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Repositioning Artificial Intelligence in Architectural Conceptual Design: An Experimental Comparative Model for Data-Driven Spatial Decision-Making

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Abstract

Integrating artificial intelligence (AI) into the built environment has greatly improved building automation and performance optimization. However, the potential of AI to inform early spatial configuration, user-oriented planning, and its role in shaping architectural decisions at the conceptual design stage have not been well studied. This study aims to compare traditional architectural design processes with AI-informed design approaches at the conceptual stage. An experimental comparative design model is employed in which two parallel design scenarios are developed for the same prototype: a conventional, architect-led concept design and an AI-informed concept design. The comparative evaluation framework is structured around five multidimensional criteria: Space Utilization Efficiency, Daylight Performance, Circulation Optimization, User Scenario Compatibility, and Spatial Adaptation Capacity. This study examines whether AI-informed conceptual design generates spatial configurations that differ measurably from conventional approaches. The findings will contribute to the development of data-driven, adaptive, and user-centered architectural methodologies.

Keywords: Artificial Intelligence, Architectural Conceptual Design, Data-Driven Design, Conventional Design, User-Centered Design

1. Introduction

The field of architecture is experiencing a transformative shift, as Artificial Intelligence (AI) increasingly reshapes how we design and build. Moving beyond traditional, rule-based systems, the integration of AI promises a new era of adaptive learning and performance optimization (Cudzik & Radziszewski, 2018; Yousif & Bolojan, 2024). While AI is now impacting various stages of the architectural process, its influence is most keenly felt in the early conceptual design phase, where it's accelerating idea generation and enabling the exploration of innovative forms and spatial arrangements (Lere & Bilkisu, 2025; Saliu & Elezi, 2025).

The rise of Generative AI (GenAI) is transforming early-stage design processes. Architects can now quickly produce conceptual sketches and test multiple design options simply by describing their ideas (Akdağ & Künyeli, 2025; Paananen et al., 2024). Tools like Midjourney, DALL·E, and Stable Diffusion are opening new creative possibilities, while methods such as Generative Adversarial Networks (GANs) make it easier to develop building massing studies and floor plans (As et al., 2018; Paananen et al., 2024; Newton, 2019). Beyond visual appeal, AI also helps optimize workflows, from recommending efficient spatial arrangements to guiding material choices, ultimately enhancing the architect's creative potential (Rane, 2023; Rane et al., 2023). In particular, spatial layout generation has been identified as a complex computational problem, requiring the integration of functional relationships, circulation logic, and environmental performance within a unified framework (Hu et al., 2020; Yan et al., 2025). Within this context, space layout design can be understood as a combinatorial problem, requiring the simultaneous resolution of multiple spatial and functional constraints (Kakooee & Dillenburger, 2024).
However, a critical gap remains in our understanding of AI's potential. While the application of AI to generate architectural forms—often termed "form-finding"—is gaining traction, its capacity to inform early spatial configuration and user-centered planning, and to guide complex architectural decisions at the conceptual level, remains largely unexplored. Khan et al. (2025) state that despite rapid progress in generative design, AI-informed design focuses on form generation rather than structured evaluation, with limited attention to how AI-informed alternatives can be systematically compared and selected based on multi-criteria spatial performance. Current literature acknowledges that human expertise remains vital

for making the nuanced spatial and contextual choices that shape compelling architecture (Pena et al., 2021; Lu, 2025). While specialized tools offer performance feedback (e.g., ApproxiFramer and Deep Performance), a comprehensive model capable of evaluating spatial configurations across multiple user-centered criteria is still lacking (Ampanavos et al., 2021; Yousif & Bolojan, 2024).

This research addresses this critical deficiency with an experimental comparative design model to evaluate AI-informed design approaches against traditional architectural processes. By developing two parallel design scenarios – one architect-led and one AI-assisted – for a single prototype, we employ a multidimensional evaluation framework. The outcomes are rigorously compared across five key criteria: Space Utilization Efficiency, Daylight Performance, Circulation Optimization, User Scenario Compatibility, and Spatial Adaptation Capacity. Ultimately, this study aims to determine whether AI-informed conceptual design generates demonstrably different spatial configurations compared to conventional methods, contributing to the development of data-driven, adaptive, and user-centered architectural methodologies.

