The Role of AI Design Assistance on the Architectural Design Process: An Empirical Research with Novice Designers

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This study explores the integration of Generative Design Assistants (GDAs), specifically machine learning based tools, in the architectural design process. It investigates how these tools, once confined to experimental realms, are now influencing mainstream architectural practice, particularly among novice architects. The research focuses on third and fourth-year architecture students, examining how they adapt to and integrate these advanced AI tools into their design workflows. Through an empirical online workshop, the study collected data of design process recordings, design output success scores of students by an independent jury, and post-experiment surveys. This approach provided insights into the timing, frequency, and sequence of GDA usage, as well as the influence of specific GDA features on design success. The research reveals that three primary strategies emerged in students' GDA usage: continuous use throughout the design process, selective problem-solving use, and initial ideation use followed by traditional methods. However, an over-reliance on GDAs was noted to potentially limit the designer's interpretive and developmental input. The survey shows that different GDAs have distinct strengths and impacts on the design process. In terms of selected GDAs for the experiment, ArchiGAN aids in discovery and ideation, while HouseGAN excels in reframing design problems. In conclusion, the study underscores the transformative potential and challenges of GDAs in architectural design and highlights the need for balanced GDA integration. The research outputs show that future research should focus on the long-term implications of GDAs in architectural education. This research aims to guide the effective integration of AI in architecture, enhancing the human designer's role rather than overshadowing it.

Keywords: Artificial Intelligence, Generative Design, Design Assistant, Architectural Design Pedagogy, Design Cognition.

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Tasarım Sürecinde Üretken Yapay Zeka Asistanlarının Rolü: Mimarlık Öğrencileriyle Ampirik Bir Araştırma

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Uzun süre yalnızca akademik çalışmalar ile sınırlı kalmış olan üretken tasarım asistanları, makine öğrenmesi tabanlı yapay zeka teknikleri sayesinde ana akım mimari pratik için de erişilebilir olmuştur. Bu çalışma, gelecekte daha da yaygınlaşacağı düşünülen bu üretken tasarım asistanlarının (GDA) mimari tasarım sürecine entegrasyonunu araştırmaktadır. Araştırma, üçüncü ve dördüncü sınıf mimarlık öğrencilerine odaklanarak, bu araçların tasarım sürecine nasıl entegre edildiklerini ArchiGAN ve HouseGAN araçları üzerinden incelemektedir. Araştırma kapsamında gerçekleştirilen çevrimiçi atölye çalışmasında, 12 katılımcının tasarım süreci kayıtları, tasarım çıktılarının bağımsız bir jüri tarafından değerlendirilmesi ile elde edile başarı puanları, ve son olarak atölye sonrası öğrenci anketleri ile toplanan geri bildirimler çalışmanın nicel ve nitel verilerini oluşturmaktadır. Araştırma, öğrencilerin GDA kullanımlarında üç ana stratejinin ortaya çıktığını göstermiştir: (1) tasarım süreci boyunca sürekli kullanım, (2) seçici problem çözme kullanımı ve (3)başlangıçta fikir oluşturma kullanımı ardından geleneksel yöntemlere geçiş. Araştırmada, GDA'lara aşırı bağımlılığın, tasarımcının yorumlayıcı ve geliştirici katkısını potansiyel olarak sınırlayabileceği gözlenmiştir. Anket çalışması ise, farklı GDA'ların tasarım sürecine farklı aşamalarda katkı sağladığını göstermektedir. ArchiGAN, keşif ve fikir oluşturma aşamasında yardımcı olurken, HouseGAN tasarım problemlerini yeniden tanımlama ve tasarım iterasyonu konusunda destekleyici gözükmektedir. Sonuç olarak, çalışma, mimari tasarım sürecinde GDAların dönüştürücü potansiyelini ve sürece entegrasyonlarında karşılaşılabilecek zorlukları göstermektedir. Araştırma, dengeli bir GDA entegrasyonunun gerekliliğini ortaya koymakta ve gelecekteki araştırmalar için, mimarlık eğitiminde GDAların uzun

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1. INTRODUCTION

In the historical landscape of architectural design, AI assistants have long been envisioned as augmentative tools. Initial endeavors, such as expert systems and rule-based generative models, signaled an innovative shift, yet their assimilation into mainstream architectural practice remained marginal. These pioneering technologies, while groundbreaking, often stayed confined to experimental realms, lacking widespread adoption in the field of architecture.

The landscape underwent a transformative shift with the advent of probabilistic methods like neural networks, heralding the emergence of more sophisticated and diverse AI tools. The inception of Generative Adversarial Networks (Goodfellow et al., 2014) marked a significant milestone in this evolution, which has since been propelled further by advances in technologies like diffusion models (Sohl-Dickstein et al., 2015).

Presently, the architectural domain witnesses a burgeoning array of AI tools, each designed to augment distinct phases and facets of the architectural design process. This expansion not only paves the way for heightened creativity and efficiency but also presents a complex challenge to architects: the integration of these technologies, which function not merely as tools but as independent design agents endowed with their own knowledge memory and synthesis capabilities. This integration transcends mere utilization; it necessitates the harmonization of their intrinsic design intelligence with traditional design methodologies.

This research is grounded in the historical evolution of AI tools in architecture and seeks to bridge a critical gap: comprehending how architects are assimilating technologies, particularly GANs, into conventional design paradigms. It delves into the emerging strategies architects employ to integrate these intelligent tools – which transcend the role of simple aids to become central agents of design. The study aims to uncover insights into how these tools are redefining creativity and efficiency in architectural practices, signifying a departure from traditional methods towards a more integrated, AI-augmented approach.

Focusing on the incorporation of AI tools, specifically GAN-based generative design assistants (GDAs) like ArchiGAN and HouseGAN, this study examines their utilization in the design workflows of novice architects. It centers on third and fourth-year architecture students, who, while acquainted with conventional drawing-based design techniques, are not as deeply entrenched in these practices as their more seasoned counterparts. This positions them uniquely as more adaptable and receptive to incorporating novel AI tools into their design repertoire. The selection of GAN-based plan generators as the principal investigative tool stems from their widespread accessibility and their aptitude for addressing plan configuration challenges, offering a concrete metric to gauge AI's impact on design outcomes.

