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Scaling design cognition: A project-based approach to teaching AI in architecture

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Abstrak
Studi ini menyelidiki efektivitas kerangka kerja pembelajaran berbasis proyek dalam meningkatkan kognisi desain mahasiswa arsitektur melalui integrasi terstruktur menggunakan AI, dengan memeriksa apakah pendekatan pedagogis bertingkat membantu mahasiswa bertransisi dari pengguna alat pasif menjadi pengarah aktif atas kepintaran sebuah mesin. Penelitian ini menggunakan strategi berbasis proyek yang menggabungkan model Stanford Design Thinking dengan Educational Design Ladder. Tujuh puluh tiga mahasiswa arsitektur dari Universitas Islam Indonesia berpartisipasi dalam mata kuliah Pemikiran Desain & Komputasi selama tahun ajaran 2025/2026. Mahasiswa bekerja melalui observasi alam manual, rekayasa cepat dengan model bahasa, pembuatan gambar generatif, konversi model 3D, penyempurnaan parametrik, dan fabrikasi fisik. Data dikumpulkan melalui survei, rubrik penilaian yang mengukur keterampilan berpikir tingkat tinggi, refleksi mahasiswa, dan analisis komparatif dengan kelompok non AI.Hasil menunjukkan peningkatan yang terukur, dengan nilai rata rata meningkat dari 75,3 menjadi 77,9 dibandingkan dengan kelompok non AI sebelumnya. Peningkatan signifikan terjadi dalam menerjemahkan ide ke dalam logika komputasi (+6,8 poin) dan kualitas laporan desain (+6,9 poin). Mahasiswa mencapai tingkat Sintesis dan Evaluasi dari Educational Design Ladder (79,2). Kebiasaan kognitif yang dilaporkan sendiri meningkat dari 3,60 menjadi 3,71, sementara kemampuan menulis berdasarkan petunjuk meningkat dari 3,48 menjadi 3,63. Mahasiswa menghasilkan lebih dari sepuluh alternatif desain per konsep, menunjukkan peningkatan output kreatif. Kualitas cetak 3D fisik menunjukkan sedikit penurunan, serta mahasiswa melaporkan beban kognitif selama transisi ke antarmuka berbasis node dan hambatan atas instalasi perangkat keras. Studi di satu institusi selama satu semester membatasi generalisasi. Hambatan teknis mempengaruhi beberapa peserta. Fokus pada kognisi desain tahap awal memungkinkan lemahnya retensi keterampilan jangka panjang. Implementasi di masa mendatang perlu memperkenalkan komputasi lebih awal dalam kurikulum, menyediakan infrastruktur perangkat keras dan dukungan teknis yang kuat, dan melakukan studi longitudinal tentang aplikasi profesional. Penelitian ini menyediakan peta jalan pedagogis yang dapat direplikasi untuk mengintegrasikan AI sambil mempertahankan otoritas kreatif manusia. Institusi pendidikan harus mengintegrasikan AI ke dalam seluruh kurikulum, menetapkan pedoman etika, dan menyediakan dukungan teknis yang terstruktur untuk membantu siswa mencapai keterampilan berpikir tingkat tinggi dalam kolaborasi manusia AI.

Kata kunci: AI generatif, kognisi desain, kolaborasi manusia AI, pendidikan arsitektur, pembelajaran berbasis proyek

Abstract
This study investigates the effectiveness of a project-based learning framework in scaling the design cognition of architecture students through structured integration of generative AI tools, examining whether a tiered pedagogical approach helps students transition from passive tool users to active directors of machine intelligence. The research employed a project-based strategy merging the Stanford Design Thinking model with the Educational Design Ladder. Seventy-three architecture students from Universitas Islam Indonesia participated in the Computational Design Thinking course during 2025/2026. Students progressed through manual nature observation, prompt engineering with language models, generative image creation, 3D model conversion, parametric refinement, and physical fabrication. Data were collected through surveys, grading rubrics measuring higher order thinking skills, student reflections, and comparative analysis with non-AI cohorts. Results showed measurable improvement, with average grades rising from 75.3 to 77.9 compared to previous non-AI cohorts. Significant gains occurred in translating ideas into computational logic (+6.8 points) and design report quality (+6.9 points). Students reached Synthesis and Evaluation levels of the Educational Design Ladder (79.2). Self-reported cognitive habits improved from 3.60 to 3.71, while prompt writing proficiency increased from 3.48 to 3.63. Students generated over ten design alternatives per concept, demonstrating expanded creative output. Physical 3D print quality showed slight decline, and students reported cognitive load during transitions to node-based interfaces and hardware installation barriers. Single institution study over one semester limits generalizability. Technical barriers affected some participants. Focus on early-stage design cognition may not capture long term skill retention. Future implementations should introduce computational tools earlier in the curriculum, provide robust hardware infrastructure and technical support, and conduct longitudinal studies on professional application. This research provides a replicable pedagogical roadmap for integrating AI while maintaining human creative authority. Institutions should embed AI throughout the curriculum, establish ethical guidelines, and provide structured technical scaffolding to help students achieve higher order thinking skills in human AI collaboration.

