Global Scientific and Academic Research Journal of Economics, Business and Management
ISSN: 2583-5645 (Online)
Frequency: Monthly
Published By GSAR Publishers
Journal Homepage Link- https://gsarpublishers.com/journals-gsarjebm-home/

The Role of Artificial Intelligence in Optimizing Sustainable Architectural Design

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Article History

Received: 21/04/2026
Accepted: 28/04/2026
Published: 30/04/2026

Vol –5 Issue – 4

PP: -55-65

Abstract

This study aims to analyze the effects of the utilization of Artificial Intelligence (AI) and architect competency on architectural design efficiency, as well as to examine the moderating role of architect competency in this relationship. The research background is based on the observed underutilization of AI in architectural practice due to limitations in human resource competencies. This study employs a quantitative approach using Partial Least Squares-Structural Equation Modeling (PLS-SEM) through SmartPLS, with a total of 394 architects and related practitioners as respondents. The results indicate that AI utilization has a positive and significant effect on architectural design efficiency. Architect competency is also found to have a positive and significant impact on design efficiency. Furthermore, architect competency serves as a moderating variable that strengthens the relationship between AI utilization and architectural design efficiency. These findings emphasize that the success of technology implementation depends not only on the technology itself but also on users' ability to optimize it. This study contributes by integrating technological and human resource factors into a conceptual model to enhance architectural design efficiency in the digital era.

***Keywords**: Artificial Intelligence, Architect Competency, Architectural Design Efficiency.*

1. Introduction

The development of Artificial Intelligence (AI) has driven a significant transformation in the architecture industry, particularly in design processes that are increasingly digitalized and data-driven (Albukhari, 2025). The integration of AI with Building Information Modeling (BIM) enables the automation of design processes, building performance analysis, and faster, more accurate decision-making (Albukhari, 2025). In addition, generative design based AI technology can produce multiple design alternatives simultaneously, thereby enhancing both efficiency and creativity in architectural design (Khan et al., 2025). AI applications have also evolved to support collaboration between architects and digital systems through language-based model integration with BIM, improving design interactivity (Jang & Lee, 2023).

On the other hand, the demand for design efficiency is increasing alongside the need for sustainable and energy-efficient buildings in response to global challenges (Yang, 2025). Consequently, design efficiency has become a key indicator for producing buildings that are technically, economically, and environmentally optimal (Attia, 2025). However, the successful implementation of AI in architecture depends not only on the technology itself but also on architects' competency in understanding and effectively utilizing these systems (Ni et al., 2024).

In current architectural practice, BIM has become a standard in the design process, yet AI utilization remains suboptimal and often limited to specific functions such as visualization or modeling (Baik, 2025). Studies indicate that many practitioners still rely on conventional or CAD-based approaches rather than AI-driven technology due to limited understanding and adaptation skills (Wardana et al., 2024). In developing countries, including Indonesia, the adoption of digital technologies in architecture faces challenges such as limited human resources and technological readiness, resulting in uneven AI integration in the design process (Yang, 2025). Although AI has great potential to improve design efficiency, its implementation in the field remains suboptimal due to a competency gap between technology and users (Valdebenito & Forcael, 2025). Many architects lack sufficient technical skills to operate and interpret AI system outputs effectively (Lin, 2024). Furthermore, AI use without a strong design understanding may produce design solutions that are less contextual and inconsistent with sustainability principles (Khan et al., 2025).

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Research shows that integrating AI with BIM can improve design efficiency by up to 32% in terms of project time and increase productivity by 28% compared to conventional methods (Attia, 2025). Moreover, AI can significantly reduce design errors through more accurate and automated data analysis (Attia, 2025). However, other studies indicate that not all organizations are capable of optimal AI implementation due to limited digital skills and technological readiness (Valdebenito & Forcael, 2025). This highlights a gap between technological potential and actual field implementation.

This study adopts the Technology Acceptance Model (TAM) developed by Fred Davis (2013), which posits that technology adoption is influenced by perceived ease of use and perceived usefulness. Additionally, the Resource-Based View (RBV) theory emphasizes that human resource competencies are strategic factors in creating competitive advantage in technology-based organizations. In this context, AI as a technology and architect competency as a human resource are key factors influencing architectural design efficiency.

