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Research Article

ARTIFICIAL INTELLIGENCE-BASED PRESENTATION TECHNIQUES IN LANDSCAPE ARCHITECTURE EDUCATION: A STUDY ON STUDENT PERCEPTION

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ABSTRACT. Generative artificial intelligence (GAN) tools are fundamentally changing many design disciplines, including landscape architecture. As the use of these tools in design presentation techniques becomes rapidly widespread, the impact of these technologies in education and how they are perceived by students are becoming a critical research topic. This study aims to assess architecture students' perceptions, attitudes, and concerns regarding the role of AI-based image and video generation methods in creating design presentations. The research adopts a quantitative approach and applies a survey to architecture faculty students. This survey study attempts to measure students' familiarity with AI tools, their perceived benefits and concerns, and questions how these technologies might impact the future of the profession and education. The findings indicate that students' awareness of AI tools is high, but their propensity to use them in their projects varies. Another key finding of the study is that, despite their uncertainty about the impact of AI on the future of design-related professions in the next five years, they strongly believe that the role of AI in education should increase. This result highlights the need to meet students' expectations of this relatively new technology and update it to encourage ethical and critical use.

Keywords: landscape design, presentation techniques, generative artificial intelligence, education

INTRODUCTION

The rapid evolution of artificial intelligence (AI) is reshaping design disciplines, and landscape architecture is no exception. Recent developments in generative models, multimodal frameworks, and deep learning techniques have expanded the possibilities for visual representation, analysis, and conceptual exploration within the field. As generative AI tools become increasingly accessible to students and practitioners, their integration into landscape architecture education has emerged as a significant area of inquiry [1].

Landscape architecture has historically relied on drawings, physical models, and later digital visualization to communicate spatial ideas. However, AI-assisted generative tools particularly text-to-image systems and diffusion models, now allow students to rapidly test design variations, simulate atmospheres, and create photorealistic visualizations without advanced technical modeling skills [2],[3]. According to [1] these emerging tools not only accelerate visualization workflows but also introduce new pedagogical opportunities that can enhance creativity, broaden representational diversity, and support more iterative design processes.

At the same time, scholars highlight that the adoption of AI in landscape architecture brings theoretical, cultural, and practical challenges. In a comprehensive survey, [4] notes that practitioners and students express both excitement about AI's transformative potential and concern about issues such as authorship, skill degradation, and the ethical use of machine-generated imagery. Similar concerns appear in related AI-driven environmental and spatial analysis research. For example, [5] emphasize that while deep learning significantly improves the accuracy of land-use classification, its application requires transparency, data literacy, and critical evaluation to avoid misinterpretation. These findings reinforce the need for educational environments that teach not only tool usage but also ethical and critical thinking frameworks.

Specifically, the integration of AI into educational settings is both promising and complex. AI applications span conceptual visualization, environmental simulation, site analysis, ecological forecasting, and participatory design processes [6]. As these technologies expand in capability, they increasingly influence how students understand landscape systems, communicate design intentions, and perceive the role of digital tools in professional practice. [2] argues that AI challenges the limits of human creativity in design disciplines, prompting educators to reconsider how creativity, authorship, and originality are taught in the studio environment.

There are many artificial intelligence image and video creation tools actively used today. The strongest and most established of these is Midjourney AI. Midjourney is a text-to-image generative AI tool known for producing highly atmospheric, stylized, and visually rich imagery. Because of its strong artistic qualities, Midjourney is frequently used in conceptual design stages to explore mood, composition, and alternative design expressions (Figure 1).

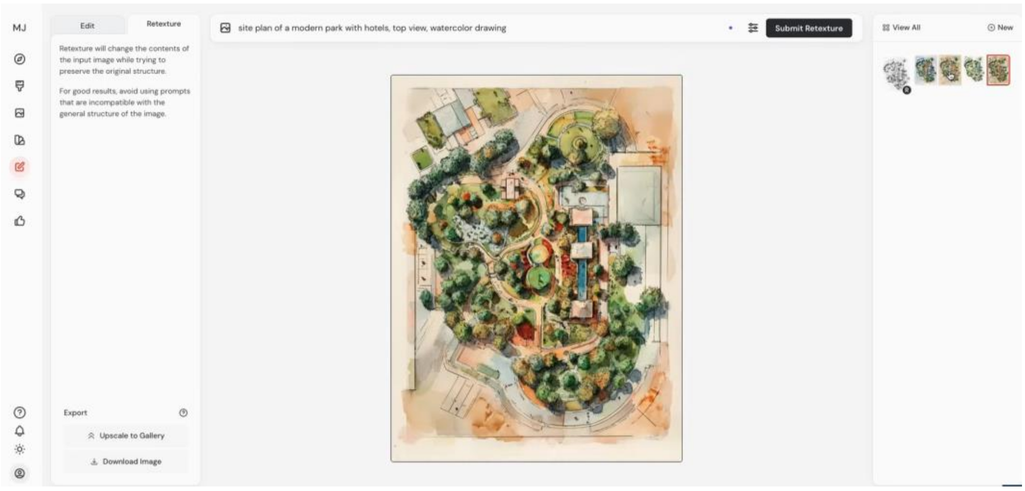

Fig. 1. *Midjourney Workflow*

Landscape architecture students often rely on it when they want to generate quick conceptual sketches or illustrate spatial atmospheres that would otherwise take hours to model. While Midjourney may not always yield geometrically precise results, its ability to accelerate ideation makes it a powerful companion during early design development.

Developed by OpenAI, DALL-E is a generative model capable of producing detailed, high-resolution images directly from natural-language prompts. One of its key strengths lies in its accurate interpretation of written descriptions, allowing users to generate consistent scenes with correct spatial relationships. In landscape architecture education, DALL-E supports conceptual visualization, alternative scenario development, and early-stage storytelling. Its ability to simulate realistic textures, lighting, and materials offers students a practical way to test visual ideas before moving into detailed modeling environments.