2. Literature Review

The integration of Artificial Intelligence (AI) is fundamentally reshaping the architectural design process, transforming it from a primarily solo endeavor to a collaborative partnership between humans and machines (Saldana Ochoa, 2024). Advanced machine learning methods are not simply automating tasks but redefining algorithmic design, with AI increasingly positioned as a "co-designer" or architectural assistant capable of handling repetitive tasks and freeing up human designers to focus on creative direction (Matter & Gado, 2024; Cudzik & Radziszewski, 2018). This collaboration is opening up "latent design spaces," allowing architects to explore a wider range of possibilities beyond traditional intuition through interconnected, deep learning models (Bolojan et al., 2023). However, despite these capabilities, AI-informed outputs still require human interpretation and critical evaluation, particularly in relation to spatial coherence and contextual decision-making (Stanimirovic et al., 2026).

The recent surge in GenAI is particularly exciting, fostering creative ideation and the serendipitous discovery of new concepts (Jaruga-Rozdolska, 2022; Paananen et al., 2024). Tools that use diffusion models, such as Midjourney and DALL·E, enable rapid concept visualization from textual prompts—a technique that is proving valuable in education for helping students develop and communicate architectural ideas (Akdağ & Künyeli, 2025; Sadek & Mohamed, 2023). Critically, the effectiveness of these tools hinges on the clarity and conceptual coherence of the prompts, highlighting AI's role as a reflective and iterative partner in the design process (Makaklı et al., 2026). This shift is also driving a move towards data-driven design, incorporating real-time feedback to optimize key performance criteria (Yousif & Bolojan, 2024). Moreover, AI has been shown to significantly enhance architectural design efficiency through automation, predictive modeling, and data-driven optimization, particularly in early-stage decision-making processes (Li et al., 2025**).**

Several areas are seeing significant advancements, such as space utilization efficiency, daylight performance, circulation and Structural Logic.

AI tools, including generative design algorithms and Generative Adversarial Networks (GANs), are increasingly employed to optimize spatial layouts and explore variations on a design concept (Lere & Bilkisu, 2025; Cudzik & Radziszewski, 2018). Function-driven deep learning approaches analyze existing designs to identify reusable elements, enabling the creation of highly optimized compositions (As et al., 2018). In particular, spatial layout generation has been identified as one of the most technically demanding problems in architectural AI, since it requires the simultaneous resolution of functional adjacency, circulation logic, and geometric consistency within a coherent design framework (Hu et al., 2020; Yan et al., 2025). Learning systems are replacing traditional expert systems, exemplified by the Deep Performance (DP) framework, which utilizes surrogate models to provide rapid and accurate daylight performance predictions during early design phases (Yousif & Bolojan, 2024). Systems like ApproxiFramer leverage machine learning to generate structural layouts from sketches, significantly reducing conflicts between design intent and engineering requirements (Ampanavos et al., 2021). Furthermore, "deep chaining" frameworks are enabling simultaneous optimization of multiple design layers, including organization, composition, and structure (Bolojan et al., 2023). Recent advancements in AI-aided design have also extended into structural and engineering domains, where machine learning models are used to support early-stage decision-making and system optimization, highlighting the potential for integrating spatial and structural reasoning (Ao et al., 2025).

Despite these substantial advancements, the current literature reveals critical gaps that hinder AI's full potential in architectural design. Despite these developments, the current body of research remains heavily oriented toward generation rather than evaluation, with limited emphasis on how AI-informed alternatives can be systematically compared and selected based on multi-criteria spatial performance (Khan et al., 2025; Yan et al., 2025). These challenges are primarily centered around Decision-Making Deficiencies.

While generative systems are effective in producing large sets of design alternatives, they often lack embedded mechanisms for structured decision-making, leaving evaluation processes largely dependent on designer intuition rather than data-driven criteria (Vissers-Similon et al., 2025; Khan et al., 2025).

Additionally, current research has not adequately addressed the role of AI in evaluating User Scenario Compatibility or Spatial Adaptation Capacity—areas demanding nuanced reasoning about a building's long-term utility (Lu, 2025; Vissers-Similon et al., 2025). User-centered considerations such as behavioral patterns, scenario-based usage, and long-term spatial adaptability remain insufficiently addressed in current AI-driven design frameworks, despite their critical importance for real-world architectural performance (Ao et al., 2025).

Current literature underscores that, while AI is expanding the boundaries of architectural design, human expertise remains essential for navigating complex spatial and contextual considerations (Karadag & Yıldız, 2024; Lu, 2025).

This highlights the need for integrated frameworks that not only generate design alternatives but also evaluate them through measurable spatial and user-oriented criteria, enabling a more structured and transparent decision-making process in conceptual design (Khan et al., 2025; Ao et al., 2025). This study addresses this gap with a comparative approach toward AI-informed design and traditional architectural design. By developing two parallel design scenarios – one architect-led and one AI-informed – for a single prototype, we employ a multidimensional evaluation framework. The outcomes are rigorously compared across five key criteria: **Space Utilization Efficiency, Daylight Performance, Circulation Optimization, User Scenario Compatibility, and Spatial Adaptation Capacity**. Ultimately, this study aims to determine whether AI-informed conceptual design generates demonstrably different spatial configurations compared to conventional methods, contributing to the development of data-driven, adaptive, and user-centered architectural methodologies. By rigorously evaluating criteria such as **Space Utilization Efficiency, Daylight Performance, Circulation Optimization, User Scenario Compatibility, and Spatial Adaptation Capacity**, this study bridges the gap between early-stage spatial organization and user-centered resolution necessary for architectural practice.