1.1 Evaluation of Generative AI Tools

In architectural design, artificial intelligence (AI) can be broadly categorized into two approaches: rule-based and probabilistic machine learning-based (Carpo, 2023). These approaches have deep roots in the field, with significant contributions from pioneers such as Marvin Minsky and Nicholas Negroponte. Minsky, a proponent of the probabilistic approach, and Negroponte, who favored rule-based systems, laid the groundwork for the diverse range of AI applications we see in architecture today.

Rule-based AI systems employ a range of mathematical models and algorithms (Singh & Gu, 2012), such as cellular automata (Wolfram, 1983), genetic algorithms (Holland, 1992), shape grammars (Stiny & Gips, 1971), L-systems (Lindenmayer, 1968), and swarm intelligence (Anderson, 2001) with multi-agent societies. These systems operate on predefined rules to generate designs that adhere to specific user-defined goals and constraints. Examples of rule-based AI in architecture can be seen in the work of the Architectural Machine group at the MIT Media Lab, which was founded by Negroponte.

Conversely, the probabilistic machine learning-based approach, as exemplified by neural networks, represents a more dynamic and adaptive method of design generation. Neural networks, as described by Kasabov (1996), are biologically inspired computational models comprised of processing elements (neurons) and their connections. These networks store mathematical information from image-based data, analyze the probabilistic logic within the dataset, and generate new images accordingly. Building on the capabilities of neural networks, Generative Adversarial Networks (GANs) further extend the boundaries of what is architecturally possible. GANs, comprising a generator and a discriminator, collaborate not to directly create high-quality designs, but to facilitate the generation of diverse design possibilities and variations, thereby assisting designers in enhancing the overall quality of their work. These networks learn from extensive datasets and employ a collaborative process where the generator produces images and the discriminator evaluates them, resulting in images that closely resemble the training data, thus offering new insights into architectural design possibilities.

The advent of probabilistic generative algorithms has spurred a new wave of AI tools capable of creating diverse design outputs (Chaillou, 2022). These advanced tools are now being employed to generate urban forms, as illustrated by the work of M. del Campo et al. (2019). Similarly, they are used for crafting road diagrams, an approach detailed by Chu et al (2019).

In architectural planning, such AI assists in developing plan layouts, different techniques described by Nauata et al. (2021) and Chaillou (2019). Newton (2019) explores GANs for generating and analyzing architectural plans, even with small datasets, illustrating AI's capability to contribute to architectural plan development and analysis. Rodrigues et al. (2024) apply AI to space allocation in housing, showcasing AI's role in creating efficient mass-customized layouts. Complementing these insights, Özman and Selçuk's study on GANs in mass housing plan generation in Turkey enriches the narrative, illustrating the possible practical applications of AI in addressing real-world architectural challenges (2023).

The design of facades has also been revolutionized, with systems offering facade suggestions highlighted in work of Kelly et al (2018). Moreover, these algorithms enhance the creation of views and perspectives, a concept explored in the GAN model of Kyle Steinfeld (2019) They extend to the engineering domain as well, aiding in the design of structures as noted in R. Danhaive and C.T. Mueller’s paper (2021), and have notable applications in simulation analysis for performance optimization, as discussed by Quintana et al.(2020). And finally Eroğlu and Gül (2022) demonstrate StyleGAN's potential in architectural form generation, offering a new dimension to design inspiration.

These examples mark a significant milestone in the application of AI within the design discipline, showcasing the versatility and depth of probabilistic methods.

1.2 Co-Designer or Design Assistance?

In the architectural landscape of the 1970s, Nicholas Negroponte emerged as a forerunner, advocating for an interactive synergy with intelligent machines. At the MIT Media Lab's Architecture Machine Group, his pioneering work culminated in the development of Urban 2 and 5, early forays into Computer-Aided Design (CAD) systems. These systems were tailored to aid architects in crafting floor plans and optimizing room layouts for various factors such as adjacencies, lighting conditions, and modular grid integration. Urban 5, in particular, delved into the synergistic relationship between architects and intelligent agents, balancing tasks through a blend of machine-implemented implicit rules and architect-specified explicit parameters (Negroponte, 1969;1970). This endeavor underscored an evolving paradigm in computer-aided design processes, wherein these systems transcended mere drafting tools, actively suggesting layouts and identifying potential design conflicts.

Concurrently, Cedric Price in the UK was exploring the autonomous capabilities of AI in architecture. His 1976 project, the Generator, envisioned a self-adapting building. This concept hinged on a computer system capable of reconfiguring partition layouts either in response to user behavior or spontaneously, aiming to foster novel environmental conditions. Price's work presciently recognized the potential for machines to act as autonomous design agents (Furtado, 2008), foreshadowing the expanding role of AI in architectural software.

The foundational experiments by Negroponte and Price laid the groundwork for contemporary discussions on the role of AI in architecture. Their pioneering insights have only gained in pertinence as AI technology has become more accessible and affordable, transitioning from niche research to a staple in mainstream architectural practice. However, it is important to acknowledge that these early rule-based AI approaches underwent a period of dormancy during the so-called AI winter, as they grappled with the challenge of moving from theoretical research to practical application. The resurgence and evolution of neural networks and probabilistic methods have reignited interest in AI as a design assistant, reinstating these technologies at the forefront of architectural innovation.

Carta (2021) critically challenges the oversimplified and fundamentally erroneous belief that computers will replace human designers. The study underlines a pivotal concern in the use of algorithmic design tools: while there is an abundance of data that is easily accessible and interpretable, insufficient attention is paid to the architectural merit of the training plans used. Current applications of these technologies predominantly serve as design assistants rather than replacements for human creativity and expertise. Consequently, the discussion shifts focus from the unrealistic expectation of generating flawless designs to a more pragmatic exploration of how these computational tools can meaningfully contribute to architectural practice. This shift brings to the forefront crucial questions about decision-making processes in design: How extensively will we rely on these tools, and what benefits can they bring? Moreover, it probes the potential of these technologies to enhance the design quality of architectural products, underscoring their value as augmentative tools rather than replacements for human designers (As & Basu, 2021).

1.3 AI and Design Pedagogy: Emerging Perspectives

The emergence of new AI tools has significantly triggered their application in design education, offering fresh perspectives and methodologies.

