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Artificial intelligence in architecture education: reflections through structural equation modeling

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ABSTRACT

This study explores architecture students' attitudes, awareness, and use of artificial intelligence (AI) technologies within a multidimensional framework. As AI becomes integral to education, a comprehensive evaluation is vital in architecture, where creative and technical skills converge. A questionnaire based on RIBA's 2024 Artificial Intelligence Report was administered to architecture students, and data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The model demonstrated acceptable reliability and validity (Cronbach's alpha > 0.70, AVE > 0.50). Results showed that educational components significantly affected future perceptions ($\beta = 0.242, p < 0.01$), and application effectiveness enhanced digital maturity ($\beta = 0.292, p < 0.01$). Future perceptions also improved ethical awareness ($\beta = 0.308, p < 0.05$). Although many students use AI tools, they lack systematic training, and positive perceptions do not necessarily translate into practice. Findings emphasize that AI-related learning is shaped not only by technical competence but also by digitalization, ethics, and professional transformation. The study recommends integrating AI into curricula, updating pedagogical strategies, and enhancing ethical awareness to support responsible and effective use. It contributes timely insights into how AI influences architectural education and students' readiness for future practice.

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AI; digital maturity; ethical
values

1. Introduction

Primarily, the development and rapid advancement of artificial intelligence technologies greatly affects architectural education as in many other fields (Avinç, Aycı, and Taş 2025). Architectural education, as a field of theory and practice that requires creativity and analytical thinking skills (İlerisoy et al. 2021), creates a current debate on the possible effects of artificial intelligence. In this context, this education is one of the disciplines that requires both subjective and objective skills, autonomous, and where the distinction between theory and practice is evident (Koçyiğit 2018). The knowledge required for practice depends on the knowledge of experts rather than architects. Therefore, architecture is a field that does not have precise rules from the design stage to the implementation stage. Due to this feature, it is a discipline that depends on subjective evaluations in terms of education (Glick 2011). With the development of digital tools, subjective data has become accessible and usable for everyone.

The development of artificial intelligence has made significant advances in architectural education in all areas of design, practice, theory and representation (Başarır 2022). For both educators and students, AI

tools have become an important part of education. In the field of design, AI tools play a critical role in 3D visualization, building information modeling (BIM) and parametric design processes. In the field of theory, AI tools are effectively used in data collection, analysis, evaluation and interpretation processes.

In stages such as environmental and structural analysis, building performance analysis, data collection, analysis of regulations and standards, artificial intelligence tools offer significant potentials with the analysis and accuracy of large amounts of data. In addition, various architectural floor plans can be easily obtained by processing image data with Generative Adversarial Network (GANs) technologies (Chaillou 2019). In the field of representation, design presentations and spatial perception have been significantly improved with 3D visualization technologies and the processes have become more practical compared to traditional methods. With visual AI tools such as DALL-E, Midjourney, Leonardo AI, Stable diffusion and Photoshop Beta, architectural representations can be generated from text in seconds. Concepts, thoughts and ideas can be transferred to visual representations. Through these rapid representation generation methods, the interaction between students and instructors becomes

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stronger (Başarır and Erol 2021). In the field of application, artificial intelligence tools are used in the production of models, mock-ups and prototypes and in the simulation of application processes. According to Zhang, Fort, and Giménez Mateu (2023), there are some difficulties in using artificial intelligence in architectural education (Zhang, Fort, and Giménez Mateu 2023). Artificial intelligence tools cannot imitate human thinking and may be insufficient in areas such as creativity, abstraction skills and interpretation. Therefore, limitations can be overcome by developing training methodologies and strategies for the effective use of AI tools. According to Başarır (2022), skills based on calculation and automation in traditional education systems become ordinary with artificial intelligence (Başarır 2022). Therefore, the education of the next generation of architects should take a proactive role by considering the current and future problems of the discipline in the context of technological developments.

As in many disciplines, the use of artificial intelligence in architecture and architectural education is increasing. Determining the effects of these technologies on education is an ongoing research topic. In line with this goal, the aim of this study is to investigate how students perceive artificial intelligence technologies, whether they use them in their studies, and their attitudes and awareness levels on this issue. The data to be obtained reveals strategies for a more active use of artificial intelligence in architectural education. The contribution of this research to the literature is to develop projections for the future by investigating the use of artificial intelligence, attitudes and thoughts of architecture students towards artificial intelligence. The integration of artificial intelligence tools with architectural education offers architects important gains in the design and implementation stages. Understanding the effects of artificial intelligence in education and using these tools correctly provide advantages for both architect candidates and educators.

2. Research background on artificial intelligence in education

Education is a fundamental element in the effective implementation of social and technological changes, and in this context, the integration of artificial intelligence (AI) technologies with education is becoming increasingly important (Tan et al. 2022; Ye, Sun, and Li 2021). AI, as a field that encompasses computer systems and machines that perform human-like functions such as cognitive abilities, learning, adaptation, and decision-making (L. Chen, Chen, and Lin 2020), has the potential to improve the quality of teaching and learning in educational systems (Hwang et al. 2020). The fact that AI technologies have become a rising

trend in the field of education in recent years makes the integration of these technologies into teaching processes even more important. The integration of AI technologies in education offers important opportunities in terms of future perceptions, digital maturity and educational components. While AI enhances the quality of personalized learning and teaching, the development of digital competencies plays a critical role in this process. Implementation efficacy is the efficiency of AI tools, enabling faster feedback and time management in education, while ethical values draw attention to issues such as data security and algorithmic bias. These factors call for effective and responsible use of AI in education.

2.1. AI future perception

Future-oriented perception refers to the opportunities and risks of the transformation occurring with artificial intelligence. It is the perception that technological developments are both promising and may pose professional threats (RIBA AI Report 2024). Studies on the future perception of artificial intelligence offer a common prediction that this technology will make significant progress in areas such as automation, ethical responsibilities and human-machine collaboration (Müller and Bostrom 2016). Studies conducted in key sectors such as education and health reveal that students' awareness of artificial intelligence technologies has increased and they accept the benefits of these technologies (Çetin and Aktaş 2021; Ongun 2024; Yılmaz et al. 2021). It is thought that artificial intelligence will increase patient safety and reduce medical errors, especially in the field of health, and it is predicted that it will play an important role in the future in the field of education. However, it is also seen that individuals are cautious towards these technologies due to factors such as lack of information and anxiety. In general, the perception that artificial intelligence will play an effective, beneficial and proactive role in different areas of society is strengthening (Başarır 2022; Tamori et al. 2022).

2.2. Education component

According to the RIBA AI Report (2024), the educational component refers to the educational elements that provide the necessary knowledge, skills and awareness for the use of artificial intelligence. Studies on the effects of artificial intelligence on education show that this technology provides significant contributions in areas such as personalized learning, teaching efficiency, creativity and development of problem-solving skills (Chang and Lu 2019; L. Chen, Chen, and Lin 2020; Komatina, Miletic, and Mosurović Ružičić 2024; Sadek and Mohamed 2023). Artificial intelligence accelerates the interaction between instructor and

student and assumes a proactive role in education (Başarır 2022; Başarır and Erol 2021). However, some studies emphasize that artificial intelligence may be insufficient in imitating human skills and therefore appropriate educational strategies should be developed (Zhang, Fort, and Giménez Mateu 2023). In creative fields such as architecture, it has been stated that AI can have both supportive and limiting effects (Borglund 2022). It has also been determined that although students' awareness of AI is high, they experience various limitations in access and effective use (Cheche et al. 2024). In general, although AI has a transformative potential in education, pedagogical adaptation and access opportunities need to be improved in order to utilize this potential effectively.

2.3. Digital maturity

Digital maturity refers to the level of adoption of a workplace or discipline towards digital innovations, its ability to implement technologies and its contribution to the digital transformation process in the industry. In this sense, it reveals whether the work environment directly adopts, leads or resists technology (RIBA AI Report 2024). Studies on the impact of AI on digital maturity reveal that technological transformation requires a holistic assessment not only in terms of technical infrastructure, but also in terms of human factors, organizational structure and strategic approaches (Milić and Divjak 2022; Nielsen, Egeberg, and Svihus 2024). The level of digital maturity in educational institutions is directly related to the digital competencies of teachers and the effective use of digital tools; however, access and effectiveness limitations in the use of AI for students persist (Cheche et al. 2024). Digital maturity models (DMM) attempt to measure the extent to which technologies such as AI are adopted at the institutional level, and in this context, the need for empirically based, measurable and standardized models is emphasized (Al-Ali and Marks 2022; Baihaqy and Subriadi 2023; Merzlov and Shilova 2022; Vavura and Matei 2024). The deepening of digitalization with technologies such as AI necessitates the development of new models for the evaluation of digital transformation processes and the revision of existing models in a theory-practice balance.