Keywords: Architectural education, design cognition, generative AI, human AI collaboration, project-based learning

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Pendahuluan

The current state of architectural practice is undergoing a fundamental shift in how designers relate to technology, moving from the use of simple digital tools toward a deep integration with autonomous systems (Borghoff et al., 2025; Rane et al., 2023). For decades, the relationship between architects and computers followed a master slave model in which software served as a passive instrument for drafting or technical optimization (Cheung & Dall'Asta, 2023; Basarir, 2022). However, the rise of agentic AI has introduced a new model known as Centaurian systems (Borghoff et al., 2025; Pareschi, 2024). In these setups, human intuition and machine driven logic blend into a single decision making entity, moving the professional identity from Homo Faber toward a Centaurus Faber framework (Borghoff et al., 2025). This change means that the boundary between human intent and machine execution is no longer a hard line but a permeable space for collaboration (Borghoff et al., 2025).

Solving architectural problems has always been a struggle amid wicked conditions, where goals are unclear and constraints shift constantly (Rittel & Webber, 1973; Cross, 2008). In an age defined by massive datasets and rapid computation, designers must expand their mental reach to remain effective (Borghoff et al., 2025; Rane et al., 2023). While new generative tools provide quick visual ideas, they often produce machine hallucinations that are images that look impressive but ignore structural logic or human needs (Hegazy & Saleh, 2023; Salem et al., 2024). To prevent the loss of architectural depth, designers must scale their cognitive abilities to manage these vast inputs while holding onto their creative authority (Sukkar et al., 2024; Bölek et al., 2023). This balance is necessary to ensure that technology serves to improve the built environment.

To adequately equip the next generation for this emerging reality, schools must adopt a structured way to teach these advanced interactions (Basarir, 2022). A promising approach involves merging the Stanford Design Thinking model with the Educational Design Ladder (EDL) (Wrigley & Straker, 2017). This tiered structure helps students build their skills in a logical way, moving from basic comprehension toward high level synthesis and evaluation (Fields & De Jager, 2022; Wrigley et al., 2018). By organizing lessons this way, educators can ensure that students do not just use AI as a shortcut, but as a systematic way to think through complex design challenges (Panke, 2019).

Within this framework, AI is best understood as an agent, serving as a collaborative partner rather than a replacement for the human designer. This position requires a human in the loop approach, where the architect remains the critical validator of every output the machine generates (Cheung & Dall'Asta, 2023; Salem et al., 2024). Instead of letting the algorithm make the final call, the designer uses the machine's speed to test more options while maintaining ethical and cultural responsibility for the work (Sukkar et al., 2024). This partnership allows the architect to focus on the qualitative and spiritual aspects of a building that machines cannot yet grasp (Sukkar et al., 2024; Rane et al., 2023).

The research question is how a tiered learning structure can be designed and implemented to scale design thinking, maintain creative authority, and foster ethical human AI collaboration in architectural education. This research investigates the effectiveness of the Computational Design Thinking (CDT) course in improving the mental capacity and analytical skills of architecture students at the University of Islam Indonesia. By following their progress from initial observations to the creation of 3D printed models, we aim to see how a structured integration of AI tools impacts their design logic. The study examines whether this educational model helps students move beyond simple visual outputs toward more complex, well reasoned architectural solutions. Ultimately, the goal is to provide a clear roadmap for how architectural education can evolve alongside technology without losing its essential human focus (Cheung & Dall'Asta, 2023).

The Department of Architecture at Universitas Islam Indonesia also follows the Student Performance Criteria (SPC) from the Korea Architectural Accrediting Board (KAAB) to keep its teaching up to international quality. This set of rules directly informs the CDT course, where the lesson goals are set to match these professional standards. The course specifically targets CPL 07, which focuses on a student's ability to model and record design thoughts in a clear and complete way. By using SPC 1 and SPC 5 as the main guide, the department ensures that students learn both the science of architecture and the artistic logic needed to create new forms.

The SPC serves as the main link that connects the course lessons with the Stanford Design Thinking model and the EDL. The EDL when paired with the Stanford cycle may helps students manage the speed of AI without feeling lost. This structured way of working makes sure that combining digital tools with traditional methods actually helps students grow their own design logic.

