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Enhancing Architectural Education through Artificial Intelligence: A Case Study of an AI-Assisted Architectural Programming and Design Course

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Abstract: This study addresses the current lack of research on the effectiveness assessment of Artificial Intelligence (AI) technology in architectural education. Our aim is to evaluate the impact of AI-assisted architectural teaching on student learning. To achieve this, we developed an AI-embedded teaching model. A total of 24 students from different countries participated in this 9-week course, completing a comprehensive analysis of architectural programming and design using AI technologies. This study conducted questionnaire surveys with students at both midterm and final stages of the course, followed by structured interviews after the course completion, to explore the effectiveness and application status of the teaching model. The results indicate that the AI-embedded teaching model positively and effectively influenced student learning. The "innovative capability" and "work efficiency" of AI technologies were identified as key factors affecting the effectiveness of the teaching model. Furthermore, the study revealed a close integration of AI technologies with architectural programming but identified challenges in the uncontrollable expression of architectural design outcomes. Student utilization of AI technologies appeared fragmented, lacking a systematic approach. Lastly, the study provides targeted optimization suggestions based on the current application status of AI technologies among students. This research offers theoretical and practical support for the further integration of AI technologies in architectural education.

Keywords: Artificial Intelligence; architectural education; architectural programming; sustainable design; questionnaire; interview

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1. Introduction

With the rapid development of Artificial Intelligence (AI), higher education is undergoing an unprecedented transformation [1]. This transformation not only involves technological advancements but also poses profound challenges for traditional educational paradigms [2,3]. Architectural education, as a crucial aspect of sustainable development in higher education [4,5], faces the challenge of professional knowledge and many skills becoming insufficient for students upon graduation due to the rapid changes in AI [6]. Skills that were once considered exceptional in architecture, such as computer-aided design [7,8], digital design [9,10], and parametric design [11,12], have become relatively commonplace with the popularization of AI technologies [13–15]. Architectural education must re-examine itself to cultivate students' skills in flexibly applying AI for problem analysis, information gathering, and creative design, preparing them to meet the challenges of the future in the field of architecture.

In recent years, with the continuous development of China's construction industry, relevant national policies have been successively introduced, focusing on guiding and regulating the design and management work in the construction market, advocating for the holistic study of the entire lifecycle of buildings [16,17]. With the evolution of the times and industry demands, the training objectives for professionals in the field of architecture have also undergone certain changes. Not only are students required to possess design and creative abilities, but they also need to be competent in the entire lifecycle process, including architectural programming and post-occupancy evaluation [18]. Furthermore, the theory and practical teaching of architecture's entire lifecycle have been implemented in architect education in some developed countries and recognized as successful [19,20]. Therefore, architectural education must adapt to this new trend by introducing the entire lifecycle process [21,22], cultivating students' abilities to comprehensively analyze and solve problems, training them to start from the issues, combine objective research with subjective demands, and transform them into design factors to guide subsequent creative work and design [23].

In the era of AI, facing the intricate challenges of the future construction industry, architectural education should integrate the teaching content of architectural programming and design and apply AI technologies in various aspects of teaching to cultivate students' comprehensive and efficient skills [24]. Against this backdrop, this study integrates various AI technologies to develop a novel AI-embedded teaching model, which is applied to postgraduate professional courses at—University. Furthermore, to evaluate the effectiveness of this AI-embedded teaching model, a combined quantitative and qualitative approach is employed in this study, using data collected at two stages of the course, midterm and final, to examine the application effects of the model. In summary, the study poses the following research questions:

1. How effective is the practical application of this teaching model?
2. What key factors influence the application of this teaching model?
3. What are the primary challenges encountered when integrating AI into architectural education?
4. How should the primary challenges of integrating AI into architectural education be addressed?

Subsequent sections unfold as follows: Section 2 introduces architectural education and its significance in introducing architectural programming, as well as the application of AI technologies in architectural education. Section 3 delineates the AI-embedded teaching model for architectural programming and design, encompassing its theoretical framework, instructional process, and methodological steps. Section 4 elucidates the background, methodology, and participant information of the case study. Section 5 reports the findings of the case study, while Section 6 provides corresponding optimization recommendations based on the results. Finally, Section 7 concludes this paper's research, putting forth suggestions for future work.

2. Background

2.1. Evolutionary Goals of Architectural Education

Architectural education has undergone continuous development, accompanied by a transformation in its educational objectives [25]. Initially, the focus was primarily on imparting fundamental design skills [26] and construction knowledge [27], emphasizing students' aesthetic sensibilities [28,29], creative abilities [8,30], and practical skills [31,32].

As society, technology, and industry progressed, architectural education exhibited a more interdisciplinary character [4,33]. It aimed to guide students in mastering digital and informational technologies [34,35], humanities and social science analyses [36,37], and sustainable design [38,39], fostering their comprehensive literacy in fields such as digital and information sciences [11,40], humanities and social sciences [26,41,42], and sustainable development [43,44].

In recent years, the construction industry has faced increased complexity and diversity [45], prompting architectural education to focus on cultivating students' abilities in intelligent programming [46], design [47], and construction [48]. By applying intelligent technologies throughout the entire building lifecycle, the intelligent transformation of the entire building industry chain is achieved, propelling the industry toward a more intelligent and efficient direction.

2.2. Significance of Architectural Programming

Architectural programming is not merely the initiation of a project; rather, it encompasses a comprehensive process involving project strategic planning, problem analysis, decision making regarding requirements, and feasibility studies [49]. By considering various factors comprehensively, it establishes project goals and, grounded in empirical investigations, provides methods and work plans to achieve these goals [50,51].

Currently, within architectural education, the practical aspects of architectural programming are relatively underemphasized [52]. Traditional architectural teaching tends to focus more on cultivating design skills, which can result in students potentially lacking a holistic understanding of the overall and practical feasibility of projects, along with a deficiency in the ability to think comprehensively about architectural issues [53].

However, integrating architectural programming into architectural education is crucial. Firstly, it provides students with a broader perspective, enabling them to engage in comprehensive thinking and systematic analysis of architectural issues [54]. Secondly, architectural programming is closely related to design, and the quality of its decisions directly influences the direction and effectiveness of subsequent designs [55]. By introducing architectural programming, architectural education can cultivate students' more-refined creative thinking and analytical abilities in the early stages of projects [56]. Faced with the increasingly complex and dynamic architectural environment, this comprehensive teaching approach will equip students to adapt more flexibly to various architectural projects and prepare them for future challenges.

2.3. AI Technologies in Architectural Education

The development of AI, as a rapidly advancing frontier technology, has undergone several key stages. From the initial symbolic stage [57] and the rise in neural networks [58] to the leadership of deep learning [59] and reinforcement learning [60], and the current widespread application of Large Language Models (LLMs) [61] and Artificial Intelligence-Generated Content (AIGC) [62], AI exhibits a comprehensive and innovative developmental trajectory.

The application of AI in architectural education has also undergone a progressively deepening process. Initially, AI primarily played a supporting role in architectural design, enhancing efficiency through tasks such as extensive data calculations and precise assessment simulations [63–65]. With the continuous evolution of technology, AI gradually assumes a more proactive role in architectural design. It can engage more comprehensively in the design process, including conceptual design, performance optimizations, and automated layout [13,66–68], providing students with innovative design ideas and solutions. Currently, the widespread use of LLMs and AIGC further lowers the entry barriers of AI, fostering more creative and personalized comprehensive intelligent applications [69]. AI not only aids in solving complex design problems [70] but also offers more personalized learning experiences based on individual student differences [71], thereby enhancing the specificity and effectiveness of architectural education.

Numerous studies have explored AI-assisted architectural education [6,13–15,72]. Building upon this foundation, this study innovates further. Firstly, it not only integrates AI technology with architectural design but also further combines AI technology with architectural programming, enabling students to comprehensively understand the entire process from programming to design in their course learning. Secondly, this study designs and implements a complete AI-assisted architectural programming and design course model, integrating AI technology into various stages of the teaching process, including problem exploration, decision making, initial design, and detailed design, thereby cultivating students' comprehensive architectural programming and design capabilities, enhancing their ability to respond and execute in practice. Lastly, this study emphasizes the popularization and operability of next-generation AI technologies, such as LLMs and AIGC. Its aim is to enhance students' awareness and application abilities regarding emerging AI technologies, enabling them to master AI technology more proficiently for architectural programming and design, thereby improving teaching effectiveness and student competitiveness.

3. Course Model of AI-Assisted Architectural Programming and Design

3.1. Theoretical Framework

The theoretical framework of the AI-embedded teaching model proposed in this study is built upon the fundamental principles of architectural programming and architectural design, integrating practical theories of AI technologies (Figure 1). The architectural programming and design theory section encompasses key aspects such as problem analysis, information gathering, decision making, empirical research, architectural design, and outcome evaluation. Through theoretical learning, students will acquire the skills to systematically analyze and solve social and public issues, conduct comprehensive information gathering and empirical research, and apply these theories to guide innovative architectural design. On the AI front, the model integrates its application theories in the architectural field, including database establishment, data cleaning, model training, result evaluation, and design application. Students will learn how to construct and manage architecture-related databases, perform effective data cleaning, train AI models, assess the accuracy of results, and apply AI technologies to practical architectural programming and design processes.

