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AI-Integrated BIM and Business Intelligence Frameworks for Enhancing Fenestration System Performance: Evidence from the South Indian AEC Sector

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Abstract

Over the years, the role of BIM has evolved from a coordination tool to a performance-driven design platform and is now becoming increasingly infused with artificial intelligence. This research explores the influence of BIM capability with AI technology on fenestration system performance and outcomes of the projects in the South Indian AEC sector. The method employed was quantitative where data were gathered from industry professionals of 300 respondents. Structural Equation Modeling (SEM) was used to analyze the data to assess the direct and indirect relationships. The results show that the use of AI-integrated BIM capability positively contributes to fenestration system performance ($\beta = 0.64$, $p < 0.001$), and fenestration performance positively affects the project outcomes ($\beta = 0.58$, $p < 0.001$). A significant amount of variance in fenestration performance ($R^2 = 0.61$) and project outcomes ($R^2 = 0.68$) is explained by the model. The mediation analysis results validated the partial mediation of fenestration performance between the capability of the AI-BIM and the project outcomes. Further, there are indications that BIM maturity and green building experience enhance the effectiveness of integrating AI in the moderate range of moderation results. The study is a contribution in creating a clear performance based trajectory between digital capabilities and project outcomes. The results underscore the importance of optimizing systems over just adopting the technology in the context of BIM and AI.

Keywords: AI-integrated BIM; fenestration systems; building performance; SEM; AEC sector; sustainability

Introduction

Background and Context

The structure of the architecture, engineering, and construction (AEC) industry is changing because of digital transformation. Building Information Modeling (BIM) is one of the technologies transforming the industry, which has evolved from a coordination tool to a central hub for integrated project delivery (Eastman et al., 2018; Succar, 2009). However, traditional BIM systems tend to be rigid, relying on fixed input conditions and are not able to adapt dynamically to design and environmental changes. But Artificial Intelligence is changing that reality with BIM. With the integration of AI and BIM, the design and construction process become more predictive, automated, and optimized in real-time. Such features enable project teams to go beyond visualisation and coordination to performance-driven design (Pan et al., 2021; Oesterreich & Teuteberg, 2016). Rather than fix issues during construction, teams can now predict and fix issues in the design stage. This is especially true of façade and fenestration systems. Fenestration systems including windows, glazing systems and curtain walling are important in deciding the performance of a building. They directly affect thermal behaviour, daylighting factor, energy use and comfort of the occupants. However, fenestration design is generally left to the end of the design process, after the important decisions have been made in structural and space planning. With AI-integrated BIM, this is not the case, as performance analysis becomes part of the early design phase. The designers can use the simulation and optimization algorithms to test different façade designs and choose the most efficient and effective ones.By testing different façade designs through simulation and optimization algorithms, the designers can determine the most efficient and effective design. This change will make fenestration systems active participants in the building intelligence instead of passive design elements.

Problem Statement

Although BIM has been widely used in the AEC industry, the actual building performance impact is not uniform. Most projects are still simply dealing with visualization and coordination aspects of BIM without really harnessing the full power of BIM for performance optimisation. Despite the development of AI capabilities, there is a lack of empirical evidence of how specific building systems are affected by AI. Fenestration systems offer a crucial opportunity in this regard. Several studies have been conducted about energy modeling and façade optimization, but most of them are on a simulation basis or small scale case studies. Large sample empirical studies investigating the impact of AI-integrated BIM in the industry context are still lacking. Also, digital skills and project outcomes are linked in a linear fashion without taking into account how value is generated. This oversimplification fails to account for the fact that between technology adoption and project success are performance improvements at the system level.

Research Gap

From the literature, there are three gaps that are identified.

Firstly, there is a lack of empirical evidence that shows the measurable performance of fenestration systems, when utilizing AI integrated BIM capabilities. Major studies tend to focus on the overall benefits of BIM and not system-specific benefits. Secondly, the connections between digital tools and project outcomes, via the mediation of façade performance, has not been sufficiently explored. If this is not understood, it is hard to show the impact of technological investments in terms of real benefit. Thirdly, there has been little consideration of contextual factors that can impact the value organizations can obtain from AI-supported tools, such as BIM maturity and sustainability experience.

Research Objectives

This study will seek to:

- Explore how AI-enabled BIM capability can affect fenestration system performance.
- Assess how fenestration performance affects project results.
- Analyze how fenestration performance mediates.
- Moderating effect of BIM maturity and green building experience will be investigated.
- Offer empirical evidence from the AEC sector in the South Indian region.