The goal of this research is also to see how well students master these SPC requirements when they are taught using the EDL and AI model. As new technology changes the way architects work, it is important to know if students can still reach the highest levels of thinking, such as synthesis and critical judgment. This study tracks the work of students from their firsthand drawn patterns to their final physical 3D models. By checking these results against the KAAB rules, the research will show if this teaching style can help the next generation of architects lead the design process while using machine intelligence.

Literature Review

Based on the principles of the Educational Design Ladder (EDL), the learning innovation development concept for the Design Thinking & Imitative Based Computing course is designed as a model for organizing design learning units that emphasize an iterative and user centered approach (Wrigley & Straker, 2014). There are five levels of EDL skill development: Comprehensive Knowledge, Application, Analysis, Synthesis, and Evaluation. This concept integrates empathy as a foundation for understanding user needs, exploration of concepts through collaboration, elaboration of understanding by connecting theory and practice, and contextual demonstrations for implementing solutions in the real world.

Building upon the foundational five levels of the EDL, the learning innovation concept ensures a progressive cognitive load that aligns with students' developmental trajectories (Krathwohl, 2002). At the Comprehensive Knowledge level, students are introduced to core theories of design thinking, user centered design, and the ethical use of AI tools such as image recognition and generative models (Floridi & Cowls, 2019). Moving to the Application level, learners actively employ AI tools in structured exercises, such as using pattern recognition algorithms to re interpret raw observation data or deploying generative AI to propose alternative design solutions. This shift from knowing to doing is critical for transforming abstract principles into practical skills (Kolb, 2014).

At the Analysis level, students begin deconstructing both successful and failed design cases from industry, identifying where specific AI interventions enhanced or hindered user empathy and solution viability (Rittel & Webber, 1973). They learn to compare multiple problem statements derived from the same dataset and evaluate how clustering techniques influence the framing of design challenges. This analytical competency extends to examining prototype testing loops, where students assess the reliability of 3D printed mockups as decision making artifacts. The Synthesis level then challenges students to combine AI generated ideation outputs with hand drawn sketches and collaborative feedback, creating hybrid solution pathways that neither pure human intuition nor machine logic could generate alone (Verganti, 2017).

The Evaluation level empowers students to critically judge their own and peers' design outcomes against multidimensional criteria: user satisfaction, technological feasibility, ethical soundness, and resource efficiency (Norman, 2013).

In its application, the course's learning plan applies the Design Thinking stages: empathize, define, ideate, prototype, and test. In the empathize stage, students conduct observations, which challenge them to collect in depth data and avoid assumptions; here, AI based data analysis tools, such as Image Recognition, are used to identify patterns. The define stage focuses on formulating problem statements from complex data, using clustering and pattern recognition techniques to group problems. In the ideate stage, generative AI aids brainstorming by exploring ideas and generating feasible solutions. The prototype stage involves creating prototypes using AI integrated tools, while the test stage uses 3D printed mockups to determine whether the resulting geometry demonstrates sufficient constructability. This process is also designed to foster collaboration capabilities within the technology ecosystem by simulating a real world collaborative environment.

Research Methods

This research uses a project based learning strategy that aligns a five step educational ladder with the Stanford Design Thinking Cycle (Wrigley & Straker, 2017). This tiered setup helps students build their skills in a logical way, moving from basic understanding toward high level evaluation (Fields & De Jager, 2022). By organizing the lessons this way, the course ensures that digital tools do not replace the necessary steps of human mental growth in the design field (Panke, 2019). The human designer remains in control, serving as the primary decision maker while working with artificial intelligence as a partner (Basarir, 2022).

The first stage of the work follows the Empathize phase, which focuses on manual observation of patterns in nature. Before touching any software, students look for artistic and geometric logic in their surroundings. They record these natural themes through hand drawn sketches to build a primary connection with the topic. This manual starts the design process in human sight and prevents an early reliance on automated systems (Basarir, 2022).

During the "Define" stage, students turn these manual drawings into structured stories and syntax. Participants use language tools like ChatGPT or DeepSeek to refine their project statements and clarify what they want to build (Rane et al., 2023). This part of the workflow links abstract visual ideas to the specific words required for computer tasks (Li et al., 2025). By writing down these rules, students create a clear set of instructions that both people and machines can follow.

The Ideate phase introduces generative visual tools to explore new forms. Students use Midjourney and ComfyUI to generate many 2D design options from their sketches. While Midjourney creates artistic images, ComfyUI uses a node based interface that asks students to manage the generation process's logic (Bao & Xiang, 2023). To push past their first thoughts, students must generate at least ten different results for each concept.

