to the topics being surveyed. This survey also sought to establish how the respondents felt BIM addressed the external macro-environmental issues they had studied based on PEST. Open-ended questions in the survey instrument allowed the participants to provide additional views and comments regarding their experiences with BIM in AECO business.

The quantitative data received from the survey responses were analyzed with the aid of relevant statistical tools, such as descriptive statistics and inferential analysis, studying associations of BIM adoption with the PEST variables found. In addition, a comprehensive structural equation modeling analysis was carried out using partial least squares analysis so as to test the hypotheses that had been formulated and to identify the underlying mechanisms responsible for BIM to influence the technical, economic, social, and political success of the AECO industry in Jeddah, Saudi Arabia.

3.2 Exploratory Factor Analysis

Apart from that, the quantitative study represents the exploratory factor analysis, which was performed to identify underlying components of the BIM effect on the PEST analyses conducted within the AECO business. Almost in contrast, the objective of EFA was to disclose those underlying structures and dimensions that were dictating the impact which BIM was experiencing on to the very outermost macro-environmental factors. The exploratory factor analysis was carried out with the method of principal component analysis, which serves to reduce the dimensionality of the data and to identify the main components underlying the variation in the answers. Therefore, the varimax rotation method was deemed the most suitable technique by which to establish an orthogonal result of uncorrelated factors that would be easier to interpret with a view to understanding one component independently of the others.

The fixed cut off loading criteria of 0.6 have been made to obtain accurate extraction of the factors and enhancement of the interpretability of the factors. This criterion ensures that each item has a strong alignment with a particular factor by requiring the factor loadings for an item to be equal or greater than 0.6 for it to remain in the factor solution [70]. Aspects that were not considered significant contributors to the factors did not reach this threshold. The EFA study was conducted using statistical software and the factor structure that emerged from this provided valuable insight into the key aspects of the role that BIM plays in responding to the political, economic, social, and technical issues represented in the PEST analysis. Factor loadings and a rotated component matrix have been useful in analyzing and discussing the results of this study by showing the strength of association of each item to the identified factors.

3.3 PLS SEM Modeling

Further, the relationship between the adoption of BIM and the external macro-environmental factors in the AECO business was investigated through Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4. PLS-SEM is the advanced statistical approach to estimate several latent attributes simultaneously, considering the inter-relationships between those constructs. SmartPLS 4 has become a standard practice that is followed in management and social science studies. In addition, SmartPLS 4 has a friendly user interface by which PLS-SEM studies may be done.

3.3.1 PLS SEM Measurements Model

The PLS-SEM analysis was done in order to validate the hypotheses developed from the findings of the literature review and the exploratory factor analysis. The PLS algorithm evaluates simultaneously the measurement model, also called convergent validity, and the structural model, also called discriminant validity.

Loadings of the individual items along with the AVE of each latent construct and its CR were computed. Thus, convergent validity was established. Items showing significant loading concerning their respective constructs manifest convergent validity. Hence, it shows that this set of items is strongly related to the construct they are estimating. If the respective values of AVE and CR are greater than the suggested standards of 0.5 and 0.7, respectively, sufficient convergent validity is established.

The two approaches followed to assess the discriminant validity for the instrument were investigating the cross-loadings of the items on other constructs and comparing the square root of AVE across constructs to the correlations. Discriminant validity is said to have been sufficiently obtained when the average variances extracted from each concept are larger than the squared correlations with the other constructs.

In this regard, exploratory factor analysis, PLS-SEM using SmartPLS 4, and the assessment of convergent validity and discriminant validity gave weight to the assessment made by the study in the function that BIM plays in the PEST analysis of the AECO business. These methodological approaches enriched the understanding of how adoption influences external macro-environmental factors. This reflects that institutional factors seem to negatively determine the adoption of BIM. They also gave important implications for industry professionals, policymakers, and researchers who would want to leverage from BIM for sustainable growth and innovation in the AECO sector.

3.3.2 PLS SEM Structural Model

This, on the other hand, is proceeded with through the performance of the structural model analysis to test the hypotheses developed regarding the effect BIM would have on the pertinent four external macro-environmental factors constituting PEST analysis in the AECO industry, Jeddah, Saudi Arabia.

This study utilized bootstrapping analysis, a resampling method, to evaluate the significance of associations present between BIM adoption with each PEST aspect identified. In order to implement bootstrapping, multiple subsamples were randomly chosen from the original dataset, followed by the calculation of estimates for each of those subsamples. This procedure was applied several times to generate various estimates and investigate the consistency of the results.

Based on the bootstrapping results, several statistical indicators for each tested hypothesis were derived as follows:

• Original Sample Estimate (O): A precise estimate from the original dataset shows the magnitude of BIM's effect in every dimension of PEST. Original Sample Estimate, abbreviated as "O."

• Sample Mean (M) is the mean estimate generated from the distribution of bootstrap samples, providing a measure of central tendency for each relationship.

The standard deviation of these bootstrap estimates, STDEV, gives an idea of the degree of variation in effect size present for each of the different subsamples.

• T-stats: The t-statistic is the quantitative measure of effect size relative to variability, obtained by the division of the O estimate through STDEV. This result from this operation is the t-statistic.