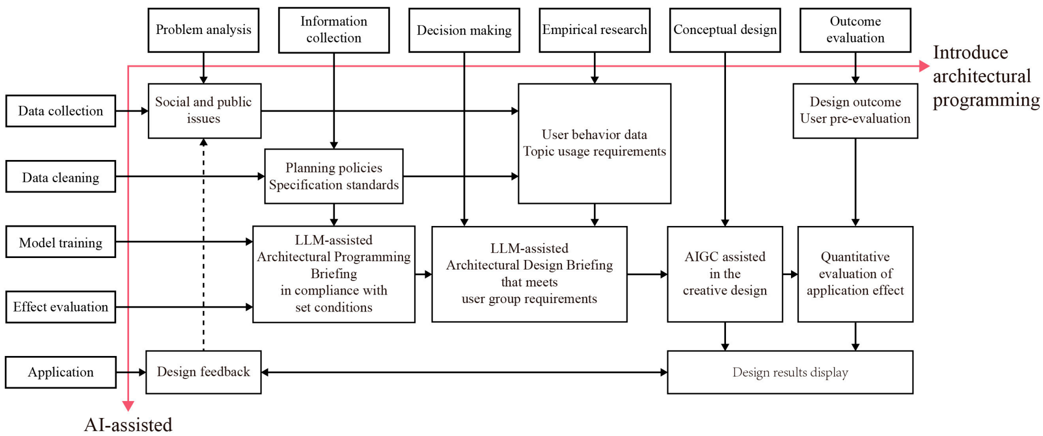


Figure 1. Theoretical framework for the AI-embedded teaching model.

Compared to traditional architectural teaching courses, this AI-embedded teaching model exhibits differences in teaching methods and design concepts. Specifically, the AI-assisted architectural programming and design in this course model emphasize systematic and intelligent teaching methods. Traditional architectural courses focus more on empirical and professionally knowledge-oriented design processes, while this course introduces advanced technological means such as AI algorithms and data mining, providing students with a more intelligent and personalized learning experience, promoting their comprehensive understanding and in-depth exploration of the architectural creation process. Secondly, the AI-assisted architectural programming and design in this course model emphasize data-driven design methods. Traditional courses lean toward designers' subjective experiences and creativity, while this course utilizes technologies like LLMs and AIGC to assist designers in decision making through the analysis of historical data and cases, enhancing the scientificity and efficiency of design.

3.2. Teaching Process

As shown in Figure 2, the AI-embedded teaching model spans a total of 9 weeks (with 8 teaching hours per week, totaling 72 h), compared to the traditional architectural design course spanning an entire semester (18 weeks, with 4 teaching hours per week, totaling 72 h). It aims to simulate the time pressure of actual architectural industry projects, enabling students to quickly adapt to and address various challenges within a limited timeframe. Furthermore, diverging from traditional design paradigms, this model emphasizes cultivating students' abilities to complete comprehensive architectural programming and in-depth design while also encouraging them to efficiently utilize AI technologies to rapidly generate and evaluate design solutions, enhancing their efficiency in decision making and execution when facing real projects.

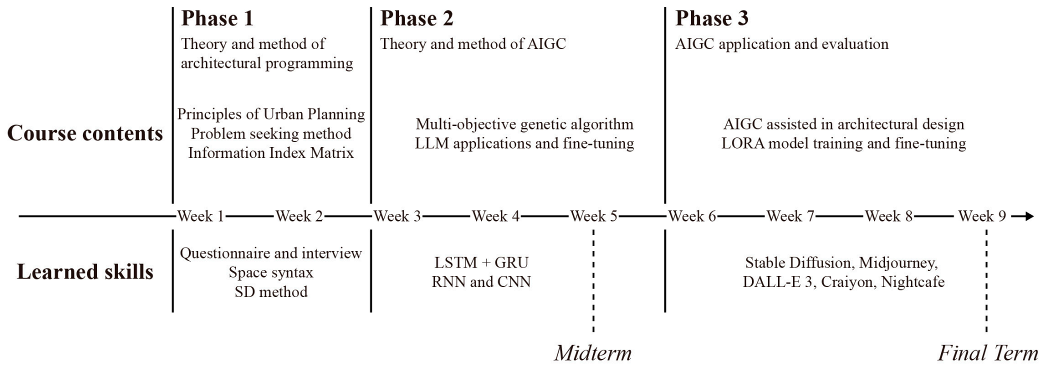


Figure 2. Teaching process of the AI-embedded teaching model.

Specifically, during the first and second weeks, students engage in problem exploration, site selection, and the literature review stages, gaining in-depth knowledge of the fundamentals of urban planning and architectural programming to prepare for subsequent design and practical phases. In the third and fourth weeks, students learn how to utilize LLMs, such as ChatGPT-4.0 and Copilot Pro, for decision fine-tuning and generating architectural briefs. Additionally, they conduct on-site investigations to understand the actual architectural environment, laying the groundwork for subsequent creative design using AIGC. The fifth week includes a midterm defense session, providing students an opportunity to showcase their theoretical and practical achievements and receive assessments and suggestions from teachers and peers. During the sixth, seventh, and eighth weeks, students apply the theoretical knowledge of AI technologies, employing tools like Stable Diffusion, Midjourney, DALL-E, etc., for creative design, preliminary design, and detailed design, conducting comprehensive applications of AI technologies in the architectural design process. The ninth week concludes with a final defense session, where students present the design outcomes of the entire project, undergo quantitative evaluations from teachers and peers, and reflect on and summarize their learning throughout the course.

It is worth noting that the AI-embedded teaching model may, to some extent, increase initial costs compared to traditional architectural education, but it also brings a series of long-term teaching benefits and outcomes. Firstly, the introduction of AI technology requires certain investment and resources, including costs related to the purchase and installation of software platforms, as well as the updating and maintenance of hardware equipment. Secondly, teaching staff need to undergo relevant training and learning to adapt to the new teaching methods and tools. However, through the application of AI technology, students can conduct architectural programming and design more efficiently in the future, saving time and manpower costs. Additionally, the AI-assisted teaching model can enhance students' interest and engagement in learning, thus improving teaching effectiveness.

3.3. Method Steps

As illustrated in Figure 3, the AI-embedded teaching model is structured into four distinct steps. Firstly, before the commencement of the course, teachers upload relevant reading materials to the university's learning platform for students' pre-study. During this stage, students can gain preliminary insights into the course's pertinent knowledge by reviewing the materials. Secondly, during the classroom sessions, teachers deliver lectures on the course content, followed by discussions and Q&A sessions to clarify students' understanding of the learning materials. Subsequently, students, organized into groups, present their progress and work content in class, engaging in interactive evaluations and discussions among the groups. Lastly, after class, students undergo online quizzes to assess their mastery of the course. Simultaneously, teachers assign post-class assignments requiring students to apply the learned theories and methods for problem analysis and resolution to consolidate their learning outcomes.

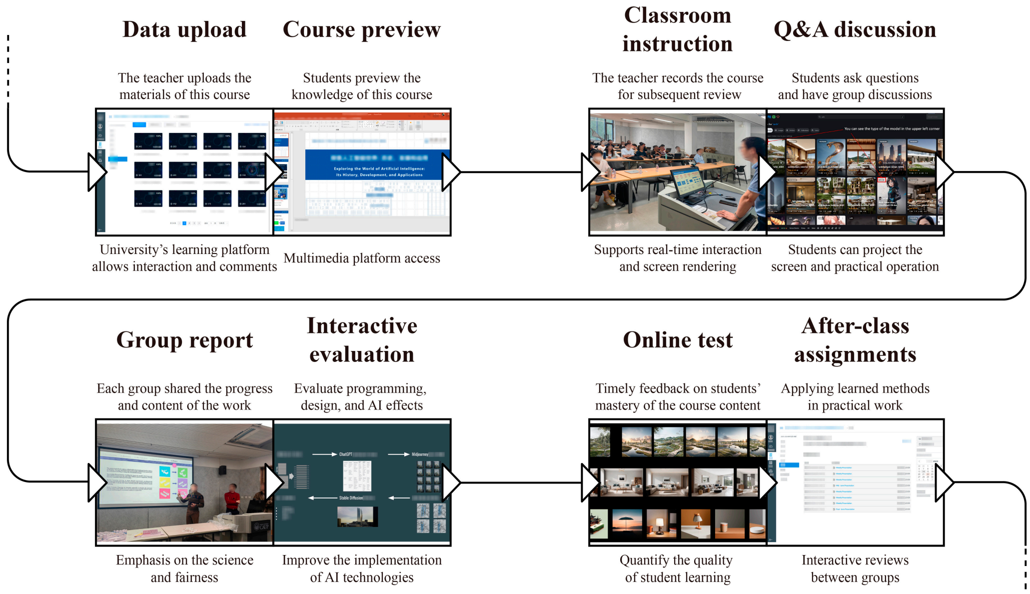


Figure 3. Method steps of the AI-embedded teaching model.

4. Case Study

This study conducted a mixed-method case study to investigate the application and effectiveness of the proposed teaching model in architecture courses. In the following sections, the course background, course outcomes, and survey methodology will be introduced separately.

