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Artificial Intelligence and Machine Learning Implementation Patterns in Architecture: A Cross-Sectional Analysis of Academic and Industry Sectors in Saudi Arabia

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Abstract

This study presents one of the first empirical assessments of artificial intelligence (AI) and machine learning (ML) adoption within architectural academia and the Architecture, Engineering, and Construction (AEC) industry in Saudi Arabia. Using a cross-sectional survey of 113 respondents—60 academics and 53 industry professionals—the research examines familiarity, current usage, perceived benefits, challenges, and future readiness for AI/ML integration. Results show high familiarity and strong perceived importance across both sectors, yet actual implementation remains uneven. Very large firms demonstrate the highest adoption capacity, while small and medium-sized firms face financial and organizational constraints. Academic institutions exhibit moderate familiarity but limited curricular and research integration due to faculty expertise gaps, restricted access to tools, and traditional pedagogical structures. Despite these barriers, both sectors consistently identify AI/ML as critical for enhancing creativity, efficiency, and industry preparedness. The study highlights organizational capacity as the primary determinant of adoption. It concludes with recommendations for curriculum reform, faculty training, industry–academia collaboration, and national policy frameworks to accelerate digital transformation aligned with Saudi Vision 2030. This research establishes a foundational baseline for future longitudinal and comparative studies on AI/ML integration in the regional architectural ecosystem.

Keywords: artificial intelligence adoption in architecture; academic-industry technology; Saudi Arabia construction technology; machine learning integration in AEC industry

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1. Introduction

Artificial Intelligence (AI) and Machine Learning (ML) have rapidly expanded across global industries, transforming workflows, decision-making, and performance optimization. Sectors such as healthcare, manufacturing, finance, and logistics have already witnessed measurable gains in efficiency and predictive capability due to the integration of data-driven algorithms, automation systems, and intelligent computational models. In recent years, architecture and the broader Architecture, Engineering, and Construction (AEC) industry have followed a similar trajectory, with AI/ML increasingly used for generative design, structural optimization, energy performance prediction, automated visualization, and construction monitoring.

Parallel advancements are taking place within architectural education, where AI-enabled tools are reshaping design studios, digital representation, and pedagogical models. Several systematic review studies demonstrate that AI and ML support personalized learning, intelligent tutoring, automated assessment, and the integration of immersive technologies—preparing future architects for computationally intensive professional environments [1,2]. As universities adopt AI-supported workflows and as design practice transitions toward algorithmic and data-centered methods, understanding the readiness, familiarity, and adoption patterns of these technologies becomes essential.

For Saudi Arabia and the wider Gulf region, the integration of AI and ML is especially timely. National initiatives linked to Vision 2030 emphasize digital transformation, innovation-driven industries, smart cities, and advanced construction technologies. The architecture and construction sectors—responsible for major urban development projects—stand to benefit significantly from AI-based optimization, enhanced productivity, and improved sustainability. However, capitalizing on these opportunities requires a clear understanding of the current adoption landscape across both academic institutions and industry settings. This motivates the present study, which examines how AI/ML is being perceived, utilized, and integrated by architects, educators, and firms within the region.

Despite the global momentum surrounding AI/ML innovations in architecture and construction, there remains limited empirical evidence on how these technologies are being adopted in the Middle East and the Gulf Cooperation Council (GCC) context. The existing literature focuses heavily on Western, European, and East Asian markets, leaving a noticeable gap in region-specific studies that explore professional readiness, educational integration, and organizational barriers. While related research such as BIM adoption studies in Saudi Arabia indicates early-stage digital maturity and challenges related to training, policy, and workflow transformation, comparable research on AI/ML has not yet been systematically documented [3].

Preliminary reports and anecdotal observations suggest that architectural firms and academic programs in the GCC vary widely in their familiarity with AI/ML, available resources, and levels of integration. However, no comprehensive, data-driven assessment has been conducted to quantify actual adoption levels, perceived benefits, challenges, or the trajectory of future implementation. This absence of evidence restricts policymakers, educational institutions, and industry leaders from making informed decisions regarding training, curriculum development, investment strategies, and digital transformation planning.

This study addresses this gap by providing the first combined assessment of AI/ML adoption across architectural academia and industry in Saudi Arabia—offering a foundational understanding of current practices, readiness levels, and critical barriers to digital innovation in the region.

The aim of this study is to examine the current state of AI and ML adoption in architectural education and professional practice in Saudi Arabia by assessing familiarity, identifying implementation trends, and understanding perceived opportunities and challenges. Specifically, the study evaluates how AI/ML technologies are being used within academic programs and professional firms, examines their perceived impact on design efficiency, visualization, project management, and innovation, and identifies the barriers limiting wider adoption. It further compares adoption patterns across academia and industry to highlight areas of alignment or divergence and concludes with evidence-based recommendations to support policy development, curriculum enhancement, and industry readiness.

This study is guided by a set of overarching research questions that collectively explore the current state of AI/ML in architectural academia and industry: it first examines the level of familiarity with AI and ML among educators and practitioners, then investigates

the extent to which these technologies are integrated into curricula, research activities, and professional workflows. It also explores the perceived benefits of AI/ML in enhancing design, analysis, learning, and project delivery, while identifying the challenges and barriers that limit adoption within both sectors. Finally, it assesses how adoption patterns differ between academic environments and the AEC industry in Saudi Arabia, providing a comparative understanding of readiness and technological maturity.

Understanding the current level of AI/ML adoption is essential for guiding strategic decisions in education, industry, and national policy. As Saudi Arabia positions itself as a regional hub for digital innovation, architectural education and the AEC industry must align with emerging technological competencies. This study provides critical contributions across multiple sectors: it offers policymakers evidence to support national digital transformation goals, workforce development strategies, and technology adoption policies; it equips academic institutions with insights to enhance curricula, faculty development, resource allocation, and the integration of AI-driven pedagogies; it helps industry practitioners assess readiness levels and prioritize training, investments, and workflow innovation; and it supplies researchers with foundational data addressing a previously underexplored regional context. By presenting the first comprehensive assessment of AI/ML adoption within Saudi Arabia's architectural academia and industry, this study establishes a baseline that will inform future longitudinal research, strategic planning, and cross-sector collaboration.

2. Literature Review

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into architecture and design has attracted significant attention from both academia and industry in recent years [4,5]. Although these technologies are still emerging, they are progressively transforming design workflows, project management, and architectural education [4,6,7].

This review synthesizes current research supporting AI/ML adoption in architectural practice and academia, placing particular emphasis on regional disparities and sector-specific challenges [6,8]. In doing so, it seeks not only to map the technological landscape but also to reflect on the lived experiences and concerns of practitioners and educators navigating this evolving terrain [6,8].

In the field of architecture, artificial intelligence (AI) and machine learning (ML) refer to computational systems that mimic human reasoning and pattern recognition to assist with tasks like generative design, optimization, and simulation [9–16]. According to a scientometric analysis of more than 40,000 studies by [17], AI techniques like neural networks, genetic algorithms, fuzzy logic, and general machine learning approaches predominate in the AEC industry today. Convolutional neural networks (CNNs) are becoming increasingly common in these techniques, which have mainly supported optimization, uncertainty management, and performance analysis. Despite the amount of research, actual implementation is still uneven and dispersed, with many opportunities—like robotics and life-cycle cost analysis—going unexplored [18–20].

Applications of AI and ML in architecture are numerous, ranging from construction management and predictive analytics to early-stage generative design [15,21–23]. According to [24]'s survey, only 6–8% of businesses have completely incorporated AI into their operations, even though it is being investigated experimentally. Most of the use is "low-invasive," with chatbots and other AI tools used for early design stages to generate images or write. According to [25] Turin's small businesses use AI to manage legal restrictions and boost creativity, particularly when developing new concepts. In a similar vein, ref. [25] discovers that AI facilitates every stage of architectural design, especially ideation and visualization.

Ref. [17] corroborate these findings, demonstrating how AI is applied across Architecture, Engineering, and Construction for purposes such as project performance management, computational simulation, and structural design optimization. Ref. [26] further note that AI enhances analytical precision and enables more strategic project planning. Additionally, ref. [3] identify Building Information Modeling (BIM) as a critical prerequisite for AI integration, particularly in the context of conflict detection and project coordination within Saudi Arabia's construction projects.