Previous research indicates that AI plays a crucial role in enhancing design efficiency through automation and complex data analysis (Attia, 2025). Other studies also find that AI improves design quality through generative design and data-driven simulation approaches (Khan et al., 2025). Furthermore, integrating AI with BIM can enhance design communication and the effectiveness of the design process (Bagasi et al., 2025). However, research also emphasizes that the success of AI use is strongly influenced by users' skills and behavior in operating the technology (Ni et al., 2024). Despite this, most studies focus only on the direct effects of AI on design efficiency without considering the moderating role of architect competency. Research linking AI with sustainable architecture remains limited, and few studies examine the relationship between AI use, design efficiency, and architect competency in an integrated model.

The novelty of this study lies in integrating technology (AI), performance output (design efficiency), and human factors (architect competency) into a single conceptual model based on sustainable architecture. This research is important because it provides a more comprehensive understanding of how AI can be optimized in modern architectural practice. Practically, it contributes to enhancing architects' competency in facing digital transformation in the construction and design industry. Theoretically, it enriches literature on integrating technology and human resources to improve architectural design efficiency.

This study aims to analyze the effect of Artificial Intelligence (AI) utilization on architectural design efficiency and to examine the role of architect competency as a moderating variable in this relationship.

2. Literature Review

2.1 Utilization of Artificial Intelligence (AI) in Architectural Design Efficiency

Artificial Intelligence (AI) has become a key technology in enhancing the efficiency of architectural design processes through automation, generative design, and big data analysis to optimize building layouts and structures. Meta-analytic studies indicate that AI can significantly accelerate design, reduce material waste, and support faster decision-making through predictive data and building performance simulations (Li et al., 2025).

AI also enables generative design, where algorithms such as Generative Adversarial Networks (GANs) and other generative models produce numerous design alternatives in a short time, allowing broader exploration of design spaces compared to traditional methods (Jang et al., 2025). Furthermore, AI is not merely an automation tool but serves as a design partner that empowers architects with models capable of rapidly evaluating energy performance, form configurations, and relevant structural options based on complex parameters (Albukhari, 2025).

A 2025 review in *Applied Sciences* highlights that AI holds substantial potential in architectural design processes, including creative development, data analysis, and problem-solving, collectively improving design efficiency (Li et al., 2025).

Hypothesis 1: Utilization of Artificial Intelligence has a positive and significant effect on Architectural Design Efficiency.

2.2 Architect Competency and Its Influence on Design Efficiency

The quality and competency of architects are proven to be crucial factors in modern architectural design. Architect competency encompasses not only aesthetic and technical abilities but also adaptability to new digital technologies such as AI and data-driven design tools. Proficiency in understanding digital software and problem-solving skills is associated with better capacity to leverage the latest design technologies (Radcliffe, 2024). Recent research in *Sustainability* (2025) emphasizes that architects need to develop strong personal skills, including critical thinking, creative thinking, and digital literacy, to enhance career prospects and respond effectively to technological demands (Zhou et al., 2025).

In the context of technology adoption in the architecture industry, a study in *Buildings* (2023) shows that users' capabilities here referring to architects or design teams in understanding and adapting to digital technology strongly influence organizational decisions to adopt new tools, which in turn impacts design output and work efficiency (Algassim et al., 2023). Research also underscores that architects' skills are not only operational but involve integrating technical, aesthetic, and technological understanding to produce superior design solutions in the context of complex challenges (Radcliffe, 2024).

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Hypothesis 2: Architect Competency has a positive and significant effect on Architectural Design Efficiency.

2.3. Moderating Effect of Architect Competency on AI Utilization and Design Efficiency

In the context of technology integration, literature highlights that the positive effects of AI utilization on design efficiency are not automatic but are strongly influenced by architect competency in leveraging the technology. Reviews indicate that while AI can enhance productivity, its benefits are maximized when used by professionals competent in interpreting AI outputs accurately and integrating them with creative thinking (Sabono, 2025).

Moreover, literature suggests that although AI can take over routine tasks, the role of the architect as a creative leader remains essential. AI is effective only when architects strategically utilize its outputs to address design complexities, including cultural, environmental, and aesthetic contexts that algorithms cannot fully manage (Albukhari, 2025). The importance of competency is also reflected in studies highlighting challenges in technology adoption, where training and skill gaps are major barriers, indicating that architect competency can strengthen the relationship between technology use and performance outcomes (Algassim et al., 2023).