Recent studies, including Basarir (2022), advocate for AI-centric courses in architectural curricula, enriching design education with new exploratory pathways. Sadek and Mohamed (2023) exemplify this by using AI to convert stories into visual designs, aiding conceptual development. Similarly, Cudzik et al. (2024) and Edirne and Öztürk (2023) explore AI's role in generating inspirational imagery and textual concepts, respectively, enhancing creativity in design studios. Bank et al. (2023) further this innovation by employing GANs to impart spatial understanding through architectural models, advancing students' design comprehension. These studies collectively suggest that AI technologies can significantly enhance the conceptual design phase, acting as potent tools for design assistance and creativity enhancement. For instance, Tong et al. (2023) envisioned AI as "a new mode of sketching," though they cautioned against its uncritical use, highlighting the importance of maintaining creativity. Ceylan (2021) further contextualized AI's role in design, advocating for its use as a supportive, rather than dominant, component in the creative process.

While numerous studies started to investigate various AI tools in architectural design education, our research focuses on the impact of these tools' features and the strategies students employ during the design process.

2. METHODOLOGY

The methodology of this study involved an empirical online workshop with 12 architecture students to investigate the impact of GAN-based Generative Design Assistants (GDAs) on the architectural design process. Participants, drawn from third and fourth-year architecture students, were split into two groups, each using a different GDA—ArchiGAN or HouseGAN—to create housing layouts. The study collected data through design process recordings, design output scores, and student surveys.

This mixed-method approach provided insights into how the timing, frequency, and sequence of GDA usage, as well as the specific features of the selected GDAs, influenced the design success of novice architects.

2.1 Design Experiment Set up

In this experimental setup, a specific design constraint of a 12 X 12-meter footprint was established. Participants, tasked with designing a single-story housing layout suitable for a family with two children, were presented with this challenge. To effectively leverage the capabilities of the Generative Adversarial Networks (GANs), a highly restrictive site, akin to a narrow and elongated parcel, was chosen. This constraint was intended to maximize the utility of both the GANs and traditional design methods.

The participants were bound by three primary rules during the design process:

*Verbalizing Thoughts: Participants were required to articulate their thoughts aloud throughout the design process, providing insights into their decision-making and creative approach.

*Utilization of GDA Interface: They were encouraged to use the GDA interface extensively, saving the layouts generated or inspired by the GDA tool. This rule aimed to foster a deeper interaction between the designers and the AI tool, encouraging exploration of AI-generated solutions.

*Adherence to Standard Drawing Practices: The use of a predefined layer system and furnishings in their AutoCAD drawings was mandated to ensure uniformity in drawing standards across all designs.

Crucially, the experiment integrated the use of both AutoCAD and the GAN-based Generative Design Assistant (GDA), allowing participants to combine the conventional design process with the AI assistant. This integration aimed to explore how traditional design methods and AI tools can synergize, enhancing the design process by combining the precision and familiarity of AutoCAD with the innovative, AI-driven capabilities of GDA. The dual-use of these tools offered a unique perspective on the blending of established architectural practices with cutting-edge AI technologies.

After the experiment completed, the results were evaluated with three jury members with different expertise and experience. One is an associate professor, another is a research assistant, and the last is a professional architect. They evaluate the final results according to functionality, structural performance, adaptivity, interior/exterior relationship, sequential perception, sophistication and creativity between 1-10.

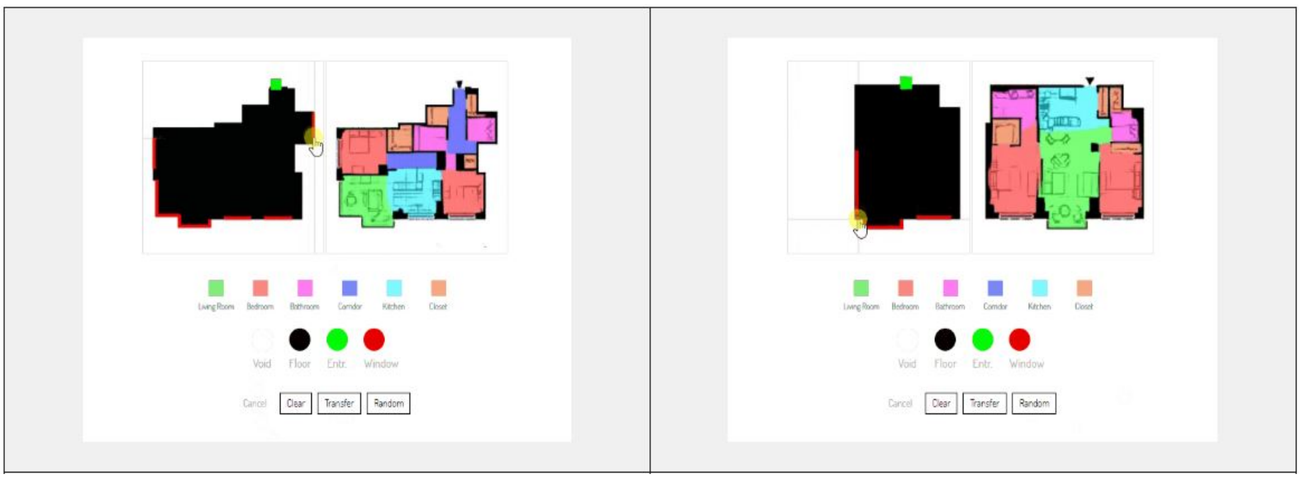
2.2 Selected Design Assistant Tools

Accurately estimating the shape and dimensions of large buildings is a critical task for architects, developers, and urban planners. This process necessitates a comprehensive consideration of the spatial arrangement, including room configurations, and the adjacencies and connections between major spaces. Despite a clear understanding of the process, it remains a notably time-intensive task. The domain of automatic floor plan generation, a research area since the 1970s, represents a pivotal approach to addressing these challenges. In recent times, studies focusing on enhancing architectural design production through Generative Adversarial Networks (GAN) have gained prominence.