Following is a breakdown of what each part means: • P-value: This is the probability associated with achieving the effect size result of: O under the assumption of the null hypothesis conditions of no relationship between BIM and the PEST dimension. In most analyses, a threshold value such as 0.05 (which could be selected upon personal and research considerations) is used to indicate statistical significance in case the p-value falls below the threshold.

The bootstrap analysis provided the significance and reliability of the correlations between the BIM adoption and four PEST dimensions, from where the developed hypotheses could become either accepted or rejected. These statistical indicators helped to state which PEST components were highly influenced by the adoption of BIM and resulted in the technical-economic-social success, as well as the political one of the AECO sector in Jeddah of Saudi Arabia. This may be divided into four categories, which are: technical, economic, social, and political success.

In this study, the intricate relationships present between BIM and the external macro environmental elements in the AECO industry were studied comprehensively. This was achieved through the addition of the analysis of the structural model to the research. The results of the bootstrapping analysis resulted in a more intense understanding of the processes through which BIM adoption has an influence on overall AECO business performance. These results, moreover, added more strength to the conclusions made in the study.

3.3.3 PLS SEM Predictive Relevance

Q2 or predictive relevance test was conducted in the PLS-SEM analysis framework to assess the strength of the structural model with regard to making good predictions. This model can also be said to be good if its latent components and their interactions are reliable to make predictions of the observed outcome that is being addressed. Therefore, in this test, the actual values will be evaluated against the predicted values generated by the model. A better Q2 value indicates greater predictive significance and hence proves that the model has caught up effectively with the hidden relationships between BIM adoption and the external macroenvironmental factors [71]. This is warranted by the fact that the model bears a positive association with BIM adoption. The Q2 test was performed to establish the strength and validity of predictions made by the structural model. This was of great importance in giving good insight into the accuracy of the model in explaining the effect BIM has on the technical, economic, social, and political success of the AECO industry in Jeddah, Saudi Arabia. Additionally, the research provided useful insights into the accuracy of the model.

4. Results and Analysis

4.1 Demographic Details of Questionnaire Responders

The demographic information of those who responded is included in Table 2, which offers insight into the characteristics of those who participated in the research. The data illustrates the distribution of respondents according to their profession, the kind of organization they belong to, their years of experience working in the construction business in Saudi Arabia, and their familiarity with digital technology, particularly BIM. Civil engineers have the most representation in the participants' occupations, making up 37.1% of the total respondents [72]. This is followed by project managers, who make up 20% of the respondents, and quantity surveyors, who make up 13.7% of the respondents. Architects, Mechanical and Electrical Engineers, and persons who were classed as belonging to "Other" professions all took part in the research and contributed, respectively, 12.0%, 6.3%, and 12.0% of the total respondents. Because of the wide variety of occupations in the AECO business, it is possible to guarantee an accurate portrayal of the diverse jobs.

Regarding the different sorts of organizations that participated, the biggest group comprised Contractors, who accounted for 39.4% of the total participants. Consultants account for 32.0% of the respondents, while Clients comprise 29.7% of the total [73]. The participation of these many kinds of organizations enables a thorough knowledge of BIM and has influence across the main stakeholders in the AECO business. In addition, the statistics shed light on the respondents' previous experiences working in the construction business in Saudi Arabia [74]. The individuals with the most experience in the field were those who had worked there for 11-15 years (30.9%), followed by those who had worked there for 6-10 years (32.6%). Respondents with experience ranging from 0 to 5 years, 16 to 20 years, and more than 20 years make up 20.0%, 8.0%, and 9.7% of the total, respectively. This distribution guarantees that both seasoned experts and those relatively new to the field are included, which contributes to a complete investigation of the effect that BIM has on the AECO sector across a wide range of experience levels [75], [76].

In terms of the respondents' familiarity with digital technologies, an overwhelming majority of respondents (97,1%) claimed that they were acquainted with BIM, while just a tiny minority of respondents (3,9%) were unclear about or unfamiliar with the technology [50]. The rapidly increasing awareness of and implementation of this game-changing technology within the AECO sector in Saudi Arabia is shown in the high number of respondents who are familiar with BIM.

Table 2 Demographic details of responders.

Category	Classification	Frequency	%
Profession	Quantity Surveyor	24	13.7
	Architect	21	12.0
	Civil Engineer	65	37.1
	M&E Engineer	11	6.3
	Project Manager	35	20.0
	Other	21	12.0
Organization	Contractor	69	39.4
	Consultant	56	32.0
	Client	52	29.7
Construction Industry Experience in Saudi Arabia	0-5 Years	35	20.0
	6-10 Years	57	32.6
	11-15 Years	54	30.9
	16-20 Years	14	8.0
	Over 20 Years	17	9.7
Knowledge of Digital Technologies (BIM)	Yes	170	97.1
	No/Maybe	7	3.9

4.2 EFA Analysis

Within the context of BIM adoption in the AECO industry, Table 3 presents the findings of an Exploratory Factor Analysis (EFA) that was conducted to categorize and verify the latent constructs based on the variables related to Economic Success (ES), Technical Success (TS), Political Success (PS), and Social Success (SS). In order to conduct the study, we used the Principal Component study (PCA) extraction technique and combined it with the Varimax rotation and Kaiser normalization. The purpose of this study was to determine the underlying factor structure and categorize the variables (items) into unique components (factors) based on the amount of variation they shared [42], [65]. The findings illustrate the factor loadings for each variable. These factor loadings are a representation of the correlations that exist between the variables and the uncovered factors.