Significance of the Study

This study is a contribution to theory and practice as it moves away from technology adoption and towards performance outcomes. It offers a framework for understanding the value creation potential of AI powered BIM systems at a system level. The findings, for industry stakeholders, provide practical ideas on how digital tools can be leveraged to improve building performance, and not just for coordination.

Literature Review

AI-Integrated BIM Capability

BIM has been developed from a visualization tool to a single platform where collaboration and data sharing with project stakeholders is possible (Eastman et al., 2018; Succar, 2009). But traditional BIM systems still have limitations when it comes to meeting the dynamic design needs. AI integration in BIM provides sophisticated analytical features within the construction modeling software systems. By integrating AI, BIM can now ingest vast amounts of data, detect trends, and contribute to predictive decision-making, making it a smart design platform (Pan et al., 2021; Zhou et al., 2021). These solutions allow automated clash checking, predictive scheduling and performance-based optimisation. Research conducted has revealed that the use of AI with BIM can increase the design accuracy, minimize rework and boost the coordination efficiency (Azhar, 2011; Bryde et al., 2013). Most research, however, has been directed towards process improvements, and not at how these capabilities affect particular systems, such as fenestration.

Fenestration System Performance

The fenestration systems are very important elements of building envelopes that directly affect energy consumption, thermal comfort and daylight penetration (Rahman & Zaki, 2020). When fenestration design is not done well, it can lead to unwanted high heat gain, glare, and reliance on mechanical systems. Methods of traditional design are mostly based on simple rules and static calculations, which are inadequate in capturing the complexity of environmental interactions (Wong & Zhou, 2015). Consequently, optimization can generally only be dealt with at a later stage of the design, which reduces its effectiveness. To achieve continuous evaluation of fenestration performance, AI-integrated BIM systems are more effective, as they allow the simulation tools to integrate into the design environment (Jalaei & Jrade, 2015). This enables performance optimisation of the building envelope during all stages of the project.

AI-Driven Design Optimization

AI-driven design optimization is a step away from deterministic design to data-driven design. Generative design algorithms can generate various design alternatives that meet the given performance criteria (Kim et al., 2013). The algorithms are used to model the complex interactions between variables like orientation, material properties and environmental conditions. Machine learning techniques also help with this, recognizing patterns and forecasting the best design solution (Mahdavinejad et al., 2018). These methods are especially useful when dealing with fenestration and façade systems that have multiple interconnected factors that affect performance results.

Digital Construction Project Outcomes

The four metrics that are generally used in the AEC sector to measure the outcomes of projects are cost, time, quality and sustainability. The benefits of BIM use have been positively correlated with better coordination, fewer errors and higher project efficiency (Bryde et al., 2013; Wang et al., 2015). The value of BIM on the final performance of a building however, relies on the degree of how BIM is implemented into the design processes. In and of itself, using digital tools does not ensure better outcomes if not integrated into performance-based decision-making (Lu et al., 2015). AI-integrated BIM can serve as a tool to create this connection by connecting design inputs with measurable design outputs.

This is where the BIM Maturity and Sustainability Experience come in and play a moderating role.

The level of maturity of the organizations affects BIM implementation efficiency. BIM maturity is the level of integration of digital workflow, standards and knowledge in an organization (Succar et al., 2012). More mature BIM organizations are better equipped to benefit from more advanced features like AI integration and performance simulation. Likewise, having first-hand experience of sustainable building can be useful for turning design upgrades into environmental impacts (Wong & Zhou, 2015). This implies that the influence of AI-driven BIM is situational and depends on the readiness of the organizations.

Research Methodology

Research Design

This study employs a quantitative approach with a cross-sectional research design to investigate how AI-integrated Building Information Modeling (BIM) influences the performance of fenestration systems and project results in the architecture, engineering, and construction (AEC) industry of South India. A quantitative approach is suitable in this study because it is designed to test a predetermined set of hypotheses that are based on theory, and to examine the causal relationships between several latent constructs through statistical modeling techniques. A cross-sectional design is used to reflect the current industry practices and perceptions about AI-enabled BIM applications at a given moment in time. While longitudinal designs can give insight into how performance changes over time, the current design is adequate for characterizing structural relationships between digital capabilities and performance outcomes. The main analysis method used is the structural equation modeling (SEM). That is, covariance based SEM is employed to evaluate the measurement model and the structural relationships between constructs. The method allows for the estimation of multiple relationships, model fit, and testing of mediation and moderation effects. The usefulness of dealing with complex theoretical models with SEM has developed into a way of using SEM widely in construction management and BIM research (Hair et al., 2019; Kline, 2015).

