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Comparing AI-Based and Traditional Digital Workflows in Urban Case Study Analysis: Senior Landscape Architecture Project

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Generative Artificial Intelligence (AI) tools are rapidly becoming embedded within landscape architecture studios, raising important questions about authorship, accuracy, and their potential to reshape core analytical and representational workflows in the classroom setting. This study evaluates the effectiveness, limitations, and pedagogical implications of AI-based design workflows and applications within an undergraduate landscape architecture curriculum. Senior-level students at the University of Guelph completed the Urban Atlas – Community Case Studies assignment, producing figure-ground maps, analytical diagrams, and public-realm visualizations for selected urban districts. Sixteen groups participated: seven employed AI-dominant workflows incorporating platforms such as MidJourney, DALL-E, Stable Diffusion, Firefly, Runway ML, Aino, Meshy, Gemini, and ChatGPT, while nine groups relied primarily on traditional digital tools including Photoshop, Illustrator, InDesign, ArcGIS, AutoCAD, Rhino, and Blender. All final submissions were evaluated blindly by external reviewers, including principals and senior associates from landscape architecture and urban design firms, using a standardized 25-point scoring rubric. Recent AI research in the environmental design disciplines has shifted from data-driven optimization and environmental modelling toward tools capable of producing images, text, diagrams, three-dimensional forms, code, and analytical diagramming with rapid iterations. Within the studio context, this technological shift raises important questions about representation, authorship, learning outcomes, and the evolving skillsets required of contemporary landscape architects. Emerging scholarship increasingly positions AI as a creative ideation platform, providing new modes of visual experimentation, conceptual development, and rapid visualizations, provided that its use is framed within critical and ethical pedagogical structures. Students using conventional design software and workflows indicate greater control over linework, mapping accuracy, hierarchy, and labeling conventions, though it can result in longer production times and less compelling visual experimentation. Reviewer comments reflected these outcomes. AI submissions were noted for visual richness and the traditional submissions were commended for stronger analytical output. The results indicate that AI tools currently function as augmentative rather than transformative components of the design studio. Their primary strengths lie in the ideation, visualization, and stylistic exploration. The traditional digital skills remain essential for accurate, measurable, scalable, and analytically outputs. The study highlights the need for pedagogical models that integrate AI literacy while preserving foundational competencies in mapping, spatial analysis, and graphic communication.

Keywords: *visual representation, Artificial Intelligence (AI), landscape architecture, site analysis, design communication*

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Introduction

Artificial Intelligence (AI) tools for visualization, mapping, and analytical representation have rapidly entered the workflow of landscape architecture design studios. Their growing presence raises questions regarding authorship, accuracy, and the broader evolution of design processes (Fernberg and Chamberlain 2023). While traditional platforms such as AutoCAD, Illustrator, Photoshop, Rhino, and ArcGIS continue to dominate industry-standard production, generative AI systems, such as MidJourney, DALL-E, Adobe Firefly, Runway ML, and ChatGPT, are increasingly being adopted in the design studio classroom. These AI tools introduce alternative modes of producing analytical and visual outputs. These technologies introduce alternative modes of producing both analytical and visual outputs, often characterized by speed, automation, and stylistic variation.

The coexistence of traditional and AI-based workflows requires educators to critically assess how these approaches compare in the production of analytical urban studies. To what extent can AI tools be integrated into the design process without compromising analytical rigor? Are final drawings generated with substantial AI assistance acceptable within professional and pedagogical standards? These questions reflect broader disciplinary concerns regarding the balance between innovation and foundational skill development.

This study examines these questions within an undergraduate landscape architecture curriculum. Senior students at the University of Guelph completed a structured assignment, *The Urban Atlas: Community Case Studies*, analyzing local and international districts through figure-ground mapping, spatial analytical diagrams, and public-realm visualizations. Sixteen groups participated; seven employed AI-dominant workflows and nine relied on traditional digital workflows. External evaluators, consisting of design principals from landscape architecture and urban design firms in Canada, blindly reviewed and scored all submissions using a standardized rubric, enabling an objective comparison of output quality and analytical performance.

Literature Review: AI in Landscape and Design Education

AI research in the environmental design disciplines has progressively shifted from data-driven optimization and environmental modelling toward tools capable of producing images, text, diagrams, three-dimensional forms, code, and analytical outputs. This transformation signals not only a technological evolution but also a broader reconfiguration of how design knowledge is generated, represented, and evaluated. Within the studio context, this technological shift raises critical questions about representation, authorship, learning outcomes, and the evolving skillsets required of contemporary landscape architects. Recent academic literature suggests that AI can function as active component of the creative process in design studios, providing new modes of visual experimentation, conceptual development, and rapid feedback—provided that its use is guided by critical and ethical awareness (Mollick and Mollick 2023). Professional commentary further describes

a temporary "AI buffer zone" surrounding landscape architecture, where the discipline's ecological complexity and relatively slower digital transformation both delay and mediate AI adoption, thereby creating space for more selective and reflective integration of these tools (Mortice 2024). Emerging scholarship extends this perspective by framing AI not merely as a technical assistant, but as a cognitive extension within design education, reshaping how students formulate prompts, interpret outputs, and iteratively refine ideas (Fernberg and Zhang 2024). Comprehensive surveys of AI-generated content in landscape architecture similarly document growing adoption in tasks such as image synthesis and diagram production, while simultaneously underscoring persistent concerns regarding accuracy, reliability, and ethical integration.