Therefore, architect competency functions as a moderating variable that determines the extent to which AI utilization translates into tangible improvements in design efficiency.

Hypothesis 3: Architect Competency strengthens or weakens the relationship between Utilization of Artificial Intelligence and Architectural Design Efficiency.

Based on the background and literature review, this research framework is developed to illustrate the relationships among Utilization of Artificial Intelligence, Architect Competency, and Architectural Design Efficiency, as well as the moderating role of architect competency in strengthening these relationships.

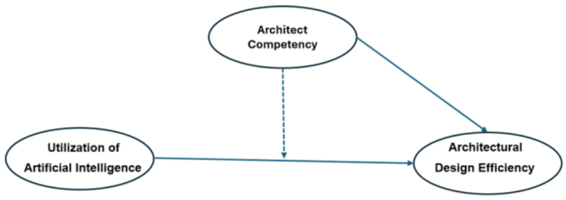

Figure 1. Research Framework

3. Research Methodology

3.1 Research Approach and Type

This study employs a quantitative approach because it aims to measure relationships and influences among variables numerically, as well as to test the formulated hypotheses using statistical tools. Quantitative research is commonly used to collect numerical data and analyze it through statistical procedures to determine causal relationships among research variables (Wikipedia, 2026). Moreover, quantitative research is designed to collect data that can be measured numerically, allowing the explanation and generalization of phenomena within a specific population, as stated in research methodology literature (Wikipedia, 2026).

The chosen research type is quantitative correlational research, which focuses on testing the relationships and effects of independent variables (Utilization of AI and Architect Competency) on the dependent variable (Architectural Design Efficiency), as well as examining the moderating role of Architect Competency in these relationships. This aligns with standard practices in causal-comparative or inferential quantitative research (Abdullah et al., 2022).

3.2 Population and Sample

The population of this study consists of professional architects or postgraduate architecture students who have experience in using AI technology for design, according to characteristics relevant to the variables being tested. In quantitative research, a population refers to the group for which the results are intended to be generalized (Wikipedia, 2026). The professional population can be quantified based on official data from the Indonesian Institute of Architects (IAI), which has 26,000 registered members across Indonesia (Ikatan Arsitek Indonesia, 2026). The purposive sampling method is employed, selecting respondents who have relevant experience with AI and architectural competency, ensuring that the survey data accurately reflects the relationships among the research variables (Emilia & Sulastri, 2025).

The minimum sample size is calculated using Slovin's formula (1960), applicable when the population size (N) is known:

$$N = \frac{N}{1 + Ne^2}$$

Where:

- nnn = sample size
- NNN = total population
- eee = margin of error

With a 5% margin of error:

$$n = \frac{26.000}{1 + 26.000\,(0.05)^2}$$

$$n = \frac{26.000}{1 + 26.000 + 0.0025}$$

$$n = \frac{26.000}{1 + 65}$$

$$n = \frac{26.000}{66}$$

n= 394 responden

Thus, a minimum of 394 respondents is required to provide a representative sample with a 5% margin of error. This calculation ensures the sample size is scientifically determined rather than assumed, allowing valid generalization of quantitative research results.

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3.3 Operational Definitions and Measurement of Variables

Each research variable is measured through indicators derived from literature review, with a closed-ended questionnaire as the primary instrument:

1. Utilization of Artificial Intelligence (AI): Measured by statements describing the frequency and intensity of an architect's use of AI in the design process.
2. Architect Competency: Measured by statements reflecting technical, digital, and creative abilities in using design technologies.
3. Architectural Design Efficiency: Measured by statements assessing the effectiveness of time management, design accuracy, and quality of design outcomes.

All variables are measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), a common practice in quantitative research to convert respondents' perceptions into numerical data (Koo & Yang, 2025).

Table 1. Operationalization of Variables and Indicators

Variable	Dimension	Indicators	Source
Utilization of Artificial Intelligence (AI)	Frequency & Intensity	1. AI is used in all stages of the design process2. AI helps accelerate the design process3. AI facilitates exploration of alternative designs4. AI improves structural calculation accuracy5. AI supports energy and material optimization	(Li et al., 2025)
Architect Competency	Technical & Digital Skills	1. Proficient in digital design software2. Able to apply generative design3. Demonstrates high creativity in design4. Able to interpret AI outputs effectively5. Able to integrate AI in collaborative team processes	(Zhou et al., 2025)
Architectural Design Efficiency	Time & Quality	1. Faster project completion time2. More accurate design outcomes3. Minimal structural errors4. Efficient use of materials5. Aesthetic quality meets standards	(Li et al., 2025)

3.4 Research Instrument

The research instrument consists of a Likert-scale questionnaire developed based on the variable indicators derived from previous theories. A pilot test was conducted to ensure the instrument's validity and reliability before actual data collection. In statistical methodology literature, validity and reliability are essential to ensure that the instrument measures what it is intended to measure consistently and accurately (Krisnawati et al., 2024).