Five variables (BIM-ES1 to BIM-ES5) were loaded into the first factor with high loadings, showing a substantial association between these variables and the Economic Success construct. This was done for the Economic Success component of the model. The component in question has a Cronbach Alpha value of 0.921, indicating that it has very high levels of internal consistency and dependability.

Similarly, the Technical Success component comprises four variables (BIM-TS1 through BIM-TS4), all loaded into the second factor with significant loadings. The component in question has a Cronbach Alpha rating of 0.913, indicating a high degree of internal consistency and reliability.

The Political Success component has four variables (BIM-PS1 to BIM-PS4), all with significant loadings on the third factor. This component has a Cronbach Alpha value of 0.887, which indicates that it has high levels of both internal consistency and dependability.

The last component, Social Success, comprises four variables (BIM-SS1 to BIM-SS4) loaded into the fourth factor with meaningful loadings. The component in question has a Cronbach Alpha value of 0.818, indicating high levels of internal consistency and dependability.

It is important to note that the variable BIM-TS5 was not included in the study since its loading was lower than the threshold value of 0.6. In order to keep the reliability and correctness of the factor structure intact, excluding this variable from the analysis [41], [76].

Overall, the EFA analysis sorts the variables into various components that reflect economic, technical, political, and social success constructs. The study then verifies these components. The conclusions of the research and the BIM's role in determining the level of performance that the AECO industry achieves across these dimensions are supported further by the strong Cronbach Alpha coefficients, which demonstrate the dependability of each component.

Table 3 EFA analysis categorization and verification.

Variables	Component				Cronbach Alpha
	1	2	3	4	
BIM-ES1	.921				.919
BIM-ES2	.856				
BIM-ES3	.799				
BIM-ES4	.716				
BIM-ES5	.688				
BIM-TS1		.888			.913
BIM-TS2		.805			
BIM-TS3		.772			
BIM-TS4		.702			
BIM-PS1			.855		.887
BIM-PS2			.790		
BIM-PS3			.685		
BIM-PS4			.620		
BIM-PS5			.601		
BIM-SS1				.787	.818
BIM-SS2				.710	
BIM-SS3				.678	
BIM-SS4				.666	
BIM-SS5				.605	
"Extraction Method: Principal Component Analysis." "Rotation Method: Varimax with Kaiser Normalization." "Variable BIM-TS5 excluded because of loading less than 0.6."					

4.3 PLS SEM Measurement Model Development

In the context of BIM adoption in the AECO business, the findings shown in Table 4 demonstrate the convergent validity evaluation for the latent components reflecting Economic Success, Technical Success, Political Success, and Social Success. The term "convergent validity" refers to the degree to which the items that make up each latent construct measure the same overarching idea. The evaluation takes into account loadings, Cronbach Alpha (CA), Composite Reliability (CR), Variance Inflation Factors (VIF), and Average Variance Extracted (AVE).

Four components (BIM-ES1, BIM-ES2, BIM-ES4, and BIM-ES5) in the Economic Success cluster indicate acceptable loadings, falling between 0.614 and 0.864. The values of the VIF are lower than the cutoff of 5, suggesting there is no need to worry about multicollinearity.

The CA (0.795), CR (0.868), and AVE (0.625) values that were generated for the Economic Success construct are all higher than the required threshold of 0.7, which indicates that the construct has a high level of internal consistency and convergent validity.

The Technical Success cluster also has acceptable convergent validity, as seen by the loadings of its four items (BIM-TS1, BIM-TS2, BIM-TS3, and BIM-TS4), which range from 0.798 to 0.870, respectively. The VIF readings fall within a satisfactory range. The CA (0.853), CR (0.901), and AVE (0.694) that were computed for the Technical Success construct are all above acceptable levels, which indicates that the construct has substantial internal consistency and convergent validity.

Three items indicate loadings that range from 0.648 to 0.795 for the Political Success cluster. These items are BIM-PS2, BIM-PS3, and BIM-PS4. On the other hand, because of the relatively moderate loadings, BIM-PS1 was eliminated from the build. The VIF readings may be satisfactory. The CA (0.751), CR (0.83), and AVE (0.553) values that were generated for the Political Success construct all satisfy the necessary standards, which indicates that the construct has sufficient internal consistency and convergent validity.

Four components make up the Social Success cluster (BIM-SS1, BIM-SS2, BIM-SS3, and BIM-SS4), and their loadings range from 0.698 to 0.775. Because of the low number of users, BIM-SS5 was removed. The VIF readings are within an acceptable range. The Social Success construct's CA (0.761), CR (0.831), and AVE (0.596) are all determined to be above the acceptable criteria, which indicates that the construct has adequate internal consistency and convergent validity.