Design education scholars argue that AI's value lies in its capacity to automate complex or time-intensive tasks while strengthening the designer's creative through an expanded range of representational possibilities, particularly during early design phases (Caramiaux et al. 2025, Agkathidis 2015). Rather than replacing design thinking, AI redistributes cognitive effort, allowing students to focus more intensively on evaluation, synthesis, and decision-making (Fernberg and Zhang 2024). Within landscape architecture specifically, generative tools facilitate the rapid production of compelling visualizations, conceptual landform studies, ecological scenarios, and site narratives, assisting students in articulating ideas that might otherwise remain abstract or underdeveloped (Rekittke and Hayles 2025). At the same time, these tools also introduce students to contemporary professional workflows, as more design firms incorporate AI applications for research synthesis, visualization, and early project development. At the policy level, large-scale public investments in AI research—including recent national AI institute initiatives—signal that AI will remain a strategic priority across sectors, intensifying expectations for design programs to cultivate robust AI competencies (National Science Foundation 2025). Integrating AI knowledge into studio education therefore aligns academic training with evolving industry demands and broader technological trajectories.

A considerable body of academic literature emphasizes that generative AI should operate within hybrid workflows rather than function as a substitute for analytical and technical expertise. This position is often described as a form of hybrid intelligence, in which computational systems support visualization, pattern recognition, and data processing, while human designers retain responsibility for contextual reasoning, spatial coherence, and environmental judgment (Braiden et al. 2025). Empirical comparisons between AI-generated and human-rendered landscape visualizations reinforce this hybrid approach. Although AI tools demonstrate increasing proficiency in replicating complex geometries and planting compositions, manual refinement remains essential to ensure material fidelity, contextual sensitivity, and artistic control (Ashari and Shafaghati 2025). These findings suggest that AI's strengths are most effectively realized when complemented by disciplinary knowledge and critical oversight.

Landscape architecture, specially, relies heavily on spatial accuracy, site and contextual understanding, and environmental data integration, areas in which generative systems remain inconsistent and occasionally unreliable. Studies evaluating AI-assisted mapping report recurring issues such as inaccurate building footprints,

omitted hydrological features, misrepresented vegetation patterns, and inconsistent land-use mapping. These limitations were also observed by students in the present studio urban analysis case study. As a result, instructors emphasize the importance of combining AI-generated images or diagrams with standard design software under informed human supervision, such as GIS, CAD, and parametric modelling platforms, to preserve accuracy and disciplinary rigor (Maniyar et al. 2025). This pedagogical position reflects broader discussions in architecture and urban planning programs, where educators argue that AI should enhance rather than displace foundational skills such as drawing, diagramming, site analysis, and evidence-based decision-making.

Beyond issues of accuracy and workflow integration, AI-driven generative models introduce new dynamics into the creative process itself. By analyzing large datasets of existing urban spaces and landscape designs, these models can reveal hidden patterns, design logics, and aesthetic strategies that may not be immediately perceptible to human designers (Doshi and Hauser 2024). This capacity for generalized learning enables designers to explore a broader and more diverse range of possibilities, potentially stimulating students' conceptual development. When combined with user-defined constraints and preferences, AI systems can function as collaborative partners, generating design alternatives that are both innovative and contextually appropriate (Wu et al. 2021). However, the pedagogical effectiveness of such collaboration depends on structured frameworks that encourage active critique and iterative refinement, rather than passive acceptance of generated outputs (Fernberg and Zhang 2024, Braiden et al. 2025).

In addition to idea generation, AI enhances scene simulation and visualization in landscape design. Recent comparative studies evaluating AI-generated renderings against traditional human outputs using metrics such as structural similarity indices (SSIM) and cosine similarity demonstrate that AI can achieve high levels of geometric and compositional alignment, although material inconsistencies and biased outputs persist (Ashari and Shafaghati 2025). With increasingly refined modelling capabilities, students can produce three-dimensional representations of proposed sites, simulate environmental conditions, model vegetation growth patterns, and anticipate pedestrian movement (Lovett et al. 2015). These capacities contribute to the development of a visual language capable of communicating spatial, ecological, and social dynamics in more tangible and accessible ways. Moreover, AI is increasingly integrated into conventional design software such as AutoCAD, SketchUp, and Photoshop through intelligent plug-ins (e.g., Enscape Premium). These integrations allow for fast rendering of design concepts, enabling clients and stakeholders to interact with and evaluate proposals in real time, and facilitating quick design iterations. The result is a more iterative and participatory design process, enhancing the clarity and appeal of landscape proposals. This may contribute to increased student confidence in design communication, by allowing AI to help bring their visions onto paper.

In other studio development projects, when the students are required to document prompts, evaluate outputs, and revise errors, they develop stronger critical thinking skills and a more deliberate design process (Agkathidis 2015, Rekittke and Hayles 2025). Similar outcomes were observed in the present studio assignment. For the Urban Atlas Projects, AI groups documented their prompts

used, the workflow, document any errors and evaluate the AI tools they used. Students learned to critique generative tools, allowing them to judge the inaccuracy and think more about the analytical mapping, which reinforces core disciplinary values such as interpretation, iteration, and judgment. This process aligns with emerging calls for AI literacy in design education, emphasizing not only operational familiarity but also the ability to interrogate data sources, recognize algorithmic bias, and evaluate reliability (Braiden et al. 2025). Such calls for AI literacy resonate with broader work on interdisciplinary collaboration, which identifies structural and cultural barriers that must be addressed when integrating new forms of expertise into established disciplines (Institute of Medicine 2000).