Stable Diffusion is an open-source text-to-image model that has gained wide adoption due to its customizability and local-installation capabilities. Because users can run it on personal computers and even fine-tune it with their own datasets, Stable Diffusion is ideal for producing personalized or site-specific landscape imagery. In educational contexts, it is used to overlay design ideas onto real photographs, generate variations of the same scene, or experiment with design details without requiring advanced rendering software. Its flexibility and open-source nature make it a powerful tool for academic experimentation (Figure 2).

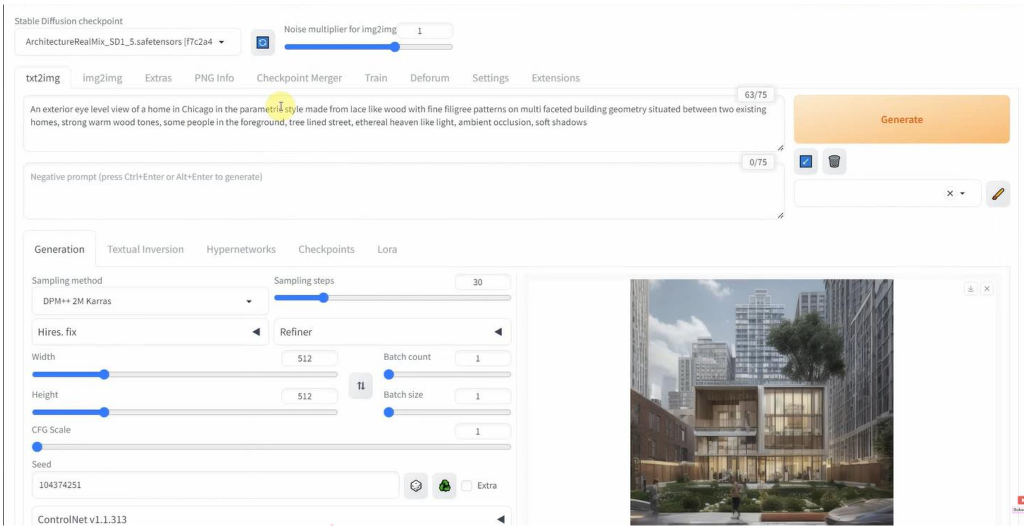

Fig. 2. Stable Diffusion Workflow

Sora is OpenAI's emerging text-to-video model that generates realistic moving imagery based on short textual inputs. For design fields, this represents a major leap from static visualization to dynamic spatial storytelling. Landscape architects may use Sora to simulate temporal shifts such as lighting changes, seasonal variations, or human activity to better communicate how space behaves over time. This ability to represent movement, atmosphere, and environmental processes makes Sora a promising tool for future design presentations and educational demonstrations.

RunwayML is a popular AI-based platform that enables users to create and edit videos and images through intuitive, code-free tools. With features like AI motion tracking, rotoscoping, and generative scene editing, it offers a practical environment for crafting design animations and visual narratives. Landscape architecture students use RunwayML to produce short animations, simulate user flows, or incorporate new design elements into existing footage. Its straightforward interface makes it suitable for courses and studios where visual communication is essential, but technical training time is limited (Figure 3).

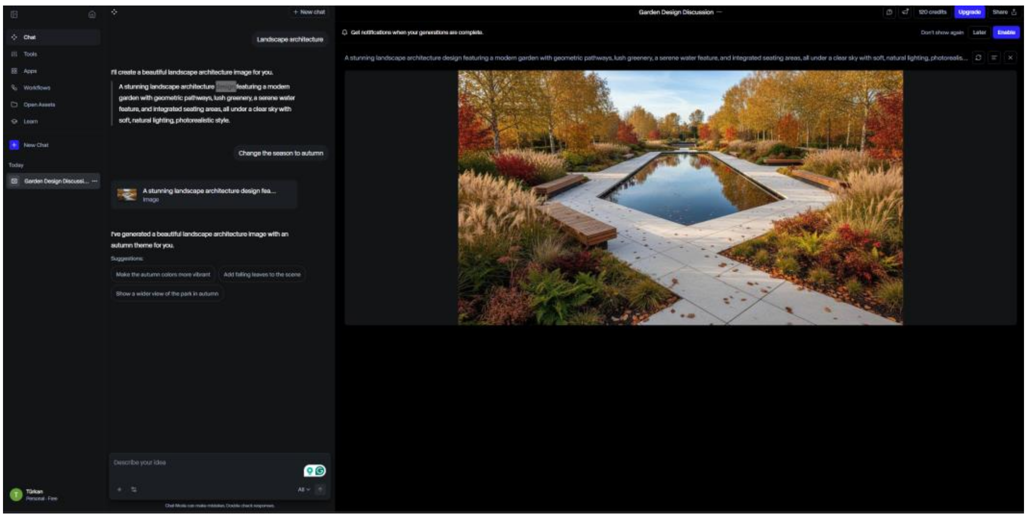

Fig. 3*. RunwayML Workflow*

Pika is a fast, creative text-to-video generator that allows users to produce short, animated scenes with stylistic control, camera movement, and atmospheric cues. In landscape architecture education, Pika is especially useful for showing how a space feels rather than simply how it looks capturing mood, movement, and experiential qualities. Students often use Pika to create narrative design clips, illustrate walking sequences, or infuse presentations with dynamic visual material. While its realism varies, its ability to support rapid experimentation makes it a valuable early-stage design tool (Figure 4).