2.4. Application activity

According to the RIBA AI Report (2024), application effectiveness refers to the extent to which AI is integrated into the discipline and its tangible contribution to the design, project design and sustainability processes. This concept encompasses the real and measurable impact of the technology on the discipline, not just its use. Studies on the application effectiveness of artificial intelligence reveal that this technology has

significant potential, especially in areas such as diagnosis, treatment and decision support systems (Oh et al. 2019). Abd El-Maksoud and Ahmed (2024) stated that AI has increased application effectiveness, but human support is still indispensable. L. Chen, Chen, and Lin (2020) emphasized that the use of artificial intelligence poses various ethical and practical challenges. Müller and Bostrom (2016) predict that AI will make progress in terms of human-machine cooperation and ethical responsibilities, and point out that the application effectiveness of this technology should be considered not only with technical but also human and ethical dimensions.

2.5. AI impact and use

AI impact and use refers to the areas in which, how often and how AI is used, as well as its impact on professional processes, outcomes and roles (RIBA AI Report 2024). Academic research on the impact and use of AI in the field of architecture reveals that this technology transforms professional processes and provides various advantages. Studies on the impact and use of artificial intelligence reveal that this technology has the potential to increase efficiency and creativity in design processes, especially in the field of architecture (Çamuşoğlu 2024; Hanafy 2023). Artificial intelligence is considered as a supportive tool in decision-making processes (Baran Ergül, Varol Malkoçoğlu, and Acun Özgünler 2022) and offers significant contributions in terms of generating design alternatives and saving time and cost (Tazefidan, Eşme, and Başar 2022). However, Tamori et al. (2022) study shows that individuals' intention to use artificial intelligence is at a moderate level of 44.7%, indicating that despite its potential, its use has not yet become widespread. These findings suggest that AI offers creative and functional benefits in architecture, but its adoption rate needs to be increased.

2.6. Ethical values

Ethical values refer to issues such as protecting intellectual ownership, fair remuneration, responsibility to society, and maintaining human-centered design approaches with the use of AI (RIBA AI Report 2024). Ethical considerations of AI show that concerns persist due to the inadequacy of laws and ambiguities of responsibility in the use of this technology (Tamori et al. 2022; L. Chen, Chen, and Lin 2020). These ethical and practical challenges cause users to be cautious, especially in sensitive areas such as healthcare, where doctors are also distancing themselves from AI due to the risk of error and ethical concerns (Oh et al. 2019). However, Müller and Bostrom (2016) predict that AI will make significant progress in the future in terms of

ethical responsibilities and human-machine collaboration, indicating that these problems can be overcome over time.

2.7. Gaps in the literature

The literature on AI in higher education, design pedagogy, and professional practice is varied. In their work, Marengo and Pange (2024) explore the transformative potential of General Artificial Intelligence in reshaping learning paradigms and pedagogical frameworks in higher education across the board. Kakhkharova and Tuychieva (2024), examining the transforming landscape of higher education from an artificial intelligence perspective, introduce a paradigm shift in teaching and learning methodologies. They demonstrate improvements in student performance, participation, and satisfaction. Artificial intelligence has the potential to revolutionise higher education by offering a personalised and effective learning experience for both students and educators, advocating for the widespread adoption of AI-enhanced pedagogy.

In the study conducted by Hemminki-Reijonen et al. (2025), the aim was to restructure sustainability teaching using generative AI-supported pedagogical characters and to design interactive learning processes according to users' needs. Eager and Brunton (2023) argued that the integration of generative artificial intelligence tools in higher education could increase the efficiency of learning environments. Reddy's (2025) article argues that AI tools necessitate fundamental changes in the curriculum, pedagogical strategies, and examination systems in teaching focused on developing critical thinking, evaluation, and creativity skills. In another important topic in the field of architecture, the architectural application process, El Moussaoui (2025) explores the multifaceted roles of artificial intelligence, emphasising its potential to increase creativity and efficiency, while also addressing its limitations in capturing the multisensory and experiential dimensions of space. Integrating AI into design paradigms in the practice process is crucial for creating spaces that resonate on a deeper and more human level. By establishing a balanced relationship between human creativity and AI's computational power, the architectural profession can leverage this technological opportunity without compromising its core values.

Although many studies have been conducted in the existing literature on the effects of artificial intelligence (AI) technologies in education and especially in architectural education, it is seen that detailed analyses specific to architecture students are limited. Studies conducted in developing countries (Dullinja and Jashanica 2024, 2025; El-Shara', Saeed, and Arouri 2025; Suryani and Nugroho 2025) and developed countries (Jin, He, et al. 2024; Cao, Abdul Aziz, and

Mohd Arshard 2023; Otermans, Roberts, and Baines 2025) have examined how students perceive AI technologies, how they use them in educational processes, and how they integrate them into future professional practices. In studies where AI in education is considered as a new research topic (Zhai et al., 2021; X. Chen et al. 2022; Luckin and Cukurova 2019; Ouyang, Zheng, and Jiao 2022; Zawacki-Richter et al. 2019), the pedagogical role of AI is emphasized. In research on the adoption and application of AI in the field of architecture (Başarır 2022; Denni-Fiberesima 2024; Kizilcec 2024; Park, Yoon Lee, and Lee 2024), the contributions of these technologies to design processes are discussed.

Studies on the integration of AI into architecture education (Komatina, Miletić, and Mosurović Ružičić 2024), AI-supported education models (Jin, He, et al. 2024; Dumitrescu et al. 2025), students' ethical and pedagogical perceptions (Han et al. 2025), students' ethical and pedagogical perceptions (M. Jin et al. 2024; Rodriguez and Joyce 2025), students' digital competencies (Elbanna 2023), the applicability of AI-supported interactive learning environments (Rodriguez and Joyce 2025), and analyze the effects on students' attitudes towards, awareness of, and educational outcomes of AI technologies. Students' awareness of tools such as Midjourney and ChatGPT (Parra-Serano and Requena-Ruiz 2023), their sources of information and their level of use (Dullinja and Jashanica 2024) have also been assessed. More broadly, themes such as the ethical principles of AI (Floridi and Cows 2019), its digital literacy and pedagogical benefits (Knoth et al. 2024; Southworth et al. 2023; Yim 2024), its employment implications in the creative industries (Financial Times 2023) and its future in the framework of professional transformation (OECD 2022) were also addressed. All this literature reveals the lack of in-depth, holistic and context-specific data on architecture students' attitudes towards AI, ethical concerns, implementation skills, digital competencies and future perceptions. Therefore, this study aims to fill an important gap in the field by examining architecture students' attitudes and awareness towards the use of AI in a multidimensional framework such as ethical values, digital maturity, application effectiveness, and perceptions towards the future, and to contribute to current approaches that will guide architectural education.

3. Materials and methods

This study is based on a methodological foundation based on a combination of exploratory factor analysis (EFA) and structural equation modeling (SEM). Adopting a similar quantitative approach, we developed a context-specific survey instrument aimed at investigating university students' multidimensional attitudes

toward artificial intelligence (AI) technologies. The questionnaire was designed in alignment with the objectives of this study, and data were collected from undergraduate students using convenience sampling. Following data collection, an Exploratory Factor Analysis (EFA) was conducted to uncover latent variables underpinning the dataset. Subsequently, a Structural Equation Model (SEM) was constructed to operationalize and validate the theoretical structure, enabling the analysis of attitudes, awareness levels, and AI usage practices in a cohesive multidimensional model. The choice of PLS-SEM was also motivated by the modest sample size ($N = 107$), as PLS-SEM provides robust results for small samples and complex models by using bootstrapping rather than covariance-based assumptions. The comprehensive methodological approach of this study is presented in Figure 1.