Research Methodology

The number of respondents in the study is 300 which meets the minimum recommended sample size for SEM based studies and ensures sufficient statistical power for the estimation of this model. To ensure a variety of views from the AEC ecosystem, a multi-stakeholder sampling strategy was used for this work, specifically involving different professionals who work directly in the fenestration design, analysis, implementation, and performance evaluation processes.

Stakeholder Group	***Frequency***	***Percentage***
Architects	72	24%
Engineers / Consultants	60	20%
Contractors	54	18%
Manufacturers / Suppliers	48	16%
Facility Managers / Building Owners	66	22%
Total	300	100%

Table 1: Target Respondent Distribution.

The involvement of several stakeholder groups allows the study to represent the point of view of the design stage and the point of view of the post-occupancy. Architects and consultants share their understanding of optimizing design and simulation, and contractors and manufacturers share their understanding of constructability and implementation. The facility managers and building owners provide data on how the system is performing and how it will perform over the long haul. The data were gathered by sending a structured online questionnaire to professionals, industry associations, and online platforms. The respondents were reached by a combination of purposive sampling and snowball sampling to obtain respondents who had experience in BIM and façade systems. The survey surveyed professionals in major cities across South India like Chennai, Bengaluru, and Hyderabad. The respondents were explained the objective of the study and informed of its confidentiality. To ensure consistency and reliability of the analysis, only fully completed responses were included in the final data set.

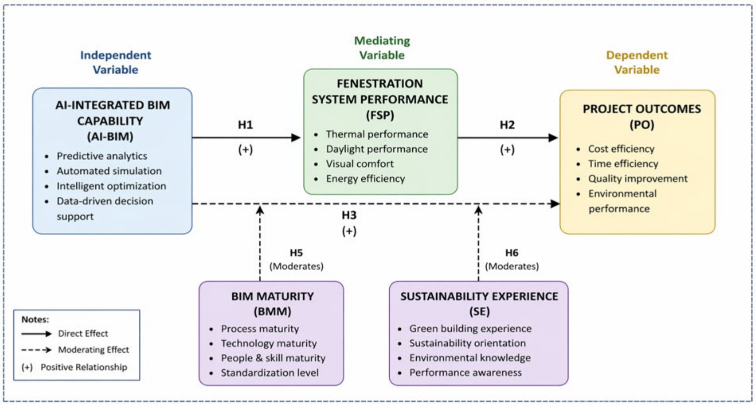

Figure 1: Conceptual research model illustrating the relationships between AI-integrated BIM capability, fenestration system performance, and project outcomes, including the moderating effects of BIM maturity and sustainability experience.

Measurement Instrument

Data collection instrument was structured and made into two sections. Section A collected data on demographic information, such as the role of the stakeholder, years of experience, the level of use of BIM and involvement in green building projects. This information is used for subgroup analysis and can be used to perform other tests like ANOVA or multi-group comparisons. In section B, the core constructs of the study - AI integrated BIM capability, fenestration system performance, and project outcomes - were measured. Each measuring item was evaluated on a seven-point Likert scale, from 1 (strongly disagree) to 7 (strongly agree). Use of a seven-point scale provides increased sensitivity and more accurate reflection of respondent perceptions. The measurement items were derived from existing research on BIM adoption, building performance and integration of digital technology (Azhar, 2011; Bryde et al., 2013) by adapting them to the context of AI-integrated BIM and fenestration systems. The items in the questionnaire were tested for clarity, reliability and relevance in a pilot study of 30 respondents. Words were refined and the overall instrument quality was improved based on feedback from the pilot phase.