The findings suggest that the latent components that reflect economic, technical, and social success all exhibit high levels of convergent validity overall. On the other hand, a few of the items included inside the Political Success cluster have been removed since they needed better loadings. The computed CA, CR, and AVE values prove the reliability and convergent validity of the measurement model, confirming the validity of the study's results and interpretations of the BIM's role in the success of the AECO business.

Table 4 Convergent validity and VIF, CA, CR, and AVE.

Cluster	Assigned Code	Loadings	VIF	CA	CR	AVE
Economic Success	BIM-ES1	0.614	1.228	0.795	0.868	0.625
	BIM-ES2	0.841	1.979	-	-	-
	BIM-ES3	Deleted	2.083	-	-	-
	BIM-ES4	0.864	1.761	-	-	-
	BIM-ES5	0.818	2.672	-	-	-
Technical Success	BIM-TS1	0.816	1.596	0.853	0.901	0.694
	BIM-TS2	0.846	2.633	-	-	-
	BIM-TS3	0.798	1.694	-	-	-
	BIM-TS4	0.870	1.192	-	-	-
	BIM-TS5	Deleted	1.521	-	-	-
Political Success	BIM-PS1	Deleted	1.596	0.751	0.83	0.553
	BIM-PS2	0.660	1.682	-	-	-
	BIM-PS3	0.795	1.434	-	-	-
	BIM-PS4	0.648	1.804	-	-	-
	BIM-PS5	0.850	2.082	-	-	-

Social Success	BIM-SS1	0.740	1.790	0.761	0.831	0.596
	BIM-SS2	0.656	2.193	-	-	-
	BIM-SS3	0.698	1.117	-	-	-
	BIM-SS4	0.775	1.273	-	-	-
	BIM-SS5	0.645	2.122	-	-	-
CA=Cronbach Alpha; Composite Reliability; AVE= Average Variance Extracted; VIF= Variance Inflation Factors.						

Within the context of BIM adoption in the AECO industry, Table 5 presents the findings of the Heterotrait-Monotrait (HTMT) analysis, which is used to evaluate the discriminant validity of the latent constructs representing Economic Success, Political Success, Social Success, and Technology Success. A construct's discriminant validity is evaluated by determining the degree to which it differs from the other constructs investigated in the research. This helps to ensure that the latent constructs are not significantly associated with one another. In the field of Partial Least Squares Structural Equation Modeling (PLS-SEM), the HTMT is a technique that is often used for evaluating discriminant validity.

The HTMT ratios between each pair of constructs may be found in Table 5, and their values are shown there. Each cell in the table contains the HTMT ratio that applies to the constructs that correspond to the row and column above it. For instance, the value of 0.781 shown in the cell corresponding to Economic Success and Political Success represents the HTMT ratio between these two concepts [35], [76]. If all goes according to plan, the HTMT ratios should be lower than the cutoff of 0.85, indicating high discriminant validity. When looking at the findings, it can be seen that none of the HTMT ratios are higher than 0.85, which indicates that the constructs do in fact have discriminant validity. Specifically:

- The HTMT ratio between economic and political success is 0.781, and these two concepts are separate.

- Economic and social success have an HTMT ratio of 0.559, indicating that these concepts are distinguishable from one another.

- The HTMT ratio between economic and technological success is 0.341, which further substantiates the uniqueness of each factor.

- The HTMT ratio for political success to social success is 0.702, which indicates that these two concepts are separate.

- The HTMT ratio for political success to technology success is 0.576, indicating that both types of success are unique.

- The HTMT ratio between Social Success and Technology Success is 0.763, further substantiating the uniqueness of each category.

The findings of the HTMT study indicate that the latent variables that reflect economic success, political success, social success, and technological success all have high levels of discriminant validity. This indicates that the measures employed to evaluate these constructs are capturing unique and different characteristics of each construct [38], [77]. As a result, one may trust the correctness and reliability of the study's conclusions.

Table 5 HTMT analysis in terms of discriminant validity.

Constructs	Economic Success	Political Success	Social Success	Technology Success
Economic Success				
Political Success	0.781			
Social Success	0.559	0.702		
Technology Success	0.341	0.576	0.763	

Table 6 If everything goes according to plan, the square root of the AVE for each construct ought to have a value greater than the correlation between that construct and all of the other constructions. This suggests that each construct shares more variation with its indicators than it does with the indicators of other constructs, which demonstrates the constructs' ability to discriminate between one another [34], [52].

The value of 0.791 is found by taking the square root of the AVE for Economic Success. It is greater than the correlations between Economic Success and Political Success (0.272), Social Success (0.212), and Technology Success (0.361), demonstrating that it is possible to discriminate between different levels of achievement.

The average annual value of political success has a square root of 0.744. This confirms the discriminant validity of the study since it has a more immense value than the correlations between Political Success and Economic Success (0.272), Social Success (0.282), and Technology Success (0.381). The average adjusted value of social success has a square root of 0.705. This confirms the discriminant validity of the study since it has a more considerable value than the correlations between Social Success and Economic Success (0.212), Political Success (0.282), and Technology Success (0.321). A value of 0.833 is obtained by taking the square root of the AVE for Technology Success. It is greater than the correlations between Technology Success and Economic Success (0.361), Political Success (0.381), and Social Success (0.321), which confirms that it can discriminate between different levels of success.