4.1. Course Background

The course case selected for this study was conducted at—University during the autumn semester of 2023 to 2024. This course is one of the compulsory design courses for master's students. The course comprised 18 master's students and 6 undergraduate students, with a gender distribution of 42% male and 58% female. The student body represented diverse countries and regions, including Asia, Europe, and South America. The varied student backgrounds will robustly support the universality of research outcomes, aiding in a more comprehensive and accurate evaluation of the model's application effects across different cultures and contexts. This diversity will provide valuable insights for the design and improvement of similar courses in the future.

4.2. Course Outcomes

The primary focus of this course was to cultivate students' awareness of architectural programming before architectural design and to develop their ability to utilize AI technologies in architectural programming and design. The course was centered around a single theme: child-friendly space renovation. Additional tasks and requirements were left for students to plan independently. Furthermore, based on students' voluntary preferences, the course was divided into 7 groups, aiming to stimulate collaborative and innovative skills in learning.

Initially, students formulated specific programming briefs by collecting social issues and objective data related to the theme. Subsequently, utilizing AI technologies such as ChatGPT and conducting on-site visits, they determined design scopes, conceptual intentions, and user requirements. A formal presentation of the architectural programming briefs was conducted midterm. These stages aim to enable students to consider various factors more comprehensively, laying a solid foundation for the subsequent design phase (Figure 4(1A–1C)).

As the course progressed, students deeply integrated architectural design with AI technologies, extensively leveraging AIGC tools like Stable Diffusion and Midjourney for creative design. This provided them with ample inspiration and influenced their design process at multiple levels: from conceptual design to parametric design, to the final in-depth design and model making. Finally, students addressed given urban issues by designing one or more architectural spaces, validating the effectiveness of their designs through a pre-assessment method. This process deeply integrated AI tools into architectural design, attempting to transition from computer-aided design to AI-assisted design (Figure 4(2A–2C)).

Students presented various unexpected and inspiring concepts. However, during the programming and design process, it was observed that, in some cases, the coding language required for AI was relatively complex for students in the architectural field and exceeded the depth intended for the course. Secondly, the holistic architectural programming and design process overturned the students' prior task-responsive design paradigm, possibly making it challenging for them to balance the workload of programming and design. Additionally, there is a certain chance that AI tools will not obtain effective results when the environment or specific parameters change, and students can only work through traditional programming and design methods. Therefore, further empirical research combining quantitative and qualitative methods is needed to validate the application effectiveness of the AI-embedded teaching model and provide valuable feedback for future improvements.

4.3. Survey Methodology

This study employed a mixed-research method combining quantitative and qualitative approaches to comprehensively assess students' learning progress in the course and the effectiveness of the AI-embedded teaching model. Specifically, this study conducted surveys at two time points (week 5 and week 9) and carried out one-on-one semi-structured interviews with the instructors and students at the end of the course (week 17).

Quantitative research was carried out mainly through questionnaire survey, utilizing the Likert scale. The questionnaire consisted of 36 questions (Appendix A), primarily divided into three parts. The first part addressed respondents' personal information, such as name, gender, grade, school, and group affiliation. The second part consisted of 18 Likert scale questions, with scores ranging from 1 to 5, where 1 indicated "strongly disagree", and 5 indicated "strongly agree". These questions primarily assessed students' perceived usefulness (PU), perceived ease of use (PEU), and attitude toward use (ATU) of the course model. These three dimensions are core factors of the Technology Acceptance Model (TAM) proposed by Fred Davis in 1989 [73], widely employed to evaluate users' acceptance of information technology [74]. The third part included 10 multiple-choice questions covering students' subjective preferences regarding the application of AI technologies. Additionally, the questionnaire included an overall effectiveness assessment and open-ended questions to gather more detailed and qualitative data. The questionnaire was distributed through an online platform and completed by 24 students enrolled in the course. To ensure the high quality of responses, the questionnaire was administered before the start of the class, and measures were implemented to prevent students from interacting during the survey, thus avoiding potential biases. The survey was distributed to all 24 students twice, and all responses were collected. Table 1 provides background information about the respondents.

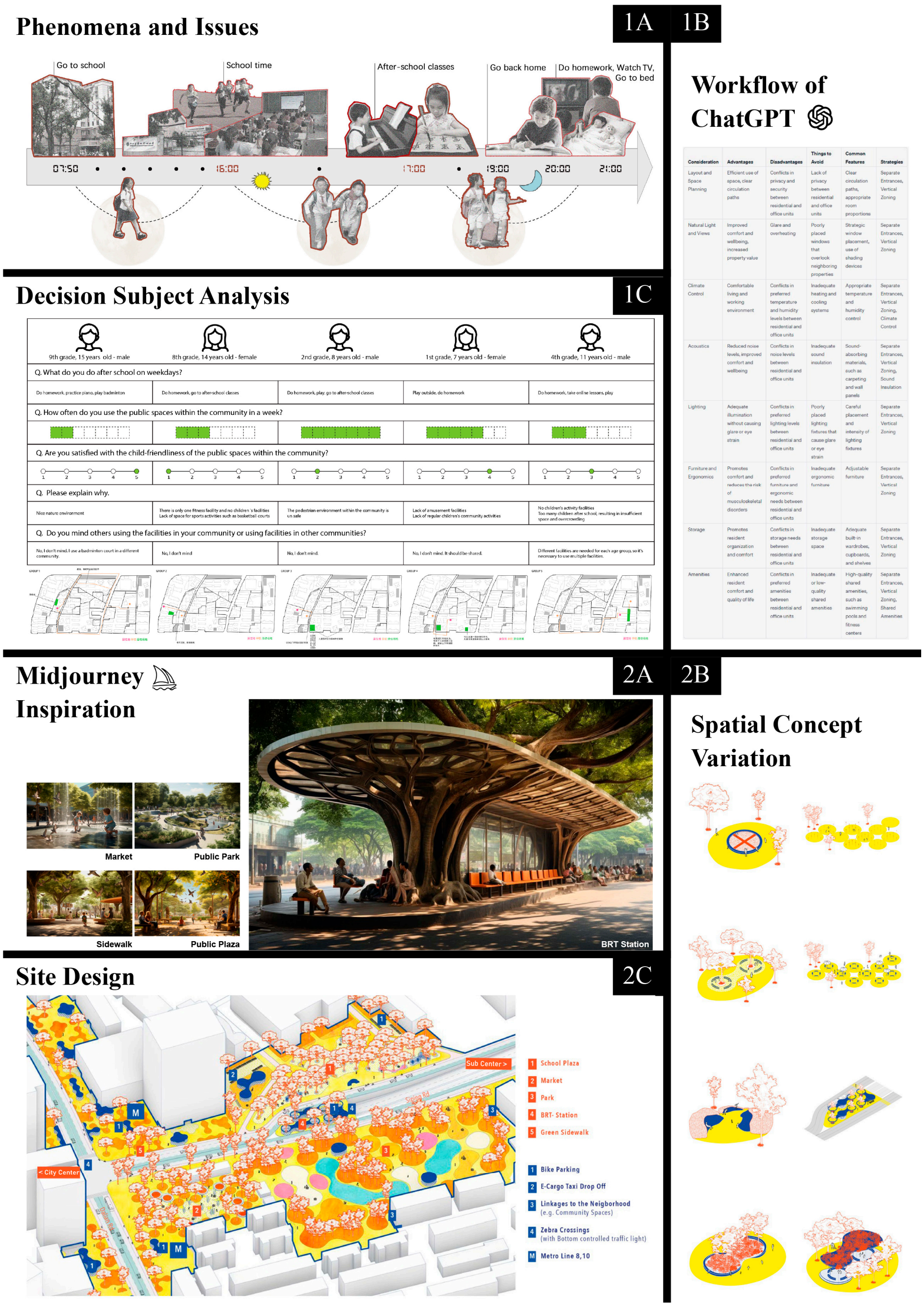
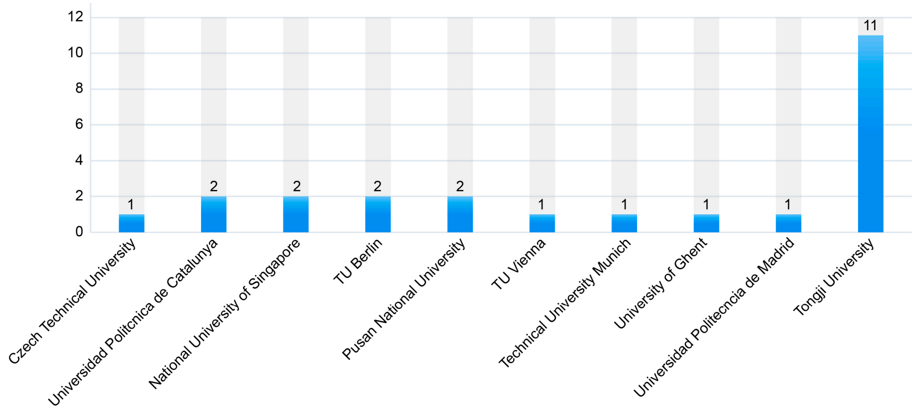


Figure 4. Example of student work in the course of AI-embedded teaching model: (**1A**) Searching for specific social and urban issues related to the research topic; (**1B**) utilizing ChatGPT for the formulation of programming briefs; (**1C**) conducting structured interviews with decision makers to clarify tasks and requirements (authors: Xiao Guanyan, Chen Shu, Hayoung, and Jung Unghui); (**2A**) creative designing with Midjourney assistance; (**2B**) after studying the current situation and demanding characteristics of the site, the author proposed conceptual design prototypes for various spatial types; and (**2C**) results of renovation design for the selected plot (authors: Joanna, Cosima, Rafa, and Jian Yixin).