Ethical considerations are increasingly embedded within pedagogical discussions of AI integration. Educators highlight concerns related to authorship, transparency, bias, and data sourcing, advocating for explicit classroom strategies such as attribution guidelines, source verification, and critical examination of the environmental and social implications of training datasets (Maniyar et al. 2025). Recent applied research in landscape visualization further emphasizes the importance of documenting AI workflows, including prompt engineering strategies, detailed reporting of checkpoints, and dataset sources, to promote transparency, reproducibility, and ethical accountability in AI-assisted design processes (Ashari and Shafaghati 2025). When implemented within such structured and reflective frameworks, AI functions not merely as a productivity enhancer, but as a medium through which students engage in informed and critical digital practice (Fernberg and Zhang 2024).

Recent literature suggests that AI's role in the landscape architecture studio is most effective when positioned as an additional layer that enhances conceptual exploration, representational diversity, and writing support for proposals, while traditional mapping, spatial analysis, and model-building continue to rely on established technical platforms and disciplinary expertise. Within this balanced configuration, AI expands the representational range and enhances new modes of inquiry appropriate for contemporary landscape challenges.

The research explores:

(1) How AI-based workflows differ from traditional workflows in producing analytic and visual content, meaning are there challenges encountered by students that output are incorrect, e.g., figure-ground results.
(2) Whether external reviewers can detect differences in workflow quality.
(3) How emerging AI workflows may influence pedagogical structures and skill expectations.

Methodology

Research Design

Sixteen groups, each comprising three to four senior-level undergraduate students, were analyzed across two parallel workflow streams.

AI Workflow Groups (n = 7): Groups in this stream were required to integrate generative artificial intelligence tools throughout the majority of their design and representation tasks. Tools included MidJourney, DALL-E, Stable Diffusion, Firefly, Runway ML, Aino, and ChatGPT. Minor non-AI refinements (e.g., post-processing in Illustrator or Photoshop) were permitted to support layout precision and graphic clarity. These groups were required to submit detailed documentation of their iterative design processes, including prompt development, image generation logs, workflow diagrams, and reflective notes on technical and conceptual challenges.

Traditional Digital Workflow Groups (n = 9): These groups employed conventional digital design and mapping workflows without the use of generative AI. Production methods included Adobe Photoshop, Illustrator, and InDesign, as well as AutoCAD, Rhino, ArcGIS, and Blender, supported by literature-based and precedent-based research practices typical of landscape architecture and urban design studios.

All groups were assigned identical project briefs, timelines, and deliverables to ensure comparability across workflow conditions.

Assignment Structure

Each group was required to produce a sequence of three analytical and representational panels:

Panel 1: Figure–Ground Mapping
Mapping of built-form fabric for a 1 km × 1 km urban area within a major city (e.g., Lower Manhattan, New York City), at 1:2000 scale, including:

- Traditional building figure–ground
- Vegetation figure–ground mapping
- Street and block morphology figure–ground

Panel 2: Analytical Diagrams
Various urban analysis of the study area, including:

- Mobility and circulation networks
- Public realm typologies
- Land-use and building-use distributions
- Identification of underperforming or opportunity areas requiring design improvement

Panel 3: Public Realm Visualization and Identity of Place
Advanced representational studies including:

– Character and experiential studies of public space
– Street sections at various scales
– Quality of space and materiality visualizations

Across all panels, clarity, accuracy, visual hierarchy, and professional standards of graphic communication were emphasized.

Evaluation Framework

Sixteen final submissions were reviewed by seven external evaluators, consisting of principals and senior associates from leading landscape architecture and urban design firms. All reviewers evaluated the work anonymously using a standardized scoring rubric:

- Graphic Quality and Visual Communication (10 points)
- Site Analysis and Urban Understanding (10 points)
- Creativity and Critical Thinking (5 points)

Total possible score: 25 points

The reviewers were not informed of the workflow type used by any group, ensuring a blind peer-review structure and reducing the risk of evaluative bias. Inter-rater reliability among the seven reviewers was assessed using an intra-class correlation coefficient (ICC), calculated with a two-way mixed-effects model for average measures (ICC(3,k)), the results of which are reported in section 3.1.

Data Collection

Three primary datasets were collected:

Student Submissions

Panels constituted the core visual and analytical dataset. All submissions were anonymized and labeled only by group number (e.g., Group 1, Group 2). Projects were compiled into standardized digital PDF packages and distributed to external reviewers for scoring.

AI Workflow Documentation

Groups using AI tools submitted supplementary process documentation to the instructors, including:

– Prompt development strategies
– Tool selection rationales
– Iterative workflow diagrams

– Reflections on technical limitations, ethical concerns, and authorship perceptions

These materials served as qualitative data to support interpretation of design outcomes and student learning experiences.

External Reviewer Scores

Quantitative data were collected from scoring sheets completed by external reviewers. These data provided measurable comparisons of performance across both workflow streams.

Analysis

Quantitative Analysis

Descriptive and inferential statistical methods were used, including means, medians, standard deviations, independent-sample t-tests, and effect size calculations using Cohen's d, to evaluate differences between workflow groups.

Qualitative Analysis

Thematic coding has been applied to student reflections and reviewer comments to identify recurring patterns related to authorship, accuracy, efficiency, creativity, and the perceived legitimacy of AI-assisted and traditional workflows.

All groups were given three and a half weeks to complete the assignment. Groups were formed to include diverse skill sets, and participation in the AI workflow has been voluntary rather than assigned, allowing students to opt into experimental AI use. AI-based groups were required to submit full prompt logs, workflow descriptions, and reflections on challenges encountered when using these tools.

To maintain anonymity and remove presentation bias, projects were submitted without oral presentations submitted without oral presentations. Some groups have used paid AI platforms such as Aino, mainly for mapping and diagrammatic tasks, while others used free or open-access tools due to financial constraints. This variation has been documented and considered as a contextual factor in interpreting workflow performance.