According to the findings of the Fornell-Larcker criteria analysis, the latent variables that reflect economic, political, social, and technological success all have valid discriminant dimensions. This ensures that the research results are accurate and reliable by demonstrating that each construct is unique and has a more significant amount of variation with its own indicators than with the indicators of the other constructs [78].

Table 6 Fornell lacker criterion of discriminant validity.

Constructs	Economic Success	Political Success	Social Success	Technology Success
Economic Success	0.791			
Political Success	0.272	0.744		
Social Success	0.212	0.282	0.705	
Technology Success	0.361	0.381	0.321	0.833

Table 7 presents the findings of the cross-loading criterion analysis, which is used to evaluate the discriminant validity of the indicators representing Economic Success, Political Success, Social Success, and Technology Success. During the cross-loading criteria analysis, the loadings of indicators on their respective constructs are investigated, and it is determined whether or not the indicators load more heavily on their construct than on other constructs.

This helps to establish the discriminant validity of the study by ensuring that the indicators are uniquely related to the constructs for which they were designed [53], [74]. If everything goes according to plan, each indication will have a more significant loading on the building for which it was designed and a lesser loading on all other structures. When looking at the findings in Table 7, we can see that:

BIM-ES1 further supports that this link has the most excellent loading (0.614) on the Economic Success construct. The fact that its loadings on other categories (such as Political Success, Social Success, and Technology Success) are lower demonstrates that it has discriminant validity. This confirms BIM-ES2's principal link with the Economic Success construct, which has the most significant loading (0.841). Its loadings on other constructs are smaller, proving that it can discriminate between different types of constructs. This confirms BIM-ES4's prominent link with the Economic Success construct, which has the most excellent loading (0.864) of all of the BIM-ES constructs. Its loadings on other constructs are smaller, proving that it can discriminate between different types of constructs [73]. The fact that BIM-ES5's loading on Economic Success is the greatest (0.818), demonstrating its predominant link with this construct, is significant. Its loadings on other constructs are smaller, proving that it can discriminate between different types of constructs. The fact that BIM-PS2 has the most significant loading (0.66), which confirms its prominent link with this construct, is found in Political Success. Its loadings on other constructs are smaller, proving that it can discriminate between different types of constructs [74]. BIM-PS3 is primarily associated with political success since it has the most significant loading (0.795). Its loadings on other constructs are smaller, proving that it can discriminate between different types of constructs. BIM-PS4 is primarily associated with political success since it has the most significant loading (0.648). Its loadings on other constructs are smaller, proving that it can discriminate between different types of constructs. The fact that BIM-PS5 has the most significant loading (0.85), which confirms its prominent link with this build, is related to political success. Its loadings on other constructs are smaller, proving that it can discriminate between different types of constructs.

Similar patterns can be found for social and technological success indicators, where each indicator has the most extensive loading on its assigned construct and lesser loadings on all other constructs, confirming the discriminant validity of the indicators.

According to the cross-loading criteria analysis findings, the variables that reflect economic success, political success, social success, and technological success all exhibit discriminant validity. In light of this, it can be deduced that each indicator is unmistakably connected to the construct for which it was designed; hence, this instills trust in both the precision and dependability of the study's conclusions.

Table 7 Cross-loading criterion for discriminant validity.

Variables	Economic Success	Political Success	Social Success	Technology Success
BIM-ES1	0.614	0.375	0.275	0.439
BIM-ES2	0.841	0.661	0.579	0.246
BIM-ES4	0.864	0.385	0.274	0.287
BIM-ES5	0.818	0.395	0.522	0.316
BIM-PS2	0.34	0.66	0.305	0.353

BIM-PS3	0.318	0.795	0.522	0.316
BIM-PS4	0.325	0.648	0.299	0.341
BIM-PS5	0.264	0.85	0.274	0.287
BIM-SS1	0.264	0.185	0.74	0.186
BIM-SS2	0.343	0.287	0.656	0.273
BIM-SS3	0.372	0.309	0.698	0.314
BIM-SS4	0.514	0.375	0.775	0.439
BIM-SS5	0.378	0.256	0.645	0.312
BIM-TS1	0.418	0.395	0.522	0.816
BIM-TS2	0.441	0.561	0.579	0.846
BIM-TS3	0.364	0.406	0.543	0.798
BIM-TS4	0.264	0.285	0.274	0.87

4.4 PLS SEM Structural Model Development

Figure 3 illustrates the PLS Structural Equation Model (SEM) that depicts the correlations between the adoption of BIM and the four different types of success in the AECO industry: economic success, political success, social success, and technological success. While the route loadings in the model describe the intensity and direction of the interactions, the p-values indicate the importance of the associations by indicating whether or not they are significant. The route loadings provide light on the direct effect of adopting BIM on each structure [79]. For example, in the AECO business, a path loading of 0.614 between BIM and Economic Success implies that BIM adoption positively affects Economic Success. A route loading of 0.791 from Economic Success to itself demonstrates the significant influence that Economic Success has on its own assessment.