3.1. Instrument design

The development of the survey tool was carried out using a two-stage approach that combines theory-based categorization with data-based construct validity. In the first stage, a set of questions developed by the Royal Institute of British Architects (RIBA) and (UNESCO 2023) Report to measure architects' relationships with artificial intelligence was

used (RIBA AI Report (2024); Unesco 2023). The 54-item question set was grouped under eight thematic categories/components reflecting conceptual areas related to the use of artificial intelligence in architecture. These eight thematic components and their corresponding questions are presented in Table 1. The sample selection included architecture students in Ankara, the capital of Turkey. Third-year students were included in the study based on the assumption that they would be inclined to use artificial intelligence at different levels of proficiency (scenario production, modeling, design, etc.). Within the scope of the research, information was provided to 137 students, of whom 107 participated in the survey.

In the second stage, the responses obtained were analyzed using Exploratory Factor Analysis (EFA) to reveal the underlying latent structure of the measurement tool. The EFA results revealed six separate thematic components grouped according to the statistical loading patterns of the original items. Some predefined categories merged under broader structures, while others were redistributed under statistically distinct components. These six thematic components formed the conceptual foundation of the model subsequently developed. Table 2 illustrates how the initial item categories

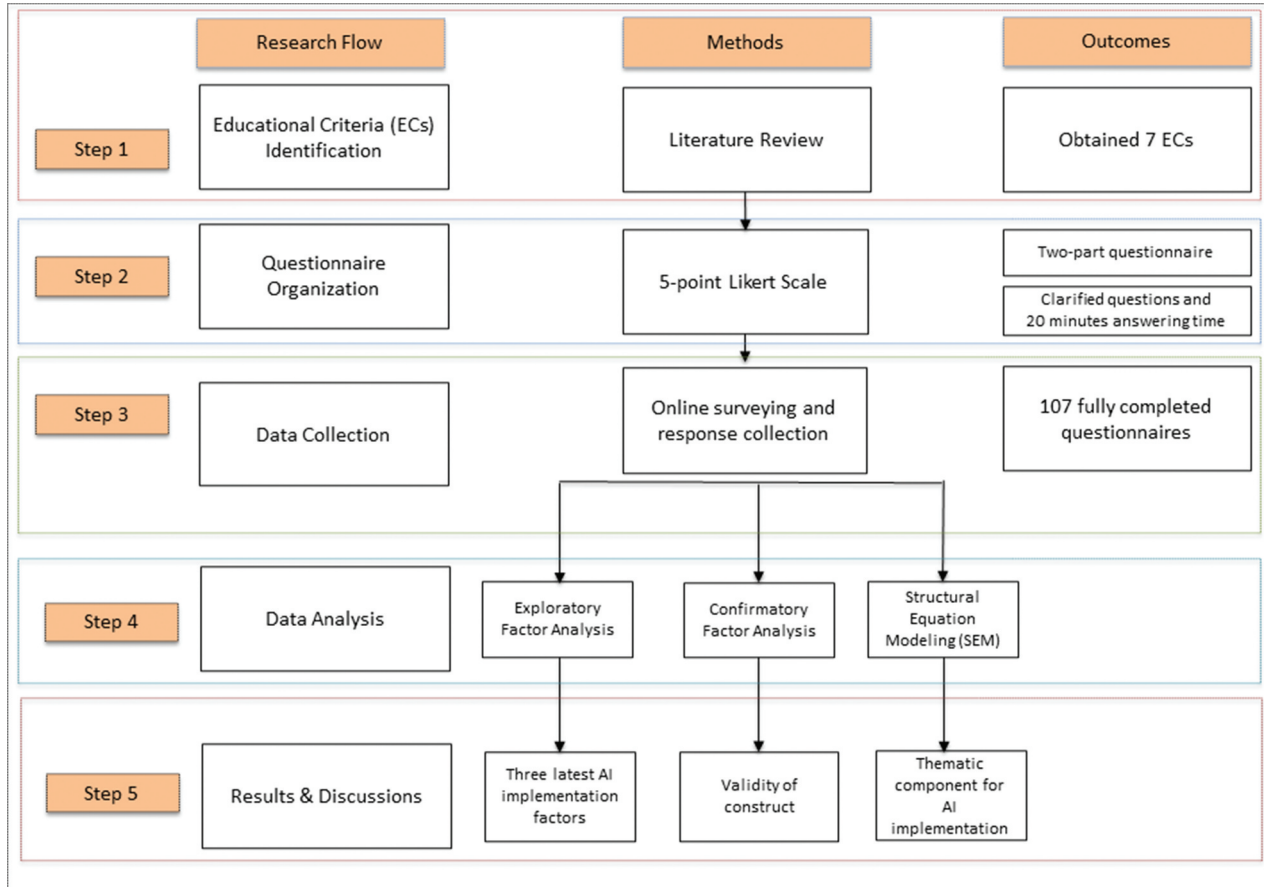


Figure 1. Flowchart of study.

Table 1. List of items in the survey.

AI Thematic Categories	Question Code	Question	Sources
TC_1 Artificial Intelligence Knowledge and Current Use	Q1	How much do you know about artificial intelligence?	RIBA AI Report (2024); Çamuşoğlu (2024); Hanafy (2023); Baran Ergül, Varol Malkoçoğlu, and Acun Özgünler (2022); Tazefidan, Eşme, and Başar (2022); Tamori et al. (2022), UNESCO (2023)
	Q2	How much do you know about how you can use AI technologies in architecture?	
	Q3	How often do you use artificial intelligence technologies in your architecture education?	
	Q4	Would you like to receive more education on artificial intelligence?	
	Q5	How does the use of artificial intelligence technologies in architectural practice affect the efficiency of your projects?	
	Q6	To what extent do you evaluate the impact of artificial intelligence technologies on the discipline of architecture?	
TC_2 Architecture and Digital Maturity	Q7	How often do you use digital tools in your student life?	RIBA AI Report (2024); Milić and Divjak (2022); Nielsen, Egeberg, and Svihus (2024); Cheche et al. (2024); Merzlov and Shilova (2022); Vavura and Matei (2024); Baihaqy and Subriadi (2023); Al-Ali and Marks (2022), UNESCO (2023).
	Q8	How does the use of digital tools affect the quality of your architectural projects?	
	Q9	How far do you think the digital transformation process has progressed in the architecture sector?	
	Q10	How do you assess the role of digital technologies on the sustainability and environmental impact of your architectural projects?	
	Q11	How does digitalization affect your creativity in your architectural education and career?	
	Q12	How does digitalization affect your creativity in your architectural education and career? How do you evaluate the potential of digital technologies to improve the quality of your architectural education?	
TC_3 Adoption of Artificial Intelligence and its Use in the Architecture Industry	Q13	To what extent do you agree that the design process with AI can ignore the human factor?	RIBA AI Report (2024); Çamuşoğlu (2024); Hanafy (2023); Baran Ergül, Varol Malkoçoğlu, and Acun Özgünler (2022); Tazefidan, Eşme, and Başar (2022); Tamori et al. (2022); Denni-Fiberesima (2024); Park, Yoon Lee, and Lee (2024); Komatina, Miletić, and Mosurović Ružičić (2024); Başarır (2022), UNESCO (2023)
	Q14	Do you think the use of artificial intelligence can improve the profession of architecture? If yes, how much?	
	Q15	Do you think AI integration will increase efficiency in your design process?	
	Q16	How do you evaluate the impact of artificial intelligence technologies on the aesthetic quality of architectural design?	
TC_4 The Impact of Artificial Intelligence in Architecture Education	Q17	I use it in early design stage visualizations.	RIBA AI Report (2024); Chang and Lu (2019); L. Chen, Chen, and Lin (2020); Komatina, Miletić, and Mosurović Ružičić (2024); Sadek and Mohamed (2023); Başarır and Erol (2021); Başarır (2022); Zhang, Fort, and Giménez Mateu (2023); Borglund (2022); Cheche et al. (2024); UNESCO (2023)
	Q18	I use it in the parametric design phase.	
	Q19	I use it in model production.	
	Q20	I use it in environmental impact modeling.	
	Q21	I use it in script writing.	
TC_5 The Future of Artificial Intelligence in Architecture	Q22	I use it in production, material selection and analysis.	RIBA AI Report (2024); Müller and Bostrom (2016); Ongun (2024); Yılmaz et al. (2021); Çetin and Aktaş (2021); Başarır (2022); Tamori et al. (2022)
	Q23	AI knowledge may compete with human knowledge in the future.	
	Q24	Artificial intelligence may be one of the causes of unemployment in architecture in the future.	
	Q25	Artificial intelligence can reach a sufficient level of architectural detail solving.	
	Q26	Artificial intelligence can increase the risk of our work being imitated.	
	Q27	I believe in the future of holistic artificial intelligence (design, detail solutions, implementation, plan-section drawings).	
	Q28	The future of artificial intelligence is unsettling ethical issues in architecture.	