Methodological Limitations

Several methodological considerations should be acknowledged when interpreting the findings of this study. First, participation in the AI workflow was voluntary rather than assigned. Students who opted into this condition may have had greater prior familiarity with generative tools or stronger motivation to engage with emerging platforms, factors that could independently influence output quality regardless of the tools themselves.

Second, access to AI tools was not consistent across workflow groups. Some groups used paid platforms, particularly Aino (approximately 20 CAD per month for the student subscription) and upgraded versions of MidJourney, which

provided greater mapping precision and functionality than the free-tier alternatives available to other groups. This disparity in tool capability introduced an uncontrolled variable within the AI condition, meaning that differences in performance among AI groups may have reflected variations in resource access as much as differences in student skill or approach. An additional complication emerged during the workflow process when some groups discovered that switching between data sources within Aino, such as from Microsoft to OpenStreetMap (OSM), resulted in substantially different levels of spatial completeness. This variability was neither disclosed in advance nor controlled across groups. Future studies should standardize tool access across participants or stratify analyses by subscription level in order to more accurately isolate the influence of AI tool quality on output performance.

Results

Quantitative Scoring Outcomes

Prior to comparing workflow outcomes, inter-rater reliability was assessed to confirm the consistency of the external evaluation. The ICC(3,k) = 0.796 (95% CI for single-measure ICC(3,1): [0.174, 0.615]), F(15, 90) = 4.905, indicating good reliability among the seven reviewers. These results support the validity of the blind scoring procedure as a dependable basis for comparing workflow performance.

Blind reviewer scoring showed minimal difference between workflows.

Project-level means:

AI groups: 18.48 / 25
Traditional groups: 19.15 / 25
Difference: 0.67 points

Individual reviewer ratings (n=112):

AI mean: 18.85
Traditional mean: 19.48
Difference: 0.63
Effect size: $|d| \approx 0.19$ (small)

A two-sample t-test indicated no statistically significant difference ($p > .05$), confirming that workflow type did not predict higher or lower reviewer evaluation.

Table 1. *Scoring from the External Evaluators – AI vs non-AI Applications*

(AI Application vs Conventional Software)	Group	R1	R2	R3	R4	R5	R6	R7	Average Score
NO AI	G1	19	19	20.5	20	20	17	22.5	19.86
AI	G2	20	20.5	18.5	18	18	19	21.5	19.64
AI	G3	19	18.5	19	20	17	20	24	19.60
AI	G4	18	21	19	17	14	19	22	18.43
AI	G5	19	21	19.25	19.5	19	17	18	18.96
AI	G6	22	20.5	21	22	19	22	22	21.21
NO AI	G7	18	19	19	19.5	11	19	19	18.07
NO AI	G8	24	19.5	20.5	20	21	22	23.5	21.60
NO AI	G9	23	20.5	20.75	21	14	21	24	20.61
AI	G10	22	19	19.5	19	9	19	19.5	18.57
No AI	G11	21	19	19	19	12	22	20.5	19.64
AI	G12	23	19.5	20.5	19	17	21	24.5	20.64
NO AI	G13	22	20	19	21	13	22.5	24	20.21
No AI	G14	25	21	19	19.5	13	24	19	19.79
No AI	G15	25	21.5	19.5	20	13	21	24	20.71
No AI	G16	21	19.5	19.5	19	9	19	19.5	18.14

Based on Table 1, the results show minimal difference between AI-assisted and non-AI workflows in overall performance, as measured by external reviewers. Average scores across both groups cluster within a narrow range (generally between approximately 18–21 out of 25), suggesting that the use of generative AI tools did not produce a statistically or perceptually significant improvement in project outcomes when compared with conventional digital production methods. Reviewers' scores show consistent overlap across both cohorts, indicating that professional evaluators did not perceive strong distinctions in graphic quality, urban analysis, or conceptual rigour attributable to workflow type. This suggests that, within the timeframe and complexity of the assignment, AI functions more as an efficiency or exploratory aid rather than as a significant part of design excellence.

These results align with emerging scholarship in landscape architecture and design education that positions AI as an augmentative rather than transformative studio tool. Recent studies *in Landscape Journal, JoDLA (Journal of Digital Landscape Architecture), and LA+* have reported that while generative AI can accelerate image production, expand stylistic exploration, and support rapid prototyping, it does not inherently improve spatial reasoning, site analysis, or critical design thinking. Research by Fernberg and Chamberlain (2023) has similarly noted that AI-supported visualization enhances speed and surface-level iteration, but that deeper landscape intelligence remains dependent on human interpretation, disciplinary knowledge, and iterative design judgment.

Studies examining AI in architecture and landscape studios have found that students using AI often produce visually compelling outputs more quickly. Students

using conventional GIS, CAD, and modeling workflows tend to demonstrate stronger control over scale, measurement, and spatial legibility. These findings reinforce the results of this study: reviewers did not observe strong qualitative differences between AI and non-AI groups because visual richness alone did not outweigh the importance of analytical rigour and spatial clarity.

Reviewer Feedback

AI submissions are applauded for visually sophisticated perspectives, atmospheric images, and stylistic branding. However, reviewers have also noted occasional issues with hierarchy, analytical integrity, and consistency.

Traditional submissions have shown strong control of mapping accuracy, labeling, and structured layout, though some have received comments noting less dynamic imagery or lower creativity.

Student-Reported Workflow Insights

A review of the submitted AI workflow documentation revealed that figure-ground inaccuracies were a recurring issue across most AI groups. Of the seven AI workflow groups, five documented the need for manual correction of AI-generated base maps, citing missing building footprints, incomplete street geometries, absent vegetation layers, and misclassified land-use boundaries. In all cases, these corrections were completed after generation using Illustrator or Photoshop, demonstrating that even AI-dominant workflows ultimately depended on hybrid production methods to achieve professional cartographic standards.