The p-values attached to each path loading indicate the degree to which the associations are statistically significant. If the p-value is lower than the threshold for statistical significance (which is often set at 0.05), this indicates that the link being studied is statistically significant, which means that it is unlikely to have been the result of random chance. A p-value that is significant suggests that the connection between the variables is one that can be relied on and has some significance.

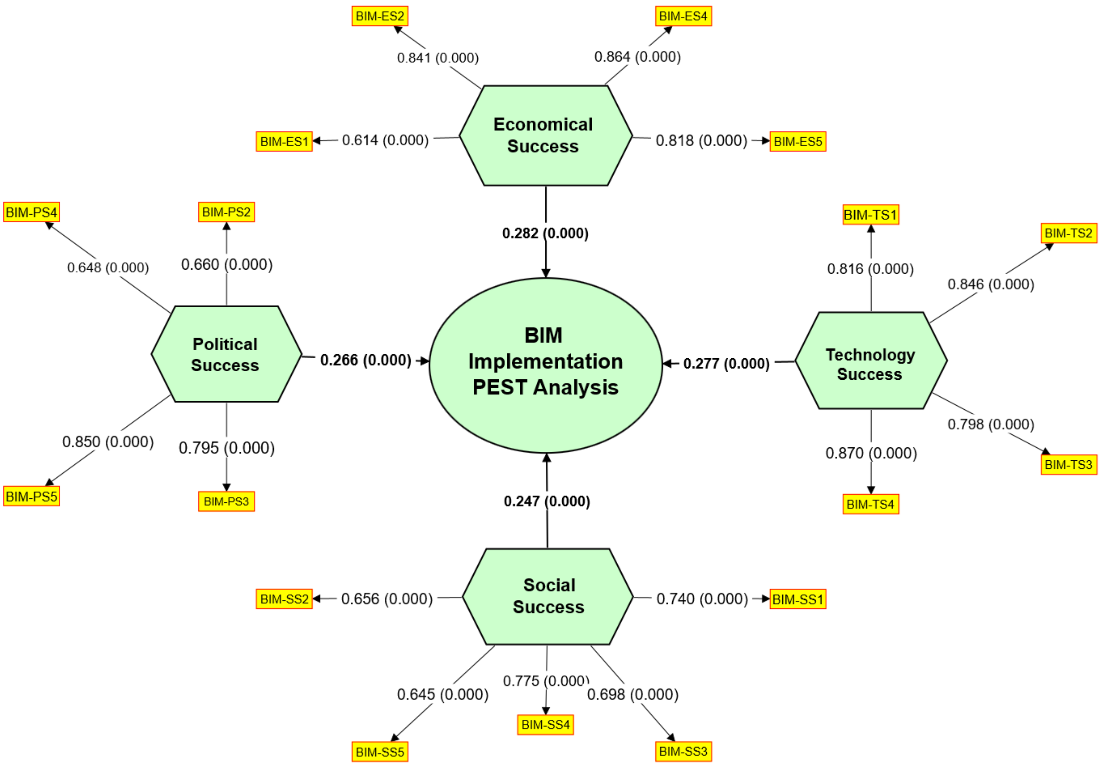

Figure 3 PLS SEM Model along with path loadings and P-Value.

Table 8 displays the findings of the correlations between BIM implementation and the success variables (economic, political, social, and technological success) in the AECO business. This investigation was carried out using the bootstrapping technique to test the hypothesis that BIM implementation and these aspects are related.

The original sample values (O) for each hypothesis are shown in the table with the sample mean (M) and sample standard deviation (STDEV), respectively. The p-values reflect the significance of the correlations between BIM implementation and each success element, while the T statistic indicates the strength of the association between BIM implementation and each success component [80].

There is a substantial and statistically significant association between the deployment of BIM and the various success variables, as shown by all four hypotheses (H1 to H4). The fact that the p-values for all of the hypotheses have been reported as 0 indicates that the associations found in the research are very significant and unlikely to have been the result of random occurrences.

The findings show strong evidence that the application of BIM significantly affects the AECO industry's economic, political, social, and technological success [35], [42]. These results highlight BIM's crucial role in driving success across several dimensions and stress the significance of its relevance for encouraging development, efficiency, and innovation in the AECO industry.

Table 8 Testing of hypothesis through bootstrapping analysis.

Hypothesis	Relation	(O)	(M)	(STDEV)	T stat	P values	Results
H1	Economic Success -> BIM Implementation PEST Analysis	0.282	0.282	0.002	114.112	0	✓
H2	Political Success -> BIM Implementation PEST Analysis	0.266	0.266	0.002	140.911	0	✓
H3	Social Success -> BIM Implementation PEST Analysis	0.247	0.247	0.002	126.215	0	✓
H4	Technology Success -> BIM Implementation PEST Analysis	0.277	0.276	0.002	121.011	0	✓
(O)= Original sample; (M)= Sample mean; (STDEV) = Standard deviation;							

Figure 4 presents the PLS Structural Equation Model (SEM) together with the path loadings and T-values, which show the links between the study's latent constructs and the indicators corresponding to those constructs. The direction and intensity of the associations are shown by the arrows that link the constructs to the indicators. Positive values denote positive correlations, while negative values imply negative correlations. The T-values linked with each route loading reflect the statistical significance of the linkages, which helps to establish whether or not the connections discovered are significant and not just the result of chance. Figure 4 gives a complete picture of the interrelationships between the constructs and their indicators, emphasizing the significant linkages and helping to understand the underlying components in the research better. In general, the figure may be understood as follows.