Even though there is a wealth of research on AI in architecture worldwide, studies that concentrate on the Middle East and GCC region are still noticeably underrepresented. According to [3], Saudi Arabia's adoption of BIM, a forerunner to AI/ML technologies, is still in its early stages of development due to a lack of training and inadequate policy frameworks. More extensive AI/ML integration is probably hampered by the same structural obstacles. To close these gaps, ref. [17] urge increased industry–academia cooperation, pointing out that institutional and regional preparedness must coincide with technological capability.

Adoption of AI/ML in business and education is still hampered by several interconnected obstacles. According to [17], effective implementation of AI tools in the industry requires a substantial investment of time, money, and infrastructure. Organizational resistance to re-engineering workflows is another point made by [3] particularly in companies without leadership support or policy incentives. According to [24], 94% of architects surveyed were concerned that AI tools might be "accurate but wrong," highlighting a general lack of confidence in dependability and trust.

Deficits in training were also identified as a major barrier. Although most stakeholders recognize the importance of digital transformation, ref. [3] note that inadequate technical training in BIM (and consequently AI/ML) continues to be a significant obstacle [26].

Refs. [1,27] share these worries about education, emphasizing the significance of data quality, algorithmic transparency, and ethical issues like bias and privacy. According to [28], there is a significant pedagogical gap because although most students are aware of AI, only 1.3% receive formal instruction. According to [8], faculty members are worried that students' creative judgment may be diminished by an excessive reliance on AI.

Ref. [17] back up these finds by pointing out AI's use in construction fields like project performance, simulations, and structural stuff. Ref. [26] further demonstrate that AI enhances the precision of analysis and supports more strategic project planning. Ref. [3] think Building Information Modeling (BIM) is key for adding AI, especially for finding problems in Saudi Arabia's building projects.

AI is assuming an increasingly prominent role in architectural education, though its integration remains uneven across institutions. Ref. [1] find that higher education institutions dominate AI education research, with primary emphasis on adaptive learning, intelligent tutoring systems, and academic performance prediction. Ref. [2] demonstrate that machine learning can enhance personalized learning outcomes and support evidence-based decision-making through the analysis of educational data. Ref. [27] concur, arguing that AI can promote educational equity and support evidence-based institutional decision-making.

Despite the recognized value of AI, its adoption in architectural curricula remains inconsistent. Ref. [29] report that AI has not yet been formally embedded in mainstream curricula, while student-led uptake of AI tools is increasing independently of institutional guidance, suggesting that learners are driving adoption ahead of formal pedagogical frameworks. Ref. [30] argues that architectural programs must revise their curricula in response to the evolving professional landscape, particularly given the emergence of human–AI co-creative workflows in contemporary practice.

Building on the reviewed literature, this study is informed by complementary perspectives from the Technology Acceptance Model (TAM), Diffusion of Innovations theory, and socio-technical systems theory to interpret AI/ML adoption in architectural academia and the AEC industry. TAM provides a lens for understanding individual perceptions of usefulness, ease of use, and readiness, which are reflected in measures of familiarity, perceived importance, and future intentions. Diffusion of Innovations theory supports the interpretation of uneven adoption across firm sizes and institutional contexts, emphasizing the roles of organizational structure, resource availability, and innovation culture. Socio-technical systems theory frames AI/ML adoption as an interaction between technological capabilities, human agency, organizational practices, and institutional norms. Together, these perspectives inform the study's analytical approach, enabling adoption patterns to be interpreted not only descriptively, but as outcomes of interconnected technical, organizational, and human factors.

Synthesizing the reviewed literature, this study adopts a conceptual framework that positions AI/ML adoption in architecture at the intersection of three interrelated dimensions: (1) organizational and institutional readiness, including resources, leadership, training, and policy support; (2) modes of AI/ML use in architectural design and education, ranging from generative design and visualization to simulation, optimization, and pedagogical applications; and (3) perceived outcomes and constraints, encompassing creativity, efficiency, sustainability, ethical concerns, and educational transformation. This framework directly informs the survey structure, variable grouping, and analytical strategy, ensuring that empirical findings are interpreted within a coherent theoretical and disciplinary context rather than as isolated indicators of technology uptake.

Table 1 presents the principal studies that informed the development of the survey questionnaire.

Table 1. Major literature reliance on questionnaire.

Citation	Focus/Objective	Key Findings	Relevance to Current Study
[1] Education/Academia	Categorizes AI applications in education; examines trends, theories, and contexts.	AI applications classified into adaptive learning, intelligent assessment, profiling, and emerging tech; higher education dominates research; calls for more practice-oriented and interdisciplinary studies.	Provides baseline for AI/ML adoption framework and theoretical underpinnings for academic survey analysis.
[2] Education/Pedagogy	Examines ML as a teaching strategy to improve learning personalization and engagement.	ML enhances personalized feedback, engagement, and academic performance; stresses ethical use, teacher training, and data governance.	Links ML-driven personalization to architectural pedagogy and professional learning contexts.
[27] Education/Technology Integration	Analyzes role of ML in personalization, adaptive assessment, and predictive analytics.	ML improves tutoring systems and predictive learning outcomes; underscores ethical AI, bias control, and interdisciplinary collaboration.	Informs framework for evaluating AI/ML adoption and readiness across academia and AEC firms.
[17] AEC Industry	Maps global AI research trends, tools, and methods in the AEC sector.	Dominant use of neural networks, fuzzy logic, and genetic algorithms; rise in CNNs and deep learning; gaps in robotics, sustainability, and LCA applications.	Establishes global benchmark for AI/ML research in AEC; highlights gaps relevant to firm-level survey.
[3] AEC Industry/Saudi Arabia	Evaluates BIM adoption, benefits, and barriers within the Saudi construction sector.	BIM adoption remains limited; key benefits include conflict detection and quality control; major barriers are workflow resistance, lack of expertise, and absence of national policy.	Provides Saudi-context foundation for assessing digital transformation readiness and parallels with AI/ML adoption barriers.

3. Methodology

This study adopts a quantitative cross-sectional research design using a structured online survey administered to two distinct respondent groups: (1) architectural academics working in Saudi universities, and (2) professionals employed in architecture, engineering, and construction (AEC) firms across Saudi Arabia. A cross-sectional approach was chosen

to capture a snapshot of the current familiarity, adoption levels, perceived benefits, and challenges related to AI and machine learning (ML) within both educational and professional environments. The design also enables direct comparison between academia and practice to identify alignment or divergence in technological readiness.

The target population comprised the following sectors. Academic Sector: faculty members, lecturers, researchers, and teaching staff within architectural and architectural engineering programs at Saudi universities. Industry Sector: architects, engineers, project managers, digital design specialists, and upper management personnel from architectural and multidisciplinary AEC firms.

A non-probability purposive sampling strategy was used to reach individuals with direct experience in architectural education or practice. A total of 113 valid responses were collected: 60 from academia and 53 from industry, ensuring adequate sample sizes for descriptive and inferential analysis. The sample reflects broad geographic and institutional diversity, including major public and private universities and firms across the Central, Eastern, and Western regions.

3.1. Sampling Strategy and Representativeness

The study employed a purposive, non-probability sampling strategy to target participants with direct involvement in architectural education and professional practice in Saudi Arabia. The target population comprised academic staff (including faculty members, lecturers, researchers, and teaching staff) from architectural and architectural engineering programs, as well as professionals from architectural and multidisciplinary AEC firms occupying roles such as architects, engineers, project managers, digital design specialists, and upper management. Survey dissemination relied on professional networks, institutional mailing lists, and industry contacts primarily concentrated in the Central, Eastern, and Western regions, reflecting the current geographic distribution of architectural institutions and AEC activity within the Kingdom. While the final sample size (n = 113) is appropriate for an exploratory cross-sectional study, it does not constitute a statistically representative national sample. Accordingly, the findings should be interpreted as indicative of prevailing trends and readiness levels rather than as fully generalizable benchmarks, with broader representativeness requiring future studies using stratified or probability-based sampling designs.