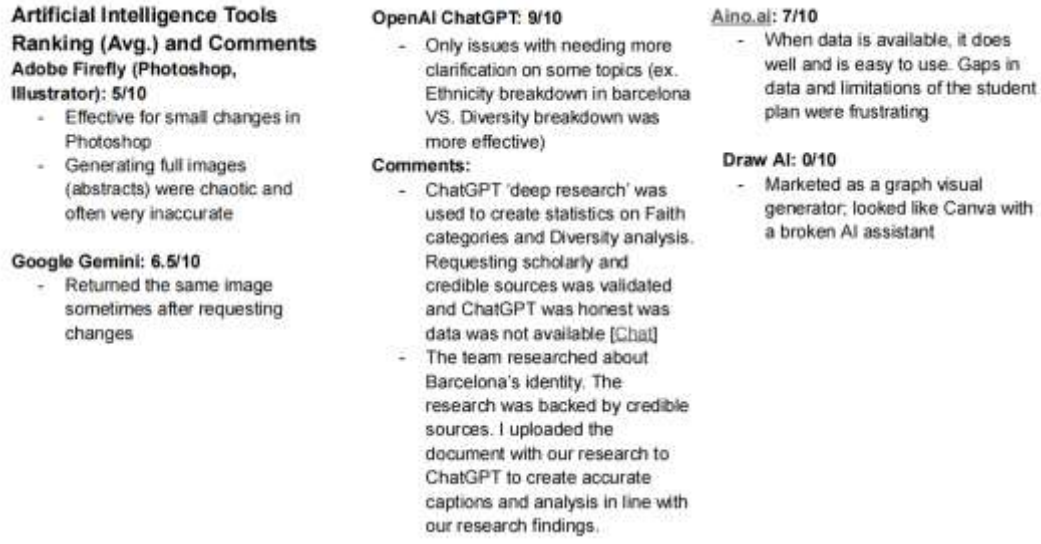
The workflow documentation submitted by Isabella Stasiulis, Habiba El Shamy, and Matteo de Florentiis provides detailed evidence of these challenges. Using Aino as the primary mapping platform, the team identified data insufficiencies across multiple analytical layers. Tree and green space data were incomplete and required manual additions. Building block courtyard infill was absent from the AI outputs and later corrected in Photoshop. Land-use typology mapping was partially misclassified because of gaps in the source data, while thin pedestrian paths were missing from the street network layer and subsequently added manually in Photoshop. The team further noted that AI tools were unsuitable for producing scale-accurate massing models or technical sections, leading them to rely on CADmapper and manual Photoshop workflows for precision drawing tasks. As noted in their reflective documentation, "AI is NOT effective at generating accurate, to-scale sections of real-world built form."

Similar challenges were documented by Natasha Rees, Emily Pham, and Krish Jain in their analysis of the Eixample and Gothic Quarter districts of Barcelona. An initial figure-ground prompt using Aino's Microsoft data layer produced incomplete outputs, with partial or entire buildings missing. The students identified this issue not as a prompting failure, but as a limitation of the underlying data library, including the incompleteness of OpenStreetMap datasets. Street network layers introduced additional problems, as pedestrian highways were incorrectly rendered as filled black areas. Multiple rounds of prompting failed to

resolve the issue, ultimately requiring manual correction in Gemini and Photoshop. Vegetation data also failed to align with satellite imagery. Circulation mapping required supplementary datasets from Barcelona's Open Data portal, while pedestrian sidewalks were cross-referenced against Google Earth and manually added in Illustrator. These examples suggest that AI-assisted mapping currently functions more reliably as a preliminary analytical tool requiring subsequent human verification and refinement, rather than as a finished analytical product.

AI teams also reported significant efficiency gains in perspective rendering, texture generation, and stylistic experimentation. However, these advantages were consistently offset by limitations in scale-dependent drawing tasks. Prompt iteration consumed substantial amounts of time, and final panel composition still required manual assembly in Illustrator or InDesign because generative tools were unable to manage layout, labeling, and spatial hierarchy at a professional standard.

Figure 1. *AI Tool Performance Ratings Submitted by a Representative AI Workflow Group*



Students: Natasha Rees, Emily Pham, Krish Jain.

The end-of-project evaluation of individual AI tools (see Figure 1) further reflects this uneven performance across task types. ChatGPT received the highest rating among the tools used (9/10), primarily because of its effectiveness in generating written analysis, synthesizing research findings, and producing contextually accurate captions for graphic panels. Aino received a rating of 7/10. While it performed adequately when source data was available, its effectiveness was constrained by data gaps, limited prompt and export quotas under the student subscription plan, and an underdeveloped editing interface. Google Gemini received a rating of 6.5/10, with students reporting recurring difficulties in prompt interpretation, particularly when attempting targeted edits to previously generated images. These issues frequently required restarting chat sessions to reset the workflow. Adobe Firefly, including Photoshop and Illustrator integrations, received a rating of 5/10, with usefulness largely restricted to minor localized edits rather than full-scale image or map generation. EDraw AI received a rating of 0/10 because its functionality was

considered inadequate for the analytical demands of landscape architecture workflows.

Traditional workflow groups reported longer production times but consistently fewer issues related to accuracy, spatial control, and output consistency. Unlike the AI groups, they reported little need for post-processing correction of base maps or analytical layers.