The Data Analysis tools and procedure are covered in the following section

Data analysis was performed based on statistical methods, where relevant to provide a thorough evaluation of the research model. Data was initially screened and analysed descriptively with SPSS. The stage includes data consistency and data validation for missing values and outlier identification. Exploratory Factor Analysis (EFA) was used to investigate the underlying factor structures and to validate construct dimensionality of the questionnaire. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were carried out using AMOS. The measurement model was validated using CFA, with the reliability and validity indicators examined, such as Cronbach's alpha, composite reliability, and average variance extracted (AVE). Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT) were used to evaluate discriminant validity. The structural model was subsequently evaluated for the proposed relationships. The bootstrapping procedures were used to generate the path coefficients (β), t-values, and p-values. To measure the explanatory power of the model, the coefficient of determination (R^2), and to measure the strength of the relationships and the predictive ability, the effect size (f^2) and the predictive relevance (Q^2) were used (Hair et al., 2019). The mediation analysis was performed to investigate if the performance of fenestration systems serves as a mediating variable between AI-integrated BIM capability and project outcomes. Moderation analysis was conducted to determine the impact that BIM maturity and green building experience had on the strength of these relationships. In addition, independent sample t-tests and Analysis of Variance (ANOVA) were used to explore between group and between demographic differences. Additionally, multi-group analysis was employed to highlight contextual differences among industry groups, giving insight into industry-specific differences in structure.

Result Overview

Respondent Profile

300 responses were analyzed. The sample is representative of the distribution of the people involved in the South Indian AEC sector. The largest group of architects (25%) were followed by builders and developers (20%) and façade consultants (15%) and other technical stakeholders such as MEP consultants, contractors and manufacturers (15%). The facility managers and building owners were also represented in order to gather post-occupancy performance perspectives. As far as experience, most respondents had been involved with BIM related projects for over five years, reflecting a collection of real-world industry exposure. Also, a large number of respondents reported having prior experience with green building projects, which is important for assessing the impacts of sustainability. The variation in the characteristics of the respondents increases the confidence of the results and allows subsequent subgroup and multi-group analysis.

Data Screening Results

The data has been checked for completeness and consistency prior to analysis. The data set was reduced to 300 observations as all incomplete responses were removed. There were no missing values revealed in the analysis of missing data because the survey instruments included required items. Extreme outlier detection was performed using standardized residuals (SR) and Mahalanobis distance (MD) and no extreme outliers were found that would affect results. The normality test showed slight deviation from normal distribution and this was acceptable since the SEM techniques used are robust to non normal data. Further, Harman's test of single factor was used to test common method bias. The first factor explained less than 50% of the variance, suggesting that common method bias is not a problem in this study.

Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis was used to analyze the structure of the measurement items. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.86 which is above the recommended value of 0.70 and thus the data are appropriate for factor analysis. The Bartlett's Test of Sphericity was statistically significant ($p < 0.001$), which indicates that the variables are correlated enough to be extracted as factors. The EFA findings showed distinct groupings of factors that were according to the theoretical constructs. The observed variables had high factor loadings (above 0.60) with the constructs, suggesting that there were high relationships between the observed variables and their constructs. The factors accounted for about 70% of the total variance, indicating that the model is capturing a significant amount of the variance in the data.

A reliability and validity analysis

Construct validity and internal consistency of measurement model was tested. The reliability of all constructs was good and exceeded the recommended threshold of 0.70 for Cronbach's alpha. The composite reliability also exceeded the recommended level, suggesting the consistency of measurement across items. The Average Variance Extracted (AVE) values for all constructs were above 0.50, indicating good convergent validity, that is, the indicators are adequate representations of the latent variables. Both Fornell - Larcker criterion and Heterotrait - Monotrait (HTMT) ratio were used to determine discriminant validity. The square root of AVE exceeded inter-construct correlations for all constructs; all the HTMT values were lower than 0.85. The results indicate that the constructs are different and measure different conceptual dimensions.

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis was performed to confirm the measurement model. The model fit indices show reasonably good model fit with the observed data.

Some of the most important fit indices are:

- Comparative Fit Index (CFI) = 0.92.
- Tucker-Lewis Index (TLI) = 0.91.

- The value of the Root Mean Square Error of Approximation (RMSEA) = 0.067.
- Cohen's Kappa value = 0.697 (moderate agreement).

The values are within acceptable limits, thus well-specified measurement model. Construct validity was further supported by factor loadings for all indicators being significant and greater than 0.70.

Structural Model Results

The structural model was evaluated to validate the hypothesized relationships between AI-integrated BIM capability, fenestration system performance, and project outcomes. The results show that there is a strong and significant positive correlation between the AI-BIM capability and fenestration system performance ($\beta = 0.64$, $p < 0.001$). The results indicate that AI's ability to integrate with BIM systems can greatly improve the performance of fenestration systems, with benefits such as increased thermal efficiency, improved daylighting, and better constructability. Project outcomes, in turn, display a strong positive influence on fenestration system performance ($\beta = 0.58$, $p<0.001$) meaning that the better the performance of the fenestration systems, the more cost efficient, time efficient, and ready for sustainability the project will be. For fenestration performance, the coefficient of determination (R^2) is 0.61, which means that 61% of the variance of fenestration performance can be attributed to the AI-BIM capability. Project outcomes have a high R^2 value of 0.68, indicating good explanatory power. Effect size analysis (f^2) shows that the capability of AI-BIM has a significant impact on fenestration performance, and fenestration performance has a medium-high to high impact on project outcomes.