3.5 Data Collection Techniques

Data were collected through online or offline questionnaires distributed to the selected sample. Questionnaires are a common data collection method in correlational research to obtain a comprehensive view of the relationships among variables in a large population (Emilia & Sulastri, 2025).

3.6 Data Analysis Techniques

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) via the latest version of SmartPLS. PLS-SEM was chosen because it is suitable for research models with latent variables, multiple indicators, and relatively small-to-medium sample sizes, and it allows simultaneous testing of direct, indirect, and moderating effects (Hair & Alamer, 2022).
The analysis was conducted in the following stages:

1. Initial Data Quality Check (Data Screening)

1. Check for missing data, extreme outliers, and respondent inconsistencies.
2. PLS-SEM is relatively tolerant to non-normal data distribution; however, outliers are still checked to avoid biased estimations.

2. Descriptive Analysis

1. Describe respondent characteristics such as age, experience, educational background, and distribution of variable indicators.
2. Provide an initial overview before conducting PLS modeling.

3. Validity and Reliability Testing Outer Model (Measurement Model):

1. Convergent Validity: Outer loadings > 0.70.
2. Average Variance Extracted (AVE): > 0.50 to ensure indicators represent their constructs.
3. Composite Reliability (CR): > 0.70 to test internal consistency.
4. Discriminant Validity: Fornell-Larcker Criterion and HTMT < 0.85 to confirm constructs are significantly distinct.

4. Structural Model Analysis (Inner Model) Direct Effects (H1 & H2):

1. Path coefficients (β) between Utilization of AI - Architectural Design Efficiency and Architect Competency - Architectural Design Efficiency.
2. Significance tested using bootstrapping (e.g., 5,000 resamples) to obtain t-values and p-values.

5. Moderation Analysis (H3)

The moderating effect of Architect Competency on the relationship between Utilization of AI - Architectural Design Efficiency was tested by creating an interaction term in SmartPLS:

1. Create interaction variable (AI - Architect Competency).
2. Insert the interaction term into the inner model.

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3. Test the significance of the interaction coefficient using bootstrapping.

Results indicate whether architect competency strengthens (positive) or weakens (negative) the effect of AI on design efficiency.

6. Overall Model Evaluation

1. R^2 is used to assess the predictive power of the dependent variable.
2. f^2 effect size evaluates the contribution of each independent variable to the dependent variable.

This procedure allows all hypotheses (H1, H2, H3) to be tested simultaneously and accurately using SmartPLS, consistent with modern quantitative research standards in PLS-SEM.

4. Results and Discussion

4.1 Results

4.1.1 Respondent Demographics

Demographic analysis was conducted to identify the basic characteristics of the research participants, including educational background, professional experience, and involvement in the use of Artificial Intelligence technology in architectural design, which provides an important context for interpreting the research results.

Table 2. Respondent Demographics (N = 394)

Characteristic	Category	Frequency	Percentage
Gender	Male	228	57.9%
	Female	166	42.1%
Age	21–25 years	102	25.9%
	26–30 years	148	37.6%
	31–35 years	78	19.8%
	>35 years	66	16.8%
Education	Bachelor's in Architecture	176	44.7%
	Master's in Architecture	168	42.6%
	Others (Professional/Certification)	50	12.7%
Work Experience	<2 years	96	24.4%
	2–5 years	142	36.0%
	6–10 years	88	22.3%
	>10 years	68	17.3%
Experience Using AI	<1 year	110	27.9%
	1–3 years	162	41.1%
	>3 years	122	31.0%
Total Respondents		394	100%

Source: Processed Data (2026)

Based on the demographic data, the majority of respondents in this study were male (57.9%), with the largest age group being 26–30 years old (37.6%), indicating that the study was dominated by a productive and technologically active age group. In terms of education, most respondents held a Bachelor's or Master's degree in Architecture, reflecting a sufficient level of academic competency in the field of architectural design. Regarding work experience, the majority of respondents had 2–5 years of professional experience (36.0%), suggesting that participants were in the early to mid stages of their careers. Furthermore, concerning experience with AI, most respondents had used AI technology for 1–3 years (41.1%), indicating that AI is relatively well-known and beginning to be integrated into architectural design practices.