Table 1. Background information of the student participants.

Attributes	**Distribution**	**Respondents % (*n* = 24)**
Gender	Male Female	73% (10) 27% (14)
Education level	Undergraduate students (Year 3 and Year 4) Master's students	35% (6) 64% (18)
University		

Qualitative research was mainly conducted through one-on-one semi-structured interviews, and the interview outline (Appendix B) included the following topics: first, users' perspectives on AI intervention in architectural education; second, the methods through which users engage in AI-assisted architectural programming and design; third, specific features of AI tools that influence architectural education; fourth, users' satisfaction with the application of AI tools; and fifth, users' needs and preferences regarding the application of AI tools in architectural education. Interview participants consisted of 2 teachers and 10 students, all of whom attended the course. One teacher served as the instructor for the course, while the other was a practicing architect. Each interview lasted between 10 and 20 min. The interviews were transcribed in full, and the interview materials were analyzed and summarized using NVivo 11 qualitative analysis software. Ethical approval for human subjects was obtained through the Institutional Review Board before the formal initiation of the survey.

Through the aforementioned mixed-research method, this study aims to provide a comparative analysis of students' attitudes, perceptions, and learning outcomes during and after the course in order to better summarize the effectiveness and shortcomings of the course. Furthermore, by integrating quantitative and qualitative data to mutually corroborate each other, a more comprehensive understanding of students' attitudes and perceptions toward the course and the AI-embedded teaching model can be achieved.

5. Results

5.1. Positive Impact of AI-Assisted Architectural Programming and Design Teaching Model

As depicted in Figure 5, a comparison of the average scores from the midterm and final student surveys reveals an overall improvement in students' assessments of the effectiveness of the AI-embedded teaching model (rising from 2.71 to 4.04). This initial evidence suggests the efficacy of the teaching model, with further enhancement observed as the course progresses.

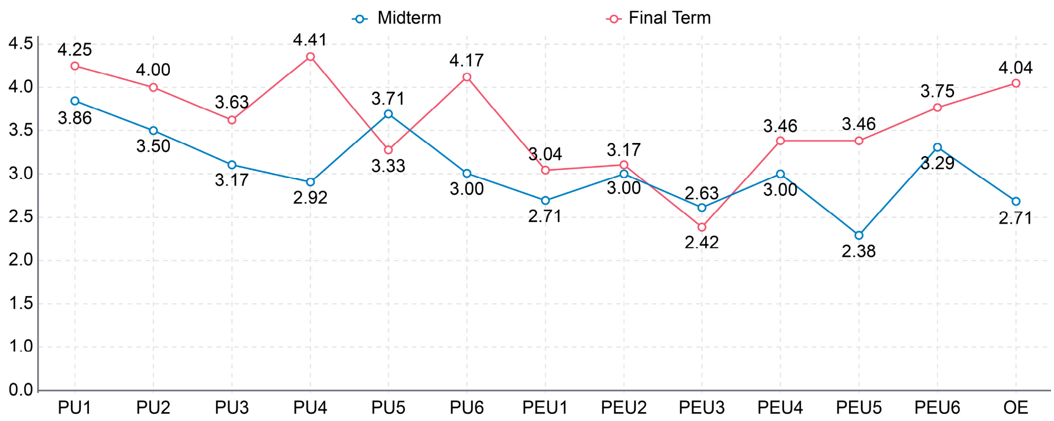


Figure 5. Average results of students' perceived usefulness (PU), perceived ease of use (PEU), and overall effectiveness (OE) evaluation.

Specifically, an analysis of students' evaluations of perceived usefulness (PU) and perceived ease of use (PEU) indicates that, at the midterm, students most agreed with the statement "AI tools exhibit strong information organization capabilities" (PU1, mean = 3.86), while their least agreement was with "AI tools demonstrate high work efficiency" (PEU5, mean = 2.38). Over the course duration, students increasingly agreed with "AI tools possess strong innovative thinking capabilities" (PU4, D-value = 1.50) and increasingly disagreed with "AI tools demonstrate strong design expression capabilities" (PU5, D-value = −0.38). By the end of the course, students most agreed with "AI tools exhibit strong innovative thinking capabilities" (PU4, mean = 4.41) and least agreed with "AI tools make resource acquisition convenient" (PEU3, mean = 2.42).

The interview results also demonstrate the positive impact of integrating AI into architectural education. Among the interviewed students, eight students (80%) mentioned their preference for more in-depth AI applications in architectural programming. One student stated, "I often use ChatGPT to assist me in problem analysis and model design. AI tools have deeply transformed the field of design, and I believe that timely understanding and use of these tools are the direction for the future development of architecture". Another student mentioned, "Architectural programming and design require multidimensional thinking. The introduction of AI tools can empower these processes. Through regular study, I have gradually mastered how to use AI tools to assist me better and faster in design". In addition, teachers' responses were more cautious, with one teacher stating, "AI tools have inevitably influenced architecture, bringing certain positive effects. However, AI is merely a tool, and excessive reliance on AI may lead to uncontrollable outcomes".

5.2. Innovation Ability and Work Efficiency as Key Factors Influencing the Teaching Model

To further explore the critical influencing factors within this teaching model, this study conducted a linear regression analysis on the final term survey data, examining the relationships between perceived usefulness (PU), perceived ease of use (PEU), attitude toward use (ATU), and overall effectiveness (OE). Firstly, IBM SPSS Statistics 26.0 was employed to conduct reliability and validity checks on the questionnaire data. The obtained Cronbach's alpha for the sample was 0.919, exceeding the threshold of 0.9, and the KMO measure was 0.757, surpassing the 0.6 threshold. The significance value from Bartlett's test was 0.000, which is below the threshold of 0.005. These results indicate that the samples obtained from the questionnaire can be subjected to factor analysis (Table 2).

Table 2. Reliability and validity check of the questionnaire data.

Cronbach's alpha		0.919
Kaiser–Meyer–Olkin Measure of Sampling Adequacy		0.757
Bartlett's Test of Sphericity	Chi-squared	175.563
	Degrees of freedom	78
	p-value	0.000

Secondly, a bivariate correlation analysis was conducted on PU, PEU, ATU, and OE variables from the questionnaire, as shown in Figure 6. It was found that there was a significant correlation between the Pearson correlation coefficients of multiple variables. This justified the establishment of a linear regression model to describe and predict the causal relationships between the variables. Before that, independent sample *t*-tests for gender information and one-way ANOVA for grade, school, and group information were conducted to control for the impact of demographic characteristics on the regression analysis. Results indicated that demographic factors had no significant influence.

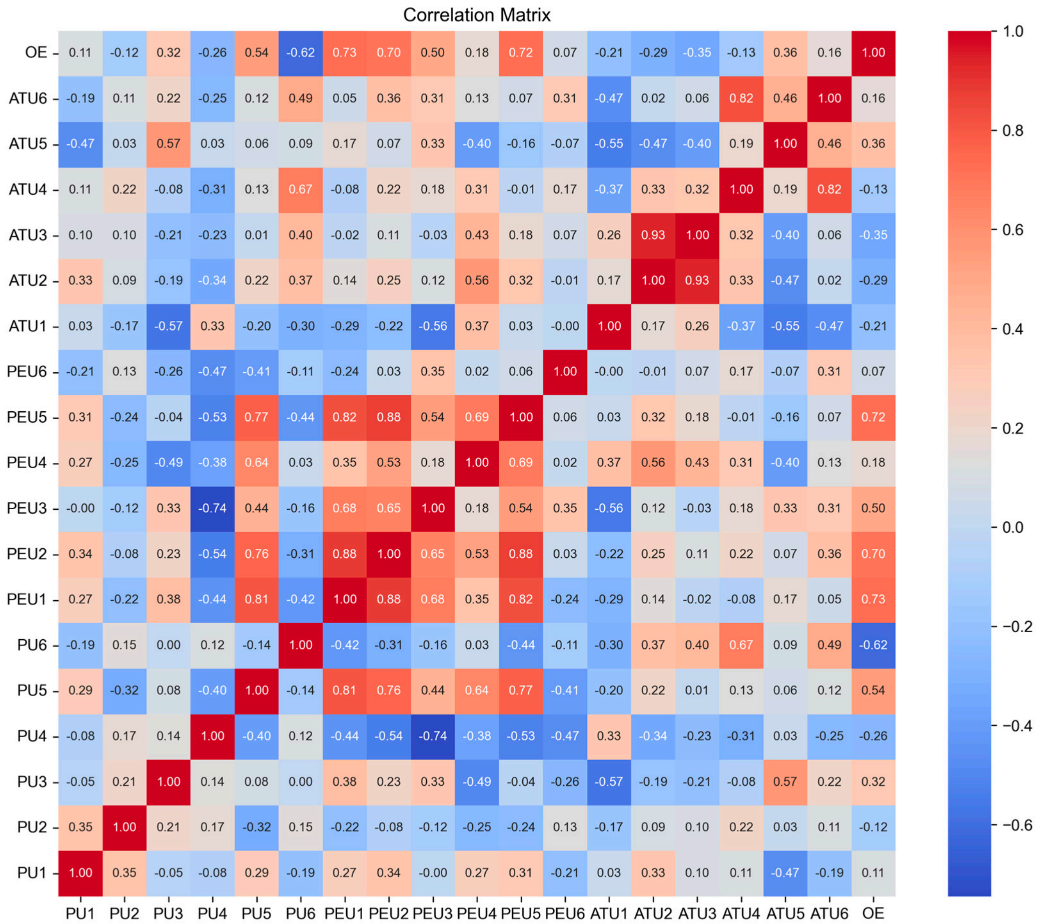


Figure 6. Correlation matrix between PU, PEU, ATU, and OE.