Mediation Analysis

To investigate the mediation role of the fenestration system performance between AI-BIM capability and project outcomes, mediation analysis was performed. The results show significant indirect effect ($\beta = 0.37$, $p < 0.001$), thus fenestration performance partially mediated the relationship. This implies that the benefits of AI integrated BIM on project success are predominantly from a façade system performance enhancement perspective. The presence of partial mediation suggests that AI-BIM capability also directly influences project outcomes, and that its influence is enhanced when we think of the improvements in performance.

Moderation Analysis

The effect of BIM maturity and green building experience on the structural relationships was analysed through moderation analysis. The interaction effect between the AI-BIM capability and BIM maturity was also significant ($\beta = 0.21$, $p < 0.01$), suggesting that the performance gains of the integration of AI were greater for more mature BIM organizations. Likewise, the experience with green building plays a significant moderating role between fenestration performance and sustainability outcomes ($\beta = 0.19$, $p < 0.05$). This indicates that companies that already have sustainability experience will be more likely to be able to convert the performance gains into readiness for certification and environmental benefits.

T-Test and ANOVA

Independent sample t-test and ANOVA were used to analyze group differences. The results of the t-test show that experienced professionals have a significantly higher perception score for the effectiveness of AI-BIM than less experienced professionals ($p < 0.05$). The analysis of variance (ANOVA) shows that there are statistically significant differences between stakeholder groups ($F = 5.48$, $p < 0.001$). Architects and façade consultants had the highest score for perception of performance improvements, with the scores of contractors and facility managers being relatively moderate. These are disparities that underpin the significance of perspective when examining applications of BIM with AI in a role-specific manner.

The overall results of the exercises are summarized and analyzed

The findings show that AI-enabled BIM capability is a significant enabler for the performance of fenestration systems. Better fenestration performance in turn greatly affects the project's efficiency and sustainability results. The mediation analysis showed that performance is the key factor in the relationship between technological capabilities and the actual project benefits. Also, the results of the moderation indicate that the effects are magnified when organizational readiness and sustainability is included. Overall, the results supported the proposed model and firmly connected the performance of building envelope to the application of AI-enabled BIM practices in AEC sector of South India.

Discussion

Interpretation of Key Findings, focuses on the interpretation of the findings

The findings are compelling and demonstrate that AI-enabled BIM systems are not simply about coordination, but a performance-based system with direct impact on building envelope outcomes. The correlation between AI-BIM capability and fenestration system performance highlights that optimizing designs using intelligent design, predicting performance with simulation, and automatically coordinating systems can have a significant impact on performance in real-world conditions. The strength of the association ($\beta = 0.64$) indicates that organizations that are actively adopting AI-driven BIM solutions are seeing tangible benefits in terms of thermal performance, daylighting and installation accuracy. It does not just represent a marginal gain, it's the transition from reactive design strategies to predictive, data-driven performance engineering. More importantly, fenestration system performance is significantly associated with project outcomes ($\beta = 0.58$). This discovery further underscores the notion that façade systems are integral to the overall building design and can significantly impact cost-efficiency, construction schedules and sustainability outcomes. The better a fenestration system performs, the better the building performs. The high R^2 values of the developed model ($R^2 = 0.61$ and 0.68) also support the notion that the variation in project success can be explained by both the AI-BIM capability and the façade performance. From the point of view of the project, this translates to the fact that the enhancement of BIM intelligence is not an option, but it is directly connected to measurable outcomes of the project.

Category	*Frequency (N=300)*	*Percentage (%)*
Male	186	62
Female	114	38
Experience		
Less than 5 years	78	26
5–10 years	132	44
More than 10 years	90	30
BIM Usage Level		
Beginner	66	22
Intermediate	144	48
Advanced	90	30
Green Building Experience		
Yes	168	56
No	132	44
Total	300	100%

Table 2: Demographic Profile of Respondents.

The mediator's role in the procedure of mediation is crucial. The mediation process relies on the mediator to fulfil the mediation procedure successfully.