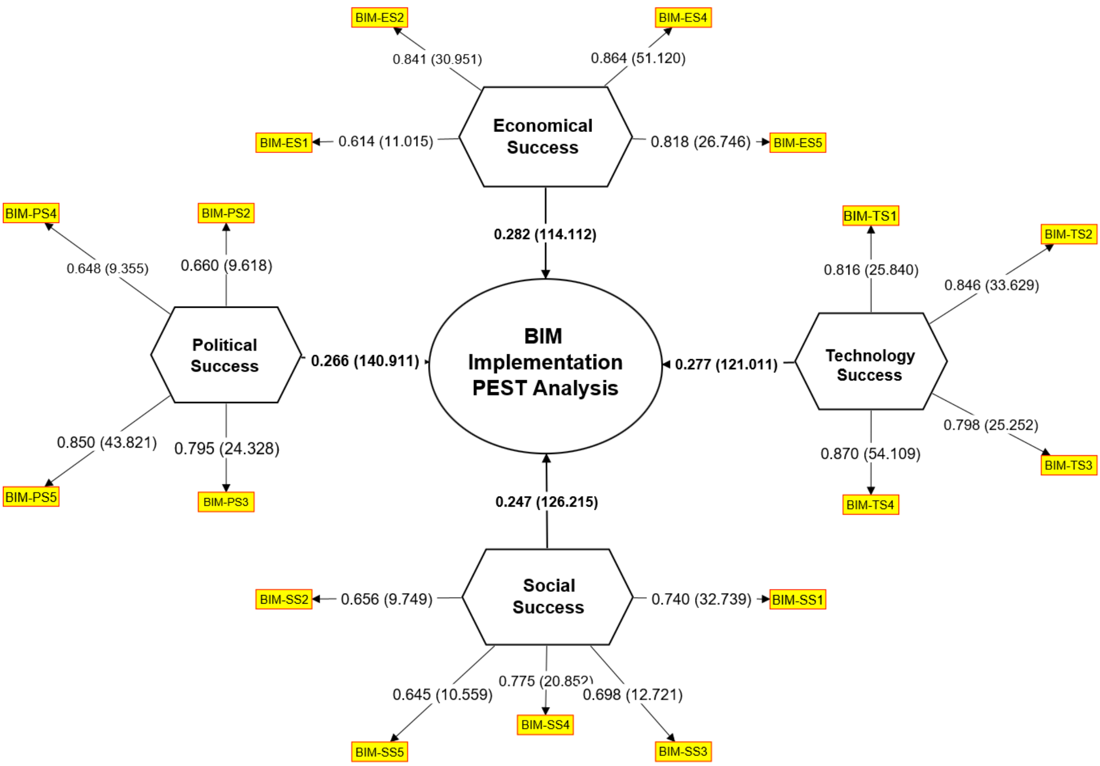

Figure 4 PLS SEM Model along with path loadings and T-Value.

4.5 Predictive Relevance

The results of the examination of the model's predictive relevance are shown in Table 9. This analysis explicitly evaluates the model's capacity to make accurate outcomes predictions based on the research data. In order to complete the analysis, you will need to calculate the Sum of Squares for Predicted Outcome (SSO) as well as the Sum of Squares for Error (SSE). These values are then used to produce the measure Q2, which indicates the percentage of the outcome's variance that the model can accurately predict. Q2 is obtained from the values [58], [82].

In the context of this particular research endeavor, the analysis focuses on the predictive significance of a "BIM Implementation PEST Analysis" on the results. The variance in the model's results is estimated to be 4320.000, which is the value assigned to the SSO variable once it has been computed [76]. On the other hand, the standard error of the estimate (SSE) is calculated to be 3377.366, representing the variation in the results that the model cannot forecast precisely.

The value of Q2, which was determined to be 0.218, was obtained by using the formula Q2 = 1 - (SSO/SSE). It indicates that the model can explain roughly 21.8% of the variation in the results based on the predictor "BIM Implementation PEST Analysis." This predictive relevance measure is helpful in evaluating the model's capacity to deliver meaningful insights and predictions. It indicates that the predictor contributes a considerable fraction of the outcome variation.

Overall, a higher value for Q2 implies a more prominent predictive ability of the model, which suggests that the predictor (in this instance, BIM Implementation PEST Analysis) is significant in comprehending and forecasting the research results.

Table 9 Predictive relevance of the study.