Finally, using PU, PEU, and ATU as independent variables and OE as the dependent variable, regression coefficients were calculated through the least-squares method to determine the impact of independent variables on the dependent variable. As shown in Table 3, the variables PU4 ("AI tools have strong innovative thinking abilities") and PEU5 ("The work efficiency of AI tools is very high") displayed significance levels below 0.01, indicating their particularly significant impact on the dependent variable within the model. The variables PU3 ("AI tools have strong logical analysis ability"), PU6 ("AI tools have strong transferability"), and ATU4 ("I prefer using AI tools in the architectural design stage") displayed significance levels below 0.05, indicating their impact on the dependent variable within the model is generally significant. The significance of the other independent variables is greater than 0.05, indicating that their impact on the dependent variable is not significant. Additionally, the Durbin–Watson statistic was 2.688, close to 2, suggesting low autocorrelation in the model. The linear regression model exhibited a good fit with an R^2 value of 0.979, signifying that the three TAM dimensions collectively explained 97.9% of the variance in the overall effectiveness assessment. The regression equation is as follows:

$$\text{Overall Effectiveness} = 1.835 + 0.679 \times \text{PU4} + 0.820 \times \text{PEU5}$$

Table 3. Summary of linear regression between PU, PEU, ATU, and OE.

Variable	B	Standard Error	Beta	T-Value	Significance
(constants)	1.835	0.879		2.087	0.091
PU1	−0.600	0.283	−0.576	−2.122	0.087
PU2	−0.158	0.106	−0.156	−1.496	0.195
PU3	0.568	0.149	0.705	3.807	0.013
PU4	0.679	0.151	0.620	4.505	0.006
PU5	0.336	0.166	0.449	2.027	0.098
PU6	−0.740	0.235	−0.720	−3.147	0.025
PEU1	−0.448	0.216	−0.596	−2.075	0.093
PEU2	0.167	0.302	0.227	0.553	0.604
PEU3	−0.135	0.180	−0.150	−0.753	0.486
PEU4	−0.293	0.455	−0.333	−0.644	0.548
PEU5	0.820	0.177	1.178	4.620	0.006
PEU6	0.418	0.221	0.453	1.894	0.117
ATU1	−0.255	0.278	−0.240	−0.917	0.401
ATU2	0.044	0.499	0.033	0.088	0.934
ATU3	−0.305	0.634	−0.231	−0.481	0.651
ATU4	2.402	0.839	1.534	2.862	0.035
ATU5	0.113	0.169	0.081	0.670	0.533
ATU6	−1.794	0.877	−1.247	−2.045	0.096
R = 0.990	R^2 = 0.979		Adjusted R^2 = 0.905		

Note: 1. Dependent variable: overall effectiveness. 2. Significance lower than 0.01 indicates that the independent variable is particularly significant, while significance lower than 0.05 indicates that the independent variable is generally significant.

Through one-on-one structured interviews, it was also found that students primarily believe that the emergence of AI tools has enhanced the "efficiency" of architectural programming and design processes, especially in terms of time efficiency. Some students mentioned, "Using Midjourney allows us to quickly sketch out ideas and make modifications or additions, saving a lot of time on drawing and rendering". Others believe that "Previously, analyzing site or architectural problems required careful consideration, but now, inputting some conditions and issues into ChatGPT for sorting and analysis can quickly yield predefined results". Although teachers did not directly use AI tools, they also noted, "The essence of AI tools lies in learning from vast amounts of data. By using constantly evolving programming algorithms, AI can respond more quickly and output computational results based on massive databases".

Moreover, discussions about the "innovative capabilities of AI tools" also emerged in the interview content. While AI is highly creative and still requires further research, most students believe that AI tools can directly or indirectly promote their innovative thinking. One student expressed, "Architectural programming involves knowledge from many other disciplines. Through AI tools, interdisciplinary and cross-domain results can be obtained, broadening the breadth of thinking". Another student mentioned, "Sometimes I don't even know how to address specific problems, but ChatGPT's responses help me to rethink my approach and ideas".

5.3. Tight Integration of AI Technologies with Architectural Programming but Unpredictable Outcomes in Architectural Design

Statistical analysis was conducted on students' attitudes toward use (ATU) evaluations, as illustrated in Figure 7. It was observed that students were more inclined to use AI tools during the architectural programming stage (ATU1), with the agreement rating increasing from 3.08 at midterm to 4.17 at the end of the course. Specifically, during the architectural programming stage, the majority of students tended to utilize AI tools for brainstorming and data analysis (ATU2 and ATU3, with agreement ratings above four). Furthermore, there was a decline in the agreement rating for students using AI tools during the architectural design stage as the course progressed, decreasing from 3.17 at midterm to 2.88 at the end of the course. In particular, students' agreement ratings for gaining inspiration and producing design outcomes using AI tools both decreased during this stage (ATU5, from 2.83 to 2.50; ATU6, from 2.79 to 2.71).

Additionally, a qualitative analysis was performed on the open-ended questions in the survey, also revealing that students were more inclined to use AI tools in the early programming stages. As shown in Table 4, after excluding invalid information and answers with a general attitude, comments from students were generally positive about the teaching model, particularly in the context of architectural programming. For instance, some comments highlighted the convenience and effectiveness of GPT in problem analysis. However, some comments indicated concerns about the shortcomings of AI tools in the architectural design phase, such as the unpredictable results in image generation by Stable Diffusion.

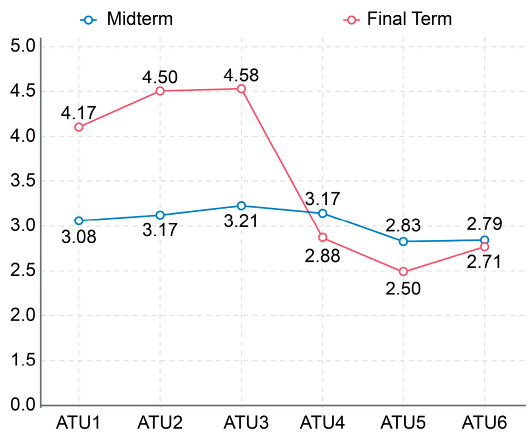


Figure 7. Average evaluation results of students' ATU.

Table 4. Coding results of student comments on the teaching model.

Positive Attitude	Negative Attitude
"GPT is convenient and effective in problem analysis"	"The image generation process of SD is unpredictable"
"AI provides logicality for programming"	"SD's generation process is like drawing cards"
"ChatGPT thinks comprehensively"	"Very complex, tuning parameters is mysterious"
"AI guides me in data processing"	
"AI has strong logical and innovative capabilities"	

Although the interview content did not distinctly yield corresponding results, overall, AI tools were perceived differently in the architectural programming and design phases. Firstly, students believe that AI tools excel in programming work, with one student mentioning "When programming a brief, AI tools can be used to analyze and organize research findings, and then generate corresponding outputs based on requirements". Teachers also share a similar viewpoint, stating "Currently, mastering AI technologies proficiently can better assist architects in preliminary planning and requirement programming. These requirements are often handled based on expert experience, but now AI can output results more quickly, making architectural programming a complete and independent step".

Secondly, AI tools can inspire more ideas and perspectives in architectural design. One student stated, "Facade and section design in architectural design are the most challenging for me. Using texts to images allows for quick selection and determination of corresponding results. Although sometimes the results may not be satisfactory, continuous fine-tuning eventually yields satisfactory results". Another student mentioned, "I can collect images with different characteristics to train different Stable Diffusion models, and finally use them in architectural design to create my own AI drawing workflow".

Summarizing the results of the survey questionnaire and interviews, it can be found that although students are more inclined to use AI tools in the architectural programming stage and have a positive attitude toward their effectiveness, there are certain challenges and limitations when using AI tools in the architectural design stage. These challenges may include algorithmic imperfections, data inaccuracies, and model instability, which require further research and improvement to address.

5.4. AI Mainly Focuses on Point Interventions and Has Not Formed Comprehensive and Systematic Coverage Currently

A statistical analysis of students' usage of AI tools under the guidance of the AI-embedded teaching model provides insights into the current state of students' proficiency in using AI tools for architectural programming and design. As depicted in Figure 8, survey results indicated that before the course commenced, only a small portion of students had not used AI tools at all (4.2%), with the majority having used AI tools once or multiple times (45.8% and 41.7%). The proportion of students who frequently used AI tools was relatively low (8.3%). During the course, most students chose to use AI tools in the decision-making stage (40%), followed by the design stage (25%), problem exploration stage (22.5%), and expression stage (12.5%). In each class, the majority of students used AI tools more than 10 times (45.8%), with fewer students reporting usage between eight and ten times or one and two times (20.8% each). Finally, half of the class expressed a strong willingness to continue using AI (50%), while a minority believed they might use AI tools in the future (29.2%), and a very small fraction indicated they might not or would not use AI tools (16.7% and 4.2%).