Summary of Workflow Traits

AI workflows:

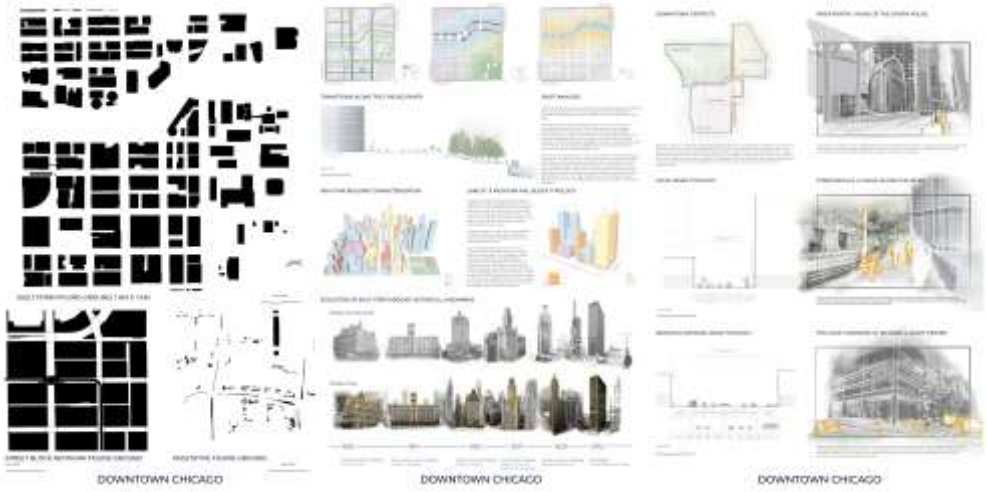
- High visual appeal; rapid iteration
- Lower reliability in scale accuracy
- Requires hybrid post-processing

Traditional workflows:

- High control, accuracy, consistency
- Slower production
- Less experimental image generation

Across the submissions, recognizable patterns have emerged at the panel level rather than in the overall reviewer scores. Conventional panels, such as Figure 2, which represents a typical project submission, demonstrate strong figure-ground reliability, precise line-work, and controlled image placements in the panel layouts using Illustrator, InDesign and Photoshop-based production. Students using traditional workflows generally have exhibited more consistent cartographic accuracy, correct labeling conventions, and well-structured layouts and visual hierarchies.

Figure 2. *Example of Panel Submission from Students Using Non-AI Applications and Workflow*



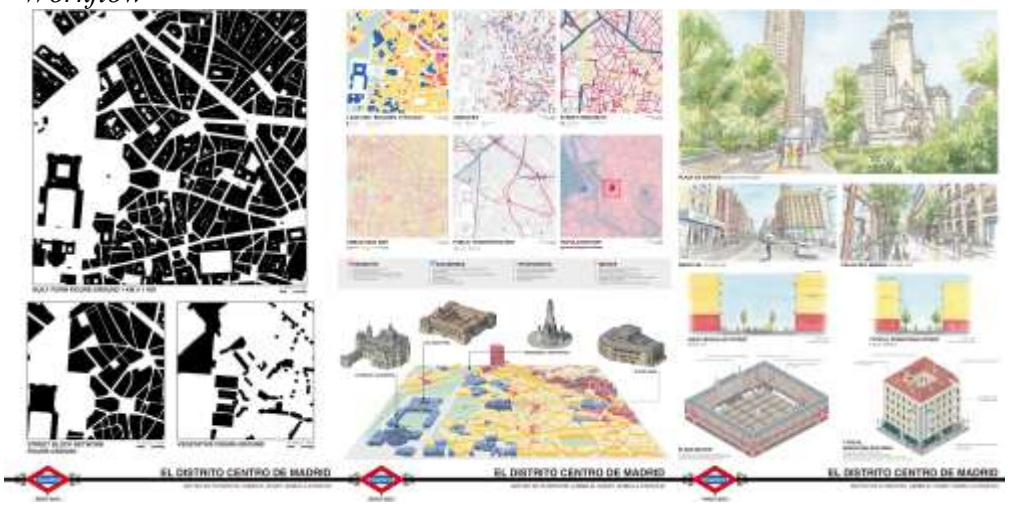
Students: Sarah Letourneau, Joyce Carrera, Sara Stekar.

In regards to the AI-led panels, these typically have showcased rapid, visually appealing outputs with strong atmospheric qualities and stylized renderings. The base maps generated through AI workflows frequently have required correction in Illustrator or Photoshop to fix imperfect building footprints, missing vegetative features, or misaligned street geometries. In regards to layout composition in AI panels, this has tended to be less consistent, suggesting that while generative models are highly effective at producing compelling individual perspectives, AI applications still struggle with the correct image placements on panels with the appropriate labelling. For more accurate mapping and figure-ground maps, students have often used 'upgraded' AI-applications such as Aino.

Across 16 projects and 112 blind reviewer scores, overall performance between AI-based and conventional workflows was essentially even. On a per-project basis, mean scores have differed by only 0.10 points on a 25-point rubric (AI = 18.48; conventional = 19.15; n = 7 vs. 9), a difference too small to be pedagogically meaningful. When scores are examined across all individual reviewer ratings, the gap has remained modest (AI = 18.85 vs. conventional = 19.48), with a mean difference of 0.63. A calculated effect size ($|d| \approx 0.19$) indicated a very small practical effect, confirming that the choice of workflow did not significantly influence scoring outcomes.

The reviewers' comments further illuminate these trends. AI-generated submissions are often applauded for their "eye-catchy," visually polished images, particularly in perspective renderings and architectural character studies. See Figure 3 representing an AI panel submission. However, reviewers have also noted tendencies toward more superficial analysis, inconsistent hierarchy, or incorrect labeling in several AI-dominant panels. With the traditional workflow submissions, these are commended for clarity, accurate labeling, and analytical thoroughness, however some are critiqued for less dynamic imagery or comparatively conservative visual presentation. Collectively, these comments support the emerging research suggesting that while generative AI excels at producing compelling conceptual or early-stage visuals, it still requires human enhancement to ensure accuracy, coherence, and interpretive clarity (Li and Amoroso 2023, Liu 2024, Schroth and Maier 2025).