This method views AI as a design partner within a Centaurian system (Borghoff et al., 2025; Pareschi, 2024). In this setup, the student acts as a validator, reviewing every machine generated image against their own goals (Cheung & Dall'Asta, 2023). This keeps the human "in the loop" to ensure the work reflects real human intent rather than random computer patterns (Hegazy & Saleh, 2023). It allows the designer to focus on the meanings of a building that algorithms cannot yet understand (Sukkar et al., 2024).

As the project reaches the Prototype phase, the focus shifts from 2D pixels to 3D shapes. Tools such as Meshy.ai or Vecto3d.xyz are used to convert selected images into initial three dimensional models. This conversion is a major test of the visual idea, as it shows whether the AI generated shapes can exist in a real architectural space (Li et al., 2025). It bridges the gap between a flat picture and a solid form.

To get exact control over the resulting forms, these initial models are refined with parametric software. Students use Rhinoceros and Grasshopper to apply mathematical rules and structural limits to their designs. By building their own scripts to manage the geometry, students fix any machine hallucinations or errors from the generative AI (Hegazy & Saleh, 2023). This step makes sure the design follows consistent architectural logic (Basarir, 2022).The final Test stage involves making the designs into physical objects. Participants use Bambu Studio to prepare their models for 3D printing and laser cutting. This stage is central because it shows how well the design can be built. Creating a physical version forces the student to check if their digital exploration can support its own weight and stay true to its look in reality (Silva, 2019).

The study gathered information through a survey of 73 students across two class sections. This collection happened in two separate windows: right after the midterm exam and again after the final project presentations. Timing was a priority to ensure students gave feedback while their experiences with the course modules were still fresh in their minds.

Participants responded to a questionnaire using a four point scale, with sections for open ended commentary. The evaluation covered several layers of the educational experience, from the logical sequence of the curriculum to the practical use of digital tools like Midjourney and Meshy.ai. Beyond technical skills, the survey checked if students felt the course helped them move into high level thinking, such as analyzing and evaluating their own design choices. It also examined the quality of instructor feedback and whether students felt their ability to write effective AI instructions improved over the term. These multiple focus areas enabled a detailed examination of how the shift toward agentic AI affected both student confidence and their creative workflows.

Measuring student performance involves both numbers and quality checks. The study uses rubrics to grade the design reports, the computer scripts, and the physical models. These grades measure the higher order thinking skills, such as the ability to analyze complex data and synthesize different needs (Fields & De Jager, 2022). The rubrics assess how well students can explain the logic behind every choice they made, from nature to the final print (Basarir, 2022).

Finally, the research tracks student growth through reflection papers and observing their work in class. This data gives a window into how their design thinking changes over time (Cheung & Dall'Asta, 2023). It shows how a structured use of AI can expand a designer's mental reach without taking away their creative power.

Findings and Discussions

1. Key findings from CDT course of the 2025/2026 academic year.

The research focused on 73 architecture students at Universitas Islam Indonesia who participated in CDT course during the first semester of the 2025/2026 academic year. These individuals were placed in two different sections, identified as Class A and Class C, to observe the effects of the new teaching plan. Data came from two surveys, with sixty-three people finishing the first and fifty nine completing the second. Since more than eighty percent of the whole group shared their feedback, the findings give a true picture of how the entire class felt about the changes.

Table 1

Questionnaire

Questionnaire Questions	Mid Semester Average Score	Final Semester Average Score
In general, the learning activities carried out (Midterm = Sessions 1 7; Final Exam = Sessions 8 14) are consistent with what is listed in the Semester Learning Plan (RPS) at the beginning of the semester.	3,65	3,73
The lecturer's explanation regarding the learning outcomes (CPMK) and their relevance to the curriculum in the early sessions was clear.	3,63	3,73
The material delivered from session to session (starting from Introduction to Imitation Reason, Design Thinking, to From Idea to Computation) has flowed sequentially and logically.	3,63	3,78
The proportion between design thinking theory (such as Plowright's theory) and computation/AI practice is balanced.	3,59	3,71
The method of delivering learning material by the Lecturer/Tutor in class is varied.	3,62	3,71
The modules and materials provided (Midterm = Modules 1 & 2, AutoCAD, Forma, Midjourney, ComfyUI tutorials; Final = Module 3, Meshy AI tutorial) are easy to understand and helpful in completing assignments.	3,37	3,68
The instructions and objectives of the weekly assignments have been clearly explained.	**3,33**	**3,78**
The Midterm/Final exam questions given have measured understanding of the concepts taught (Design Creativity, Pattern, Design Thinking, Idea to Computation).	3,54	3,75
This lecture has encouraged me to learn actively (learning by doing, thinking, and reflecting).	3,56	3,76
I feel there was good interaction and collaboration among students during the lecture process.	**3,63**	**3,71**
The feedback given by the lecturer on weekly assignments and the Midterm Exam results has helped me understand my shortcomings and how to improve my work.	3,56	3,69
The lecture process has trained my higher order thinking skills (such as analyzing, evaluating, and creating).	3,60	3,71
The explanation of the concept of "Imitation Mind" as a collaborative partner in design is clearly understood.	3,40	3,73
The tutorial on using UI AI (Google Lens, Gemini, Forma, Midjourney, Meshy) is easy to follow.	3,60	3,71
I feel that my ability to write good prompts for AI has improved.	3,48	3,63