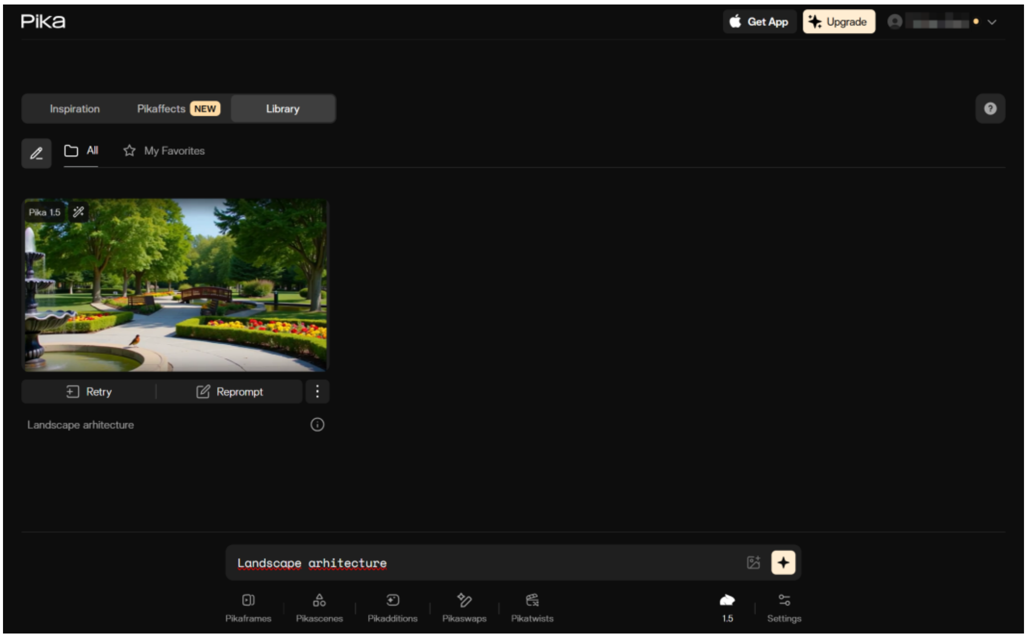

Fig. 4. *Pika Workflow*

Despite this growing interest, empirical research examining how students perceive AI-based visualization tools, especially generative image and video methods, remains limited. Understanding these perceptions is essential, as the next generation of landscape architects will work in a professional environment where AI-supported design workflows, automated environmental analysis, and data-driven spatial prediction will be commonplace.

Therefore, this study aims to investigate students' familiarity with AI tools, their perceived benefits and concerns, and their expectations regarding the role of generative AI in landscape architecture education. By examining these perspectives, the research contributes to ongoing discussions about how AI will shape design pedagogy and how educational institutions can responsibly integrate emerging technologies into landscape architecture curricula.

MATERIAL AND METHOD

The main material of the study consists of a comprehensive survey designed to gather opinions of architecture, landscape architecture, interior architecture, and urban and regional planning students on the use of artificial intelligence (AI) in landscape design presentations. The survey consisted of four sections. The first section asked students about their current department, current grade, age, and whether they had previously taken a landscape design or project course. The second section sought to measure their familiarity with AI. This section included questions about their awareness of visual generators such as Midjourney and DALL-E, and video generators such as Sora and RunwayML, and if so, their frequency of use. The third section explored the impact of AI on landscape presentation techniques under the following headings: opportunities (enhancing the process, increasing creativity, cost-effectiveness, and efficiency), and concerns (loss of control, technical accuracy, ethical issues, and impact on traditional drawing skills). The fourth and last section sought participants' opinions on future perspectives and the extent to which AI should be addressed in education. In this way, we aimed to measure the attitudes, awareness, and concerns of architecture faculty students towards the use of AI-based visual and video creation tools in design classes.

In the study, the survey responses given using the data mining method were evaluated. Data mining is a multi-stage analytical process aimed at discovering previously unknown, meaningful patterns, trends, relationships, and predictions within large datasets. In this process, statistical techniques, machine learning algorithms, and database management systems are used to extract knowledge from raw data [7]. Fundamental data mining techniques include classification, clustering, regression analysis, association rule mining, and anomaly detection. These techniques can be applied for various purposes such as predicting user behavior, analyzing design preferences, or identifying spatial trends within environmental datasets.

In landscape architecture, data mining has become increasingly valuable, particularly for the analysis of survey responses, identifying user profiles, extracting patterns of space utilization, and modeling environmental interactions. Through data mining, decision-makers can guide the design process more consciously and develop user-centered solutions based on empirical insights [8]. Python is one of the most widely used programming languages for data analysis, machine learning, and automation due to its simplicity and the richness of its ecosystem. In research environments, Python enables fast and adaptable workflows by offering powerful libraries such as Pandas for data manipulation, NumPy for numerical computation, and Scikit-learn for machine learning. Within landscape architecture, Python is increasingly applied to thermal imaging analysis, spatial data processing, climate modeling, and pattern detection. Its flexibility allows students to evaluate ideas, run simulations, and interpret environmental data in ways that directly support design exploration.

Orange is an open-source, modular, visual programming–based data mining and machine learning software. Developed in Python, Orange allows users to perform data analysis, modeling, and visualization without requiring any coding knowledge, thanks to its drag-and-drop interface [9]. The platform offers a wide range of tools for core machine learning tasks such as classification, regression, clustering, dimensionality reduction, model evaluation, and feature selection. It also provides interactive visualization, model comparison, and real-time analysis features, making it a powerful and accessible tool for both educational and professional research settings. Orange is particularly useful for tasks like survey analysis, user profile classification, and modeling various environmental datasets In fields such as landscape architecture where design, user behavior, and environmental analysis are closely intertwined. For example:

Classifying survey data that reflects user preferences (e.g., decision trees, logistic regression),

Predicting landscape-related choices using machine learning,

Discovering visual similarity patterns in image datasets,

Modeling vegetation distribution using multivariate environmental variables.