Various housing layout design assistant approaches and GAN-based applications, such as DCGAN (Uzun et al., 2020), ActFloor-GAN (Wang et al., 2023), ArchiGAN (Chaillou, 2020), and HouseGAN (Nauata et al., 2020), exist in the field. However, a notable limitation of these tools is the absence of user interfaces to facilitate experimental application. For the purpose of this research, HouseGAN and ArchiGAN were selected due to their specific features and relevance.

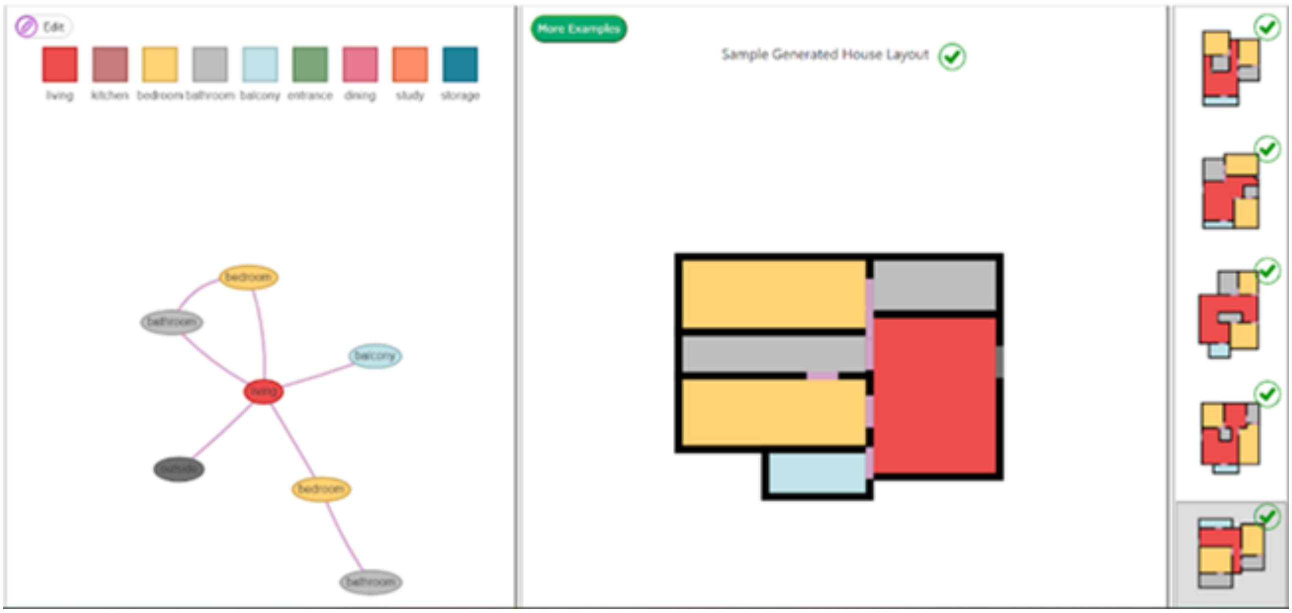
ArchiGAN, developed by Chaillou, emphasizes plan organization and style transfer. It features a sophisticated three-step deep network stack for generating floor plans, including the creation of RGB representations of building footprints, room layouts, and furniture arrangements. Users can modify inputs at each stage by altering images, though it lacks high-level control features, such as specifying room dimensions and specifications.

Figure 1: ArchiGAN interface used in the experiment (created by authors).



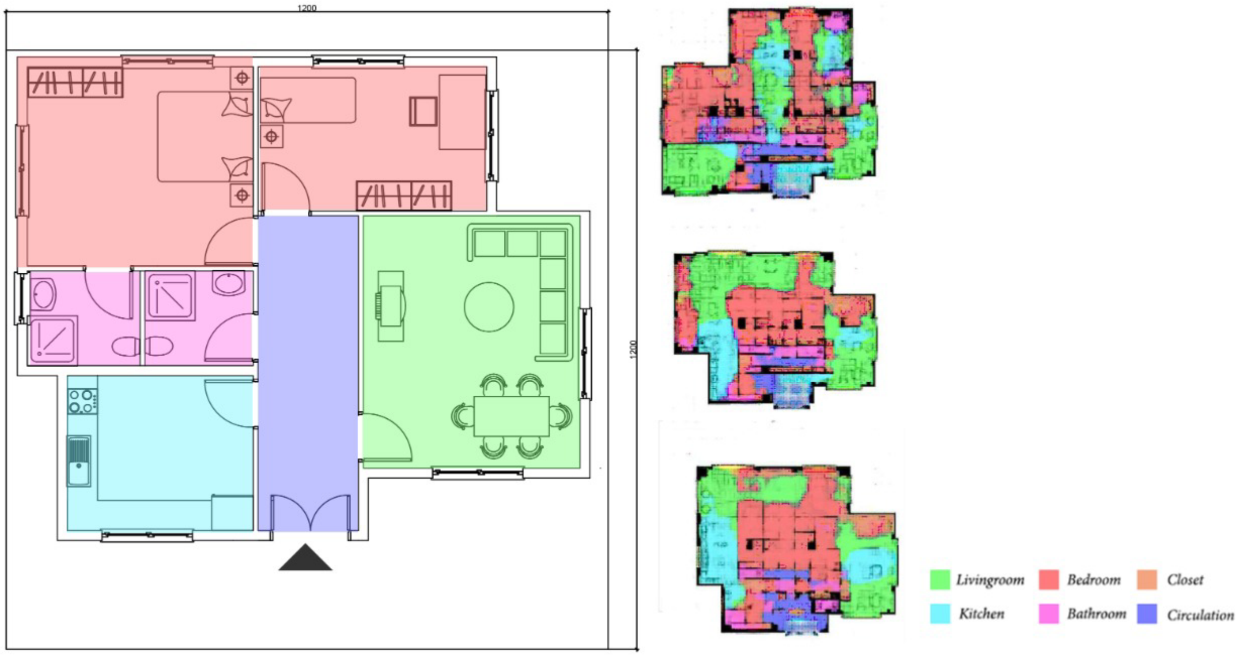
HouseGAN, on the other hand, introduces a novel approach with its relational generative adversarial network. It addresses house layout generation as a problem, proposing a graph-constrained solution. The architecture of this innovative network is based on relational design principles. It embeds constraints directly into the graph structure of its relational networks. The network aims to generate a set of axis-aligned bounding boxes for rooms, adhering to architectural constraints represented as graphs. The generated house plans are evaluated based on realism, variety, and compliance with input graph constraints. In HouseGAN, a bubble diagram is graphically represented, where nodes encode room categories and edges denote spatial adjacencies.