Furthermore, AI tools are generally classified based on their conceptual definitions and applications into generative AI (or text-to-image generators) [75,76], such as Midjourney, Stable Diffusion, DALL-E, and conversational AI (or chatbots) [77,78], such as ChatGPT. In this study, AI tools are categorized into general AI (e.g., ChatGPT), design-assistive AI (e.g., Stable Diffusion), and expressive-assistive AI (e.g., Midjourney and DALL-E) according to their application scenarios in architectural creation. This was to further explore the specific stages of architectural programming and design in which students use AI tools, as well as the frequency of their use. According to the survey results illustrated in Figure 9, general AI was generally used during the architectural programming stage, especially in the decision-making phase. Some students also utilized this tool in the design and expression stages. Design-assistive AI tools were used only in the design and expression stages, particularly in the early design phase. Lastly, most students used expression-assistive AI tools in the final stage of presenting outcomes, although some also used them in problem exploration and early design to generate ideas and creativity.

The conclusion is also reflected in the interview content, with the majority of students stating that they would not use AI tools for architectural design on a full-time basis. The main reasons cited are the ongoing rapid development of AI and the need for more practical applications. One student mentioned, "Currently, AI is like a tool with specific functions. For example, ChatGPT can handle Q&A-style demands, but it cannot accurately analyze multi-modal data. Midjourney and Stable Diffusion can generate various image contents, but they cannot control and process specific image information. I believe they lack the ability to fully take over the entire workflow of architectural programming and design".

Some students also believe "The AI knowledge currently learned cannot comprehensively address real-life problems, thus limiting its broader usage". Teachers also noted, "The integration of AI and design is still in its early stages, especially in complex workflows like architecture. Academia can refine it according to the characteristics of current AI tools and develop point-to-point, end-to-end solutions".

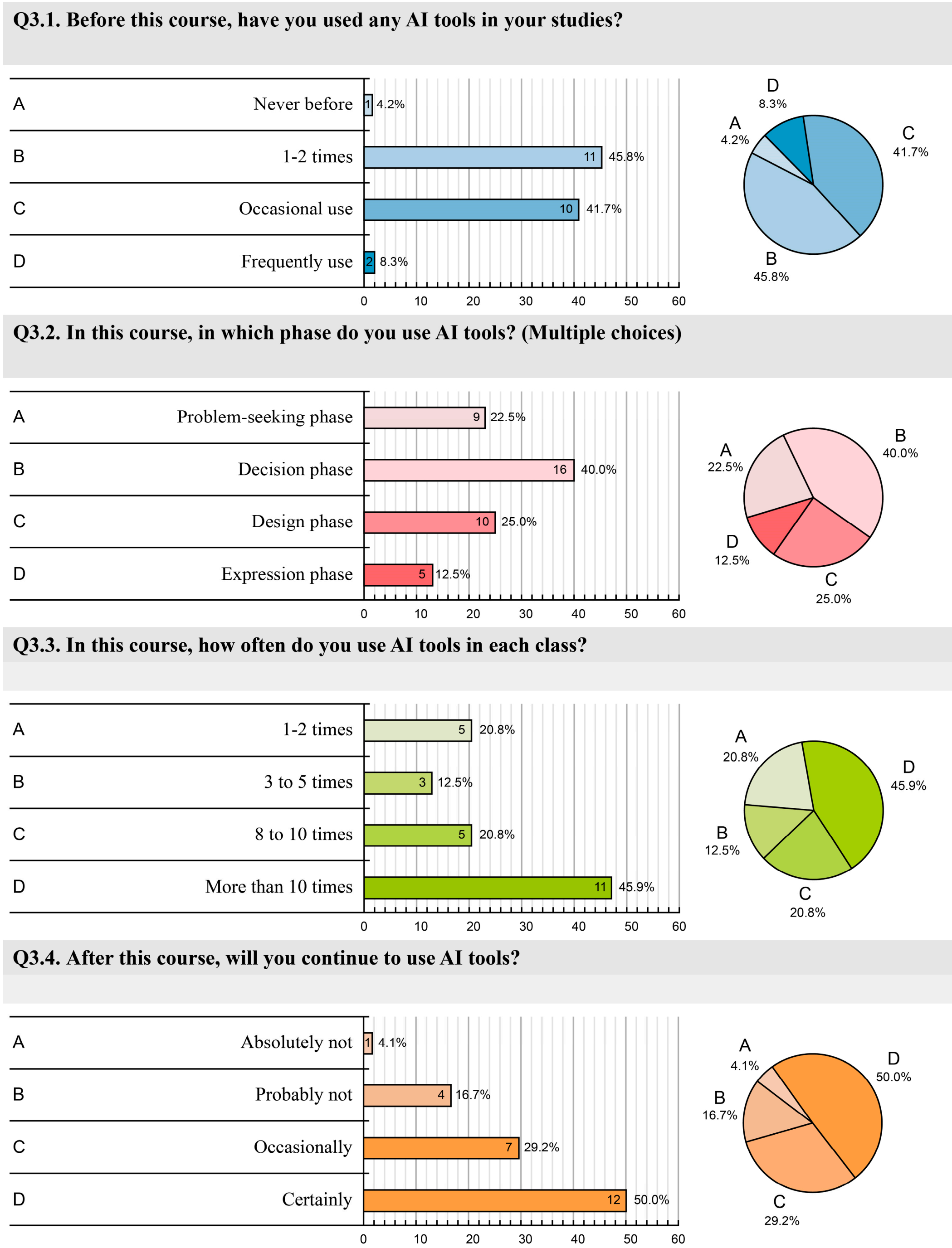


Figure 8. Analysis of the usage of the AI-embedded teaching model.

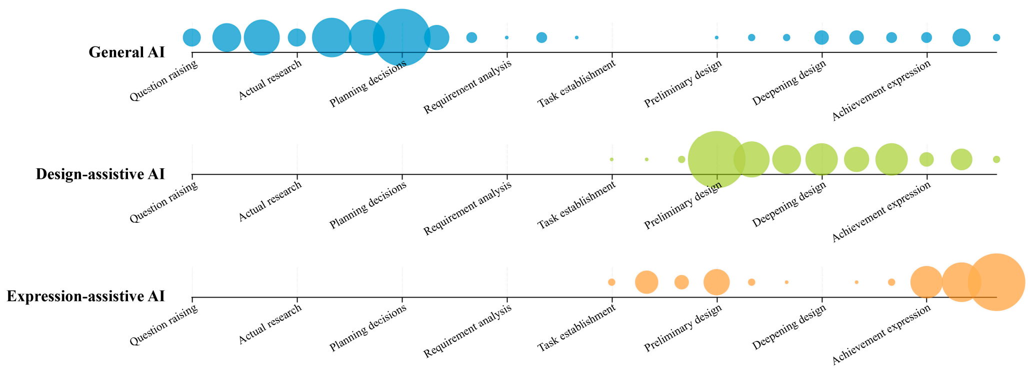


Figure 9. Single-axis scatter plot of the usage frequency and distribution of three types of AI.

In summary, while students demonstrated improvement in early programming, idea generation, and outcome expression with AI assistance, none of the students achieved comprehensive and systematic use of AI throughout the entire process of architectural programming and design. Currently, the AI assistance appeared to be more sporadic, addressing specific issues rather than forming a comprehensive and systematic architectural workflow. In the future, as the role of AI tools continues to increase in architectural education, students may need to invest more time and effort to adapt and learn, potentially increasing the learning burden of the course. Additionally, due to the rapid development and evolution of AI technology, course content and teaching methods may need frequent updates and adjustments to keep pace with the latest technological developments, which could pose additional challenges and pressures for teachers. Furthermore, while AI tools can provide some degree of assistance and guidance, excessive reliance on AI technology may lead to insufficient understanding and mastery of traditional theories and methods in architectural programming and design methods among students. Therefore, in designing and implementing AI-assisted architectural programming and design courses in the future, it is essential to weigh the pros and cons, fully considering the actual situation of the course and the needs of students, to ensure that the course achieves optimal teaching effectiveness.

6. Discussion

This study delved into the AI-assisted architectural programming and design teaching model and obtained the research results as shown in Table 5. Through a combination of quantitative and qualitative approaches, this study validated its positive impact on student learning and identified creativity and efficiency as critical factors for the success of this model. However, it also found issues such as the uncontrollable outcomes and incomplete systematic integration of AI technology in architectural education. Therefore, to optimize this teaching model, we propose the following three optimization strategies focusing on balancing usability and stability, enhancing the ubiquity and acceptance of AI technologies, and promoting interdisciplinary integration and development.

Table 5. The main research findings of this study.

Quantitative Research Methods	Qualitative Research Methods	Research Findings
descriptive statistics of Likert scale	one-on-one structured interviews	The AI-assisted architectural programming and design teaching model has a positive impact on student learning.
linear regression analysis of Likert scale		The “innovative thinking ability” and “work efficiency” of AI tools are significant factors affecting students’ overall effectiveness evaluations.