Thanks to its visual workflow interface, Orange enables researchers to experiment with complex algorithms, interpret outputs through visual dashboards, and easily compare the performance of different machine learning models. Orange Data Mining, a comprehensive tool for performing the analyses needed within the scope of this study, was evaluated. The created workflow is shown in Figure 5.

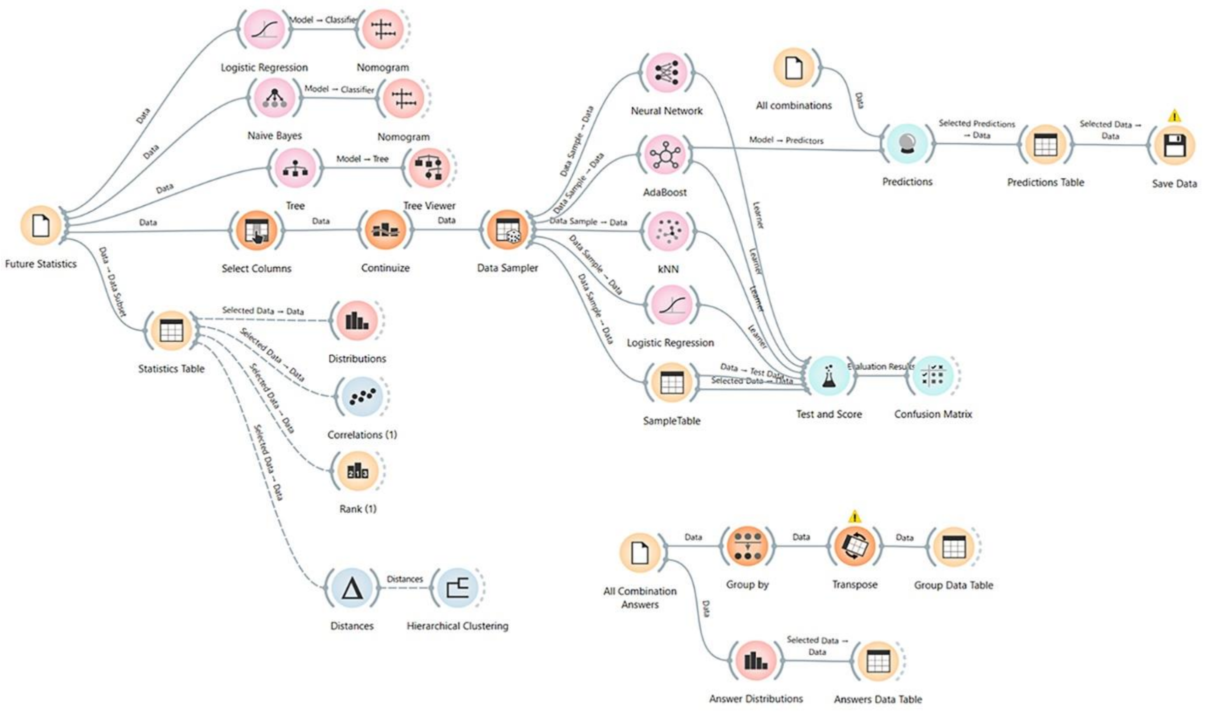

Fig. 5. *Orange Data Mining Flow Chart*

For this purpose, the software was used to perform statistical analyses of the responses, examining distributions, correlations, and hierarchical clustering. Using nomograms and tree viewer analyses, the variables most closely related to the question investigating the impact of artificial intelligence on design presentations and their role in five years and education were identified. Following this stage, the numerical data was controlled using “Continuize” widget, based on the six input variables from the survey to perform the data mining process. The data was then divided into Train (80%) and Test (20%). Neural Network, AdaBoost, Logistic Regression, and kNN models were evaluated for the data mining process, and the model that produced the most efficient results was selected for evaluation. Finally, in the data analysis phase, the All-combinations operation was performed to ensure a complete evaluation of the data for each of these six variables, and predictions were made for these combinations for the most robust model. The resulting data were grouped, their distributions were determined, and they were grouped based on distributions and previous conditions.

The results were discussed, and suggestions were developed in the light of the examination of the survey data and the answers given by the students and the data obtained.

RESULTS

Survey Data

A total of 320 people participated in the survey. To ensure equal representation in the sample group from each of the four main design disciplines (Landscape Architecture, Architecture, Interior Architecture, and Urban and Regional Planning), eighty volunteers from each were recruited to participate in the survey. Including equal participants from each department is crucial for homogeneous results. Distribution of survey participants according to their departments is given in Table 1.

Table 1. *Distribution of Survey Participants According to Their Departments*

Department	n	%
Landscape	80	25%
Architecture	80	25%
Interior	80	25%
Planning	80	25%

Most survey participants (79%) were students in their first three years of undergraduate education. Participation was particularly high among sophomores and juniors, while participation was lower among seniors (16%) and graduate students (6%). This is considered important for understanding the perspective of AI among those actively learning design tools and methods. Distribution of survey participants class information is given in Table 2.

Table 2. *Distribution of Survey Participants According to Their Class*

Class	n	%
Undergraduate first year	77	24%
Undergraduate second year	88	28%
Undergraduate third year	85	27%
Undergraduate fourth year	51	16%
Master of Science	19	6%

An examination of the age distribution data reveals that the participant profile is comprised of young adults. Seventy-five percent of the participants are between the ages of 18 and 23. The largest group, 43%, consists of students between the ages of 21 and 23. This finding suggests that the sample group comprises a generation defined as digital natives and highly adaptable to new technologies. Distribution of survey participants age groups is given in Table 3.