Data were collected using an online questionnaire distributed via institutional emails, professional networks, and social media channels commonly used by architectural communities in Saudi Arabia. Participation was voluntary and anonymous. The survey included clear instructions, estimated completion time, and consent information. Two parallel versions of the survey were designed—one for academia and one for industry—allowing for contextualized questioning while maintaining comparability across key variables. Data collection occurred over a four-week period.

The survey instrument was structured into thematic sections derived from the literature review and aligned with global AI/ML assessment frameworks.

Different Likert scale ranges were intentionally employed to align with the nature of each construct: familiarity and perceived importance were measured using 3-point scales to capture broad levels of awareness, while perceived benefits, challenges, and future intentions were assessed using 5-point scales to allow finer-grained attitudinal differentiation.

The following section presents the survey questions used in both the AEC and educational sector instruments. Each question was selected on the basis of its relevance to the existing literature, as shown in Table 2, providing the scholarly justification for each item's inclusion.

Table 2. Questionnaire with literature relevancy.

Thematic Sections	AEC Survey Question	Supporting Data and Insights
Demographic and Organizational Information	(Regional Setting) (Typology of Firm and its focus) (Size of Firm) (Participant Role in the Firm)	- The authors' case study findings show that company size can influence technology adoption [3].
Familiarity and Awareness of AI/ML	(Familiarity of the Participant in AI/ML)	- "Lack of awareness" justified by the authors act as cultural barrier of BIM adaptation in Gulf [3].
Current Adoption and Use of AI/ML	(Firms Adoption of AI/ML Technologies in their Processing) (Duration of Adoption of Firms' AI/ML)	- They describe AI Adoption in AEC as an "emerging area" and as needing more research [17]. - They note that Saudi Arabia still had to adopt fully BIM despite its benefits. They describe the usage of AI/ML tools in Saudi Arabia as limited [3]; (general) PR actioners are experimenting with using AI and the adoption mostly has a "low-invasive" use—only 8% of firm leaders using it and its potential in integrating into practice [24].
Areas of AI/ML Application	(Areas of Practice in the Participant's Firm using AI/ML	- The comprehensive case study results show that AEC communities use AI techniques in 'optimization, simulation, uncertainty analysis, project management' and more specifically for structural design [17].
AI/ML Tools or Techniques Used	Types of AI/ML Usage by Participant)	- With the scientometric analysis that the authors made they have found that AI usage in AECI firms is primarily in optimizations, genetic algorithm, neural network, simulations, uncertainty, construction management, fuzzy logic, fuzzy sets, machine learning, artificial intelligence, etc. [17].
Training in AI/ML (Workforce training)	(Firms Initiatives for Training (ongoing/had been undergone) (Future Plans of AI/ML Training for employees)	- The authors highlight that their survey observed that although people recognize the importance of BIM, the lack of training to produce a skilled staff will hinder its adoption [3]. - The paper stated that construction companies need to adjust their corporate structure to incorporate AI into their network [26].
Decision-Making Process	Decision-Making Process AI/ML adoption)	- The authors emphasize the importance of AI methods for efficiency and effectiveness in the AEC tasks and urge the optimization of implementation of AI's cost to achieve the value of its implementation [17]. - Since there is a lack of policy reinforcement of BIM adoption in Saudi Arabia, this suggest that the decision-making process in internal leadership plays a critical role in implementing BIM [3].
Perceived Benefits of AI/ML	(Benefits the Firm has experienced using AI/ML)	- They note that in the AEC industry, AI provides advantages for dealing with a diversity of difficult and complex engineering issues that can be hard to solve by any conventional computational methods-based solutions [17]. - BIM applications may include lots of improvements in construction projects such as visualization, fabrication/shop drawings, facilities management, cost estimating, conflict, interference, and clash detection [3]. - The survey they conducted had findings that AI enhances efficiencies and creativity in initial design phases and that firms in Turin, Italy must use it to address complex legal and project specific constraints [25]. - Ref. [31]'s survey has found that there are exceeding possibilities to enhance architectural design processes in AI-generated architecture. He also found that AI has a role in all phases of architectural design [31]. - The article states that AI increases accuracy in data analysis and formulates better strategies that benefit all parties [26].

Table 2. *Cont.*

Perceived Challenges of AI/ML	(Challenges the Firm has experienced using AI/ML)	- The authors noted that AI methods require a significant amount of time, effort, and money in [17]. - They note that the need to re-engineer many construction projects towards BIM can be challenging, and some businesses refuse to change their work processes (resistance to change) [3]. - Generally, he states that 94% of the architects were concerned about AI inaccuracy or 'looking correct but wrong' [24].
Adoption Intentions Future AI/ML plans	(If the firm is not adopting AI/ML, reasons and intentions of when is the perceived time of adopting AI/ML)	- The authors encourage the widespread adoption of AI methods in AEC industry as they mentioned lots of important advantages and enhancements [17]. - A survey: Larger firms are leading the AI Adoption as they own resources to train the employees in [24].
Views on Future Importance of AI/ML	(Participant's vision of the importance of AI/ML)	- They have used (CNN) convolutional neural networks to show how AI in the AEC industry can reinforce deep learning methods in ML to produce outcomes that can be taught to humans [17]. - Ref. [30] states that only 15% of architects' tasks are in high-risk of automation while the other is a co-creative job between AI and architects as it relies on creativity [30].
Thematic Sections	**Educational Survey Question**	**Supporting Data and Insights**
Demographic and Organizational Information	(Academic Institution Name) (Participant's Role)	- For research purposes in this article, the research spans of educational purposes ask for specifying which stage of the AI-ED methods [1].
Familiarity and Awareness of AI/ML	(Participant's Familiarity of AI/ML application in Architecture)	- The authors state the need to understand how technologies can enhance education through knowing the educator's level of education in machine learning [2]. - A survey done by the authors revealed that 99.6% of students are aware of AI but only 1.3% have received formal training, indicating a clear educational gap between [29]. - Structural equation modeling (SEM) was employed for data analysis and the study found low-level of awareness in GAI (generative AI) into architectural education through knowledge [28].
Current Adoption and Use of AI/ML	(Integration of AI/ML in Architectural Course or Research at the institution)	- Their coding revealed that AI/ML is used frequently in research methodology; several learning theories and higher education are the most frequent research contexts [1]. The authors specify that several categories were grouped to see the implication of the learning management system (LMS), a type of facilitation in teaching and management tasks. Specifically, they found that classroom and exam management function relies on the integration of various old technologies to enhance classroom teaching [1]. - The authors stress that AI in architectural pedagogy is regarded as a promising development—it offers new opportunities in realms of sustainability and creative thinking in helping in the selection of appropriate material and shaping conscious strategies [29]. - Their quantitative results have found a significant result between AI Usage and its relationship with year of study; students are beginning to actively explore and integrate AI in their coursework to a more design-oriented initiative of their training [29]. - Their findings can inform the development of new courses or integration of AI content into existing modules [29]. - The author's results show that architects in firms need to adapt AI technology which influences the way they are trained at university [30].

Table 2. *Cont.*

AI/ML Tools Used (Software or platforms in use)	(What are the tools used for AI/ML in this institution)	- The paper compares the effectiveness of various machine learning algorithms and the studies that revolve around the development of AI-Based teaching support systems. The authors specify how these AI-Model frameworks are fundamental to the field of AI-ED and its research topics [1].
Areas of AI/ML Use (Teaching, research, administration)	(Institution reinforcements in offering specific courses/workshops for AI/ML in architecture)	- The authors specify that there are several uses of ML in scientific research such as cyber security, environmental sustainability, as well as the educational field—personalization of learning, recommendation of educational content, automated assessment, identifying early intervention needs, educational data analysis, automation of administrative, adaptive learning, online education, plagiarism and cheating detection, and teacher training [2].
Perceived Benefits of AI/ML (in architectural education)	(Academician Perceived Benefit in using AI/ML in Architectural Education)	- The authors mentioned that ML is used to analyze large education datasets and therefore improve teaching methods and curriculum design [2]. - The authors emphasize that integration of AI into educational technology—encompassing Virtual learning, information and mapping, and ML methods—has led to significant advancement of educational efficiency [29].
Perceived Challenges of AI/ML (in architectural education)	(Academician Perceived Challenges in using AI/ML in Architectural Education)	- Challenged of AI-ED technical aspects (content production and recommendation), personal aspects (lifelong learning assessment and evaluation), and social aspects (learning networks and diversity and fairness of algorithms) in the development of AI-ED. Also, deep learning education concerns about data quality [1]. - Ethical consideration as a challenge of ML algorithms on educational equity privacy, and autonomy [27]. - The authors revealed that the faculty members were hesitant about using AI in architecture learning context as some were voicing concerns about overreliance on it which can compromise students' creativity [8].
Importance and Future Integration of AI/ML (Outlook in education)	(Importance of AI/ML in architectural education in the future) (Further integration of AI/ML in other areas in architectural education)	- A review from this article expressed the importance of inter-stakeholder partnership between AI-developers, educators, and researchers to develop effective AI-ED applications [1]. - The authors argue that integration of AI in architecture should not only be considered from the standpoint of technical efficiency but also through the lens of human-centered design principles including ethics and accessibility [29].