(Continued)

Table 1. (Continued).

AI Thematic Categories	Question Code	Question	Sources
TC_6 Artificial intelligence and the risk of imitation in architecture	Q29	Is artificial intelligence a threat to the profession? Please rate.	RIBA AI Report (2024); Zhang, Fort, and Giménez Mateu (2023); Borglund (2022); L. Chen, Chen, and Lin (2020); Müller and Bostrom (2016), UNESCO (2023).
	Q30	Rate your concern about the impact of AI on the profession of architecture.	
	Q31	Do you think that designs produced by artificial intelligence can be disrespectful to human labor? Please rate.	
	Q32	Do you think there is a risk that AI-supported designs will imitate the work of their designers?	
	Q33	Do we need more and better digital tools such as artificial intelligence in the field of architecture profession with technological developments in today's conditions?	
	Q34	Can designs created with artificial intelligence have limitations in terms of originality and innovation? Rate them.	
	Q35	Should measures be taken to prevent the risk of imitation by AI? Please rate.	
	Q36	Do you think that designs produced by artificial intelligence may lack human sensitivity and aesthetics?	
TC_7 Ethical Values in the Use of Artificial Intelligence	Q37	Do you think the use of artificial intelligence can increase architecture students' ethical awareness in their design processes?	RIBA AI Report (2024); Tamori et al. (2022); L. Chen, Chen, and Lin (2020); Oh et al. (2019); Müller and Bostrom (2016), UNESCO (2023)
	Q38	Do you think architecture students need more education on professional responsibilities and ethical values in relation to the use of artificial intelligence?	
	Q39	With the use of AI-powered design tools, will architecture students encounter more issues with ownership and plagiarism?	
	Q40	Could architecture students undergoing an educational process in which projects are produced using artificial intelligence lead to reliability and communication problems in customer relations in the future?	
	Q41	When we consider fundamental ethical values in architecture, architects must consider not only the interests of individual clients in their designs, but also the general welfare of society. Do you think artificial intelligence tools can be effective in providing social benefits?	
	Q42	Do you think AI-based design processes can increase architecture students' awareness of sustainability and environmental ethics issues?	
	Q43	Do you consider it ethical for a student participating in an architectural design competition to use artificial intelligence applications to prepare their project?	
	Q44	To what extent do you think AI-assisted design could affect fair competition among students in architectural competitions?	
	Q45	Does the use of AI-powered design tools diminish the value of students' personal effort on a project?	
	Q46	Could AI-based design processes cause architecture students to neglect human-centered design principles?	

(Continued)

Table 1. (Continued).

AI Thematic Categories	Question Code	Question	Sources
TC_8 Artificial Intelligence in Architectural Design and Implementation	Q47	Do you think it is important for artificial intelligence to save time in both the design and implementation stages of architectural projects?	RIBA AI Report (2024); Oh et al. (2019); Abd El-Maksoud and Ahmed (2024); L. Chen, Chen, and Lin (2020); Müller and Bostrom (2016), UNESCO (2023)
	Q48	Does the decline in collaboration between architecture and other scientific disciplines due to artificial intelligence have a negative impact on you?	
	Q49	Do you think it is important that ideas are easier to implement in terms of workload and manpower during the construction phase with artificial intelligence?	
	Q50	Do you think it is possible to make progress in the construction phase with fewer workers and in less time using artificial intelligence, thereby increasing the amount of time workers have for themselves?	
	Q51	Does the fact that some ideas derived from artificial intelligence cannot be directly implemented or may encounter issues in real-life applications affect you and your design?	
	Q52	Would it be beneficial for you if artificial intelligence could predict extra costs that may arise on the construction site and come up with solutions?	
	Q53	Does the improvement in indoor living conditions achieved through AI-based building quality analysis make your daily life easier?	
	Q54	How does artificial intelligence help you visualize and promote projects in the construction phase more quickly?	

Table 2. Initial conceptual categories and final thematic components identified via EFA.

Initial Thematic Component	Mapped Final Thematic Component	Notes
1. Knowledge and Current Use of AI	Artificial Intelligence Impact and Current Usage	Direct conceptual alignment
2. Architecture and Digital Maturity	Digital Maturity	Mostly retained as is
3. Adoption of AI and Its Use in the Architecture Industry	Educational Component	Some items merged with The Impact of AI on Architectural Education
4. The Impact of AI on Architectural Education	Educational Component	Direct conceptual alignment and some items merged with Adoption of AI and Its Use in the Architecture Industry
5. The Future of AI in Architecture	Perceptual Future Orientation	Refocused into a future-oriented latent factor
6. The Risk of Imitation in Architecture through AI	Ethical Values	Partially combined with ethical concerns
7. Ethical Values in AI Usage	Ethical Values	Some items merged with Merged with the The Risk of Imitation in Architecture through AI
8. AI in Architectural Design and Implementation	Application Effectiveness	Refocused, keeping mostly as is

were conceptually grouped and how these groups correspond to the final components obtained through EFA.

Each of these data-based components was measured using a subset of the original 24 items. All items were evaluated using a five-point Likert scale ranging from 1 (Strongly disagree) to 5 (Strongly agree). The resulting final structure allowed for the application of psychometric evaluation methods such as Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM).

3.2. Data analysis

The dataset collected from the participants was coded and analyzed using SPSS 23.0 and SmartPLS 4 software.

The study utilized SmartPLS 4 to conduct Partial Least Squares Structural Equation Modeling (PLS-SEM). This method was chosen due to its suitability for exploratory studies with small sample sizes and formative constructs (Hair et al. 2021). Given the total sample size of 107, which falls below the threshold typically required for covariance-based SEM (CB-SEM), PLS-SEM provided a more flexible and reliable alternative, particularly for models with complex interrelations. Furthermore, PLS-SEM incorporates a non-parametric bootstrapping procedure, which allows for the estimation of standard errors and significance levels without relying on distributional assumptions. This enhances the model's generalizability and statistical validity even in studies with modest sample sizes (Hair, Hult, et al. 2017; Henseler, Ringle, and Sarstedt 2014). The analysis process included the assessment of internal

consistency (reliability), exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and the construction of a structural equation model (SEM).

To uncover the underlying latent structure of the constructs measured, an Exploratory Factor Analysis (EFA) was conducted. EFA is a statistical technique widely used to explore the dimensionality of data and to identify clusters of interrelated variables without imposing a predefined structure (Fabrigar and Wegener 2011). Participants' responses were entered into SPSS 23.0, and EFA was performed with varimax rotation. An eigenvalue threshold of 1 was set to determine the number of factors to retain (Kaiser 1960). Variables with factor loadings greater than 0.50 were considered significant (Hair, Black, et al. 2017). Based on the results, principal components were extracted and identified as independent constructs.

Following the Exploratory Factor Analysis (EFA), a Confirmatory Factor Analysis (CFA) was conducted using SmartPLS to assess the construct validity of the identified latent factors. CFA is a crucial step preceding Structural Equation Modeling (SEM), as it tests whether the observed data adequately fit the hypothesized measurement model (Hair, Black, et al. 2017). Construct validity refers to the extent to which a set of observed variables accurately represents the underlying theoretical constructs (Cronbach and Meehl 1955; Lavrakas 2008). High construct validity suggests that the survey items effectively capture the conceptual dimensions they are intended to measure.