Figure 2: HouseGAN interface used in the experiment (created by authors).



These Generative Design Assistant (GDA) interfaces enable designers to leverage both collective and individual expertise as a design aid. Moreover, they allow designers to make comparative analyses between iterative design solutions generated under the same functional relationship criteria. However, these tools, created with different data sets and possessing varied design control capabilities based on their generative logic, are compared to understand their potential and limitations, alongside designers' strategies.

Figure 3: Integration of GAN Tool in Student's Design Workflow (created by authors).



2.3 Participant Survey

Following the design experiment, an extensive participant survey was conducted to gather in-depth feedback from the students. This survey was meticulously structured to include a diverse array of question types, including multiple-choice questions, open-ended inquiries, and Likert scale assessments, providing a comprehensive evaluation of the students' experiences with the Generative Design Assistants (GDAs).

The survey incorporated Likert scale questions to quantitatively gauge the students' perceptions of the GDAs' impact. These questions were designed to measure both the positive and negative influences of the GDA on their design process and speed, the effect on their decision-making process, and the degree to which they attributed authorship of the final design to themselves. These questions required responses on a scale from 1 to 10, with 1 being the least impactful and 10 being the most.

In addition to these structured quantitative questions, the survey also featured open-ended questions. These queries aimed to delve deeper into the students' subjective experiences with the GDAs. Questions included inquiries about the perceived usefulness or redundancy of specific program interface features, the impact of the program on the manageability of the design process, preferences for this method of design, suggestions for AI's role during the design phase, desired additions to the GDA, and a comparative analysis of the advantages and disadvantages of using different GDAs.

Furthermore, the survey included multiple-choice questions to identify specific aspects of the design process where AI support was most frequently utilized and to understand which facets of their designs were most influenced by the GDA alternatives.

This multifaceted approach to the survey was crucial in providing a holistic understanding of the students' experiences, preferences, and suggestions regarding the integration of AI tools in the architectural design process. The diversity of question types ensured that both quantitative data and qualitative insights were gathered, allowing for a nuanced analysis of the GDAs' impact on novice designers in the field of architecture.

3. RESULTS AND FINDINGS

3.1 Design Process Diagrams

Utilizing the comprehensive design process records, a specialized diagram was created for each student (S), encapsulating the time allocation between AutoCAD and the Generative Design Assistant (GDA). This diagram meticulously quantified the duration spent in both AutoCAD for traditional drawing and the GDA for AI-assisted design. Additionally, it highlighted 'Decision Making Moments'—key instances where crucial design decisions were made, marking a shift in the use of design tools.

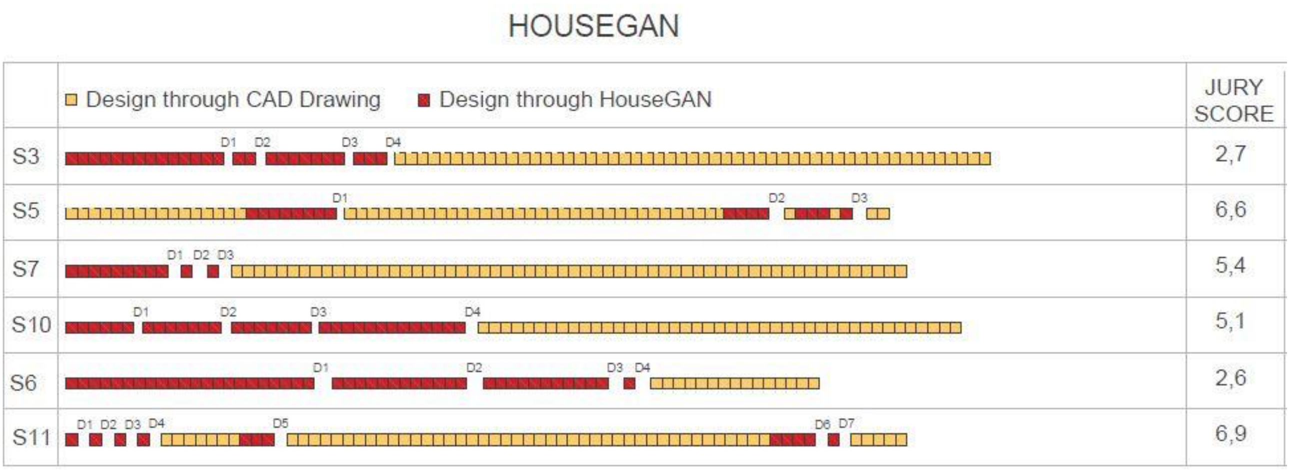
In the diagram, each unit, represented by a box, corresponded to a half-minute timeframe within the design process. The color coding within these boxes differentiated between periods spent using AutoCAD and the GDA, providing a visual guide to the tool usage pattern. Notably, the areas marked 'D' pinpointed the 'Decision Making Moments.' These moments were critical junctures where designers integrated their insights with the outputs from the AI assistant, influencing the direction and evolution of their design concepts.