Collected data were analyzed using IBM SPSS Statistics, Statistical Package for the Social Sciences, version 30.0.0.0 to generate both descriptive and inferential outputs. The analysis included:

- Descriptive Statistics: (a) Frequencies and percentages for categorical variables (e.g., tool usage, challenges) and (b) means and standard deviations for familiarity and perceived importance.
- Inferential Statistics: (a) Chi-square tests to examine associations (e.g., firm size × AI/ML adoption; academic role × course integration) and (b) ordinal logistic regression to explore predictors of familiarity and perceived importance.

These analytic methods allow identification of patterns, group differences, and structural relationships between variables.

Inferential statistical procedures were selected in accordance with the categorical and ordinal structure of the survey variables. Chi-square tests were employed to examine asso-

ciations between nominal or ordinal categories, while ordinal logistic regression was used to explore relationships between ordered outcome variables and explanatory factors. Prior to analysis, diagnostic checks were conducted to confirm the suitability of these methods, including verification of expected cell counts for contingency tables and assessment of proportional odds assumptions for ordinal models. Given the exploratory nature of the study and the modest sample size (n = 113), the inferential analysis is interpreted as indicative rather than confirmatory, and results are discussed in terms of observed tendencies rather than causal relationships.

Where necessary, category groupings were reviewed to avoid sparse data structures and to maintain the validity of statistical testing.

To enhance narrative clarity, overlapping descriptive tables have been consolidated, and detailed tabulations are provided in the Appendices A–C, allowing the main text to focus on analytical patterns rather than repetitive descriptive statistics.

3.2. Reliability and Validity

Instrument validity was ensured through content validation, whereby survey items were developed and grouped, as shown in Table 3, based on the established literature on AI/ML adoption in architecture, education, and the AEC industry, and subsequently reviewed by three experts in architectural education and digital technologies to assess clarity, relevance, and potential bias. A pilot test involving 10 participants (five academics and five professionals) further confirmed the clarity and flow of the questionnaire, leading to minor refinements in wording and sequencing. The reliability analysis of collected data (n = 113) demonstrated strong internal consistency, with Cronbach's alpha values exceeding the acceptable threshold of 0.676 across all multi-item constructs as Table 4 shows, including perceived benefits, challenges, and familiarity scales. Ethical considerations were strictly followed, ensuring voluntary and anonymous participation, the exclusion of any identifying information, informed consent from all respondents, and secure handling of collected data for research purposes only.

Table 3. Summary of variables, indicators, and measurement scales.

Variable Category	Variable/Indicator	Type	Scale	Example Item
Demographics	Academic role/Firm role Institution/Firm size Years of experience	Categorical Categorical Categorical	Nominal Nominal Ordinal	Lecturer/Architect Small/Medium/Large 0–1/1–3/3–5/>5
AI/ML Familiarity	Self-reported familiarity Perceived importance	Perceptual Perceptual	3-point Likert 3-point Likert	Not familiar → Very familiar Not important → Very important
Current Adoption	AI/ML usage Types of tools used	Binary Categorical (multi-select)	Yes/No Nominal	Uses AI in workflow Grasshopper + AI plugins
Perceived Benefits	Creativity enhancement Efficiency improvement	Perceptual Perceptual	5-point Likert 5-point Likert	Strongly disagree → Strongly agree Strongly disagree → Strongly agree
Challenges/ Barriers	Lack of expertise Limited access to tools	Perceptual Perceptual	5-point Likert 5-point Likert	Strongly disagree → Strongly agree Strongly disagree → Strongly agree
Future Intentions	Intention to expand AI/ML integration Future importance	Perceptual Perceptual	5-point Likert 3-point Likert	Very unlikely → Very likely Low → High

Table 4. Reliability analysis of the survey instrument (Cronbach's Alpha).

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	*n* of Items
0.676	0.659	31

4. Results

This section presents the empirical findings from two parallel surveys examining the adoption and perception of artificial intelligence (AI) and machine learning (ML) within architectural academia and industry in Saudi Arabia. The results are organized

thematically to provide a contextualized understanding of demographic characteristics, familiarity levels, current adoption practices, perceived benefits and challenges, and key statistical relationships between variables.

Across academia (n = 60), respondents represented a diverse range of Saudi universities, with the largest clusters coming from King Saud University, Al Yamamah University, and Alfaisal University, indicating broad engagement across major architectural education institutions. The academic roles reflected a typical distribution for architecture-related departments: lecturers accounted for 45%, professors 35%, and the remaining 20% comprised researchers and other academic staff. As illustrated in (Figure 1), lecturers formed the largest group of survey participants, followed by professors, researchers, and others, respectively, with a detailed tabulation of these results presented in Appendix A. Industry respondents (n = 53) reflected a similarly varied profile, spanning a wide range of professional environments, with the highest regional representation from firms in the Eastern Region (41.5%) and the Central Region (32.1%). Architecturally focused firms dominated the sample (34%), while participants also reported roles in engineering, project management, digital services, and real estate development. Firm size varied substantially, from small practices with fewer than 20 employees (17%) to very large organizations exceeding 100 employees (24.5%). Nearly half of industry respondents (43.4%) reported more than five years of professional experience, suggesting a mature and knowledgeable sample that is likely familiar with organizational processes and technological adoption. (Figure 2) visualizes the geographic distribution across Saudi regions, while (Figure 3) demonstrates the proportional firm sizes represented in those regions, and (Figure 4) highlights respondents' years of experience. Appendix B consolidates these data in tabular form.

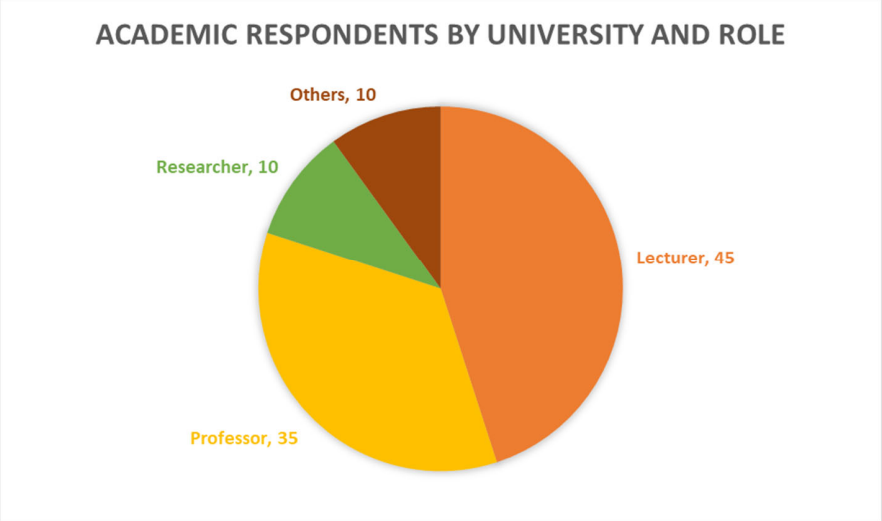


Figure 1. Academic respondents by university and role.