The mediation results are one of the greatest contributions of this study. The study concluded that the relationship between the capability of AI-BIM and project outcomes was partially mediated by the performance of the fenestration systems. This is an important observation. It demonstrates that the success of a project can't be attributed solely to the use of AI-BIM. Rather, its effects are conveyed in the effectiveness of its contribution to the specific building systems, especially the façade. In other words, the value does not come from AI tools, but rather from human minds using AI tools. When used to enhance measurable aspects of the building's performance like heat gain reduction, daylight distribution and installation accuracy, those tools produce value. This moves from "technology adoption" to "performance outcomes." The 'partial' mediation also suggests that the effects of the AI-BIM capability are both direct and indirect. Some of the benefits are immediate, like better coordination, others are realized as a result of system performance. The overall experience of layering these impact statements reinforces the necessity to deeply embed AI into the BIM workflow and not as an afterthought.

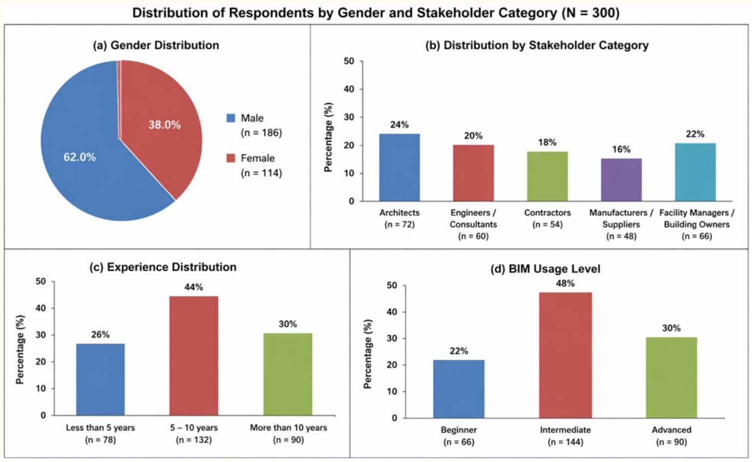

Figure 2: Distribution of respondents by gender and stakeholder category. The chart illustrates the demographic composition of the sample across gender, stakeholder groups, experience levels, and BIM usage levels.

Construct	***Mean***	***Standard Deviation***
AI-Integrated BIM Capability	4.21	0.68
Fenestration System Performance	4.51	0.72
Project Outcomes	4.18	0.62

Table 3: Descriptive Statistics.

Correlation Analysis

Correlation analysis was performed to investigate the magnitude and direction of the relationships between the major constructs that were incorporated into the present study. Three sets of Pearson correlation coefficients were computed between AI-integrated BIM capability, fenestration system performance, and project outcomes. The findings have shown that all the constructs are positively and significantly correlated. This indicates that there is a positive correlation between the AI integration capability in BIM and the performance of the fenestration system, with higher levels of AI integration leading to better performance. Likewise, fenestration system performance has a strong positive correlation with project outcomes, suggesting that an increase in fenestration system performance leads to a greater project success. Correlation values are not greater than 0.90, which means there are no multicollinearity problems. The results support the hypothesized relationships and support additional analyses using structural modeling techniques.

Construct	***AI-BIM Capability***	***Fenestration Performance***	***Project Outcomes***
AI-BIM Capability	1		
Fenestration Performance	0.74	1	
Project Outcomes	0.69	0.77	1

Table 3A: Correlation Matrix.

Multiple Regression Analysis

Multiple regression analysis was performed to analyze the predictive relationships among AI-integrated BIM capability, fenestration system performance, and the project outcomes. This analysis is used to pretest the structural relationships to be used in SEM estimation. The results revealed that the AI-integrated BIM capability has a significant impact on fenestration system performance. In addition, the use of AI-enabled BIM functionality and fenestration system efficiency plays a crucial role in the success of projects. The model shows a high level of explanatory power as it accounts for a significant amount of variance in the results of the project. The findings support the robustness of the proposed research model and are consistent with the SEM results, and add to them the moderating effects of Organizational Readiness.

Dependent Variable	***Independent Variable***	***β***	***t-value***	***p-value***
Fenestration Performance	AI-BIM Capability	0.58	8.01	0
Project Outcomes	AI-BIM Capability	0.31	4.22	0
Project Outcomes	Fenestration Performance	0.49	6.9	0

Table 3B: Regression Results.