Table 5. *Cont.*

Quantitative Research Methods	Qualitative Research Methods	Research Findings
descriptive statistics of Likert scale	one-on-one structured interviews, content coding analysis of interview transcripts	Students hold positive attitudes when using AI tools in the architectural programming stage, but encounter challenges and limitations when using AI tools in the architectural design stage.
statistical analysis of single-choice questions	one-on-one structured interviews	Most students are willing to use AI tools in architectural creation in the future. Currently, students only use AI tools partially, failing to form a comprehensive AI-assisted architectural working methodology system throughout the process.

6.1. Balancing the Usability and Stability of AI in Architectural Programming and Design

While AI demonstrates outstanding usability, stability, and precision in the architectural programming stage, challenges persist in the design stage [79], particularly regarding the controllability and stability of drawing results. To balance the usability and stability of AI in architectural programming and design, optimizations can be made in several areas.

Firstly, efficiency in AI-generated graphics or diagram creation can be improved to trade time for outcome quality. Advances in deep learning technology offer the possibility of enhancing generation speed [80]. Through more efficient algorithms and hardware support, AI can rapidly generate design outcomes, providing more high-quality creative concepts and design solutions in a shorter timeframe [81]. This allows users to spend less time on repetitive and technical tasks, enabling them to channel more energy into creativity and innovation [82]. Currently, methods such as Latent Consistency Models (LCMs) can be utilized to enhance the generation speed of text-driven AI tools. This algorithm can generate high-quality images in two to nine steps, significantly improving the efficiency of AI tools in the field of architecture [83]. Additionally, the derivative model LCM-Lora can be applied to various Stable Diffusion models without the need for adaptive training, expanding its applicability.

Secondly, as technology advances, AI can offer more personalized and customized design services. By better understanding and predicting user preferences, AI can deliver more personalized and tailored design outcomes to meet specific needs [84]. This includes a precise grasp of design styles, functional requirements, and aesthetic preferences, aligning the generated designs more closely with user expectations [85]. In addition to directly training large models, personalized and customized design services can now be achieved through specialized adaptations like LoRA (Low-Rank Adaptation of Large Language Models). LoRA, akin to hyper-networks and ControlNet, functions as a plugin for Stable Diffusion models. It allows for the creation of custom styles, IPs, or characters using minimal data without modifying the Stable Diffusion model itself [86], making it suitable for community users and individual developers who require fewer training resources compared to training Stable Diffusion models.

Lastly, the development of diffusion models that offer a broader range of artistic styles and expression modes is critical. The continuous evolution of AI technology enables it to simulate and integrate various artistic styles, including but not limited to traditional, modern, and abstract styles [87]. By expanding the artistic expression possibilities in design, AI can comprehensively satisfy the pursuit of diversity and innovation by designers and users, thereby achieving superior performance in terms of outcomes [69,88]. Stability AI has introduced a new generation of image synthesis models: Stable Diffusion XL Turbo. This model employs the Adversarial Diffusion Distillation (ADD) algorithm to reduce the inference steps of pre-trained diffusion models to one to four sampling steps while maintaining high sampling fidelity [89]. In addition, the new generation of models also integrates more attributes and styles, further improving the diversity and integrity of the model. It can not only improve the robustness of AI in architectural creation, enabling it to better adapt to various environments or parameter changes, but also reduce the possibility of manual intervention by Artificial Intelligence in specific situations, improving its reliability and effectiveness in the design process.

6.2. Further Enhancing the Ubiquity and Acceptance of AI Technologies

Despite the immense potential of AI technologies, their ubiquity and acceptance in architectural programming and design remain pressing issues. The acceptance, trust, and reliance of students on AI-assisted programming and design need to be gradually cultivated through continuous education and training. To achieve this goal, optimizations can be made in several areas.

Firstly, a transformation in the framework and content of architectural education is essential. As AI technology progressively infiltrates the field of architecture, educational frameworks need to keep pace with the trends of the times. Guiding students to gain a deeper understanding and mastery of AI programming and design skills through simulation and experimental platforms is crucial [90]. This educational transformation not only helps students better integrate AI into the thinking process but also contributes to the refinement of AI technology within the architectural discipline. Currently, multiple architectural design software platforms are developing their own AI tools. For example, Rhino and Grasshopper are establishing AI-assisted modeling experiments through Python language [91], while the third-party application market of Revit is witnessing a growing number of real-time AI modeling plugins [91]. The continuous updates and iterations of AI technologies are driving changes and advancements in tools within the field of architecture, enabling students to access a better and higher quality architectural education.

Secondly, the establishment of a more user-friendly man–machine interaction platform is paramount. Students' expectations regarding AI tool usage patterns align with the habits of the internet era. Software platforms that are more intuitive and concise can reduce the learning curve for users, emphasizing user autonomy, logic, and operability [92]. Constructing a more user-friendly and efficient user interface that aligns with students' usage habits lays the foundation for the widespread acceptance of AI technology in their learning and practice [71]. At present, the mainstream AI drawing frameworks include WebUI, ComfyUI, and Fooocus, all based on Stable Diffusion. In the era of traditional deep learning, frameworks like PyTorch, TensorFlow, and Caffe served as the foundation for running traditional deep learning models. With the advent of AIGC, WebUI is likened to "PyTorch", ComfyUI to "TensorFlow", and Fooocus to "Caffe". These AI frameworks can integrate Stable Diffusion models, LoRA models, ControlNet models, GAN models, and various AI drawing-assistant plugins, forming diverse "workflows" to help users create better AIGC content according to their needs.

Lastly, there is a need for increased computing power and algorithm optimization for AI tools. To propel the widespread application of AI technology in architecture, intensified efforts are required in the development of underlying computing power and algorithmic technologies. Improving the performance of AI tools, including more efficient algorithms and enhanced computing capabilities, better satisfies students' demands for interactivity and real-time responsiveness in practical work scenarios [93,94]. This will further encourage students to actively embrace and rely on the support provided by AI technology. As a leading technology company driving the development of Artificial Intelligence, NVIDIA optimizes graphic processing units (GPUs) and related technologies globally. With AI becoming mainstream, NVIDIA's GPU shipments have exceeded 100 million units [95]. In October 2023, NVIDIA released the TensorRT-LLM for Windows library, accelerating the inference performance of LLMs like Llama 2 and Mistral by five times. Additionally, through NVIDIA's TensorRT algorithm acceleration, the usage performance of Stable Diffusion XL and SDXL Turbo can also be boosted by up to 60%.

6.3. Multi-Domain Integration Development of AI Technologies

The widespread application of AI technologies will not be limited to traditional problem analysis, data processing, and flat design but will expand into various domains such as decision management, 3D modeling, virtual reality, and augmented reality. This interdisciplinary integration creates broader development opportunities for the architectural industry [6]. Specifically, optimizations can be made in the following areas:

Firstly, the integration of AI technologies with the theoretical background and fundamentals of architecture is crucial. With the advent of the era of large models, the theoretical knowledge and practical experience of architectural studies can deeply integrate with AI tools. This integration aims to create intelligent architectural large models capable of addressing specific problems, making demand-driven decisions, and enabling management and control [96]. This model is designed to provide the field of architecture with more intelligent and personalized AI tools to better support related research and practices. Additionally, facing the lack of timely and effective predictive methods and tools in the early programming stages of architectural education, AI technologies can greatly assist in understanding the performance and behavioral cognition of built environments. For instance, using AI algorithms such as machine learning, deep learning, and reinforcement learning to analyze and predict vast amounts of architectural data can technically cultivate architectural students' awareness of ecological environments and public interests [97,98]. Both the preliminary surveys and later interviews reveal that both teachers and students are willing to accept and adapt to architectural education integrated with AI technologies. With the continuous iteration and updating of technology, AI-assisted architectural programming and design will become an important component of future architectural theoretical frameworks.

Secondly, AI should integrate with architectural software. According to research findings, most students expect AI technology to provide more user-friendly, stable, and precise assistance in programming analysis, creative production, and design expression. Deep integration of AI with software such as AI with BIM [84,99,100] and AI with Grasshopper [101] can enhance the efficiency of intelligent work, making AI a powerful support for the core work of a wide range of users. Students expressed their views on the combination of AI tools with architectural software in both the questionnaire and interviews. The majority of students believe that compared to the workflow of architectural design, the characteristics of AI tools are more suitable for the workflow of architectural programming. This is because architectural programming mainly involves early-stage decision analysis and later-stage usage evaluation, processes that require handling large volumes of structured data, aligning more closely with AI's data analysis workflow. With the deep application of various AI technologies, the tool platform in the field of architecture will become the most important emerging theory and temporal growth point in university architectural education.

Finally, AI should integrate with the field of virtual reality. Guidance in architectural programming is crucial for design, and the pre-assessment of architectural design outcomes can provide forward-looking feedback for programming. Virtual reality, as a key means of pre-assessment, needs to be combined with AI technology to achieve more efficient and comprehensive programming guidance, forming a complete loop in the architectural workflow [102]. This innovative integration will propel the architecture industry toward greater intelligence and efficiency, providing users with richer and more comprehensive decision-making tools. Both teachers participating in the interviews expressed their positive views on the future development of VR technology with AI integration in the field of architecture. Currently, the theoretical and practical teachings of architectural programming and design education are widely conducted in universities. However, further development of research tools and methods at the higher education level in architecture is needed to keep pace with the demands of the era and the industry. Traditional quantitative and qualitative research methods commonly used in the field of architecture can be optimized and innovated with the integration of current AI tools. For example, VR scenes rendered by

AI combined with subjective evaluation surveys, interactive architectural models combined with AI-generated images for testing application feedback, etc., can facilitate innovative developments in architectural education that meet the demands of the times, enabled by AI-driven VR tools.