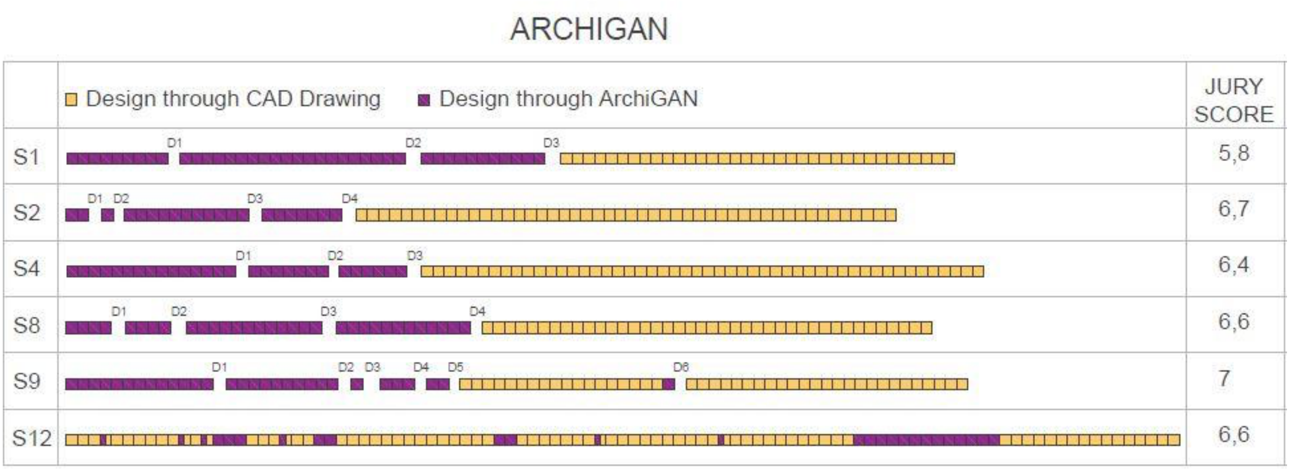
This analytical approach through the use of the diagrams, enriched with the jury scores reflecting how each student's work was evaluated overall by the jury according to predefined criteria. This scoring provided an additional layer of assessment, offering insights into the effectiveness and impact of the design choices made by the students

To analyze the designers' strategies, the diagram employed a duration-scaled approach. This method was instrumental in revealing:

*The specific points in the design process where the GDA was incorporated,
*The sequence and order in which the tools were used,
*The frequency of transitioning between AutoCAD and GDA,
*The length of time each tool was engaged.

Figure 4: Students' design process diagrams with jury success scores (created by authors).





3.2 Metrics From Survey

The design process in architecture is a multifaceted path, one that encompasses the generation of initial concepts to the final decision-making stages that solidify a project's direction. The integration of Generative Design Assistants (GDAs) into this journey has the potential to significantly influence each phase. In this section, we present the findings from the survey that explored how students evaluated the impact of two specific GDAs, ArchiGAN and HouseGAN, across different stages of their design processes (**Table 1**).

Table 1: Metrics of design assistant usage for different aims according to the survey (created by authors).

	ArchiGAN	HouseGAN
Discovery	**0.5**	0.17
Identifying Design Criteria	**0.5**	0.17
Regenerating Prob. And Design Criteria	0.17	**0.5**
Generating Alternative Solutions	**0.5**	**0.67**
Research	0	**0.33**
Defining Design Problem	0	**0.33**
Generating Solution	0.17	**0.33**
Reasoning	0.17	0
Evaluating	**0.33**	0.17
Comparison	0.17	**0.33**
Decide	0.17	**0.33**

3.2.1. Discovery and Ideation

ArchiGAN emerged as the more effective tool during the discovery phase and in identifying design criteria, with scores indicating that its interface or algorithmic approach may facilitate the initial exploration and conceptualization stages more efficiently. This suggests that ArchiGAN could be particularly useful for architects in the early, creative phases of design, where a wide range of ideas and inspirations are considered.

3.2.2. Problem-Solving and Iteration

HouseGAN was favored for its capacity to regenerate problems and iterate on design criteria, a feature that is crucial for refining design solutions and responding to evolving project needs. Its higher score in this area implies a robust capability for managing design alterations, making it a potential asset for stages requiring adaptability and reevaluation of initial design assumptions.

3.2.3. Alternative Solutions and Analysis

Both GDAs demonstrated significant utility in generating alternative solutions, with HouseGAN slightly outperforming ArchiGAN. This indicates that while ArchiGAN provides substantial support in diversifying design options, HouseGAN might offer a more expansive set of alternatives or a user interface that better supports this exploration.

3.2.4. Research and Definition

HouseGAN's higher effectiveness in supporting research and defining the design problem suggests that it may be better equipped to assist designers in the analytical aspects of the process, such as understanding context, setting objectives, and conceptualizing the overarching design approach.

3.2.5. Evaluation and Reasoning

ArchiGAN was perceived to be more helpful in the evaluation of design options, which is pivotal for assessing potential solutions against project criteria. However, both GDAs scored lower in aiding reasoning, indicating a potential area for development in enhancing how these tools support the understanding and justification of design decisions.

3.2.5. Comparison and Decision Making

In the latter stages of the design process, where comparison and decision making are key, HouseGAN was again favored. Its higher scores suggest that it may provide more effective mechanisms for contrasting different design solutions and facilitating informed decision-making.

4. DISCUSSION

4.1 Design Strategies: Navigating GDA Integration

The examination of the design process diagrams reveals that the strategies employed by designers can be categorized into three distinct groups. An intriguing pattern emerges when we juxtapose these strategic groupings with the jury evaluations: certain strategies appear to correlate with higher jury scores (**Figure 5**).

Strategy 1: GDA as an Integral Tool Across Stages

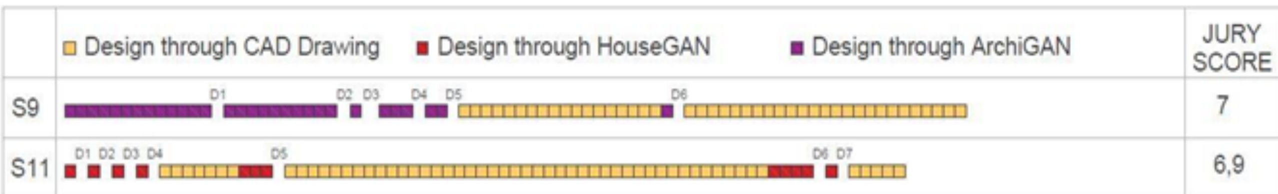


Figure 5: Design process diagrams and success scores of students who used Strategy 1 (created by authors).

A noteworthy observation is that a particular approach, employed by two students referred to as S9 and S11, correlated with the highest jury scores within their respective groups. These students, one using ArchiGAN and the other HouseGAN, initiated their design process with the GDA not merely for early ideation but also returned to it at various stages. This recurrent engagement indicates a more integrated use of artificial intelligence, suggesting its role as a continuous consultative presence throughout the design workflow.

These designers took advantage of the GDAs to generate a multitude of design alternatives and went on to synthesize elements from several different plans. This synthesis was directly used without additional modifications to suit the context, demonstrating a reliance on the solutions provided by the GDAs. Interestingly, despite the GDA occupying only a small portion of their overall design time, its influence was significant. The GDA here acted not just as a generator of design options but also as a stimulant for creative thinking, influencing the overall design strategy.