4.1.2 Outer Model Assessment

1. Outer Loading Test

The outer loading test is conducted to evaluate the convergent validity of each indicator in measuring the latent constructs in the research model. The outer loading value indicates the extent to which an indicator reflects the latent variable it represents, with a common criterion being a loading value above 0.70, which is considered to indicate good validity.

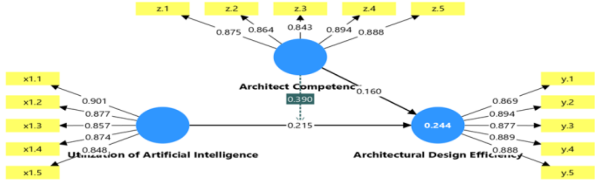

Figure 2. Outer Loading Diagram

Source: Processed Data (2026)

Table 3. Outer Loading Test

	Architect Competency	Architectural Design Efficiency	Utilization of Artificial Intelligence	Architect Competency x Utilization of Artificial Intelligence
x1.1			0.901	
x1.2			0.877	
x1.3			0.857	

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	Architect Competency	Architectural Design Efficiency	Utilization of Artificial Intelligence	Architect Competency x Utilization of Artificial Intelligence
x1.4			0.874	
x1.5			0.848	
y.1		0.869		
y.2		0.894		
y.3		0.877		
y.4		0.889		
y.5		0.888		
z.1	0.875			
z.2	0.864			
z.3	0.843			
z.4	0.894			
z.5	0.888			
Architect Competency x Utilization of Artificial Intelligence				1.000

Source: Processed Data (2026)

The results of the outer loading test indicate that all indicators for the variables Utilization of Artificial Intelligence, Architect Competency, and Architectural Design Efficiency have values above 0.70. This demonstrates that all indicators meet the criteria for convergent validity and are suitable for further analysis. The loading values for each variable are also relatively high (≥0.84), indicating that the indicators strongly represent their respective constructs, whether measuring AI utilization, architect competency, or architectural design efficiency. Meanwhile, the moderating variable shows a value of 1.000, indicating that the interaction construct in the model is properly formed. Thus, the measurement model in this study is considered valid, allowing the analysis to proceed to the structural model testing for hypothesis evaluation.

2. Construct Reliability and Validity Test

The construct reliability and validity test is conducted to ensure that each construct in the research model has adequate reliability and validity. This evaluation examines Composite Reliability (CR) ≥ 0.70 as an indicator of internal consistency and Average Variance Extracted (AVE) ≥ 0.50 as an indicator of convergent validity. A construct is considered to meet the criteria if the resulting values exceed these thresholds, making it suitable for subsequent structural analysis.

Table 4. Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Architect Competency	0.923	0.947	0.941	0.762
Architectural Design Efficiency	0.930	0.934	0.947	0.780
Utilization of Artificial Intelligence	0.921	0.931	0.940	0.759

Source: Processed Data (2026)

Based on the test results, all variables in this study show Cronbach's Alpha ≥ 0.70 and Composite Reliability ≥ 0.70, indicating that the constructs have very good reliability. Furthermore, Average Variance Extracted (AVE) ≥ 0.50 for all variables demonstrates that the constructs meet convergent validity requirements. Specifically, the variables Architect Competency, Architectural Design Efficiency, and Utilization of Artificial Intelligence each have AVE values above 0.75, indicating that the indicators explain more than 75% of their construct variance. This shows that the measurements of architect competency, AI utilization, and architectural design efficiency in this study are highly representative. Consequently, all constructs in the research model are considered reliable and valid, allowing them to be used to test the relationships between variables, including the effects of AI utilization and architect competency on architectural design efficiency.

3. Discriminant Validity

The discriminant validity test is conducted to ensure that each construct in the research model is clearly distinct from the others. This evaluation uses the HTMT (Heterotrait-Monotrait Ratio) ≤ 0.85, where a construct is considered discriminantly valid if the resulting value falls below this threshold.