Figure 3. *Example of Panel Submission from Students Using AI Applications and Workflow*



Students: Matteo de Florentiis, Habiba el Shamy, Isabella Stasiulis.

Discussion

The student AI workflow processes highlight insight into where reviewers have perceived strengths and weaknesses in the AI-generated submissions. Perspectives and stylistic renders, such as "watercolour/sketch" effects, are produced quickly and with a more compelling visual appeal. These are used with platforms like Gemini and MidJourney. These tools have excelled in generating atmospheric images, conceptual perspectives, and mood-driven representations that would often need more time using conventional digital illustration techniques.

The students' reflections on AI workflow processes also reveal recurring challenges. Figure-ground mapping, land-use diagrams, and vegetation layers have often required substantial manual correction due to missing features, misclassified elements, or incomplete spatial coverage produced by AI tools such as Aino. However, Aino seems to produce more accurate outcomes because of their upgraded package. In several cases, students have noted that pedestrian linkages, courtyard infill, and fine-grain urban details are omitted or inaccurately rendered, which then required their additional editing in Illustrator or Photoshop to achieve cartographic accuracy.

Although Aino demonstrates relative strength in producing initial figure-ground and mapping visualizations, its outputs still lack the precision and consistency expected in technical analysis panels. Students have reported that while AI could generate compelling starting points, these draft layers required verification and refinement against authoritative sources such as municipal open data, GIS databases, or Google Earth imagery.

AI-assisted text generation, such as SWOT analyses produced through ChatGPT, is reported as helpful for early conceptual thinking and framing the overview of selected districts. However, graphics that showcase history timeline, panel layout organization, and scale-accurate sections, have continued to rely on

traditional software with manual creation. Students consistently found that generative AI lacked the ability to maintain scale, adhere to measurement constraints, or respect conventional drawing standards, especially in analytically complex aspects.

Some of the students' comments included the following for AI usages. The platform used for mapping and diagramming work was Aino. Other AI image generators have lacked the ability to analyze the specific contextual data of the site, as they did not have access to detailed map information. As a result, the free platforms could not distinguish between different building types, complex street networks, trail systems, and waterways unless the colours of each feature have been manually adjusted to make them clearly distinguishable.

Aino itself is also limited in the data it could provide through the basic subscription. Data such as land-use zoning and specific tree diameter data are unavailable and have to be obtained separately from the official City's Open Data website. Aino does not offer the option to convert line styles to dashed lines, although it has provided three fill-pattern options for shapes. The platform also carries a cost of more than $20 per month for the basic student version.

Even though this platform has these limitations, Aino is effective in several key areas. It is fairly successful for mapping by allowing the groups to retrieve data within a defined site radius through text prompts or by importing datasets from the City's Open Data website. The platform has enabled clear manipulation of line weights and colours for both lines and shapes, and it offers a variety of base map layers, with the option to switch to a solid background colour when preferred. One of Aino's strengths includes its ability to generate walking-radius diagrams. For instance, prompting the system to "create a 500 m radius around this pin" has produced an accurate circular buffer around the selected location, demonstrating its usefulness in basic spatial analysis and visualization tasks.

Other groups provided more feedback regarding the use and efficiency in producing maps, diagrams, and images for landscape architecture. Many groups have commented that Google Gemini performed well in crafting realistic 3D model renderings. It has frequently struggled to interpret prompts accurately, particularly when asked to edit its own generated images. As more iterations were produced, the system became increasingly inconsistent, often requiring new chat sessions to reset the workflow.

ChatGPT has been effective for generating written content, such as inventory descriptions, site analyses, and explanatory text that supports design thinking. It has not been as successful in rendering detailed or visually refined images, making it better suited for conceptual development and not customized renderings.

Meshy AI has demonstrated strong performance in creating accurate 3D models of buildings from photographs and producing meshes that could be further edited in Blender, making it useful for integration into more advanced modeling workflows. The platform requires payment to access full rendering capabilities and performs best only with individual objects, buildings, or people. It lacks efficiency when applied to large-scale neighbourhood or district-level modeling.

Aino is strong in generating visually pleasing graphic map styles, offering a variety of templates and a large selection of symbols for diagramming. The platform

occasionally misinterprets or mislabels source data when generating map content, limiting accuracy. Its interface lacks advanced editing features, including control over object shapes, colour palettes, and basic undo/redo functions.

Another group has evaluated the AI tools as the following. Adobe Firefly, used through Photoshop and Illustrator, has received an average ranking of 5 out of 10. It has been effective for making small, localized edits within Photoshop. The outputs have often been chaotic, lacking accuracy in form and overall intent. For tasks that have required precise landscape features, coherent spatial patterns, or stylized diagrammatic aesthetics, Adobe Firefly's generative capabilities are not as strong. Its usefulness has been limited to minor adjustments rather than full-scale image creation or map-based visualization.

According to the student users, Google Gemini has ranked better at 6.5 out of 10. When the group prompted the platform to revise or adjust an image, Gemini often returned the exact same output and did not applying the requested changes. ChatGPT has received a high user evaluation at 9 out of 10 due to its performance in generating written content, conducting research-supported analysis, and assisting in the creation of captions and narrative descriptions for graphic panels. In this evaluation, ChatGPT was used to perform "deep research" on topics such as demographics, cultural diversity, and urban identity, for example, for Barcelona as the case study for the urban analysis project. The platform has acknowledged when data was unavailable and has validated scholarly sources when requested. The research team uploaded their findings directly into ChatGPT, and the system successfully synthesized the material into clear, concise captions aligned with landscape architecture communication standards. For example, when prompted to write captions for the Street Network sections of Barcelona, specifically Las Ramblas and the Superblocks, the platform has generated detailed and contextually rich narrative descriptions.