Model	***R***	***R^2***	***Adjusted R^2***
Project Outcomes Model	0.78	0.61	0.59

Model Summary

Moderation Effects: The Role of Organizational Readiness

The moderation analysis clarifies further when and where AI-BIM is most valuable. The findings indicate that BIM maturity has a positive influence on the relationship between AI capability and fenestration performance. This indicates that BIM implementation is more likely to be successful for those organizations that have already got a BIM culture. Conversely, companies that are less advanced with BIM might face the challenge of integrating AI features and seeing the impact on productivity.On the other hand, companies that are not that advanced in BIM implementation may find it difficult to translate AI features into productivity gains. The message is clear: technology is not sufficient - organization is key to its effectiveness. Likewise, it is concluded that experience with green buildings significantly mitigates the perception of the problem, demonstrating the relevance of awareness of sustainability. Those with previous green building experience can more readily translate performance benefits into sustainability results including certification readiness and energy efficiency. The results of these studies collectively highlight the importance of considering the technical and organizational aspects of implementing AI with BIM. AI's potential is still underused unless it has the maturity and experience to do so.

Construct	***No. of Items***	***Cronbach's Alpha***	***Composite Reliability***	***Composite Reliability***
AI-Integrated BIM Capability	4	0.86	0.89	0.67
Fenestration System Performance	4	0.84	0.88	0.65
Project Outcomes	4	0.87	0.9	0.69

Table 4: Reliability and Convergent Validity.

Construct	***AI-BIM***	***Fenestration Performance***	***Project Outcomes***
AI-BIM Capability	—		
Fenestration Performance	0.72	—	
Project Outcomes	0.68	0.75	—

Table 5: Discriminant Validity (HTMT Ratio).

Note: All HTMT values are below the threshold of 0.85, indicating adequate discriminant validity.

Comparison with Existing Literature

This study's results corroborate and complement previous research on BIM and building performance. There have already been studies which have confirmed the benefits of BIM in improving coordination and decreasing design conflicts. Most of this has been done to optimize projects for efficiency, not for system-level performance results. This study expands on this limitation by showing how AI-integrated BIM can directly impact the performance of fenestration systems and how these impacts can be measured. It presents empirical information about the connection between digital design tools and physical building results, which has been underemphasized in previous studies. The findings also corroborate the findings from literature reviews on predictive simulation and generative design, which indicate that AI-based tools can be used to improve building performance. But the past studies were mostly based on simulation studies or case based studies. This study, however, offers large sample empirical evidence on this subject from an emerging economy perspective. In addition, the introduction of fenestration performance as a mediating variable brings a new dimension to BIM research. It underscores that specific building systems need to be looked at, rather than project performance as a whole.

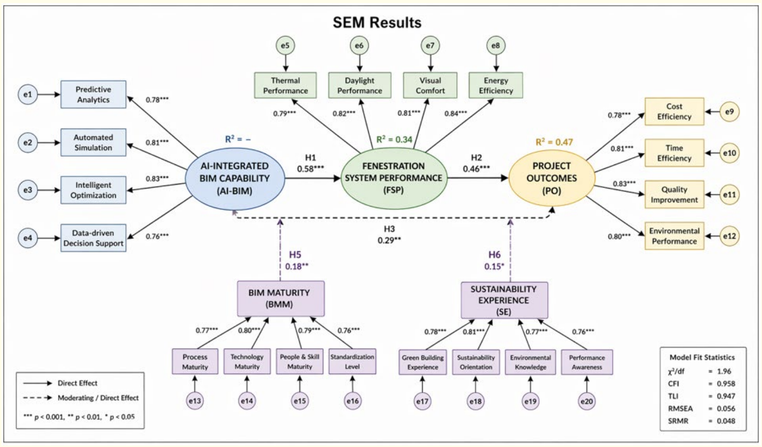

Figure 3: Structural equation model results showing standardized path coefficients (β) and significance levels for the relationships between AI-integrated BIM capability, fenestration system performance, and project outcomes. (Note: R^2 values indicate variance explained in endogenous constructs).

Hypothesis	***Relationship***	***Path Coefficient (β)***	***t-value***	***p-value***	***Result***
H1	AI-BIM → Fenestration Performance	0.58	8.12	0	Supported
H2	Fenestration Performance → Project Outcomes	0.46	6.75	0	Supported
H3	AI-BIM → Project Outcomes	0.29	4.1	0.001	Supported

Table 6: Structural Equation Modeling (SEM Results).