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Table 5. Discriminant Validity

	Architect Competency	Architectural Design Efficiency	Utilization of Artificial Intelligence	Architect Competency x Utilization of Artificial Intelligence
Architect Competency				
Architectural Design Efficiency	0.172			
Utilization of Artificial Intelligence	0.072	0.247		
Architect Competency x Utilization of Artificial Intelligence	0.058	0.436	0.080	

Source: Processed Data (2026)

Based on the discriminant validity test using HTMT values, all relationships between constructs in the model show values below the threshold of 0.85. This indicates that each variable has good discriminant validity and can be clearly distinguished from one another. The highest value is found in the relationship between Architect Competency combined with Utilization of Artificial Intelligence and Architectural Design Efficiency, which is 0.436, yet it remains below the specified limit. Meanwhile, other inter-variable relationships show relatively low values, such as the relationship between Architect Competency and Utilization of Artificial Intelligence at 0.072, confirming that these two constructs do not overlap. These results indicate that the variables of AI utilization, architect competency, and architectural design efficiency in this study are conceptually and empirically distinct. Therefore, the research model meets the criteria for discriminant validity and is suitable to proceed to structural model analysis for hypothesis testing.

4.1.3 Inner Model

1. R-square

The R-square test is conducted to measure the ability of the independent variables to explain the variation in the dependent variable within the research model. The R-square value indicates the predictive strength of the model, with the following criteria: 0.75 for strong, 0.50 for moderate, and 0.25 for weak predictive power.

Table 6. R-square

	R-square	R-square adjusted
Architectural Design Efficiency	0.244	0.238

Source: Processed Data (2026)

Based on the results, the R-square value of 0.244 and the adjusted R-square value of 0.238 for the variable Architectural Design Efficiency indicate that Utilization of Artificial Intelligence and Architect Competency are able to explain 24.4% of the variation in architectural design efficiency. This value falls into the weak category, suggesting that although AI utilization and architect competency have an effect on design efficiency, there are still other factors outside the model that influence this variable. Therefore, these results indicate that the research model has limited predictive power but remains relevant for explaining the relationship between AI utilization, architect competency, and architectural design efficiency in the context of this study.

2. F-square

The f-square test is conducted to measure the effect size of each independent variable on the dependent variable within the research model. The f-square values are interpreted according to the following criteria: 0.02 for small, 0.15 for medium, and 0.35 for large effect sizes.

Table 7. F-square

	Architect Competency	Architectural Design Efficiency	Utilization of Artificial Intelligence	Architect Competency x Utilization of Artificial Intelligence
Architect Competency		0.033		
Architectural Design Efficiency				

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Utilization of Artificial Intelligence		0.060		
Architect Competency x Utilization of Artificial Intelligence		0.206		

Source: Processed Data (2026)

Based on the f-square results, the variable Architect Competency has a value of 0.033 on Architectural Design Efficiency, which falls into the small effect category. This indicates that architect competency influences design efficiency, but its contribution is relatively limited. Meanwhile, the variable Utilization of Artificial Intelligence has an f-square value of 0.060, also classified as a small effect, suggesting that AI utilization affects design efficiency, yet its impact is not dominant in explaining its variability.

In contrast, the moderating variable Architect Competency × Utilization of Artificial Intelligence has an f-square value of 0.206, which is considered a medium effect. This indicates that the moderating role of architect competency has a substantial influence on the relationship between AI utilization and architectural design efficiency. Therefore, it can be concluded that while the direct effects of each variable are relatively small, the interaction between architect competency and AI utilization contributes more significantly, emphasizing the importance of combining technology and individual capability to enhance design efficiency.

4.1.3 Hypothesis Testing

Hypothesis testing was conducted to examine the relationships between variables in the research model using bootstrapping analysis in SmartPLS. The significance of the relationships was determined by evaluating the path coefficients, t-statistics (greater than 1.96), and p-values (less than 0.05).