According to the student users, Aino received user evaluation of 7 out of 10. When data inputs are available, the platform has performed well and has offered a user-friendly interface. It has generated visually appealing maps and diagrams and has supported a range of presentation-ready graphic styles. The platform has data missing and labeling errors, and the limitations of the student subscription plan have created barriers. Restricted access to the number of prompts, limited export options, and the absence of advanced editing tools have made the workflow not efficient.

According to the student users, EDraw AI was evaluated as a 0 out of 10, because it has functioned more like a simplified version of Canva with an unreliable AI assistant. Its outputs have lacked intelligence, accuracy, and meaningful integration with landscape architecture workflows. As a result, it has provided little practical value.

Several teams have attempted to use AI for 3D massing or spatial modeling but have found the outputs to be unreliable, inconsistent in scale, or visually distorted. Most students have reverted to hybrid workflows involving Google Earth for reference geometry, Procreate for massing sketches, or Adobe tools for refined digital models. These observations reinforce findings in recent literature emphasizing that generative AI currently struggles with geometric accuracy,

reproducibility, and spatial reasoning and the limitations that require human oversight and post-processing correction.

The interpretation of the results suggests that AI-dominant workflows and traditional digital workflows currently perform at comparable levels when evaluated on professional criteria. The lack of significant scoring differences aligns with recent literature showing that generative AI excels at early-stage visualization but still depends on human oversight for accuracy and analytic depth (Li and Amoroso 2023, Liu 2024, Schroth and Maier 2025). The small effect size further supports that workflow choice alone does not determine quality.

The reviewers' comments indicate that AI advantages focus on the visual experimentation and atmospheric rendering, which are aspects that are attractive in early design phases. The analytic clarity, map accuracy, and hierarchy remain more evident in traditional workflows, supporting the importance of keeping technical proficiency in GIS, CAD, and Adobe software.

AI prompt logs revealed that students often relied on manual corrections after AI output, supporting arguments that workflow should be hybrid. AI tools demonstrated particular strengths in ideation and visual exploration, while traditional tools remained superior for precision, scalability, and analytical accuracy. AI applications are quickly evolving and this could change.

The student workflow documentation and reviewer feedback together point to a consistent pattern: AI tools contributed most effectively to visual quality and early-stage exploration, while precision, analytical depth, and cartographic accuracy continued to depend on conventional platforms and human judgment. This distinction has important implications for how AI should be positioned within landscape architecture curricula.

At present, the findings support an augmentative rather than transformative role for AI in studio education. An augmentative approach treats AI as an additional layer within an existing technical foundation, where students first develop core competencies in GIS, CAD, and graphic communication, and then use AI tools selectively to support visualization or conceptual development. A transformative approach, by contrast, would reorganize the curriculum around AI literacy as a primary learning outcome, potentially reducing emphasis on foundational technical skills. Given that the AI workflow groups in this study consistently required manual correction to address spatial inaccuracies and analytical gaps, such a transformative shift appears premature and may weaken competencies that remain essential to professional practice.

Several practical directions emerge from these findings. Maintaining GIS, CAD, and graphic communication as core studio requirements remains important. Structured AI components, in which students document prompts, critically evaluate outputs, and verify results against authoritative data sources, can be integrated alongside existing workflows rather than replacing them. Project briefs that explicitly require comparisons between AI-generated and manually produced outputs provide one practical model for implementation. Incorporating AI ethics, attribution, and source transparency as assessed elements within studio practice could further encourage informed and critical use of these technologies. As AI

platforms continue to evolve, the appropriate scope of their role within design education will require ongoing reassessment.

Conclusion

The results demonstrate an overall equilibrium between traditional and AI workflows: neither approach has dominated the reviewers' scoring. The class itself has been nearly evenly divided between students using conventional software versus those more keen to explore AI-generated applications and methods. Although individual groups have been assigned a single workflow rather than testing both, each three- to four -person group has been formed to ensure balanced skillsets, and to minimize bias in comparing outputs. Several limitations include paid and free AI applications that tend to offer different benefits. Some groups did not use upgraded – paid AI applications, which could have offered more visual accuracy and customization. Other limitations include allowing both sets of groups to re-do the same project using both AI and conventional digital software. Additionally, participation in AI-based workflows was voluntary; students were not compelled to use AI applications, and only those interested in experimenting with these tools elected to do so. This self-selection may have influenced levels of engagement and outcome quality.

Overall, the findings suggest that AI tools in landscape architecture studios currently function most effectively as complementary instruments rather than replacements for traditional methods. As AI tools continue to evolve, future research should examine longer-term learning impacts, hybrid workflow models, and the potential for AI to meaningfully support ecological modelling, climate-responsive design, and evidence-based spatial decision-making, extending beyond compelling conceptual representational outputs.

The implications for pedagogy are evident, that is, students benefit most from hybrid knowledge and skills (Mollick and Mollick 2023). Generative AI offers speed, stylistic outcomes, and iterative capacity, while traditional tools remain essential for accuracy, mapping, scale, and deeper analysis. As AI platforms advance, transparency, prompt documentation, human quality control, and ethical awareness must remain central components of curriculum design. AI transforms landscape architecture by enhancing creative complexities, enhancing visualization, enabling intelligent site management, and optimizing design solutions. By integrating AI into the design workflow with more conventional design processes, landscape architectural students can improve ideation, enhance design quality, and make more evidence-based decisions.

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