Table 3. *Distribution of Survey Participants According to Their Age Groups*

Age	n	%
18-20	104	33%
21-23	134	42%
24-26	56	18%
> 27	26	8%

Survey participants were asked whether they had ever taken a landscape design or landscape design course. 139 (43%) of them answered "Yes," while 181 (57%) answered "No." This suggests that a huge portion of the study group had not yet experienced a specific landscape project process, but the high percentage of those with landscape supervision, at 43%, demonstrates a sufficient level of competence to assess the potential of AI tools to meet professional needs. This balanced, heterogeneous structure allows for a comparative analysis of AI perceptions across both those with technical knowledge and those with a general design vision.

The second part of the survey assessed familiarity and use of AI tools using a 5-point Likert-type question ranging from "1 - Never Heard of" to "5 - Actively Using." Participants' awareness of AI-based video creation tools (mean: 3.12) was higher than that of visual creation tools. This may be attributed to the popularity of video-based content on social media and the impact of new-generation tools like Sora. Students' general propensity to use AI in design projects is at a moderate level of 2.93. Although 37% of participants (Levels 4 and 5) consider AI tools an active component in their projects, the high standard deviation (approximately 1.30) suggests a significant polarization in AI adoption among students; one group has adopted and used the technology, while the other remains only at the awareness stage of these applications. Awareness and usage levels of AI tools is given in Table 4.

Table 4. *Awareness and Usage Levels of AI Tools*

Familiarity	Use in Projects	Create Image	Create Video	Total
1	52	54	45	151
	16%	17%	14%	16%
2	80	82	62	224
	25%	26%	19%	23%
3	68	78	78	224
	21%	24%	24%	23%
4	77	62	77	216
	24%	19%	24%	23%
5	43	44	58	145
	13%	14%	18%	15%
Average	2.934	2.875	3.128	2.979
STD	1.295	1.290	1.307	1.301

The third section of the survey sought to gather participants' opinions on the advantages and disadvantages of AI tools. Participants had a divided view on the advantages of AI. The fact that all items were remarkably close to the mean of three and the high standard deviation indicated that there was no consensus yet. Participants' positive responses were to "creativity" (46%) and "cost/convenience" (40%). Students viewed AI's potential for faster and more economical visual production compared to traditional rendering applications as the most significant advantage. However, the high percentage of participants (39%) who disagreed with the suggestion that "AI videos are more effective than static images" could be perceived as an indication that, despite being familiar with video production tools, they are still inadequate to deliver the "atmosphere and experience" expected in project presentations. Furthermore, the divergence of opinions regarding AI's ability to accelerate the concept development process suggests that some students use AI as a "thought partner," while others view it as a tool that complicates the process or lacks control. Participant views on the advantages of AI, evaluated with a Likert scale (Scale: 1 = Strongly Disagree, 5 = Strongly Agree), is given in Table 5.

Table 5. *Participant Views on the Advantages of AI*

Advantages	Concept Dev.	Creativity	Cost and Easy	Effective	Total
1	56	52	52	52	212
	18%	16%	16%	16%	17%
2	64	66	56	72	258
	20%	21%	18%	23%	20%
3	95	87	102	97	381
	30%	27%	32%	30%	30%
4	70	68	61	59	258
	22%	21%	19%	18%	20%
5	35	47	49	40	171
	15%	25%	21%	14%	13%
Average	2.887	2.975	2.996	2.884	2.936
STD	**1.244**	**1.288**	**1.278**	**1.245**	**1.264**

An examination of the evaluations regarding disadvantages reveals a moderate level of ambivalence, but a decrease in concern about certain issues. The disadvantage most agreed with was "I have concerns about the freedom and copyright of AI content" (mean: 2.98). Thirty-seven percent of participants shared this concern. This may reflect the pressure placed on students by the unresolved "authorship" debate in the academic and professional world. The rate of those who disagreed (41%) than agreed (32%) with the view that AI tools would negatively impact students' traditional drawing skills. This finding suggests that participants tend to view AI tools as complementary rather than a replacement for traditional methods. However, the responses suggest that participants may be uncomfortable with the ethical ambiguity created by these tools. Participant views on the disadvantages of AI, evaluated with a Likert scale (Scale: 1 = Strongly Disagree, 5 = Strongly Agree), is given in Table 6.

Table 6. *Participant Views on the Disadvantages of AI*

Disadvantages	Lose Control	Not Realistic	Copyright	Dulling	Total
1	71	71	54	63	259
	22%	22%	17%	20%	20%
2	59	73	72	67	271
	18%	23%	23%	21%	21%
3	83	74	76	85	318
	26%	23%	24%	27%	25%
4	59	64	61	59	243
	18%	20%	19%	18%	19%
5	48	38	57	46	189
	15%	12%	18%	14%	15%
Average	2.856	2.766	2.984	2.868	2.869
STD	1.357	1.319	1.345	1.320	1.336

The fourth section of the survey surveyed participants' opinions about the future role of AI in their professions and educational demands. Responses to the question "What will the role of AI be in the next five years?" remained moderate, with a mean score of 3.11. However, the demand for the inclusion of AI tools in the educational curriculum (Mean: 3.36) was stronger. Fifty-one percent of participants indicated that AI-related courses should be included in the curriculum, whether compulsory, elective, or workshop. This result suggests that while students may not fully anticipate the future role of AI, they are both necessary and eager to learn these tools to enhance their professional competencies and prepare for technological advancements. Participant views on future perspective and education are given in Table 7.

Table 7. *Participant Views on Future Perspective and Education*

Future	Role in 5 years	Role in Education	Total
1	28	37	65
	9%	12%	10%
2	70	44	114
	22%	14%	18%
3	98	76	174
	31%	24%	27%
4	88	93	181
	28%	29%	28%
5	36	70	106
	11%	22%	17%
Average	3.106	3.359	3.233
STD	1.134	1.281	1.216

Survey Analysis

Data was analyzed using Orange Data Mining "Rank" widget to identify the factors that most influence participants' belief in the future importance of AI and their desire to include it in courses. The strongest predictor of whether participants believe AI will be important in the future was their familiarity with AI visualization tools (Info Gain: 0.104 and x2: 26.756). This was followed by their familiarity with video creation tools. This finding demonstrates that students familiar with and using technology are more likely to believe these tools will dominate the future.