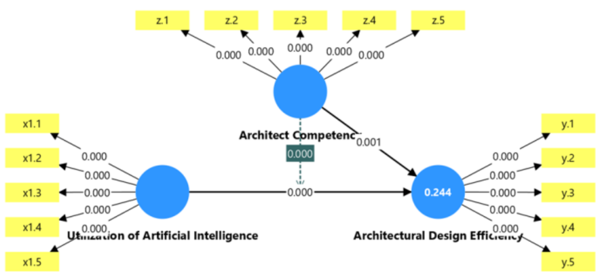

Figure 3. Path Coefficients Diagram

Source: Processed Data (2026)

Table 8. Hypothesis Testing

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Architect Competency -> Architectural Design Efficiency	0.160	0.166	0.047	3.400	0.001
Architect Competency x Utilization of Artificial Intelligence -> Architectural Design Efficiency	0.390	0.386	0.048	8.164	0.000
Utilization of Artificial Intelligence -> Architectural Design Efficiency	0.215	0.217	0.046	4.659	0.000

Source: Processed Data (2026)

1. Hypothesis 1 (H1)

The test results indicate that the path coefficient of Utilization of Artificial Intelligence on Architectural Design Efficiency is 0.215, with a t-statistic of 4.659 and a p-value of 0.000 (less than 0.05). This demonstrates that AI utilization has a positive and significant effect on architectural design efficiency. Therefore, H1 is supported, meaning that higher levels of AI utilization lead to greater design efficiency.

2. Hypothesis 2 (H2)

The relationship between Architect Competency and Architectural Design Efficiency shows a path coefficient of 0.160, with a t-statistic of 3.400 and a p-value of 0.001 (less than 0.05). These results indicate that architect competency has a positive and significant effect on design efficiency. Hence, H2 is supported, suggesting that higher architect

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competency contributes to increased efficiency in architectural design.

3. Hypothesis 3 (H3)

The moderation test shows that Architect Competency moderating the relationship between AI Utilization and Architectural Design Efficiency has a path coefficient of 0.390, with a t-statistic of 8.164 and a p-value of 0.000 (less than 0.05). This indicates that architect competency significantly moderates the effect of AI utilization on design efficiency. The positive coefficient implies that higher architect competency strengthens the influence of AI on architectural design efficiency. Therefore, H3 is supported, meaning that as architect competency increases, the positive impact of AI on design efficiency becomes stronger.

4.2 Discussion

4.2.1 Hypothesis 1: The Effect of Utilization of Artificial Intelligence on Architectural Design Efficiency

The results of the study indicate that the utilization of Artificial Intelligence has a positive and significant effect on architectural design efficiency. This finding suggests that the use of Artificial Intelligence can enhance speed, accuracy, and effectiveness in the design process. However, in practice, the utilization of Artificial Intelligence is still not optimal and tends to be limited to specific functions such as visualization or modeling. This demonstrates a gap between the potential of Artificial Intelligence and its actual implementation, as some architects continue to rely on conventional approaches such as computer-aided design due to limited understanding of the technology.

Theoretically, this finding aligns with the Technology Acceptance Model developed by Fred Davis in 2013, which states that technology will have a positive impact if users perceive it as useful. In this context, Artificial Intelligence provides tangible benefits in improving design efficiency. This finding also supports the studies of Attia in 2025 and Khan and colleagues in 2025, which indicate that Artificial Intelligence can enhance design efficiency and quality through automation and data-driven analysis. Therefore, higher utilization of Artificial Intelligence corresponds to greater potential improvements in architectural design efficiency. Organizations that optimally adopt Artificial Intelligence are likely to gain advantages in productivity and design quality compared to those relying on conventional methods.

4.2.2 Hypothesis 2: The Effect of Architect Competency on Architectural Design Efficiency

The study results indicate that architect competency has a positive and significant effect on architectural design efficiency. This finding shows that technical skills, creativity, and digital literacy are critical factors in producing efficient designs. In practice, one of the main barriers to technology adoption is limited human resources, particularly in understanding and operating Artificial Intelligence. This underscores that architect competency is a key factor in determining the success of the design process.

Theoretically, this finding is consistent with the Resource-Based View, which emphasizes that human resource competency is a strategic asset for creating competitive advantage. In this context, architect competency represents a primary resource influencing design efficiency. The finding is further supported by research conducted by Ni and colleagues in 2024, which states that successful technology adoption depends heavily on the ability of users to operate it effectively. Therefore, higher architect competency leads to greater design efficiency. The implication is that enhancing architect competency through training and the development of digital skills is a critical strategy for improving architectural design performance.

4.2.3 Hypothesis 3: The Moderating Role of Architect Competency on the Relationship between Artificial Intelligence and Design Efficiency

The results indicate that architect competency significantly strengthens the relationship between Artificial Intelligence utilization and architectural design efficiency. This means that Artificial Intelligence has a greater impact on design efficiency when used by architects with higher competency levels.