Since this study used PLS-SEM, conventional CB-SEM fit indices (e.g., CFI, TLI, RMSEA) are not applicable. Instead, SRMR was reported as the primary model fit indicator, in line with PLS-SEM best practices (Hair et al. 2021). Model adequacy was evaluated using the Standardized Root Mean Square Residual (SRMR), which serves as the primary model fit indicator in Partial Least Squares Structural Equation Modeling (PLS-SEM). SRMR values below 0.08 are generally considered acceptable, indicating a good fit between the model and the observed data (Henseler, Ringle, and Sarstedt 2014). Additionally, standardized path coefficients were examined to assess the strength of relationships between latent constructs. Path coefficients below 0.1 suggest weak relationships, around 0.3 indicate moderate effects, and 0.5 or higher reflect strong relationships (Hair, Black, et al. 2017). In this study, *t*-values exceeding 1.96 were considered statistically significant at the 95% confidence level, based on bootstrapping procedures with 5000 resamples. In addition to the assessment of path coefficients and their significance, we also calculated effect sizes (f^2) to evaluate the relative contribution of each exogenous construct to its corresponding endogenous construct. The f^2 statistic is derived by comparing the R^2 value of an endogenous construct when a predictor is

included versus excluded from the model (Chin 1998; Hair, Hult, et al. 2017). According to Cohen's (1988) guidelines, f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively, while values below 0.02 are considered negligible.

After confirming the measurement model's reliability and validity through EFA and CFA, the study proceeded to the structural model analysis. Structural Equation Modeling (SEM) was employed to test the hypothesized relationships among the latent constructs and to evaluate the overall conceptual framework proposed in this research.

3.3. Ethical considerations

All participants were informed about the purpose, scope, and voluntary nature of the study, and verbal informed consent was obtained prior to their participation. The research was conducted in compliance with the ethical principles outlined in the Declaration of Helsinki.

4. Results

4.1. Exploratory factor analysis

As a preliminary step, an Exploratory Factor Analysis (EFA) was conducted to identify the underlying dimensions of the dataset. Out of 54 initial survey items, 24 items were retained based on their factor loadings and theoretical relevance. The EFA results revealed a six-factor structure, with each factor subsequently labeled according to the thematic content of its associated items. These factors were named as follows: Educational Component, Perceptual Future Orientation, Application Effectiveness, Digital Maturity, Ethical Values, and Artificial Intelligence Impact and Current Usage. Table 3. Results of Exploratory (EFA) and Confirmatory (CFA) Factor Analyses.

This factor structure aligns with the primary aim of the study, which is to investigate the influence of architectural education on perceptions and practices related to artificial intelligence. The identified constructs provide a conceptual foundation for further validation through confirmatory factor analysis and structural modeling.

To explore the underlying factor structure of the measurement model, an Exploratory Factor Analysis (EFA) was employed. The analysis yielded six distinct latent factors based on the Kaiser criterion (eigenvalues > 1), cumulatively accounting for 61.479% of the total variance. This proportion of explained variance is deemed acceptable for behavioral and social science research, signifying that the extracted factors adequately represent the original dataset's dimensionality. Specifically, the Perceptual Future Orientation factor alone explained 14.405% of the variance, followed sequentially by Educational Component (12.899%), Digital Maturity (10.899%),

Table 3. Results of Exploratory (EFA) and Confirmatory (CFA) factor analyses.

Representative items	Items Code	Assigned Name	EFA		CFA
			Eigen value	%of variance	Factor Loadings
Thematic Components		Perceptual			
TC_1		Future Orientation			
[Q24]	[PO1]		4.369	14.405	.772
[Q26]	[PO2]				.870
[Q28]	[PO3]				.876
[S29]	[PO4]				.671
[Q30]	[PO5]				.657
[Q31]	[PO6]				.666
TC_2		Educational Component			
[Q15]	[EC1]		3.87	12.899	.607
[Q18]	[EC2]				.795
[Q19]	[EC3]				.735
[Q20]	[EC4]				.770
[Q22]	[EC5]				.638
TC_3		Digital Maturity			
[Q7]	[DM1]		2.514	10.899	.780
[Q8]	[DM2]				.702
[Q11]	[DM3]				.756
[Q12]	[DM4]				.805
TC_4		Application Effectiveness			
[Q52]	[AE1]		2.068	8.463	.761
[Q53]	[AE2]				.698
[Q54]	[AE3]				.749
TC_5		Artificial Intelligence Impact and Current Usage			
[Q1]	[AR1]		1.66	8.364	.859
[Q2]	[AR2]				.790
[Q3]	[AR3]				.683
TC_6		Ethical Values			
[Q39]	[ET1]		1.504	7.277	.757
[Q40]	[ET2]				.694
[Q45]	[ET3]				.507
Sample Adequacy and Factorability Test					
	Total explained variance			61.479	
	Kaiser-Meyer-Olkin (KMO) value			.692	
	Bartlett's test of sphericity	Approx.Chi-Square		1137.620	
		Df		325	
		Sig.		.00	

Application Effectiveness (8.463%), Artificial Intelligence Impact and Current Usage (8.364%), and Ethical Values (7.277%). The relative dominance of the first component supports its centrality within the conceptual framework.

The Kaiser-Meyer-Olkin (KMO) measure was calculated as 0.692, indicating a moderate level of sampling adequacy for factor analysis (Pallant 2005). Furthermore, Bartlett's Test of Sphericity produced a statistically significant result ($\chi^2 = 1137.620$, $df = 325$, $p < 0.001$), confirming that the inter-item correlations were sufficient to justify the application of factor analysis. All retained items demonstrated factor loadings exceeding the critical threshold of 0.50, thus evidencing strong convergent validity within each identified dimension (Hair, Black, et al. 2017). The thematic interpretation of each factor was undertaken based on the semantic content of the associated items, ensuring conceptual alignment with the overarching aim of investigating the integration of artificial intelligence in architectural education.

4.2. Specification of the hypothetical structural model

To investigate the structural relationships between the latent constructs identified in the exploratory phase, a hypothetical model was developed and is presented in Figure 2. The model includes five core constructs: *Educational Component (EC)*, *Perceptual Future Orientation (PO)*, *Application Effectiveness (AE)*, *Ethical Values (ET)*, and *Digital Maturity (DM)*. Based on the theoretical framework and the results from the EFA and CFA, the following hypotheses were proposed (Table 4). Although the Exploratory Factor Analysis (EFA) identified six distinct components, only five of these were retained in the final Structural Equation Model (SEM). The component labeled as "Artificial Intelligence Impact and Current Usage" (AR) was excluded from the model due to its lack of statistical significance in the hypothesized structural paths. Specifically, AR demonstrated no meaningful contribution to the overall explanatory framework, failing to establish reliable or theoretically consistent

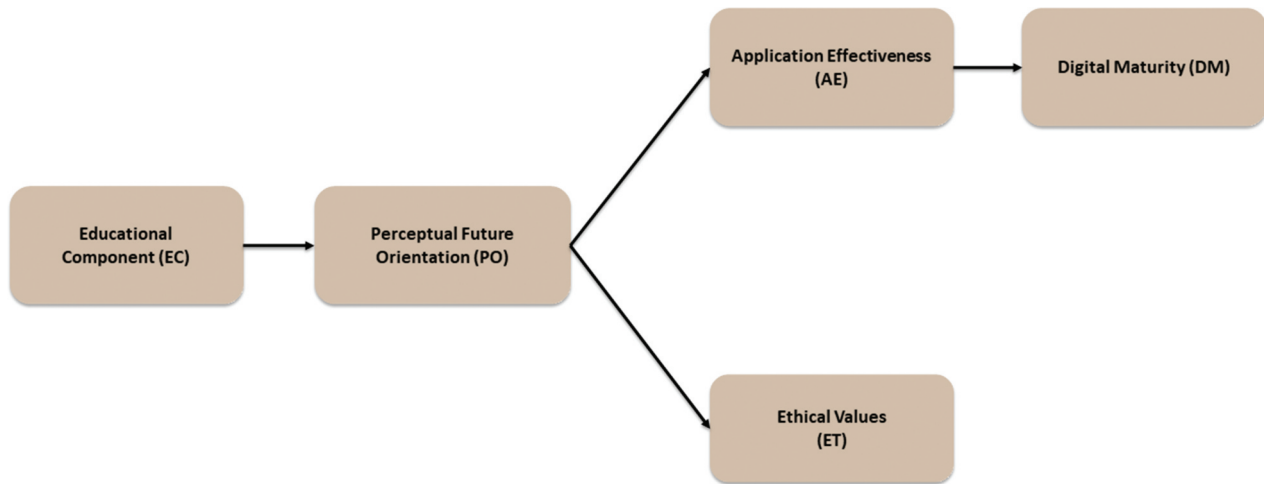


Figure 2. Hypothetical structural model of AI integration in architectural education.