Scoring data from the term shows a clear rise in student work when using automated tools compared to groups from the year before. The average grade for the class moved up from 75.3 to 77.9, which shows the plan was helpful for the majority of the students. Jumps of nearly seven points were seen in the quality of design reports and the way students turned abstract ideas into computer rules. These results show that the new tools helped people move past simple drawings to build more layered digital models. While digital work was strong, there was a small drop in the quality of physical 3D prints, perhaps because students spent so much effort on the screen based part of their project.

Written feedback from the group shows that people felt much more skilled in their thinking habits by the end of the term. Scores for habits like analyzing and making choices rose from 3.60 to 3.71 out of 4.00. Students noted that they became better at writing specific rules for the machine, with skill levels in this area rising from 3.48 to 3.63. This growth meant that people could guide the AI to match their own specific goals instead of just hoping for a good result. By reaching the top levels of the learning path, the participants proved they could combine theoretical ideas into one solid finished project.

Every part of the course evaluation received high marks, with all scores staying above the 3.00 line. The biggest change was in how clearly the teachers explained the weekly tasks, which saw an improvement of 0.45 points. Participants said the step-by-step way the class was run felt right and helped them see the whole goal of the course. This data supports the idea that the current plan builds the mental habits needed for modern design work.

2. **Comparative performance with other class**

The data reveals a clear upward trend in student performance after introducing AI into the design workflow. Comparison between the AI integrated group and previous non-AI cohorts shows a rise in average grades from 75.3 to 77.9. This shift suggests that the structured inclusion of automated agents yields a measurable benefit for participants' academic success.

Table 2

Comparison table of student achievement based on AI and Non-AI SLP in the same lecturer's class with different academic years.

Lecturer: FHS	Design Creativity and Pattern (CPL7/SPC 1)	Design Thinking Theory (CPL 7/SPC 5)	Idea to Computational (CPL 7/SPC 5)	Design Report (CPMK 07.1)	3d Print Model (CPMK 07.2)
AY 24/25 Non AI Class (Baseline)	73.9	71.3	70.5	71.5	71.2
AY 25/26 AI Class (Grant)	78.2	76.1	77.3	78,4	70.6

Table 3

Comparison table of student achievements based on AI and Non-AI RPS in different lecturers' classes.

AY 25/26	Design Creativity and Pattern (CPL7/SPC 1)	Design Thinking Theory (CPL 7/SPC 5)	Idea to Computational (CPL 7/SPC 5)	Design Report (CPMK 07.1)	3d Print Model (CPMK 07.2)
Non AI Class Lecturer: AS (Baseline)	74.6	72.9	75.1	80.5	79.7
AI Class Lecturer: MGG (Grant)	80.4	76.2	75.4	80.9	76.7

Looking at individual assessment areas, the most dramatic growth occurred in the translation from conceptual ideas to computational logic, with a 6.8-point leap. Similarly, the quality of design reports improved by 6.9 points, showing that students were better equipped to explain their creative choices when supported by digital partners. These figures show that the technology did more than just create pictures; it helped organize the entire thought process.

One of the most striking findings involves the volume of creative output. Before this intervention, students often felt satisfied after developing a single concept. With AI tools, they consistently produced more than ten distinct design alternatives from a single natural pattern, forcing them to look past their first instincts. This ability to generate many options in a short time directly challenged the limits of traditional manual methods. The technology acted as a spark for expanding the visual imagination, allowing students to see varied forms that would have taken days to sketch by hand. Observers noted that this rapid feedback loop kept students excited and willing to take risks with their shapes.

The growth of technical communication was another key result. Scores for writing effective machine instructions rose from an initial 3.48 to 3.63 by the end of the term. This reflects a growing command over the specific language needed to steer generative systems toward architectural goals. Students moved from trial and error toward more intentional control of the software.

Rather than just getting lucky with random outputs, students learned to write better prompts that aligned with their specific design intentions. They began to use more precise architectural terms to guide the AI, showing they were thinking about material and space even in the early stages. This progress shows that they became active directors of the technology rather than just passive users.