As shown in Table 5, faculty familiarity with AI and ML was moderate, with a mean score of 2.20 (SD = 0.61) on a three-point scale, and respondents generally agreed that these technologies are becoming increasingly important to architectural education, reflected in a mean importance rating of 2.82 (SD = 1.40). Notably, differences in academic rank—whether lecturer, professor, or researcher—did not correspond to meaningful differences in adoption, as a chi-square test showed no statistically significant association between academic role and whether AI/ML is currently integrated into courses or research activities, χ^2 (6, n = 60) = 4.51, p = 0.608. By contrast, as shown in Table 6, industry familiarity with AI/ML was substantially higher, with a mean score of 2.91 (SD = 0.30), and 90.6% of industry respondents reporting that they were "very familiar". A chi-square test similarly indicated

no significant association between years of experience and familiarity with AI/ML, χ^2 (3, n = 53) = 1.016, p = 0.797, suggesting consistently high awareness across both junior and senior professionals.

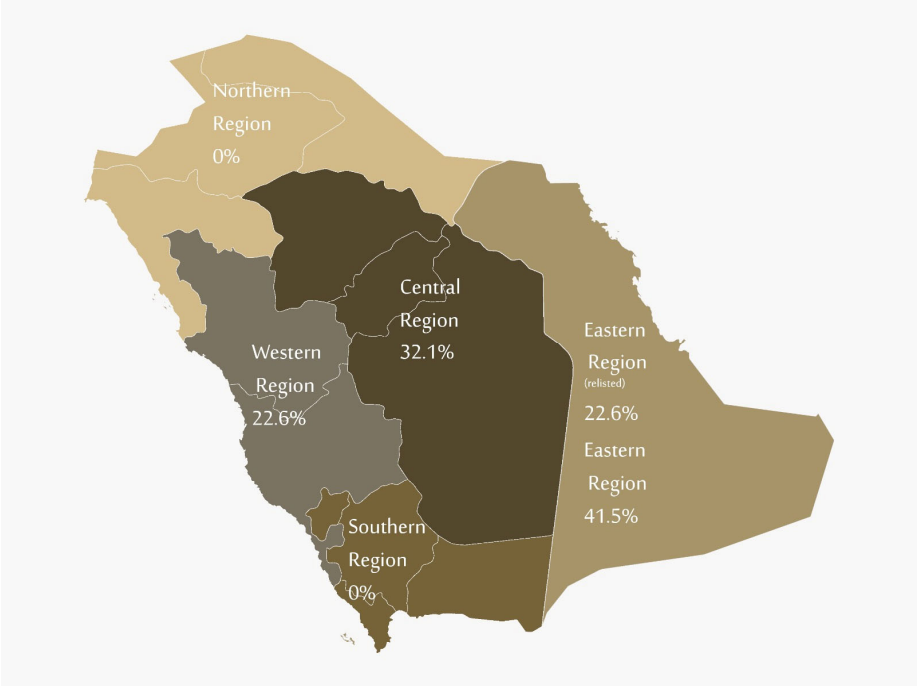


Figure 2. Saudi Arabian regional map with percentage distribution of survey-takers.

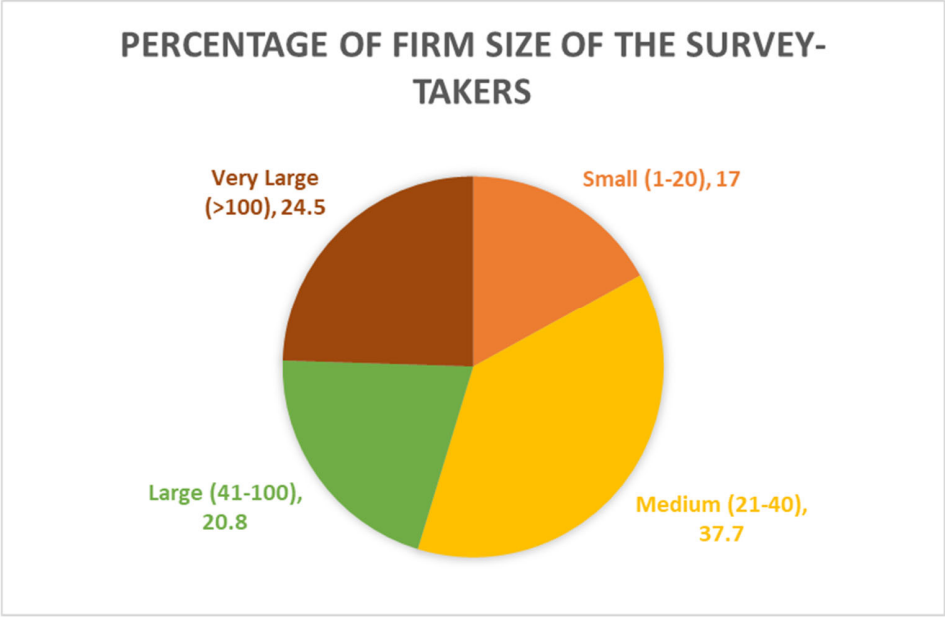


Figure 3. Percentage distribution of survey-takers by firm size.

Table 5. Familiarity and integration in academia.

Measure	Mean	SD	*n*
Familiarity with AI/ML	2.20	0.605	60
Perceived Importance in Education	2.82	1.396	60

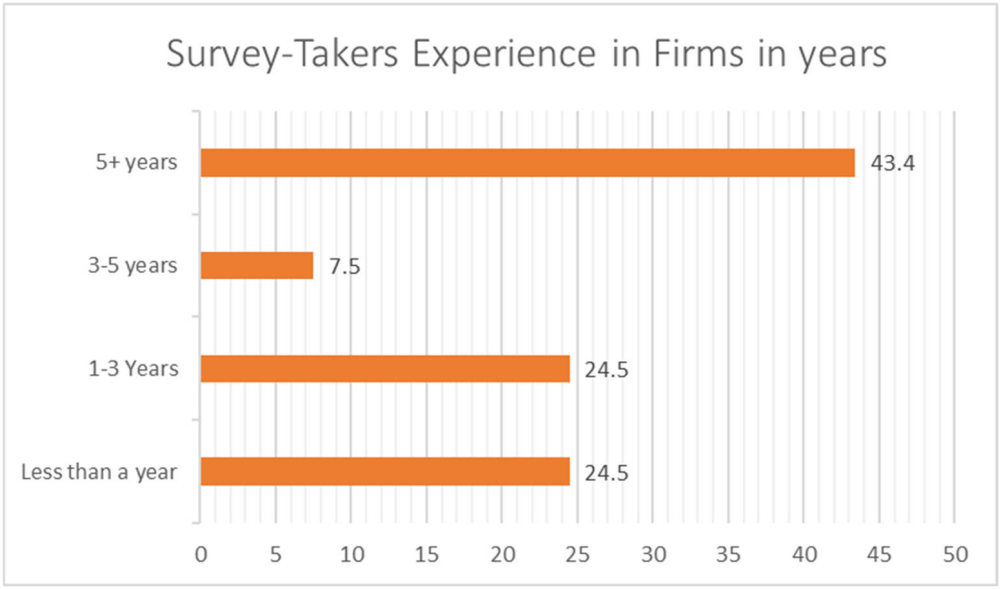


Figure 4. Survey-takers experience in years.

Table 6. Industry familiarity with AI/ML.

Response	*n*	%
Very familiar	48	90.6
Somewhat familiar	5	9.4
Not familiar	0	0

Although familiarity was moderate, actual tool usage varied. The most used tools were generative design platforms (25%), Grasshopper with AI plugins (16.7%), and AI-driven visualization tools such as MidJourney and Stable Diffusion (6.7%). More advanced tools, such as predictive analytics and custom ML models, were used minimally. Figure 5 shows the current AI/ML tools used in architectural programs. Appendix C shows these data in table format.