Table 4. Hypothesis description.

Description	Hypothetical path	Assigned code
The <i>Educational Component</i> positively affects <i>Perceptual Future Orientation</i>	EC to PO	H1
<i>Perceptual Future Orientation</i> positively affects <i>Application Effectiveness</i>	PO to AE	H2
<i>Application Effectiveness</i> positively affects <i>Digital Maturity</i>	AE to DM	H3
<i>Perceptual Future Orientation</i> positively affects <i>Ethical Values</i>	PO to ET	H4
<i>Perceptual Future Orientation</i> mediates the effect of <i>Educational Component</i> on <i>Application Effectiveness</i>	EC to PO to AE	H5
<i>Perceptual Future Orientation</i> mediates the effect of <i>Educational Component</i> on <i>Ethical Values</i>	EC to PO to ET	H6
<i>Application Effectiveness</i> mediates the effect of <i>Perceptual Future Orientation</i> on <i>Digital Maturity</i>	PO to AE to DM	H7

relationships with the other latent variables. Given the model's aim to elucidate significant and theoretically grounded pathways, the exclusion of AR was necessary to maintain parsimony and ensure conceptual clarity within the SEM structure.

The model hypothesizes both direct and indirect effects, with *Perceptual Future Orientation* acting as a mediating variable between *Educational Component* and both *Application Effectiveness* and *Ethical Values*. Furthermore, *Application Effectiveness* is expected to serve as a key determinant of *Digital Maturity*, emphasizing the role of practical AI engagement in enhancing digital competencies. These structural relationships reflect a theoretically grounded framework designed to evaluate how educational experiences with AI influence students' forward-looking perspectives, practical usage capacity, and ethical sensitivity – ultimately contributing to their overall digital maturity.

4.3. Measurement model evaluation

4.3.1. Confirmatory Factor Analysis (CFA)

A CFA was performed within the framework of Partial Least Squares Structural Equation Modeling (PLS-SEM)

to validate the factor structure identified through the EFA. As shown in Table 3, all standardized factor loadings exceeded the 0.50 threshold – except for ET₂, which fell below the acceptable limit. Therefore, ET₂ was excluded from the hypothetical model to improve overall construct reliability.

4.3.2. Reliability and construct validity

Multiple statistical indices were evaluated to assess the internal consistency and construct reliability of the measurement model, including Cronbach's Alpha, Composite Reliability (pc), and Average Variance Extracted (AVE). These indicators were used to validate the consistency and reliability of the latent variables within the proposed structural model, as detailed in Table 5. reliability results and AVE results of constructs/latent factors.

Reliability and validity were evaluated according to PLS-SEM standards, including Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). As shown in Table 5, all constructs demonstrated acceptable levels of composite reliability, with values exceeding the threshold of 0.70 as suggested by Fornell and Larcker (1981). Specifically,

Table 5. Reliability results and AVE results of constructs/latent factors.

Name of TC	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AE	0.845	0.851	0.886	0.567
DM	0.744	0.764	0.839	0.569
ET	0.559	0.628	0.813	0.687
EC	0.777	0.783	0.857	0.601
PO	0.699	0.715	0.832	0.623

Application Effectiveness (AE), *Digital Maturity (DM)*, *Educational Component (EC)*, and *Perceptual Future Orientation (PO)* achieved strong composite reliability scores ranging from 0.764 to 0.886. While the *Ethical Values (ET)* construct showed a lower Cronbach's Alpha (0.559) and rho_A (0.628), its composite reliability ($\rho_c = 0.813$) and AVE (0.687) surpassed the recommended cut-off values, suggesting sufficient reliability for exploratory research purposes (Hair, Black, et al. 2017).

Regarding AVE values, all constructs exceeded the minimum threshold of 0.50, thereby supporting the convergent validity of the measurement model (Hair, Black, et al. 2017). The results indicated that a significant proportion of the variance was captured by the latent variables, and thus the items adequately represent their respective constructs. Discriminant validity was assessed through cross-loadings analysis in Figure 3. Each indicator showed a higher loading on its intended construct than on any other, supporting the distinctiveness of the latent variables and confirming adequate discriminant validity (Chin 1998; Hair, Black, et al. 2017).

These results, supported by the path coefficients and outer loadings shown in Figure 2, confirm the reliability of the model constructs and justify further analysis using Structural Equation Modeling (SEM). In summary, the measurement model demonstrated acceptable reliability, convergent validity, and discriminant validity. Despite minor limitations in global fit indices, the overall results support the adequacy of the model for explaining the relationships among the constructs in the context of artificial intelligence integration in architectural education.

4.3.3. Model fit assessment

The SRMR value of 0.089 slightly exceeded the commonly accepted threshold of 0.08 as originally proposed for CB-SEM applications (Hu and Bentler 1999), but considering the exploratory nature and complexity of the model, it was deemed tolerable within acceptable bounds for PLS-SEM (Hair et al. 2021).

4.4. Evaluation of structural model

Following the establishment of the measurement model's reliability and validity, the structural model was assessed to test the hypothesized relationships among the latent constructs. This evaluation involved examining both Path Coefficients and Hypotheses Testing

4.4.1. Path analysis and hypothesis testing

Based on the conceptual framework illustrated in Figure 2, a structural equation model was constructed, as shown in Figure 4, displaying the standardized path coefficients associated with each proposed hypothesis. The structural model's path coefficients and their significance levels are presented in Table 6. Among the seven hypothesized relationships, three were found to be statistically significant:

As shown in Figure 5, while the direct effects were statistically significant except PO does not directly translate into practice AE, the indirect (mediated) paths were found to be non-significant. These results indicate that *Educational Components* significantly influence students' perceptions of the future of AI (H1), which in turn has a direct and positive impact

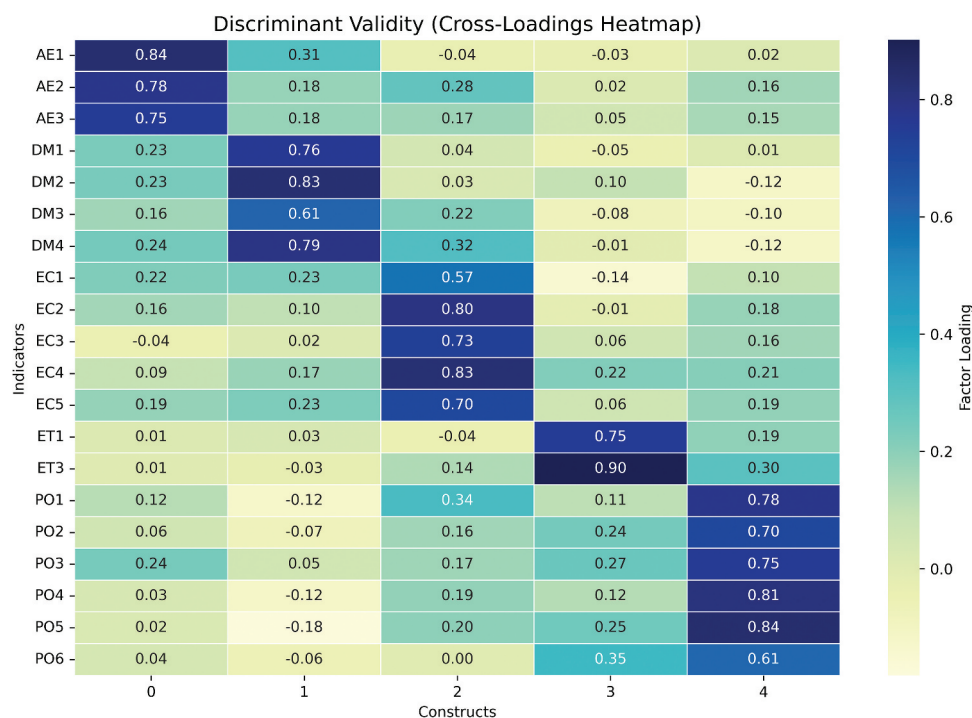


Figure 3. Discriminant validity analysis.