This approach underscores a refined utilization of GDAs where the tools are not merely used for singular tasks but are revisited as an integral part of the design development. The favorable reception by the jury suggests that the integration of AI at various stages could potentially enhance the final design outcomes. Moreover, this strategy raises pivotal questions about the evolving role of AI in design pedagogy and professional practice, hinting at a future where AI is seen less as an auxiliary tool and more as a constant collaborator in the creative process (**Figure 6**).

Strategy 2: Integrating GDA Problem-Solving into AutoCAD Drafting

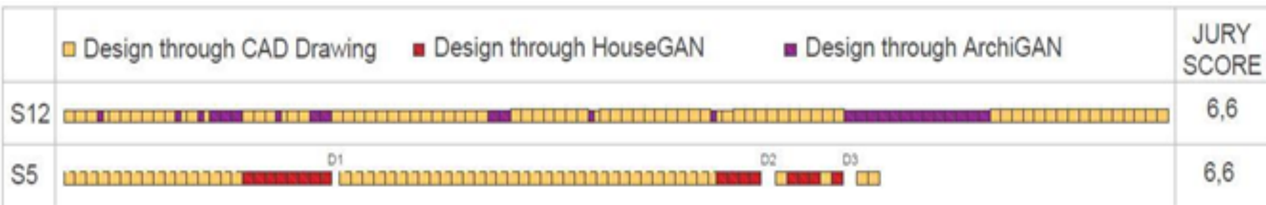


Figure 6: Design process diagrams and success scores of students who used Strategy 2 (created by authors).

Continuing with the analysis of design strategies, Strategy 2 was employed by two other students, labeled as S12 and S5, who attained scores that were above the group average in their respective categories—ArchiGAN and HouseGAN. The utilization of this strategy is depicted in Figure X.

This particular approach is characterized by an initial engagement with AutoCAD, where students formed their preliminary design concepts. Unlike those employing Strategy 1, these students interspersed their design process with frequent transitions between AutoCAD and the GDA. This pattern suggests that the GDA was not the primary source for initial design generation but was rather utilized as a tool for addressing specific challenges within the designs that were initially conceived through traditional drawing methods. Similar to the first strategy, these students also returned to the GDA during the later stages, which demonstrates a thoughtful integration of artificial intelligence at various points in their workflow.

In this case, the students leveraged the GDA for the generation of different design alternatives, ultimately selecting a specific plan layout. Notably, they proceeded to refine and evolve this chosen plan, making contextual adjustments to better fit the design requirements.

Moreover, similar to Strategy 1, the overall time devoted to the GDA was a minor component of the total design process. This suggests that the students viewed the GDA not as the central tool of design but as a means to resolve particular issues that arose during their design development in AutoCAD. The GDA, in this context, served as an ancillary resource, aiding in problem-solving and enriching the design process rather than dominating it (**Figure 7**).

Strategy 3: Initial GDA Use with Limited Follow-Through

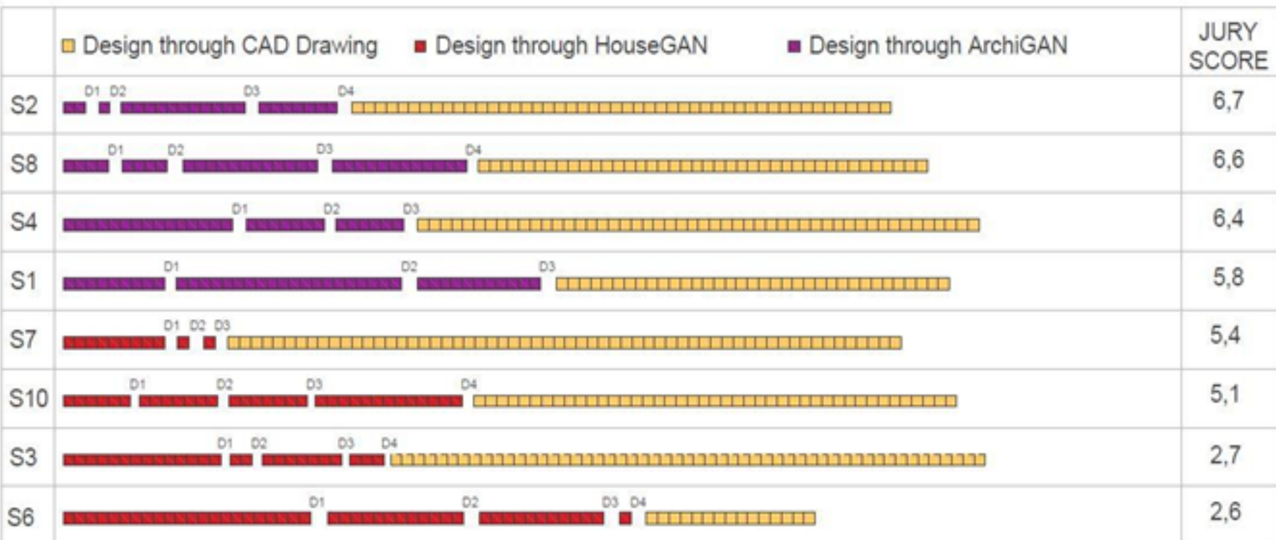


Figure 7: Design process diagrams and success scores of students who used Strategy 3 (created by authors).

The examination of the design process strategies revealed that the majority of students—S2, S8, S4, S1, S7, S10, S3, and S6—adopted what has been categorized as Strategy 3. Interestingly, within this group, students utilizing ArchiGAN (S2, S8, S4, S1) received higher jury scores compared to their HouseGAN counterparts (S7, S10, S3, S6), suggesting that the choice of GDA tool might play a role in the perceived success of the design outcomes. The specifics of how each selected GDA influences success are explored further in the subsequent section.

In this widespread strategy, students initiated their design process with the GDA to generate an array of design alternatives, much like Strategy 1. However, this is where the similarity ends. Unlike their peers who revisited the GDA at different stages, these students restricted the use of GDA exclusively to the initial phase, eschewing its benefits in later stages. They selected one particular design alternative but did not further adapt or develop it in context.