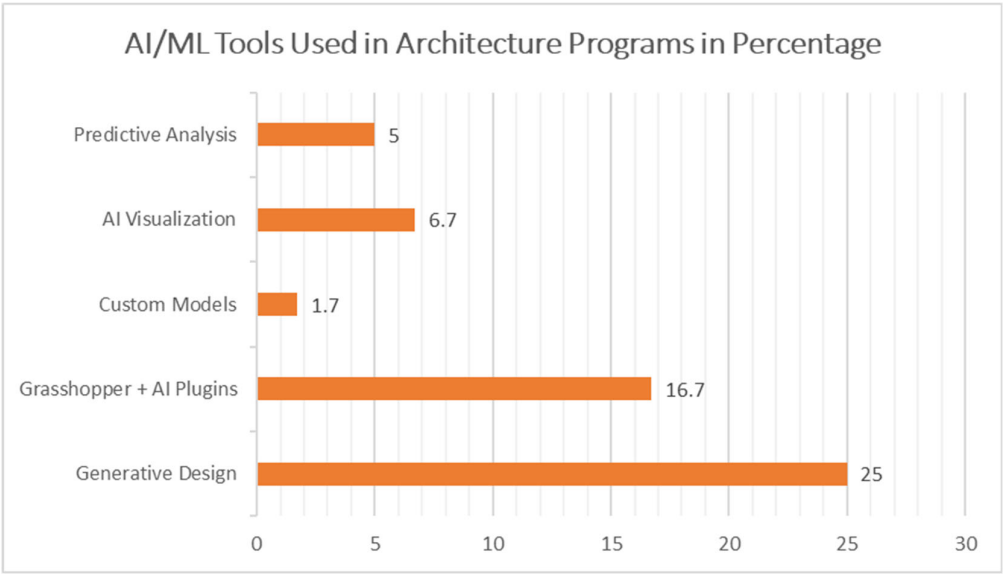


Figure 5. AI/ML tools used in architectural programs.

Approximately 34% of firms reported using AI/ML in at least one process. Adoption varied dramatically by firm size. Notably, very large firms (>100 employees) showed the highest adoption (61.5%), while large firms (41–100 employees) reported no adoption at all. Medium-sized firms demonstrated moderate uptake (40%), illustrated in Table 7.

Table 7. AI/ML adoption by firm size.

Firm Size	Users (%)	Non-Users (%)
Very Large (>100)	61.5	38.5
Medium (21–40)	40.0	60.0
Small (1–20)	22.2	77.8
Large (41–100)	0.0	100.0

A chi-square test confirmed that firm size was significantly associated with AI/ML adoption, χ^2 (3, n = 53) = 10.943, p = 0.012.

Faculty identified several academic benefits from integrating AI/ML into architectural education. Table 8 shows the findings; the most prominent were enhanced design creativity (23.3%), increased efficiency (20%), and better preparation for industry adoption (15%). Industry professionals overwhelmingly viewed AI/ML as important for the future of practice (M = 2.77, SD = 0.42), with 77.4% rating it "very important." No significant differences were found between experience levels and perceived importance, χ^2 (3, n = 53) = 1.329, p = 0.722.

Table 8. Key benefits of AI/ML in education.

Benefit	%
Creativity and exploration	23.3
Efficiency	20.0
Industry readiness	15.0
Research enhancement	5.0

The leading barriers faced by academic institutions included limited access to AI/ML software (26.7%), lack of faculty expertise (25%), resistance to traditional instructional approaches (8.3%), and a high learning curve for students (5%), as shown in Table 9. Industry challenges tended to be structural and resource driven. Smaller firms cited limited financial and technological capacity to implement AI/ML tools, aligning with the earlier chi-square evidence showing lower adoption rates among firms with fewer employees.

Table 9. Challenges in integrating AI/ML in architecture programs.

Challenge	%
Limited access to tools	26.7
Lack of expertise	25.0
Resistance to change	8.3
Student learning curve	5.0

5. Areas for Future AI/ML Integration

Table 10 shows the recommended areas for further integration. Academic respondents emphasized the need to expand AI/ML across multiple domains, including undergraduate curricula (26.7%), graduate research (18.3%), digital fabrication and robotics (1.7–6.7%), and AI-driven smart cities applications (6.7%).

Table 10. Recommended areas for further integration.

Area	%
Undergraduate curriculum	26.7
Graduate research	18.3
Digital fabrication/robotics	6.7
Smart cities and urban AI	6.7

Ordinal logistic regression conducted on industry responses revealed that while the overall models were statistically significant ($p < 0.001$), no individual experience category significantly predicted familiarity or perceived importance of AI/ML. Pseudo-R^2 values (Nagelkerke = 0.651 and 0.676) suggest moderate explanatory power, highlighting the complex nature of professional AI/ML perception that extends beyond mere years of experience.

The findings reveal a strong and growing interest in AI and machine learning across both academia and industry, though the depth of engagement varies between the two sectors. Industry professionals demonstrate particularly high levels of familiarity with AI/ML tools and applications, whereas academia exhibits moderate but steadily increasing familiarity as educational institutions begin integrating these technologies into curricula and research. Firm size emerged as a significant determinant of AI/ML adoption, with larger firms possessing greater capacity, both financially and operationally, to deploy advanced digital tools. In contrast, academic institutions face structural challenges, most notably limited access to specialized software and insufficient faculty expertise needed to support AI/ML-driven instruction. Despite these differences, both academia and industry share a unified perspective on the importance of AI/ML, consistently identifying these technologies as central to the future of architectural education and professional practice.

6. Discussion

This study provides one of the first empirical examinations of AI and ML adoption within architectural academia and the AEC industry in Saudi Arabia. The findings reveal a complex landscape in which interest and perceived importance of AI/ML are high across both sectors, but actual integration—particularly in academic environments—remains uneven and constrained by systemic barriers. This discussion interprets the results in relation to the global literature and highlights the regional implications for policy, education, workforce development, and digital innovation.

In interpreting these findings, a clear distinction is maintained between results directly supported by survey data and broader interpretive or forward-looking insights. Statistical associations and descriptive patterns are reported strictly as empirical outcomes, while reflections on future practice, pedagogical transformation, and theoretical implications are framed as interpretive extensions grounded in—but not directly measured by—the survey data.

The study demonstrates that industry professionals exhibit significantly higher familiarity with AI/ML than academic respondents. Over 90% of industry participants reported being "very familiar" with AI/ML tools, whereas academic familiarity remained moderate (M = 2.20). This aligns with global findings where industry adoption leads educational adoption due to greater exposure to emerging technologies, market competition, and project efficiency demands [17].

However, despite high familiarity, only 34% of firms reported active AI/ML adoption, confirming that readiness does not automatically translate into implementation. This reflects patterns noted by [3] who observed similar gaps in BIM diffusion in Saudi

Arabia—significant awareness but low integration due to organizational, financial, and policy constraints.

Academia shows a parallel pattern: moderate familiarity but inconsistent use of AI/ML tools in teaching or research. Generative design and AI-plugins in Rhino/Grasshopper are the most common tools, while advanced ML and predictive analytics remain rare. This mirrors the global AI-in-education landscape described by [1] where higher education institutions focus more on conceptual knowledge and exploratory instruction rather than technical implementation or sustained AI-supported pedagogy.

A major contribution of this study is the identification of firm size as a statistically significant predictor of AI/ML adoption. Very large firms (>100 employees) demonstrated the highest adoption rate (61.5%), while medium firms showed moderate adoption and large firms (41–100 employees) reported no adoption at all. This suggests that digital transformation is resource-intensive, consistent with [17]'s assertion that AI requires substantial investment in data infrastructures, training, and workflow restructuring.

Although firm size emerged as a statistically significant predictor of AI/ML adoption, the finding that large firms (41–100 employees) reported no adoption warrants careful interpretation. This result does not necessarily indicate a lack of organizational capacity, but rather points to strategic and structural dynamics specific to this firm category. In the Saudi AEC context, many large firms operate within mature BIM- and ERP-centered workflows and may prioritize consolidating existing digital systems over experimenting with emerging AI/ML technologies. As a result, AI-enabled functionalities embedded within commercial software platforms may not be explicitly recognized or reported by respondents as "AI/ML adoption." Additionally, large firms often emphasize risk management, regulatory compliance, and project delivery efficiency, which can limit organizational flexibility for piloting novel technologies in the absence of clear return on investment. Unlike very large firms, which typically maintain dedicated R&D or digital transformation units, large firms may lack the strategic mandate or leadership-driven innovation culture required to institutionalize AI/ML initiatives. Resource allocation decisions—favoring hardware upgrades, BIM maturity, or sustainability compliance—may further crowd out investment in AI/ML despite sufficient overall resources. Finally, a conservative interpretation of AI/ML adoption among respondents from large firms may have contributed to this pattern, suggesting that definitional ambiguity and reporting thresholds influence perceived adoption rates. Collectively, these factors indicate that organizational capacity alone is insufficient to drive AI/ML adoption without strategic alignment, leadership support, and institutional readiness.