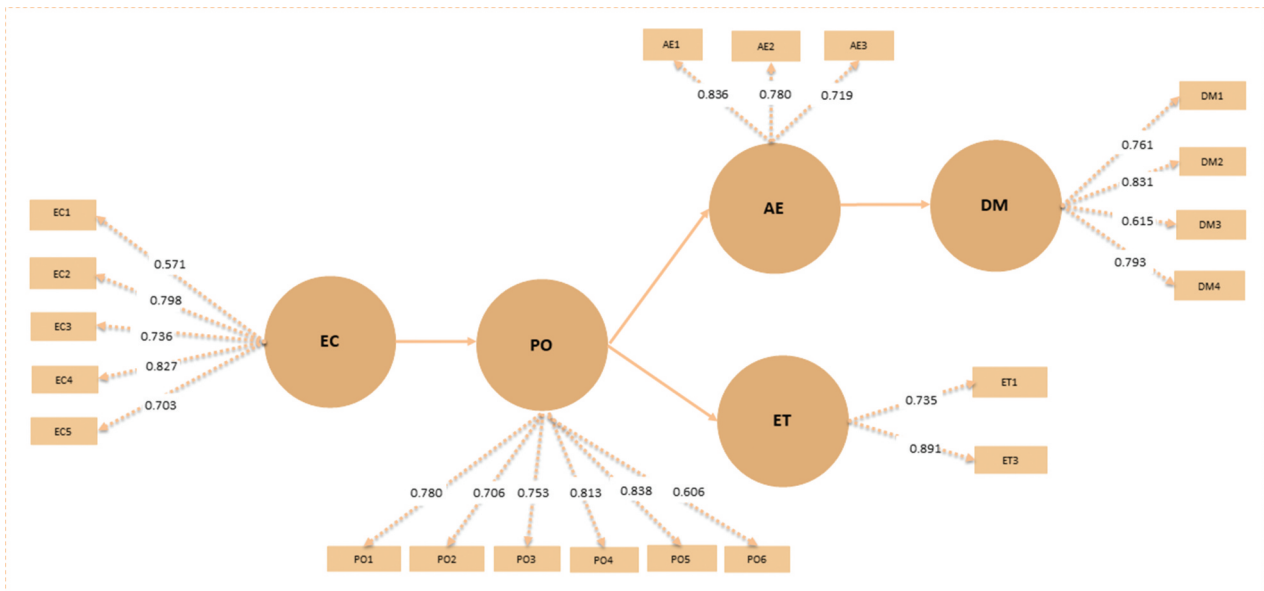


Figure 4. Proposed latent variable model.

Table 6. Hypotheses evaluation based on path coefficients and t-statistics.

Code	Path Coefficient**	t value	p value	f ²	Interpretation
H1	0.242	2.838	0.005	0.062 small	Supported
H2	0.126	0.841	0.400	0.016 (negligible)	Non Supported
H3	0.292	3.296	0.001	0.16 moderate	Supported
H4	0.308	2.430	0.015	0.093 small moderate	Supported
H5	0.030	0.602	0.547	–	Non supported
H6	0.072	1.530	0.126	–	Non supported
H7	0.037	0.727	0.467	–	Non supported

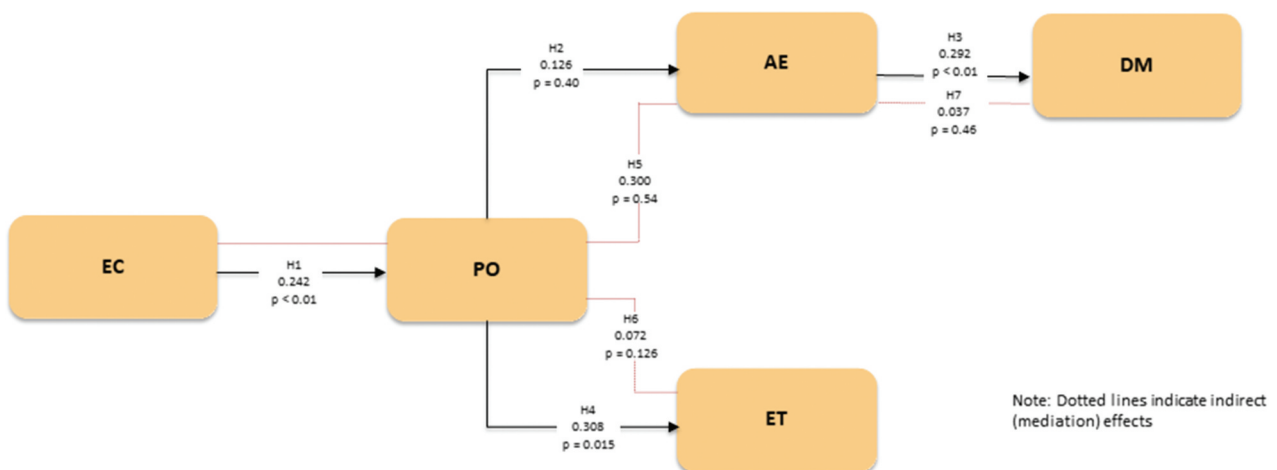


Figure 5. Structural Equation model showing direct and indirect (mediating) effects.

on *Ethical Values* (H4). Moreover, *Application Effectiveness* is critical in fostering *Digital Maturity* (H3). However, the hypothesized relationship between *Perceptual Future Orientation* and *Application Effectiveness* (H2) was not statistically supported, suggesting that positive attitudes toward AI may not

directly translate into practical competence without further pedagogical or institutional support. While the primary objective of the study was to examine the direct relationships between the core constructs – particularly the effects of Educational Component (EC), Perceptual Future Orientation (PO), Application

Effectiveness (AE), and Digital Maturity (DM) – additional hypotheses regarding potential mediating effects were incorporated to ensure conceptual completeness of the proposed framework. These mediation paths (H5, H6, and H7) were theoretically plausible and consistent with the broader literature on structural equation modeling; however, the empirical results did not support these indirect effects, indicating that the proposed relationships are best explained through direct associations, consistent with the original conceptual emphasis of the research. The effect size analysis (f^2) revealed that Educational Components had a negligible impact on Future Perceptions ($f^2 = 0.062$), Application Effectiveness showed a small-to-moderate effect on Digital Maturity ($f^2 = 0.16$), and Future Perceptions exerted a negligible effect on Ethical Awareness ($f^2 = 0.093$). By contrast, Future Perceptions has a negligible impact on Ethical Awareness ($f^2 < 0.02$). These findings suggest that, although the hypothesised relationships were statistically significant, the explanatory contributions of individual predictors remained modest. This outcome is consistent with exploratory applications of PLS-SEM in the social sciences, where relatively small effect sizes are common (Hair et al., 2019).

5. Findings

This section presents the findings derived from the quantitative data analysis conducted through Structural Equation Modeling (SEM), which constitutes the core of this study. The theoretical model developed in line with the research objectives aims to examine the relationships between key constructs such as educational components, application effectiveness, digital maturity, ethical values, and future-oriented perception. Accordingly, the structural validity of the measurement tool was first tested using Exploratory Factor Analysis (EFA), followed by Confirmatory Factor Analysis (CFA) and SEM to model the hypothesized relationships. These analyses enable a comprehensive, multidimensional evaluation of students' attitudes, awareness levels, and practical engagement with artificial intelligence. In the subsections below, the empirical results of these analyses are presented in detail, and the hypothesized relationships are interpreted based on statistical significance and theoretical consistency. As delineated in Table 4, the evaluation of the structural model yielded nuanced findings. Of the four hypothesized pathways, three demonstrated statistical significance, thereby corroborating the proposed theoretical linkages. Specifically, the relationship between Education and Perceptual Future Orientation (H1) was substantiated ($\beta = 0.242$, $p = 0.005$), indicating that educational experiences substantially enhance forward-looking perceptions regarding artificial intelligence in the architectural context.

Furthermore, Application Effectiveness was found to exert a significant influence on Digital Maturity (H3) ($\beta = 0.292$, $p = 0.001$), suggesting that practical engagement with AI technologies contributes meaningfully to achieving digital competence. The pathway from Perceptual Future Orientation to Ethical Values (H4) also attained significance ($\beta = 0.308$, $p = 0.015$), underscoring the critical role of anticipatory attitudes in shaping ethical considerations surrounding AI adoption. Conversely, the proposed relationship between Perceptual Future Orientation and Application Effectiveness (H2) did not achieve statistical significance ($\beta = 0.126$, $p = 0.400$), implying that while perceptual orientations are theoretically relevant, they may not independently translate into effective application behaviors without the mediation of other organizational or contextual factors. Collectively, these findings offer robust empirical support for the conceptual framework, affirming that educational interventions and perceptual dimensions critically underpin the ethical and practical integration of AI within architectural practice.