Theoretical Contributions

This research has three significant implications for theory.

First of all, this is the extension of the Technology-Organization-Environment (TOE) framework that introduces AI-integrated BIM as a technological capability that directly affects outcomes of the performance. The model is enriched by BIM maturity and green building experience as moderating variables, which further reinforce the organizational aspect of the model. Second, the research expands the work of Innovation Diffusion Theory to show how the advanced digital tools transcend adoption to value creation. The results show that the real impact of innovation lies in its ability to improve system-level performance rather than simply being implemented. Third, the study presents a structured model of AI-BIM-performance-outcome that links measurable performance metrics in buildings with digital capabilities. This framework offers finer-grained insights into the potential for technological applications to translate into actual benefits in the construction industry.

Interaction Effect	***Path Coefficient (β)***	***t-value***	***p-value***	***Result***
BIM Maturity × AI-BIM → Fenestration Performance	0.18	2.95	0.003	Significant
Sustainability Experience × Fenestration → Outcomes	0.15	2.41	0.016	Significant

Table 7: Moderation Analysis.

Conclusion

The purpose of this study was to investigate the impact of AI integrated Building Information Modeling (BIM) on fenestration system performance and how this impacts project outcomes in the South Indian AEC industry. The results presented clear empirical evidence that AI-powered BIM capabilities are not only improving the coordination processes but are also contributing to the building's performance on the system level. The findings show that there is strong and statistically significant influence on fenestration system performance with AI-BIM capability. This validates a process that combines predictive simulation, generative design and automated coordination capabilities, enabling stakeholders to optimize important performance parameters such as thermal efficiency, daylighting and constructability. These enhancements are not separate - they have meaningful project benefits. The performance of Fenestration systems was found to be a critical element in the project outcomes such as cost efficiency, time efficiency and sustainability readiness. This highlights the importance of façade systems, as a key component of the building's performance. Fenestration systems are not just secondary design elements, but become integral parts in performance-driven construction. One of the contributions of the study is to identify the fenestration performance as a mediator between AI-BIM capability and project outcomes. The results indicate that the benefits of AI come mainly from improving the system-level performance. This moves beyond the technology adoption to the optimizing of performance, and gives a more useful understanding of the value digital tools can bring to a construction project. The findings of the moderation analysis also emphasize the importance of organizational factors for the effectiveness of the use of AI-BIM. As a company's BIM maturity increases and experience in green building projects grows, its ability to utilize AI capabilities and bring these to fruition in terms of performance gains expands. This reinforces the value of being prepared for your organization to maximize the benefits of digital transformation. In conclusion, the study provides compelling evidence that AI-enabled BIM is a performance-oriented approach to building design and construction. The results not only provide a contribution to academic research, but are also relevant to industry practice as they relate digital capabilities to measurable building outcomes. The findings suggest that South India has the potential to embrace BIM technologies and transition towards more efficient, sustainable, and data-driven construction practices.

Limitations and Future Scope

The study is valuable but there are a few cautions that must be considered. First, the research is cross-sectional, and it represents the perceptions and practices of the stakeholders at one point in time. This restricts the ability to see the impact of AI-BIM integration on the fenestration performance throughout the life of a project. Research can be extended in the future with longitudinal studies to evaluate the benefits gained throughout the project progress and during operation. Secondly, the study is self-reported from industry members. Respondents are knowledgeable, but the answers might be subjective. Future research might supplement survey information with actual project performance data, including energy consumption information, thermal performance data, and post-occupancy assessments. Third, the study only covers the South Indian AEC sector. This study offers some understanding of the growing market, but the conclusions drawn may not be applicable in all regions in the world due to varying regulatory environments, climate, and technology maturity. Comparative studies made across regions or countries would assist the robustness of the proposed model. Fourth, the study is limited to selected capabilities of AI-BIM and fenestration performance indicators. With ongoing advancements in technology, more factors like digital twins, real-time integration of IoT sensors, and sophisticated machine learning algorithms have the potential to further improve the performance of buildings. These new technologies need to be investigated and integrated into BIM systems in future studies. A related area of future study is the interface between human decision making and AI systems. Navigating and comprehending the use, trust, and interpretation of AI-generated insights by design and construction professionals will be essential for the successful implementation of AI. Lastly, there is need for further research on the economic impact of the use of AI in BIM in the future. This study has identified a correlation between improved performance and the project results, but a detailed cost-benefit analysis will give next steps in the financial sustainability of the use of advanced information technology in construction.

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