To clarify the varying depth of AI/ML implementation observed in the data, adoption patterns can be interpreted through a conceptual maturity lens, distinguishing experimental, operational, and strategic levels of integration (Table 11).

Academic institutions reported structural barriers similar to industry challenges: lack of faculty expertise, limited access to software, and resistance to altering traditional pedagogical practices. These findings reinforce the concerns noted by [27], who argue that lack of training, ethics guidance, and technical capacity hinder AI/ML deployment in education.

Collectively, the results show that organizational capacity—not motivation—is the primary determinant of adoption. Both sectors recognize AI/ML's importance, but neither is fully prepared to support its systematic integration.

Both groups agree on the transformative potential of AI/ML. In academia, the most frequently cited benefits relate to enhancing design creativity, improving efficiency, and preparing students for industry expectations. These findings mirror global research, such

as [2,29], who emphasize AI's role in personalization, feedback, adaptive learning, and increasing the depth of design experimentation.

Table 11. Conceptual levels of AI/ML adoption maturity in architectural academia and AEC practice.

Adoption Level	Description	Typical Characteristics Observed in This Study	Organizational Implications
Experimental Adoption	Early-stage or exploratory use of AI/ML tools without formal workflow integration.	Use of generative design, AI visualization tools, or occasional experimentation in studios or projects.	Reflects curiosity and innovation interest but limited institutional support or structured strategy.
Operational Adoption	Partial integration of AI/ML into specific tasks or workflows.	AI-assisted simulation, design optimization, or selected course modules incorporating AI tools.	Indicates growing capability, requiring training investment and workflow adaptation.
Strategic Integration	Organization-wide embedding of AI/ML supported by policies, training, or digital transformation agendas.	Observed primarily in very large firms with structured adoption initiatives and higher organizational capacity.	Demonstrates alignment between leadership vision, infrastructure, and long-term innovation strategy.

In industry, the overwhelming majority (77.4%) identified AI/ML as "very important" for the future of practice. Practitioners emphasized enhanced analysis, efficiency, and optimization—consistent with applications outlined in [17] including simulation, uncertainty reduction, and project performance improvement.

The convergence of benefits across sectors signals an important regional opportunity: academia and industry already share aligned expectations, creating fertile ground for joint initiatives, curricular reforms, and collaborative training programs.

The study reveals several structural and contextual barriers that continue to impede the diffusion of AI/ML across Saudi Arabia's architectural ecosystem. In academia, limited access to specialized software, insufficient faculty expertise, resistance to shifting away from traditional pedagogical models, and steep student learning curves collectively slow meaningful integration—challenges that echo global concerns regarding AI governance, ethical use, and the need for robust training and pedagogical transformation [1,8]. Within industry, high implementation costs, unclear strategic frameworks, limited policy mandates, and pronounced resource constraints among small and medium-sized firms contribute to fragmented adoption patterns, mirroring early-stage BIM diffusion challenges previously documented in Saudi Arabia [3]. Together, these barriers indicate that despite strong interest, Saudi Arabia's AI/ML maturity remains emergent, posing potential limitations to the architectural sector's ability to contribute effectively to major national priorities under Vision 2030—including smart city development, sustainability-driven design, and digital construction innovation. Without coordinated alignment between academia, industry, and policymakers, the region risks developing a widening skills gap and lagging behind global advancements in AI-driven architectural and engineering practices.

Several of the reported benefits of AI/ML adoption align directly with sustainability objectives. In both academia and industry, the use of generative design, simulation, and predictive tools supports environmentally sustainable outcomes by enabling early-stage performance optimization, reduced material waste, and more energy-efficient design decisions. Additionally, perceived gains in efficiency and industry preparedness contribute to economic sustainability by lowering design iteration costs and strengthening long-term workforce readiness, while expanded AI/ML integration in education supports social sustainability through improved skill equity and future-oriented training.

Beyond patterns of adoption and perceived efficiency, the findings of this study invite reflection on the evolving relationship between artificial intelligence, creativity, and

architectural agency. While respondents frequently associated AI/ML with enhanced efficiency and exploratory capacity, these perceptions can be interpreted within a broader architectural discourse that understands creativity not merely as individual authorship, but as an iterative, situated process shaped by tools, constraints, and external systems. In this sense, AI/ML functions not simply as a productivity enhancer, but as a co-creative design agent that expands the design solution space, introduces probabilistic and data-driven reasoning, and reshapes early-stage ideation.

The use of generative design platforms, AI-assisted visualization, and simulation tools—reported by both academic and industry respondents—suggests a shift from deterministic, linear workflows toward exploratory and parametric modes of thinking, where designers curate, evaluate, and steer algorithmically generated alternatives. This reframing aligns with contemporary theories of computational design that emphasize human–machine collaboration rather than technological substitution. Architectural agency, therefore, becomes distributed across the designer, the algorithm, and the datasets that inform design outcomes, raising critical questions about authorship, responsibility, and decision-making.

In educational contexts, AI/ML adoption also carries important pedagogical implications. Rather than replacing foundational design skills, AI/ML challenges architectural education to recalibrate its emphasis toward critical judgment, ethical reasoning, and design intent, positioning students not as passive users of automated systems but as reflective authors capable of interrogating algorithmic outputs. The moderate but growing integration of AI/ML in curricula observed in this study highlights both the opportunity and necessity for pedagogical frameworks that treat AI as an epistemic partner in design thinking rather than a neutral tool.

By situating AI/ML adoption within these theoretical perspectives, the study contributes not only to understanding how frequently such technologies are used, but also to how they are reshaping architectural creativity, agency, and pedagogy. While deeper theoretical exploration through studio-based research or design experimentation lies beyond the scope of this survey, the findings provide an empirical foundation for future research at the intersection of AI, architectural theory, and design cognition.

The findings of this study underscore the necessity of making AI/ML literacy a fundamental component of architectural education, as gaps in faculty expertise, inconsistent tool adoption, and reliance on traditional pedagogical approaches currently limit meaningful integration. Addressing these challenges requires sustained institutional investment in faculty development, AI/ML-enhanced design studios, interdisciplinary training that bridges architecture with data science and computation, and robust partnerships with industry to embed real-world digital workflows into academic practice—echoing global calls for more practice-oriented, application-driven AI education [1,28]. At the policy level, the results highlight an urgent need for national frameworks that enable digital transformation across the GCC's AEC sector, including the development of AI/ML standards for architecture and construction, incentives to support firm-level adoption, public–private research collaborations, funding for workforce upskilling, and strong data governance mechanisms to ensure ethical use. These priorities align closely with international AEC research emphasizing the centrality of policy, training, and multi-stakeholder coordination in accelerating technological maturity and ensuring equitable, sustainable innovation [17].

Although the overall sample size (n = 113) was sufficient for descriptive and comparative analyses, some subgroups—such as respondents from the Southern Region and highly specialized AEC firms—were underrepresented due to the geographic concentration of architectural institutions and digitally active firms in the Central, Eastern, and West-

ern regions of Saudi Arabia, as well as the study's focus on mainstream academic and professional practice contexts.

Overall, the results reinforce that Saudi Arabia's architectural ecosystem stands at a critical point: interest in AI/ML is high, and the perceived value is clear, yet actual integration is constrained by capacity, resources, and institutional readiness. Bridging this gap will require coordinated efforts in curriculum reform, policy development, investment in digital infrastructure, and cross-sector partnerships.

7. Conclusions and Recommendations

This study provides one of the first empirical investigations into the adoption of artificial intelligence and machine learning within architectural academia and the AEC industry in Saudi Arabia, revealing a landscape defined by strong interest yet uneven implementation. While industry respondents demonstrated high levels of familiarity with AI/ML-driven by exposure to digital workflows, competitive pressures, and emerging project demands—actual adoption remains inconsistent and heavily influenced by organizational capacity. Very large firms are leading implementation efforts, whereas small and medium-sized practices continue to face substantial resource constraints, limited strategic direction, and insufficient access to advanced technologies. Within academia, familiarity with AI/ML is moderate; however, integration into curricula, course delivery, and research activities remains limited due to faculty expertise gaps, traditional pedagogical structures, and restricted access to specialized software. Despite these barriers, both sectors agree that AI/ML will play a critical role in shaping the future of architectural design, education, and professional practice, underscoring the need for coordinated national and institutional strategies that align educational preparation with emerging industry requirements.