The department factor ranked third, demonstrating that perspectives on the future differ across disciplines. Despite this, when it comes to training demand, the Create Image/Video variables do not rank highly. Instead, the most significant factor is grade level. This suggests that students' demand for AI training stems less from their familiarity with the tool and more from their own conventional views of its impact on their academic maturity and professional abilities. Those in the upper grades and those concerned about traditional skills place greater emphasis on AI being taught in a controlled manner within the educational environment (Table 8).

Table 8. *The 5 Most Important Factors Affecting "Future Role" and "Role in Education" Perception*

			Info. gain	Gain ratio	Gini	χ^2	ReliefF	FCBF
Role in 5 Years	1	Create Image	0.104	0.053	0.025	26.756	0.077	0.053
	2	Create Video	0.064	0.033	0.018	25.283	0.023	0.000
	3	Department	0.067	0.033	0.019	16.941	-0.024	0.033
	4	Age	0.037	0.021	0.010	9.077	0.016	0.000
	5	Concept	0.038	0.019	0.010	7.821	-0.006	0.000
Role in Education	1	Age	0.057	0.031	0.014	12.385	0.043	0.000
	2	Dulling	0.067	0.034	0.019	11.781	0.006	0.033
	3	Creativity	0.069	0.036	0.016	11.241	0.035	0.034
	4	Lose Control	0.054	0.028	0.014	10.905	0.003	0.026
	5	Copyright Issue	0.052	0.027	0.017	10.891	0.035	0.026

The "Correlation" widget was used to determine the relationship between variables in terms of their influence on each other, along with the most key factors, which are the target variables. Table 9 lists the variables with the highest positive and negative correlations in terms of Spearman Correlation. Accordingly, the highest correlation is observed between age and grade (positive 86.6%), which is particularly correlated with the ages of university enrollment and completion. The next most significant correlation, also positive, is between Create Image/Video and Role in 5 years. The Create Image and Create Video factors are also positively correlated with each other (positive 25.8%). The Creativity factor exhibits the highest correlation with Role in Education. This correlation level remains negative at 20%. The remaining factors exhibit weaker correlations.

Table 9. *The Highest Positive and Negative Correlations in Terms of Spearman Correlation*

Spearman Correlation				
1	0.866	Age	:	Class
2	0.350	Create Image	:	Role in 5 years
3	0.267	Create Video	:	Role in 5 years
4	0.258	Create Image	:	Create Video
5	-0.202	Creativity	:	Role in Education
6	0.170	Role in 5 years	:	Use in Projects
7	0.168	Not Realistic	:	Role in Education
8	0.163	Create Image	:	Dulling
9	0.159	Class	:	Not Realistic
10	-0.155	Class	:	Create Video

Hierarchical cluster analysis was applied to uncover the conceptual map in participants' minds and the relationships between the survey questions. This analysis produces a dendrogram that visualizes which concepts participants perceive as close and related to each other. As a result of the analysis, four main clusters were identified for the factors excluding the category-specific section. Cluster C1, which can be considered the ethics and skill concerns cluster, demonstrates that concerns about AI are not isolated, and that individuals with copyright/ethical concerns also fear professional atrophy. Cluster C2, which can be classified as the practical use cluster, is deeply related to the tendency to integrate AI tools into projects and the ability to produce with these tools. Cluster C3 can be classified as the demographic maturity cluster. The data showing the highest correlation is within the same cluster. Cluster C4, which can be considered the Perception and Evaluation cluster, contains the rest of the survey questions. Hierarchical Clustering of Survey Factors is given in Figure 6.

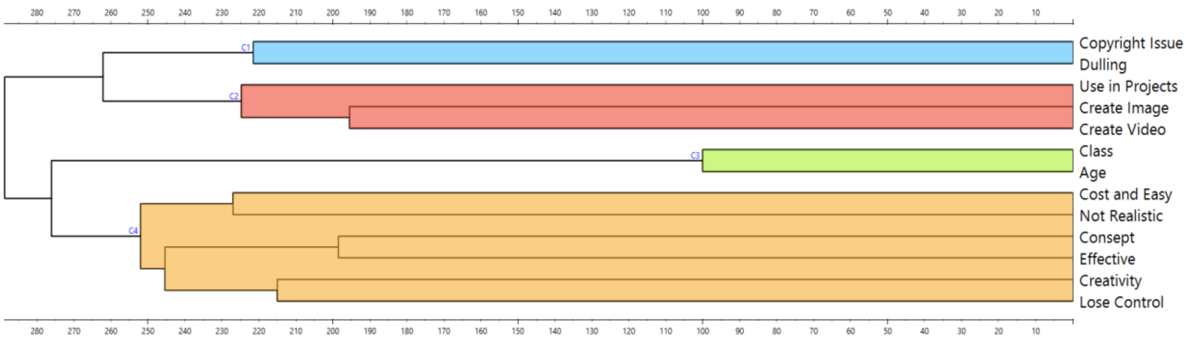

Fig. 6. *Hierarchical Clustering of Survey Factors*

Prediction Model Creation

The variables most closely related to the research question on the impact of artificial intelligence on design presentations and its role in five years and education, were identified using nomograms and tree viewer analyses. Logistic Regression, Naive Bayes, and Tree models were used for this purpose. Questions on demographics and familiarity with AI tools and frequency of use were identified as the most important sections of the survey. The question "Have you ever taken a landscape design or landscape design course?" was excluded from the evaluation due to its low correlation.

As part of the research, four different machine learning algorithms were evaluated using participant six factor responses. Model performance was evaluated using Area Under Curve (AUC), Classification Accuracy (CA), F1 Score (F1), Precision (Prec), Recall and Matthews Correlation Coefficient (MCC) metrics. The results are presented in Table 10.