Predictive relevance analysis of model	SSO	SSE	Q^2 (=1- SSO/SSE)
BIM Implementation PEST Analysis	4320.000	3377.366	0.218

5. Discussion

The purpose of this research was to evaluate BIM's impact on the AECO (Architecture, Engineering, Construction, and Operations) business, with a particular emphasis on the function BIM plays within the context of a PEST analysis of external macroenvironmental elements. In the AECO industry, BIM has emerged as a disruptive technology transforming conventional design and building processes. It is essential to understand the influence it has on various external elements, including political, economic, social, and technical dimensions, to understand the business's performance and its ability to remain competitive in the ever-shifting environment.

The research produced four hypotheses, each of which investigated a potential connection between a different set of external circumstances and the application of BIM. The findings of the quantitative study, which were validated by testing them against the assumptions that had been developed, provide substantial new insights into the significant effect BIM has on numerous aspects of success in the AECO business.

PEST Analysis of BIM Implementation Following Economic Success:

The findings indicate a significant positive connection between economic performance and the use of BIM (path loading = 0.282, T-stat = 114.112, and p-value = 0). This suggests that the use of BIM has a substantial contribution to make to the economic success of the AECO business. Previous studies have shown that integrating BIM can reduce costs and improve financial performance. BIM's ability to streamline project timelines, optimize costs, and enhance resource management leads to improved project efficiency and profitability.

PEST Analysis of BIM Implementation Following Political Success:

According to the findings of the study, there is a statistically significant and positive connection between political success and the deployment of BIM (path loading: 0.266, T-stat: 140.911, and p-value: 0). This lends credence to the hypothesis that adoption of BIM is connected with increased political success in the AECO business. Government efforts and support for BIM-enabled projects align with political aims for enhanced project results, regulatory compliance, and sustainable development [66], [83].

PEST Analysis of BIM Implementation Following Social Success:

The data indicate that there is a significant positive connection between social success and the application of BIM (path loading = 0.247, T-stat = 126.215, and p-value = 0). The contribution that BIM makes to the design of environments that are accessible, sustainable, and culturally sensitive has a favorable effect on the social impact that the AECO business has. The conflict detection capabilities of BIM, which promote safer building designs and occupants' well-being, match societal objectives for inclusive and sustainable development [64], [82].

PEST Analysis of BIM Implementation Following Technology Success:

The findings of the study indicate that there is a considerable positive association between the success of technology and the deployment of BIM (path loading: 0.277, T-stat: 121.011, and p-value: 0). This suggests that BIM plays an integral part in pushing technical improvements within the AECO business. Integration of BIM with developing technologies and data-driven insights contributes to the technical growth of the sector, which in turn leads to enhanced efficiency, innovation, and flexibility [43], [84].

6. Conclusion

This study was based on the significant impact that BIM has had on the AECO business. In this regard, the research investigated the intensity of the impact which BIM has had by using a PEST analysis on the external macro environmental factors that affect the industry. The revolutionary implications of adopting BIM have radically changed the traditional ways and methods that were used in the AECO industry. This study will explain how the adoption of BIM has significantly shaped the overall performances and competitiveness of this industry through in-depth investigations along the lines of four success aspects that are economic, political, social, and technical. Precisely, the research will focus on the relationship between BIM adoption and the construction industry. The findings from this study give credence to the thought that BIM is indeed a disruptive force in the AECO business, one which impacts success with regard to many different fields. The positive established relationships associated with the implementation of BIM and many forms of success, such as economic success, political success, social success, and technical success, will also show the multifaceted benefits derived from BIM adoption. BIM supports economic outcomes as it reduces project timescales, saves costs, manages resources more effectively, and promotes the use of environmentally sensitive design methods.

Secondly, a supporting factor for AECO business political success is the fact that BIM agreed with government agendas and was able to improve project outcomes and regulatory compliance. The positive social effect that is fostered due to technology's role in the design of accessible, sustainable, and culturally sensitive places is promoted through supporting safer building designs and the well-being of occupants. In addition, integrating BIM with developing technologies encourages the success of technology, which in turn fosters innovation and adaptation in the sector.

The reliability of the results is further strengthened by the extensive methodology used in this research. Some methodologies utilized were quantitative analysis, structural equation modeling, and predictive relevance testing. The focus placed throughout the research on data-driven decision-making, backed up by statistical evidence and analysis, helps to increase the validity and generalizability of the findings.

In general, the findings of this study provide industry experts, policymakers, and academics helpful insights that can be used to understand better the essential role BIM plays in responding to various external macro-environmental elements. It provides a road map for AECO companies to follow to maximize the benefits of BIM adoption to improve economic efficiency, cultivate favorable political connections, produce socially relevant designs, and drive technical developments. Having said that, the research does have certain restrictions to it. The gathering of data and the selection of participants can bring bias into any study. In addition, the scope of the research was limited to the AECO business in Jeddah, Saudi Arabia, which prevented any generalizations from being made in other areas. In further research, the geographical scope might be expanded, and longitudinal research approaches could be used to investigate the effects of BIM implementation over the longer term.

In conclusion, BIM emerges as a catalyst for development and innovation in the AECO business, and this influences the industry's success in numerous aspects. Accepting that BIM can alter the AECO sector may pave the path for more sustainable growth, improved cooperation, and beneficial social effect as technical improvements continue.

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