By establishing an empirical baseline and identifying the structural conditions that shape AI/ML adoption, this study provides evidence-based guidance for policymakers, academic institutions, and industry leaders in Saudi Arabia seeking to design targeted strategies for sustainable digital transformation in architectural education and practice.

Based on these findings, several key recommendations emerge. Academic institutions should embed AI/ML literacy across the curriculum, invest in faculty development, expand digital infrastructure, and foster interdisciplinary collaboration, while aligning programs with industry needs through advisory partnerships and practice-integrated learning experiences. For industry, firms should develop structured AI/ML adoption frameworks, invest in workforce upskilling, collaborate with universities on research and training, and begin piloting AI-enabled workflows to build internal capacity. Policymakers play a vital enabling role and should establish national AI/ML standards for the AEC sector, provide incentives for technological adoption, support industry–academia partnerships, and invest in digital infrastructure and data governance frameworks consistent with Vision 2030's digital transformation agenda. This conceptual framework is illustrated in Figure 6.

While the study's recommendations are aligned with Saudi Vision 2030, the research does not empirically evaluate existing national AI policies or institutional frameworks; therefore, policy implications should be interpreted as evidence-informed rather than policy-tested.

Like any empirical study, several limitations must be acknowledged. The cross-sectional design captures perceptions at a single point in time, self-reported data may include biases, and the sample—while diverse—may not represent all academic programs or firm types across the Kingdom. The relatively modest sample size may constrain statistical power and the stability of multivariate modeling; therefore, inferential findings should be interpreted cautiously and validated through larger, stratified datasets in future research.

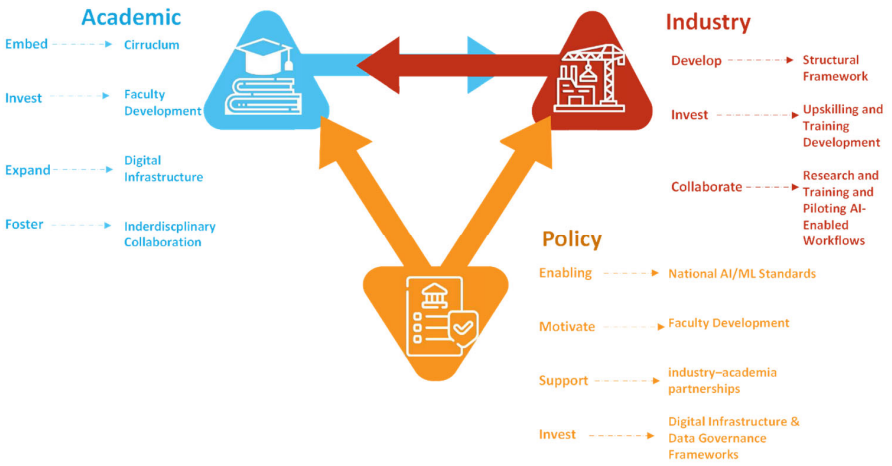


Figure 6. Triangular cycle framework for different institution collaboration for AI/ML adoption.

Furthermore, the study does not differentiate between specific AI/ML tools or assess technical proficiency levels, limiting tool-specific insights. These constraints create avenues for future research, including longitudinal studies tracking adoption over time, qualitative investigations into organizational culture and implementation challenges, comparative analyses across GCC countries, and technical assessments evaluating the performance of AI-enabled workflows in real projects. Additionally, pedagogical research is needed to understand how AI-enhanced teaching methods influence student learning, creativity, and design performance.

Future research could adopt a comparative GCC–OECD benchmarking framework evaluating AI/ML readiness, adoption depth, sustainability outcomes, and governance conditions across architectural academia and the AEC industry using harmonized indicators and standardized survey instruments. Such an approach would enable contextualized yet globally comparable assessment of Saudi Arabia's AI/ML trajectory.

The intersecting priorities and shared responsibilities of these three stakeholder groups are illustrated in the Venn diagram presented as Figure 7.

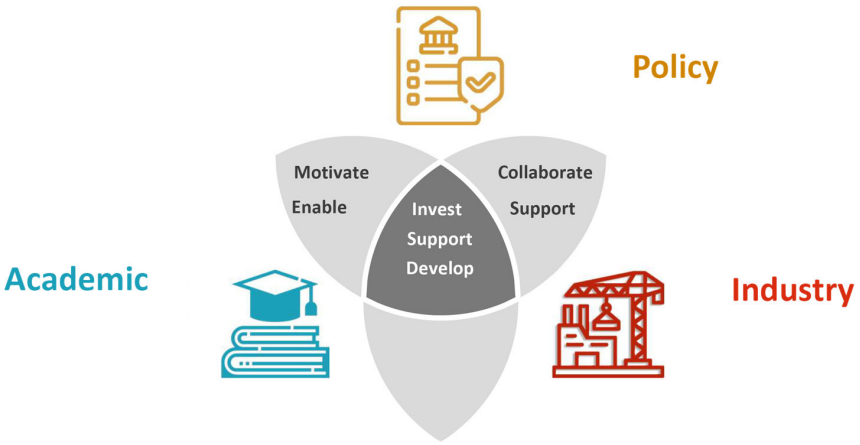


Figure 7. Collaborative keywords reflecting the interdependence of key institutional roles in AI/ML adoption.

Overall, the study highlights that Saudi Arabia stands at a pivotal moment in its digital transformation trajectory. While enthusiasm for AI/ML is strong and Vision 2030 provides an enabling national framework, coordinated and sustained efforts across academia, industry, and government are essential to convert potential into meaningful practice. By addressing current gaps, investing in capacity-building, and fostering cross-sector collab-

oration, the architectural ecosystem in Saudi Arabia can position itself at the forefront of global innovation in AI-driven design and construction.

Author Contributions: Conceptualization, A.A.; methodology, A.A. and S.M.; software, A.A. and M.A.; validation, A.A., M.A. and S.M.; formal analysis, A.A., M.A. and S.M.; investigation, A.A., M.A. and S.M.; resources, A.A., M.A. and S.M.; data curation, A.A., Z.A., N.A.T. and S.M.; writing—original draft preparation, A.A.; writing—review and editing, A.A., M.A. and S.M.; visualization, A.A. and S.M.; supervision, A.A. and S.M.; project administration, A.A. and S.M.; funding acquisition, A.A. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The study was conducted using a non-interventional and anonymous survey to explore participants' perceptions and attitudes. The research did not involve patients, human biological material, or human tissues, and no personally identifiable information was collected. According to institutional and national guidelines, ethical review and approval were not required for this type of study.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data can be found in: https://acrobat.adobe.com/id/urn:aaid:sc:eu:8e11abf0-ecfa-49dd-9938-2d006c5fb5a6 (accessed on 29 March 2026). https://acrobat.adobe.com/id/urn:aaid:sc:eu:bbf6378e-5825-480a-922b-85eeb629c1bd (accessed on 29 March 2026).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Academic Role Respondents weight in Academic Survey conducted.

Variable	Category	*n*	%
University	Multiple institutions across KSA	60	100
Academic Role	Lecturer	27	45.0
	Professor	21	35.0
	Researcher	6	10.0
	Other	6	10.0

Appendix B

Table A2. Industry respondents by region, firm type, and experience. (APPROVED).

Variable	Category	*n*	%
Region	Eastern Region	22	41.5
	Central Region	17	32.1
	Eastern (relisted)	12	22.6
	Western Region	2	3.8
Firm Size	Medium (21–40)	20	37.7
	Very Large (>100)	13	24.5
	Large (41–100)	11	20.8
	Small (1–20)	9	17.0
Experience	More than 5 years	23	43.4
	1–3 years	13	24.5
	Less than 1 year	13	24.5
	3–5 years	4	7.5

Appendix C

Table A3. AI/ML tools currently used in architecture programs and AEC Firms (APPROVED).

Tool Category	%
Generative design	25.0
Grasshopper + AI plugins	16.7
Custom models	1.7
AI visualization	6.7
Predictive analytics	5.0

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