The study found that students successfully reached the higher rungs of the EDL. Specifically, the scores for the Synthesis and Evaluation levels were consistently 79.2. Reaching this level is difficult because it requires bringing many different ideas together into a single, working plan. The data proves that the students didn't just understand the parts; they understood the whole system.

Table 4

Table of achievement based on the Educational Design Ladder (EDL).

	Depth of DT+AI Process	Achievement of EDL Level: Synthesis	Human AI Collaboration	Quality of Presentation & Documentation	3D Print Model (CPMK 07.2)
Average score Lecturer: FHS	79.2	79.2	77.3	78.7	79.2
Average score Lecturer: MGG	79.2	79.2	77.8	79.2	78.5

This synthesis was not limited to digital screens; it involved linking abstract design theories with real world outcomes. The data confirms that students could take a theoretical idea and translate it through multiple computational steps into a coherent architectural proposal. This shows a level of thinking that usually appears later in the degree program.

The final proof of this learning journey was the creation of physical 3D printed models. Reaching the final test phase required students to check their digital shapes against the realities of material and gravity. While the physical modeling scores were slightly lower than the digital ones, the presence of a finished object showed that the students could take a natural observation and turn it into a solid object. Collectively, these results show that combining tiered learning with AI integration strengthens the mental capacity of design students. The participants did not just finish a task; they proved they could analyze, build, and critique complex systems with high confidence.

Discussion

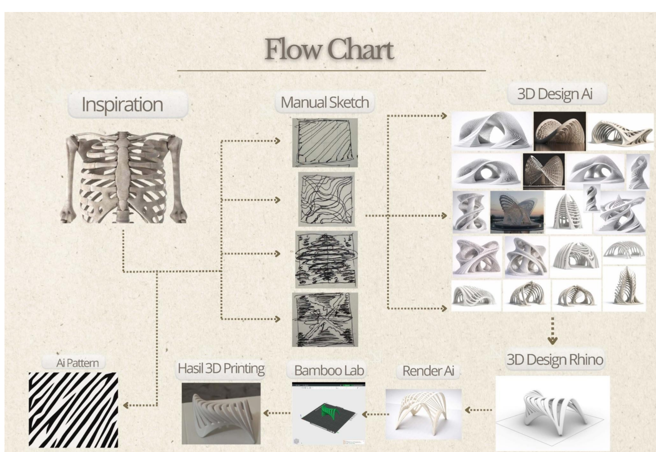
The practical application of AI in the classroom reveals that students do not simply use digital tools as passive instruments; instead, they operate within a unified decision-making framework (Borghoff et al., 2025). This movement from being a traditional tool user toward a Centaurus Faber identity means the boundary between human creative intent and machine execution has become permeable (Borghoff et al., 2025; Pareschi, 2024). Data from student evaluations confirm that the participants felt they held full control over design decisions and originality, even when working with generative agents. By treating the machine as a collaborative partner, learners avoid a subservient relationship and instead engage in a reflective conversation that refines their own architectural vision (Cheung & Dall'Asta, 2023).

Placing the human in the loop is a central requirement to prevent architectural meaning from being lost to random algorithmic patterns (Cheung & Dall'Asta, 2023). While generative models produce striking visuals at high speed, they often suffer from machine hallucinations that ignore physical reality or structural stability (Hegazy & Saleh, 2023; Salem et al., 2024). The research findings show that students move beyond initial satisfaction with a single AI output and instead act as critical validators, comparing multiple alternatives against their original goals. This active role ensures that design ethics and cultural sensitivity remain a priority, as the machine cannot yet grasp the intangible or spiritual values of a space (Sukkar et al., 2024). Ultimately, student's ability to justify every choice from the original natural pattern to the final 3D printed model demonstrates that their cognitive capacity has scaled without losing human authority (Basarir, 2022).

The "AHA moments" recorded by participants highlight a specific cognitive shift in which the gap between abstract natural forms and digital logic disappears. Many learners experienced this turning point when they successfully translated hand drawn observations of natural patterns into structured computational scripts. This finding supports the theory that design is an active mental process involving both imaging and systematic presentation. By using AI to explore multiple variations, students were pushed to look past their first instincts, leading to a deeper understanding of how geometry and rules interact (Basarir, 2022). This suggests that the tiered learning approach helped learners reach the analysis level of the educational ladder, enabling them to explain the logic behind their creative decisions rather than relying solely on random outputs, reflecting higher order cognitive skills at the level of analysis (Bloom, 1956; Nurmatova & Altun, 2023).