6. General evaluation and discussion

The findings of this study examine the pedagogical, ethical, and practical effects of artificial intelligence (AI) technologies in architecture education in a multidimensional manner. It is consistent with trends in the literature and offers new interpretations in some respects. The structural model (SEM) developed in the study analyzed students' attitudes and experiences regarding AI through five key dimensions and identified meaningful relationships between these factors. The factors evaluated in the study were: perception of the future, educational components, digital maturity, application effectiveness, and ethical values. The findings confirm some trends in the literature while enabling new interpretations in some areas. According to the demographic data of the study, artificial intelligence is widely used by students in architecture education, and at the same time, students consider artificial intelligence to be quite useful for architecture. Students benefit from artificial intelligence in the development of design scenarios and rendering stages. These findings are consistent with the literature emphasizing the growing importance of integrating artificial intelligence into the education system (Müller and Bostrom 2016; Ongun 2024; Tan et al. 2022; Ye, Sun, and Li 2021).

6.1. Factor 1: perception of the future

SEM analysis revealed that educational components significantly strengthened students' perceptions of AI in the future (H1 supported). This shows that AI tools

integrated into the curriculum contribute not only to students' technical knowledge but also to their development of a forward-looking vision. This finding is consistent with analyses emphasizing AI's proactive role in pedagogical applications, as highlighted in studies such as Başarır (2022) and Komatina, Miletić, and Mosurović Ružičić (2024). Students' use of AI tools in studio-focused applications such as visualization, parametric design, and environmental modeling demonstrates that these technologies have become not only auxiliary tools in architectural pedagogy but also actors that transform the creative process. In particular, the rapid representation capabilities of tools such as DALL-E, Midjourney, and Leonardo AI deepen teacher-student interaction and increase pedagogical dynamism in design studios (Basarır and Erol).

6.2. Factor 2: educational components

In terms of educational components, it has been observed that students' perceptions of AI do not directly reflect their practical skills (H2 is not supported). This result suggests that a positive perception alone is not sufficient; practical environments and guidance that enable students to use AI tools in real-world scenarios need to be addressed (Chang and Lu 2019; L. Chen, Chen, and Lin 2020; Komatina, Miletić, and Mosurović Ružičić 2024; Sadek and Mohamed 2023; Basarır and Erol ; Başarır 2022; Zhang, Fort, and Giménez Mateu 2023; Borglund 2022; Cheche et al. 2024).

6.3. Factor 3: digital maturity

Another strong relationship in the model is that application effectiveness significantly increases digital maturity (H3 is supported). This emphasizes that digital tools play a role in supporting not only instrumental but also comprehensive digital competence development. This finding supports the findings of studies such as Milić and Divjak (2022) and Nielsen, Egeberg, and Svihus (2024), which highlight the critical role of individual application experience in digital transformation processes. Architecture students' active use of AI in areas such as rendering, model production, and scenario design enhances their proficiency with digital tools, positively influencing their digital maturity levels. This result shows that technological proficiency can be strengthened not only through cognitive awareness but also through experiential learning. The study findings show that the vast majority of students actively use AI tools but have not received formal training in this area. Additionally, students primarily learn about AI from YouTube, Instagram, and open digital platforms. This situation is

consistent with the issues of institutional access and digital inequality raised in studies such as Başarır (2022) and Cheche et al. (2024). Providing students with access to secure and free AI tools and integrating AI-related modules into the curriculum would be important steps toward addressing these access limitations.

6.4. Factor 4: ethical values

One of the most important findings of the study is that perceptions of AI increase ethical awareness among students (H4 is supported). This finding is consistent with the view expressed by Müller and Bostrom (2016) and L. Chen, Chen, and Lin (2020) that ethical awareness plays a central role in the use of technology. Students view AI not only as a production tool but also as an element that influences the social responsibility dimension of design. As a result, it demonstrates the need to redesign architecture education to develop not only technical competence but also ethical reflexes.

6.5. Factor 5: application efficiency

In the model, the effect of perception on application skills was not found to be significant (H2 rejected). This result is consistent with the findings of Tamori et al. (2022) and Cheche et al. (2024), which show that despite high awareness of AI, application effectiveness is limited. Although students understand the potential of AI at a theoretical level, they struggle to develop application-oriented competence due to the lack of practical settings and guidance that would enable them to actively use these technologies. This situation highlights that the integration of AI in architecture education is not only dependent on technology access but also requires pedagogical restructuring and practice-based learning strategies.

Finally, the fact that the vast majority of students learn AI tools informally emphasizes the lack of a systematic curriculum and the need for institutional support. In addition, while the study provides meaningful insights through structural modeling, the relatively small sample size ($n = 107$) remains a methodological limitation. To address this, the study employed Partial Least Squares Structural Equation Modeling (PLS-SEM), which is appropriate for small sample sizes and complex models. The use of non-parametric bootstrapping further enhanced the statistical robustness and internal validity of the results. Given the exploratory nature of this study and the sample size, the findings should be interpreted with caution regarding their generalizability. The conceptual model proposed here can serve as a theoretical foundation for future research, but empirical testing with larger, cross-institutional samples is recommended. Such studies

could provide more generalizable evidence and uncover contextual differences in students' experiences with AI in architectural education.

7. Conclusion

This study provides a comprehensive analysis of students' attitudes and experiences by examining the perception, use, and pedagogical effects of artificial intelligence (AI) technologies in the context of architecture education within a multidimensional framework. The theoretical framework developed using structural equation modeling (SEM) has revealed the relationships between key factors such as educational components, digital maturity, ethical values, and application effectiveness; the model's statistical validity and conceptual integrity have been confirmed in line with the literature. The findings of the study indicate that the integration of AI into architecture education requires not only a technical transformation but also a comprehensive restructuring process that includes pedagogical and ethical dimensions. Although students' general awareness and interest in AI technologies is high, this awareness does not directly translate into practice. This situation indicates the need to increase experiential learning opportunities and strengthen guidance mechanisms in educational environments. The indices obtained in the SEM analysis revealed that the model demonstrated an acceptable level of fit. The direct effect of the digital maturity variable on application effectiveness was found to be significant, and the mediating relationship between ethical awareness and future perception was also confirmed. These results demonstrate that the pedagogical and ethical dimensions of artificial intelligence complement each other. Therefore, they indicate that ethical awareness must be addressed in an integrated manner alongside technical competence in educational designs.

Based on the findings, the main conclusions are a lack of pedagogical contribution, practical and digital competence, ethical awareness, and a lack of institutional support for the effective integration of AI into architectural education. Accordingly, as a pedagogical contribution, integrating AI tools into educational environments strengthens students' farsightedness skills and enables them to build a more informed perception of the future. However, in the context of application and digital competence, the hands-on AI experience directly increases students' digital competence levels, which in turn encourages active participation in the digital transformation process. In addition, students' perceptions of artificial intelligence also affect their sensitivity to ethical values. This situation requires a re-examination of the concepts of social responsibility and design ethics in the architectural profession. Finally, the fact that the vast majority of

students learn AI tools informally emphasizes the lack of a systematic curriculum and the need for institutional support.

Within this framework, the study offers important recommendations for architectural education at both the theoretical and practical levels. From a theoretical perspective, it proposes a unique structure that models the multi-layered effects of AI in the educational environment. From a practical perspective, it demonstrates that AI should be evaluated not only as a technology but also as a pedagogical and ethical tool. Future studies could include comparative analyses based on different university samples, as well as in-depth examinations of the pedagogical and professional qualities of the outputs produced by students using AI tools in their design processes. This would contribute to the more effective, fair, and ethically grounded use of AI in architecture education.

Author contributions

Hilal Ayçi, Esra Betül Kınacı, Güneş Mutlu Avınç, and Aslı Taş collaboratively conceived and designed the study, contributed equally to the interpretation of the data, participated in drafting the manuscript, and provided critical revisions for important intellectual content. Esra Betül Kınacı was responsible for conducting the statistical analyses and processing the data. All authors have reviewed and approved the final version of the manuscript and accept full responsibility for the integrity and accuracy of the work.

Disclosure statement

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

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