Furthermore, when considering the time invested in the GDA in relation to the entire design process, a pattern emerged: those who spent a greater proportion of time engaged with the GDA tended to have lower jury scores within their groups. This was exemplified by students S1 and S6, who dedicated 53% and 75% of their design time to the GDA, respectively. This trend suggests a potential pitfall of becoming too reliant on the GDA for producing variations, to the detriment of engaging in the interpretive and developmental aspects of design. Such a reliance points to a diminished interpretative control by the designer, which is critical for translating GDA-generated options into refined, contextually appropriate design solutions.

This strategy underscores the necessity of a balanced approach to the use of GDAs in the design process. It reflects the importance of the designer's interpretive role and suggests that while GDAs are valuable for initial ideation, the human element is crucial in the subsequent design development for achieving successful outcomes.

4.2 Feature Dynamics: ArchiGAN vs. HouseGAN

The survey results provide insightful revelations about the usage and effectiveness of the two Generative Design Assistants (GDA) interfaces, ArchiGAN and HouseGAN, in the architectural design process. These findings underscore the distinct functionalities and impacts of each GDA, shaping how participants approach and execute their design strategies.

ArchiGAN is noted for its deductive approach in generating iterative solutions. It initiates the design process with decisions about the building's footprint and the relationships between exterior and interior spaces. This approach steers the GDA to later adapt and meet the functional needs of the layout. This methodology is particularly conducive to facilitating discoveries and identifying design criteria, as ArchiGAN tends to generate more ambiguous design solutions compared to HouseGAN. The ambiguous nature of these solutions fosters a space for exploration and innovation. Furthermore, ArchiGAN's capability to create detailed furniture layouts offers substantial feedback for spatial usage, prompting higher evaluation metrics from the participants.

In contrast, HouseGAN adopts an inductive method, where designers first determine the functional relationships, which then inform the creation of the layout footprint. This process makes HouseGAN a more suitable tool for regenerating design problems and design criteria based on user decisions. Consequently, it becomes a preferred option for generating alternative solutions to a given design problem and is used more frequently than ArchiGAN for comparative purposes. The survey indicates that this ability to compare different design options is instrumental in aiding decision-making processes (Table 2).

Feature	Design through ArchiGAN	Design through HouseGAN	Design through drawing
Mass design	X		X
Void design	X		X
Function types (livingroom, kitchen etc.)		X	X
Number of rooms		X	X
Functional relationships		X	X
Relationship with exterior (windows)	X		X
Relationship with exterior (doors)	X	X	X
Room size			X
Deduction	X		X
Induction		X	X
Feedback of spatial usage	X		X
Structural feedback			
Topologic relationships (3d)			
Iterative solutions	X	X	
Comparison		X	X
Collective expertise	X	X	
Individual expertise	X	X	X

Table 2: GAN-based design tools and CAD-based drawing comparison.

5.CONCLUSION

The conclusion of this research draws together insights on the role and impact of Generative Design Assistants (GDAs) in architectural design, with a specific focus on ArchiGAN and HouseGAN. This study, which involved third and fourth-year architecture students, delves into how these emerging AI tools are integrated into traditional design processes and their effect on design outcomes.

The research findings highlight that both ArchiGAN and HouseGAN offer unique advantages in the design process. ArchiGAN is particularly effective in the discovery and ideation phases, facilitating exploration and the generation of diverse design concepts through its deductive approach. HouseGAN, on the other hand, excels in regenerating design problems and iterating on design criteria, proving invaluable in the later stages of design development with its inductive methodology.

The study identifies three primary strategies adopted by the students in integrating GDAs: continuous use throughout the design process, selective use for specific challenges, and initial use for ideation followed by traditional methods. These varied approaches underscore the flexibility and adaptiveness of GDAs in architectural design. However, an over-reliance on GDAs was observed to potentially limit the designer’s interpretive and developmental contributions, suggesting the need for a more balanced integration of these tools.

Considering the educational implications of our study, it's clear that introducing Generative Design Assistants (GDAs) into architectural education invites a thoughtful reconsideration of teaching methods in design. Because, incorporating Generative Design Assistants (GDAs) into architectural education introduces a multifaceted challenge: how to blend traditional design principles with emerging AI technologies. Our findings with ArchiGAN and HouseGAN illuminate this complexity, suggesting that while GDAs can broaden the design horizon for students, they also necessitate a deeper pedagogical strategy. This strategy should not only facilitate technical proficiency but also encourage a critical examination of how AI influences design choices and outcomes.

Moreover, the transition towards integrating GDAs in education requires rethinking assessment criteria and learning outcomes. It prompts a discussion on developing new frameworks that evaluate both the creative process and the ability to critically apply AI tools. By addressing these aspects, educators can foster an environment that not only values innovation but also cultivates a reflective design practice, preparing students for a rapidly evolving professional landscape.

Adding to this complexity is the observed tendency towards over-dependence on AI tools among some students. Our study identified diverse strategic approaches to GDA usage, ranging from continuous integration throughout the design process to selective application for specific challenges, and initial ideation followed by traditional methods. These varied strategies underscore the importance of guiding students towards a balanced use of technology—where GDAs serve as aids that enhance creativity and problem-solving rather than as crutches that limit personal initiative and critical thinking. Educators face the challenge of instilling in students the discernment to leverage these powerful tools judiciously, ensuring that the reliance on AI does not overshadow the development of their design intuition and capabilities. Encouraging a varied approach to GDA use can help students navigate the potential pitfalls of over-reliance, fostering a generation of architects who are both technologically adept and deeply engaged in the creative process.

In conclusion, this research establishes a foundation for understanding the integration of AI tools in architectural design, revealing both their transformative potential and the challenges they pose. Looking ahead, further studies are essential to explore the long-term implications of GDAs in professional practice, their impact on design quality, and the evolution of architectural education to include these advanced technologies. Such future research will be crucial in guiding the effective integration of AI in architecture, ensuring that these tools augment rather than overshadow the essential role of the human designer.

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Conflict of Interest Statement

The authors of the study declare that there is no financial or other substantive conflict of interest that could influence the results or interpretations of this work.

Author Contribution

The authors declare that they have contributed equally to the manuscript.

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