7. Conclusions

This study developed an AI-embedded teaching model and evaluated its effectiveness through student usage assessment and current usage surveys. Compared to existing research, this study conducted a comprehensive and in-depth exploration of the integration of AI technology with architecture and addressed the current lack of feedback on the application of AI technology in architectural education. In contrast to traditional architectural teaching models, this study not only limited AI technology to the architectural design stage but also emphasized its close integration with architectural programming. The research findings indicate that (1) the AI-embedded teaching model has a positive impact on student learning; (2) the "innovative thinking ability" and "work efficiency" of AI tools were identified as critical factors significantly affecting students' overall effectiveness evaluations; (3) although students hold positive attitudes toward using AI tools in the architectural programming stage, they face challenges and limitations when using AI tools in the architectural design stage; and (4) most students express willingness to use AI tools in architectural creation in the future, but currently, they only use AI tools partially during the architectural programming and design stages, failing to form a comprehensive AI-assisted architectural working methodology system throughout the process.

Based on these findings, this study proposes optimization strategies for the future of AI-assisted architectural programming and design education. First, balancing the usability and stability of AI in architectural programming and design can be achieved by improving the efficiency of AI algorithms and the comprehensiveness of models to address the challenges students encounter in the design stage, thereby enhancing their learning experience and effectiveness. Second, further enhancing the accessibility and acceptance of AI technology can be achieved by improving the user interface design and logical framework content of AI tools to reduce the time and cost of learning and training in AI technology, enabling students to apply AI tools more easily in architectural creation. Finally, promoting the interdisciplinary integration and development of AI technology can be achieved through interdisciplinary collaboration and communication, integrating AI technology with fields such as architecture and computer science to drive innovative applications of AI technology in the field of architecture.

Furthermore, this study provides practical applications and insights for the future integration and development of AI in architectural education. Firstly, the application of AI technology in architectural education can not only improve teaching effectiveness but also cultivate students' innovative and practical abilities, laying a solid foundation for their future career development. Secondly, the results of this study have certain reference significance for teaching reforms in the field of architectural education, providing educators with a new teaching model and methodology. Finally, this study offers valuable suggestions for the future application and development of AI technology in architectural education, such as balancing the usability and stability of AI in architectural programming and design and further enhancing the accessibility and acceptance of AI technology, all of which contribute to the continuous innovation and progress of architectural education.

However, this study has some limitations. Firstly, the sample size is small, which may restrict the generalizability and representativeness of the results. To address this issue, future research should use a larger sample size to assess the long-term impact of the AI-embedded teaching model on student learning. Secondly, the study lacks a control group and did not conduct a more rigorous comparison with traditional teaching methods. Introducing a control group in future research will help to evaluate the superiority of this teaching model more comprehensively and objectively.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/buildings14061613/s1.

Author Contributions: Conceptualization, S.J. and Y.L.; methodology, S.J., H.T., Y.F., F.X. and K.L.; software, S.J. and J.L.; validation, S.J., H.T., J.L., Y.F., Z.Q., F.X., K.L. and Y.L.; formal analysis, S.J.; investigation, S.J., H.T., J.L., Y.F. and Z.Q.; resources, S.J., H.T., J.L., Y.F., F.X. and K.L.; data curation, S.J.; writing—original draft preparation, S.J.; writing—review and editing, S.J., H.T., J.L., Y.F. and Z.Q.; visualization, S.J. and H.T.; supervision, H.T.; project administration, H.T.; funding acquisition, H.T. 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 in accordance with the Declaration of Helsinki and approved by the Institutional Review Board of the College of Architecture and Urban Planning, Tongji University, authorization number: 2023092301.

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

Data Availability Statement: Data is contained within the article or Supplementary Material.

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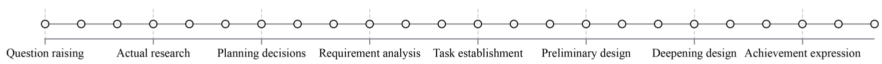
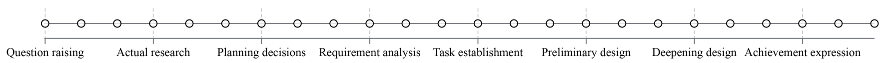
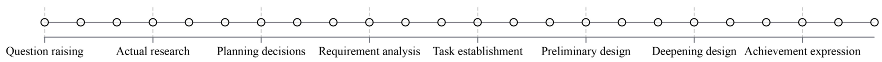
Conflicts of Interest: Author Yuwei Fang was employed by the company Shanghai Pinlan Data Technology Co., Ltd. Author Fan Xu was employed by the company Shanghai Shaliyun Technology Co., Ltd. Author Kun Liu was employed by the company Shanghai Chengguohui Technology Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

1. Demographical Characteristics	
1.1 Your Name: 1.2 Your Gender: 1.3 Your Grade: 1.4 Your University: 1.5 Your Group:	
2. Teaching Model Evaluation Scale	
☐1: Completely disagree ☐2: Disagree ☐3: Neutral ☐4: Agree ☐5: Strongly agree	
Categories	Questions
Perceived Usefulness (PU)	PU1: AI tools have strong information sorting ability. PU2: AI tools have strong decision-making ability. PU3: AI tools have strong logical analysis ability. PU4: AI tools have strong innovative thinking ability. PU5: AI tools have strong design expression ability. PU6: AI tools have strong transferability.
Perceived Ease of Use (PEU)	PEU1: AI tools have a clear theoretical framework. PEU2: AI tools have a simple operational process. PEU3: AI tools have convenient resource access. PEU4: AI tools' model fine-tuning is easy. PEU5: AI tools have high working efficiency. PEU6: AI tools have high compatibility.

Attitudes Toward Using (ATU)	ATU1: I prefer using AI tools in the architectural programming stage. ATU2: I like using AI tools for brainstorming in the architectural programming stage. ATU3: I like using AI tools for data analysis in the architectural programming stage. ATU4: I prefer using AI tools in the architectural design stage. ATU5: I like using AI tools for inspiration in the architectural design stage. ATU6: I like using AI tools to complete design outcomes in the architectural design stage.			
3. Teaching Model Descriptive Statistics				
3.1 Before this course, have you used any AI tools in your studies?				
☐Never before	☐1–2 times	☐Occasional use	☐Frequent use	
3.2 In this course, in which phase do you use AI tools? (Multiple choices)				
☐Problem-seeking phase	☐Decision phase	☐Design phase	☐Expression phase	
3.3 In this course, how often do you use AI tools in each class?				
☐1–2 times	☐3–5 times	☐8–10 times	☐More than 10 times	
3.4 After this course, will you continue to use AI tools?				
☐Absolutely not	☐Probably not	☐Occasionally	☐Certainly	
Categories	Questions			
general AI (e.g., ChatGPT)	In this course, at which stage do you use this category of AI tools?  How often do you use this category of AI tools in this course?			
	☐Never	☐1–2 times	☐3–5 times	☐Always
design-assistive AI (e.g., Stable Diffusion)	In this course, at which stage do you use this category of AI tools?  How often do you use this category of AI tools in this course?			
	☐Never	☐1–2 times	☐3–5 times	☐Always
expression-assistive AI (e.g., Midjourney and DALL-E)	In this course, at which stage do you use this category of AI tools?  How often do you use this category of AI tools in this course?			
	☐Never	☐1–2 times	☐3–5 times	☐Always
4. Overall Evaluation of the Teaching Model				
☐1: Completely disagree	☐2: Disagree	☐3: Neutral	☐4: Agree	☐5: Strongly agree
4.1 This course has been very effective for my learning.				
5. Open-ended Questions				
5.1 Share your thoughts on this teaching model with us.				

Appendix B

1. Users' Views on the Involvement of AI in Architectural Education
1.1 Reasons for agreeing with the integration of AI into architectural education, citing examples from practical applications. 1.2 Reasons for disagreeing with the integration of AI into architectural education, citing examples from practical applications. 1.3 Views on the future development of AI in architectural education. 1.4 Additional comments.

2. Methods in Which Users Utilize AI in Assisting Architectural Programming and Design
2.1 Frequency and effectiveness of using AI tools. 2.2 Views on different types of AI tools, such as universal AI, design-assist AI, and expression-assist AI. 2.3 Challenges encountered during the process of using AI in architectural programming and design. 2.4 Additional comments.
3. Specific Features of AI Tools that Influence Architectural Education
3.1 How these features affect your work in architectural programming and design, with examples from practical applications. 3.2 Whether you believe these features of AI tools have a positive impact, with examples from practical applications. 3.3 Identified shortcomings of AI tools, with examples from practical applications. 3.4 Additional comments.
4. Users' Satisfaction with the Application of AI Tools
4.1 Satisfaction with the use of AI tools in architectural education, with examples from practical applications. 4.2 Satisfaction with the use of AI tools in the architectural programming phase, with examples from practical applications. 4.3 Satisfaction with the use of AI tools in the architectural design phase, with examples from practical applications.
5. Users' Needs and Preferences for the Application of AI Tools in Architectural Education
5.1 Demands and suggestions for using AI tools in architectural programming and design. 5.2 Preferences for the future development of AI tools in architectural programming and design. 5.3 Additional comments.

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