Table 10. *The Evaluation Model Metrics*

Model	AUC	CA	F1	Prec	Recall	MCC
AdaBoost	0.98174	0.82031	0.81921	0.83346	0.82031	0.76711
Neural Network	0.94638	0.71093	0.70460	0.71771	0.71093	0.62476
kNN	0.83485	0.52343	0.51127	0.51587	0.52343	0.37196
Logistic Regression	0.71616	0.41015	0.39303	0.40059	0.41015	0.20891

The AdaBoost algorithm clearly outperforms other models in all performance metrics. AdaBoost achieved near-perfect discrimination with an AUC of 0.982 and an overall accuracy rate of 82% (CA: 0.820). This result demonstrates that the developed model can predict target variables with high accuracy based on participant responses to the survey questions. Confusion Matrix of AdaBoost Algorithm is given in Table 11.

Table 11. *Confusion Matrix of AdaBoost Algorithm*

		Predicted					
		1	**2**	**3**	**4**	**5**	**∑**
Actual	**1**	100.00%	13.20%	0.00%	0.00%	4.80%	**23**
	2	0.00%	83.00%	15.80%	0.00%	0.00%	**56**
	3	0.00%	0.00%	84.20%	16.90%	4.80%	**78**
	4	0.00%	3.80%	0.00%	83.10%	21.40%	**70**
	5	0.00%	0.00%	0.00%	0.00%	69.00%	**29**
	∑	**14**	**53**	**76**	**71**	**42**	**256**

The Neural Network model was the second most successful with an accurate rate of 71.1%, while the kNN (52.3%) and Logistic Regression (41%) models performed poorly. The low performance of Logistic Regression demonstrates that the factors influencing student attitudes have a non-linear, complex structure, and that ensemble-based methods like AdaBoost are much more capable of modeling this complexity.

A control dataset was prepared using the values of each of the six variables Department (4), Class (5), Age (5), Use in Project (5), Create Image (5), and Create Video (5) and their combinations. This data table contains 12,500 variables and is called "All combinations." This data table was evaluated with a machine learning algorithm built with the AdaBoost model, generating predictions for each variable. This resulted in a more broadly distributed dataset than could have been obtained with 320 surveys.

In the Extended Dataset, "Role in Five-Year Distributions," the highest predicted value is 3 with 4747 predictions (37.98%). This suggests that users haven't made a clear decision about the future of AI. Specifically, there is no significant difference between students who have completed or are about to complete their specializations and those who have just started their education. However, there are significant differences between departments. The algorithm's lowest value of “1”, with a significant portion of the distribution of 443 predictions (51.93%), was recommended for architecture students. However, the 1070 predictions (39.76%) for “2” again suggest that architecture students believe AI will play a minor role in the future. However, in the evaluations of students in interior architecture and urban and regional planning, this rate appears to lie more frequently between “4” and “5”. It is particularly striking that value “1” for urban and regional planning remains very low at 73 (8.56%). Extended dataset role in five years distributions is given in Table 12.

Table 12. *Extended Dataset Role in Five Years Distributions*

Role in Five Years	1		2		3		4		5	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Architecture	443	51.93%	1070	39.76%	953	20.08%	271	10.10%	388	25.43%
Landscape Arch.	113	13.25%	730	27.13%	1248	26.29%	677	25.23%	357	23.39%
Interior Arch.	224	26.26%	524	19.47%	1136	23.93%	892	33.25%	349	22.87%
City and Urban Pl.	73	8.56%	367	13.64%	1410	29.70%	843	31.42%	432	28.31%
Undergraduate 1st	150	17.58%	544	20.22%	916	19.30%	645	24.04%	245	16.06%
Undergraduate 2nd	156	18.29%	525	19.51%	1189	25.05%	403	15.02%	227	14.88%
Undergraduate 3rd	185	21.69%	558	20.74%	937	19.74%	441	16.44%	379	24.84%
Undergraduate 4th	185	21.69%	492	18.28%	869	18.31%	608	22.66%	346	22.67%
Master of Science	177	20.75%	572	21.26%	836	17.61%	586	21.84%	329	21.56%
Total	**853**	**6.82%**	**2691**	**21.53%**	**4747**	**37.98%**	**2683**	**21.46%**	**1526**	**12.21%**

In the Extended Dataset, the highest predicted value for the Role in Education Distributions is observed to be 3, with 4130 predictions (33.04%). However, while not particularly sharp, the above-average prediction rate of 40.97% emphasizes the importance of AI tools as a part of education. Like the judgments made for future roles, the predictions for architecture students show a distribution below average, while the predictions for interior architecture and urban and regional planning students show a distribution above average. Furthermore, the predictions for landscape architecture students show a distribution between the two extremes of 1 and 5. The most significant finding during the evaluation is the finding regarding education level. It is noted that the algorithm's predictions, particularly for first-year students, emphasize the importance of AI tools training. It is predicted that these rates will decrease as grades advance and expertise in other tools is achieved, and the demand for education will decrease. Extended dataset role in education distributions is given in Table 13.