Figure 1

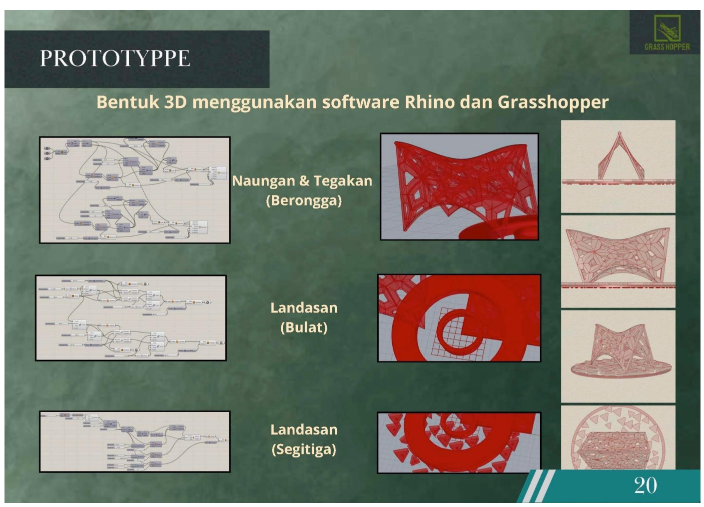
Student Flow Chart



The transition from a digital screen to a tangible artifact through 3D printing provided the final validation of the student's learning journey. This moment of physical creation served as a powerful motivator, allowing participants to witness their abstract ideas holding up to the rules of reality and gravity. Within the framework of embodied cognition, this process links the designer's mind with the material outcome, ensuring that the work remains grounded in human experience (Sukkar et al., 2024; Mallgrave, 2013). Reaching this evaluation stage is difficult, yet the data confirm that overcoming software technical errors was exactly what triggered the most growth in self-confidence (Fields & De Jager, 2022). It moves the educational experience from simply knowing to doing, which remains a hallmark of effective design thinking pedagogy (Panke, 2019).

The promise of rapid design iteration enabled by AI is often met with significant technical friction during implementation. Findings indicate that while students could quickly generate visual concepts, they faced a steep learning curve when attempting to translate these ideas into precise geometries using software like Rhinoceros and Grasshopper. This struggle reflects a broader challenge in architectural education where students from non-computational backgrounds must bridge the gap between abstract intent and rigid algorithmic logic (Cheung & Dall'Asta, 2023). Many learners identified the node-based interface of tools like ComfyUI as a major cognitive barrier, finding the visual programming approach far more confusing than standard chat based interfaces. These difficulties align with the theory that simply providing advanced tools is insufficient; without a grounded theoretical base and sufficient time to internalize the logic of computation, the transition from a traditional tool user to a collaborative designer remains incomplete (Basarir, 2022; Fields & De Jager, 2022).

Figure 2
Prototyping Phase



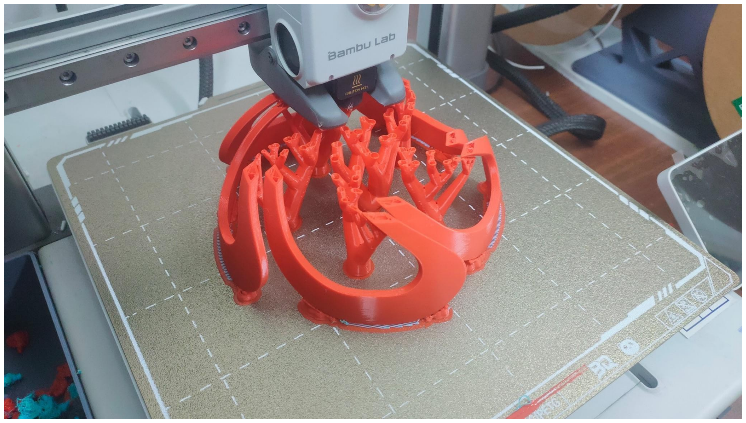
Furthermore, the research highlights that accessibility to advanced AI is not merely a matter of software literacy but is also tied to physical infrastructure. A significant portion of participants reported failures in installing open-source AI platforms due to high hardware requirements, specifically regarding GPU capabilities and driver compatibility. This creates a practical hurdle where the benefits of cutting-edge technology are limited to those with high performance devices, suggesting that user acceptance is influenced by financial and systemic factors as much as cognitive ones (Cheung & Dall'Asta, 2023). The resulting cognitive overload during the prototyping phase often led to frustration and a sense of being overwhelmed (Fields & De Jager, 2022). To mitigate these issues, future pedagogical frameworks should prioritize scaffolding technical skills earlier in the curriculum and providing more robust institutional support for hardware intensive workflows (Basarir, 2022).