In practice, although Artificial Intelligence has great potential, its implementation is often suboptimal due to limited capability in interpreting Artificial Intelligence outputs and integrating them into the design process. Using Artificial Intelligence without sufficient competency may result in designs that lack contextual relevance. Theoretically, this finding integrates the Technology Acceptance Model and the Resource-Based View, suggesting that technology will provide maximum benefits when supported by adequate human resource competency. This result extends previous research, as most prior studies, such as those by Attia in 2025 and Bagasi and colleagues in 2025, focused primarily on the direct effects of Artificial Intelligence without considering the moderating role of human competency.

The implication is that organizations need not only to adopt Artificial Intelligence but also ensure that architects possess sufficient competency to maximize the technology's benefits. The integration of technology and human competency is therefore key to achieving optimal and sustainable architectural design efficiency.

5. Conclusion

5.1 Conclusions

This study demonstrates that the utilization of Artificial Intelligence and architect competency are key factors in enhancing architectural design efficiency. The analysis results indicate that the use of Artificial Intelligence has a positive and significant effect on design efficiency, confirming that data-driven and automated technologies can improve the speed, accuracy, and quality of the architectural design process. In addition, architect competency also has a positive and significant impact on design efficiency. This finding highlights that technical skills, creativity, and digital literacy of architects are crucial elements in optimizing design outcomes, especially in the context of digital transformation within the architecture industry.

Furthermore, the study finds that architect competency serves as a moderating variable that strengthens the relationship between Artificial Intelligence utilization and architectural design efficiency. In other words, the positive effect of Artificial Intelligence on design efficiency is maximized when supported by high architect competency. This underscores that successful technology implementation depends not only on the availability of technology but also on the readiness and capability of human resources to utilize it effectively. Overall, this research contributes by integrating technology factors (Artificial Intelligence), human factors (architect competency), and performance outcomes (design efficiency) into a comprehensive model. The findings confirm that the synergy between technology and human competency is the key to achieving optimal and sustainable architectural design efficiency in the digital era.

5.2 Implications

5.2.1 Practical Implications

The findings of this study have several practical implications for architecture professionals and organizations. First, the positive impact of Artificial Intelligence on design efficiency suggests that firms should invest in AI technologies not only for visualization but also for design analysis, simulation, and data-driven decision-making. This can lead to faster project completion, reduced errors, and optimized use of resources.

Second, architect competency plays a critical role in leveraging technology effectively. Organizations must therefore focus on developing architects' technical skills, creativity, and digital literacy through continuous training, workshops, and skill enhancement programs. High competency ensures that AI tools are used to their full potential, maximizing design efficiency and innovation.

Third, the moderating role of architect competency indicates that the integration of human skills and technology is essential. Firms that combine AI adoption with skilled architects can achieve a competitive advantage by delivering high-quality designs efficiently.

5.2.2 Theoretical Implications

This study contributes to theory by integrating the Technology Acceptance Model and Resource-Based View within the context of architectural design. The results confirm that technology alone is insufficient to drive efficiency; human resources with high competency are equally necessary to realize the full benefits of AI. Moreover, the study extends previous research by demonstrating the moderating effect of human competency in the AI design efficiency relationship. Most prior studies focused only on the direct impact of AI, overlooking the critical role of human factors in maximizing technology benefits. This provides a more comprehensive understanding of how technology and human capabilities interact to influence design outcomes.

5.3 Recommendations

Based on the study findings, it is recommended that architecture practitioners enhance the utilization of Artificial Intelligence more optimally throughout the design process. This should go beyond visualization and include design analysis, simulation, and data-driven decision-making to improve work efficiency. Architecture organizations and companies should prioritize the development of architect competency, particularly in digital skills and Artificial Intelligence application, through training, workshops, and continuous learning programs. This ensures that adopted technologies are fully leveraged rather than serving merely as supportive tools.

For academia, the results of this study can serve as a foundation to integrate Artificial Intelligence and digital technology into architectural curricula, preparing graduates to meet the increasing demands of a technology-driven industry. For future research, it is recommended to include additional variables such as design innovation, team collaboration, or organizational factors, and to broaden the research scope to provide a more comprehensive understanding of the factors influencing architectural design efficiency.

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