Table 13. *Extended Dataset Role in Education Distributions*

Role in Education	1		2		3		4		5	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Architecture	352	31.68%	940	43.99%	826	20.00%	331	11.74%	676	29.35%
Landscape Arch.	391	35.19%	467	21.85%	974	23.58%	600	21.28%	693	30.09%
Interior Arch.	320	28.80%	458	21.43%	955	23.12%	965	34.23%	427	18.54%
City and Urban Pl.	48	4.32%	272	12.73%	1375	33.29%	923	32.74%	507	22.01%
Undergraduate 1st	84	7.56%	376	17.59%	546	13.22%	555	19.69%	939	40.77%
Undergraduate 2nd	212	19.08%	506	23.68%	976	23.63%	499	17.70%	307	13.33%
Undergraduate 3rd	264	23.76%	422	19.75%	920	22.28%	578	20.50%	316	13.72%
Undergraduate 4th	287	25.83%	425	19.89%	818	19.81%	594	21.07%	376	16.33%
Master of Science	264	23.76%	408	19.09%	870	21.07%	593	21.04%	365	15.85%
Total	**1111**	**8.89%**	**2137**	**17.10%**	**4130**	**33.04%**	**2819**	**22.55%**	**2303**	**18.42%**

As part of the study, an Extended Dataset Awareness and Usage Levels of AI Tools Distributions were prepared. Data from Use of AI Tools, Create Image, and Create Video were combined to produce predictions based on a general usage approach. While the distributions are centered, predictions regarding the future of AI are generally high for those who use AI tools, while those who don't show a clear clustering. This may be due to individuals who are familiar with AI tools being aware of their potential future impact. Similarly, predictions for individuals who use and are already proficient in these tools vary significantly. Those familiar with the tools generally emphasize the necessity of AI tool training, while predictions for users who don't use or are unfamiliar with the tools generally emphasize the need to avoid training. Extended dataset awareness and usage levels of ai tools distributions is given in Table 14.

Table 14. *Extended Dataset Awareness and Usage Levels of AI Tools Distributions*

		1		2		3		4		5	
		n	%	n	%	n	%	n	%	n	%
Role in 5 Years	ALL-1	173	20.28%	579	21.52%	1124	24%	428	16%	195	13%
	ALL-2	175	20.52%	651	24.19%	952	20%	519	19%	203	13%
	ALL-3	232	27.20%	509	18.91%	917	19%	500	19%	342	22%
	ALL-4	135	15.83%	453	16.83%	946	20%	640	24%	327	21%
	ALL-5	138	16.18%	499	18.54%	808	17%	595	22%	459	30%
	Total	**853**	**6.82%**	**2691**	**21.53%**	**4747**	**38%**	**2683**	**21%**	**1526**	**12%**
Role in Education	ALL-1	280	25%	546	26%	969	23%	320	11%	386	17%
	ALL-2	224	20%	551	26%	789	19%	508	18%	429	19%
	ALL-3	287	26%	361	17%	811	20%	645	23%	396	17%
	ALL-4	200	18%	358	17%	852	21%	596	21%	494	21%
	ALL-5	120	11%	322	15%	710	17%	750	27%	598	26%
	Total	**1111**	**9%**	**2137**	**17%**	**4130**	**33%**	**2819**	**23%**	**2303**	**18%**

CONCLUSION

This study provides a comprehensive overview of the current integration and perception of AI-based image and video production tools in spatial design and planning. The findings reveal a level of awareness that might initially have been anticipated but not anticipated; some participants are already using AI tools for project development and visualization.

The study design questions, "Is there a significant difference in AI use across departments?" and "Is there a difference observed in terms of grade and education level?" were specifically addressed. While the results could be interpreted as suggesting that some professional groups perceive AI tools as a potential risk to their professions, others will rapidly adopt these tools for their own purposes. The observed differences across professions, particularly regarding AI training, demonstrate that the initial research questions were well-posed.

The data indicates a strong consensus on the future role of AI; the majority of participants anticipate that these technologies will become an integral part of professional practice within the next five years. Therefore, it is imperative that educational institutions and professional organizations proactively adapt their curricula and training programs to ensure that future practitioners can fully leverage the transformative potential of AI.

In this situation, various strategic directions become necessary. First, the curricula of design-related programs should be updated to include AI-powered image and video production tools not as supplementary material but as an integral part of studio courses and project development processes. Technical training and courses focused on "AI design literacy" will help students understand the broader ethical, legal, and methodological implications of working with algorithmic tools.

Second, short-term workshops and certification programs should be developed to provide rapid and practical training for professionals already working in the field but unfamiliar with these technologies. More intensive programs that facilitate the transition of new graduates to the professional world and introduce advanced AI workflows will further support this need.

Third, Ethical guidelines should be developed to address issues such as awareness of algorithmic biases in design decisions, transparency, and designer accountability. Clear information about copyright and intellectual property boundaries for outputs produced with AI should be provided and legal developments in this area should be complied with.

Fourth, collaboration between universities and industry should be strengthened through joint pilot projects applying AI tools to real-world design problems and research partnerships aimed at developing domain-specific AI models tailored to the needs of landscape architecture, urban planning, and related disciplines.

Finally, academia should encourage research that critically examines the relationship between AI and creativity whether these tools merely accelerate existing processes or facilitate entirely new creative directions and support research on how human-AI collaborations are reshaping design practices and impacting the quality of spatial outcomes.

Recent research has begun to address the use of artificial intelligence in design education, yet the scope and emphasis of these studies differ considerably from the focus of current work. [10] investigated AI-assisted visualization within landscape design, but their sample consisted of academics, professionals, and students together; therefore, the educational aspect and student-specific perceptions of presentation techniques remained limited. [11] discussed early applications of generative AI tools in landscape architecture studios, relying mainly on descriptive insights rather than a structured analysis of student views, and their work did not examine the role of AI in presentation practices. Similar tendencies appear in architectural education studies. The research of [12] concentrated on how architecture students perceive AI during project development in general, without addressing how AI affects the preparation or delivery of design presentations. [13] focused on generative image tools used in studio production, and again, presentation-oriented processes were not evaluated.

In contrast to these examples, the present study places landscape architecture students at the center of the analysis and examines how AI supported presentation techniques influence their learning experience, their perception of advantages and limitations, and the clarity of visual communication in design education. The existing literature does not provide an empirical investigation that combines AI, presentation quality, and landscape architecture pedagogy within a single framework. The current study responds directly to this gap.

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