The inclusion of automated systems during the conceptual stages of design offers a practical way to translate abstract mental images into tangible visual forms. While traditional sketching methods can be slow and limited by manual skill, AI provides a rapid feedback loop, allowing students to view their ideas as concrete images in a short time (Hegazy & Saleh, 2023). This speed is particularly helpful because it allows learners to see and test many options they might have previously ignored due to the sheer effort required to draw them by hand (Basarir, 2022). By using these digital partners, designers are better equipped to overcome the difficulty of explaining complex architectural ideas through words alone (Mitchell, 2019). This ability to visualize once indescribable concepts helps maintain high interest and encourages students to take creative risks with their shapes (Cheung & Dall'Asta, 2023).

However, the introduction of these advanced tools creates a significant mental cost, especially as the design moves toward the final physical creation (Vogel & Schwabe, 2016). Findings indicate that adding AI based tasks alongside traditional project requirements increases cognitive load during the prototype stage. This increase in pressure occurs because students must manage the rules of new software, the technical demands of 3D printing, and the project's creative goals all at once (Fields & De Jager, 2022). This experience of mental overload aligns with theories of self-efficacy, which warn that new learners can become frustrated when faced with too much complex information at once (Bandura, as cited in Fields & De Jager, 2022). Despite this friction, the evidence suggests that working through these challenges leads to a clear turning point in understanding, provided the tools remain accessible and well supported (Basarir, 2022; Cheung & Dall'Asta, 2023).

Figure 3

Prototyping Model

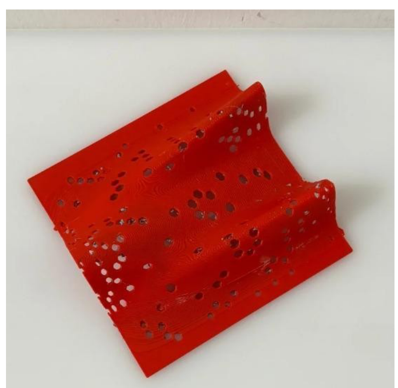


The findings from the classroom trials suggest that machine intelligence is most effective when it is a permanent part of the design path rather than a single elective. Data shows that students often struggle with the sharp transition from drawing by hand to using complex node-based systems, highlighting the need for a broad institutional roadmap. This strategic plan should move beyond treating software as an isolated tool and instead build a mental foundation that prepares future architects for a deep partnership with machines (Basarir, 2022). A long-term plan for this merging of skills ensures that the mental growth seen in the study becomes a standard professional habit. For such a shift to succeed, schools must have tutors who are technically aware and ready to help students through those epiphanies that occur when logic and creativity meet (Cheung & Dall'Asta, 2023).

Setting official rules for automated systems is also necessary to prevent the loss of creative power. Although generative tools give quick visual choices, they fail to grasp the social or spiritual layers that define a building (Sukkar et al., 2024). The evidence confirms that without a critical human in the loop, the design process risks making generic shapes that ignore physical rules or cultural context (Hegazy & Saleh, 2023). Because of this, institutions need a formal set of guidelines that define the ethical limits of AI, particularly concerning who owns the work and how to stay true to the original concept (Cheung & Dall'Asta, 2023). Creating these standards is a necessary step to ensure technology helps rather than replaces the architect, keeping responsibility for the final result in human hands (Borghoff et al., 2025).

Figure 4
Final Model 1

Figure 5
Final Model 2



Conclusion

The evidence from this study confirms that a tiered learning structure, such as the EDL, is an effective way to scale student's design thinking when working with automated systems. By tracking student progress from manual natural observations to the creation of solid physical models, the research shows that participants moved beyond being passive users to becoming active directors of the technology. This progress proves that a structured pedagogical approach expands mental reach while keeping the architect in full control of the creative and ethical direction of a project. The results show that students did not just learn to use a new set of tools; they learned how to maintain their creative authority within a complex decision-making unit.

The data collected on student performance shows that incorporating AI into the workflow helps students look beyond simple, surface level visual ideas toward a deeper architectural logic. The sharp rise in grades for translating ideas into computational scripts suggests that students bridged the gap between abstract thoughts and technical results. This proves that the Stanford Design Thinking steps provide a solid base for systematic problem solving even when machine intelligence is part of the team.

This research suggests that architectural institutions should stop treating machine learning as a separate elective and instead adopt a broad educational roadmap. AI needs to be a permanent thread throughout the entire curriculum so that digital literacy becomes a standard part of a student's professional identity. It ensures that schools stay relevant in a world where technology is evolving every day.

The success of this tiered learning path depends on strengthening technical support for students at the very start of their studies. Because software like Grasshopper or Rhino can be very hard to learn, introducing these tools earlier in the semester would give students more time to master the logic of computation. Schools should also focus on having tutors who are aware of the mental changes that occur when people and machines work together.

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