3. Methodology

This study employs an experimental comparative design framework to examine whether an AI-informed conceptual design process produces spatial configurations that differ from those developed through **an architect-led design workflow** under the same architectural brief. The comparison is limited to the conceptual stage, focusing on spatial organization, program distribution, circulation logic, and inter-floor relationships. The objective is to compare spatial decision-making between two approaches: a human architect and a GenAI system.

To ensure methodological consistency, both scenarios are developed from an identical project definition, including the same site conditions, spatial program, and floor distribution. The comparison, therefore, underscores differences between the two approaches on how each one interprets and resolves the same architectural problem.

3.1 Research Design and Scenario Definition

The study is structured around a single residential design prototype to minimize variability and isolate workflow-related differences. The proposed case is a three-level family villa located on a rectangular plot of 306 m², defined by a fixed architectural brief that includes site dimensions, built area, setback conditions, and floor-by-floor function configuration. These constraints are applied equally in both scenarios to ensure comparability under practical design conditions.

The plan is structured as an L-shaped footprint, oriented with an open courtyard that incorporates a swimming pool. This arrangement requires the simultaneous resolution of core conceptual design problems, including zoning, circulation continuity, vertical organization, spatial adjacency, and indoor–outdoor relationships. The ground floor accommodates shared spaces (living, dining, kitchen, service areas), while upper floors contain private functions (bedrooms, bathrooms, terraces).

The project is defined within a contemporary residential architectural context characterized by simplified geometric forms, extensive glazed surfaces, cantilevered volumes, and an emphasis on spatial continuity between interior and exterior areas. In both scenarios, the stylistic framework operates as a limiting parameter rather than a performance target, preserving analytical comparability without embedding preconceived design results. All design outputs are required to comply with the same spatial brief and constraints.

3.2 Scenario A: Conventional Architect-Led Design

In Scenario A, the conventional conceptual design process was conducted by the authors as senior architects. The project was developed using sketching tools. The design was generated by the interpretation of the design brief, spatial program, site constraints, and functional requirements. The design process centered on organizing spatial zones with a focus on circulation clarity, functional relationships, privacy hierarchy, and floor coherence, defining functional adjacencies, and establishing floor-by-floor layout logic. The layout served as a baseline, representing a conventional, human-led conceptual design approach.

3.3 Scenario B: AI-informed Conceptual Design

Scenario B presents the AI-informed conceptual design process. In this scenario, the architectural brief is translated into structured textual prompts and is submitted to generative image-based AI systems, namely DALL·E 3 and Nano Banana 2, which generate annotated two-dimensional layouts plans.

To preserve the AI system's creative autonomy, the prompts define only the essential problem conditions, such as spatial program, dimensional constraints, geometric relationships, and staircase continuity. The prompts intentionally exclude qualitative or performance-oriented instructions (e.g., daylight optimization, spatial quality enhancement, or circulation improvement) to avoid embedding evaluation criteria into the generation phase. This approach ensures that the AI outputs reflect independent spatial configurations rather than guided or optimized responses.

The AI-informed outputs are treated as pure conceptual responses to the defined architectural brief. No manual correction, redrawing, optimization, or refinement is applied.

DALL·E 3 and Nano Banana 2 are used in this study. Their technical characteristics, input structures, and output formats are summarized in Table 1. Current AI-informed approaches primarily generate concepts in image-based formats, which constitutes a significant limitation, as they lack the capacity to produce detailed technical specifications.

Multiple layouts are generated for each floor level based on consistent prompt structures. The generated floor layouts are assessed solely based on compliance with non-negotiable criteria (e.g., staircase position, program inclusion, footprint logic). The selected layouts are then used for the final evaluation. No selection is based on perceived design quality, ensuring that the comparison remains unbiased.

Table 1. AI tools employed in Scenario B and their technical specifications.

Tool	Type	Role in Study	Input	Output
DALL·E 3	Text-to-image diffusion model	Generate 2D floor plan images from structured prompts	Structured textual architectural prompt	Raster (PNG) layout image with annotated zones and furniture
Nano Banana 2	LLM-guided layout generation system	Interprets spatial constraints and produces annotated 2D layouts	Structured program requirements and spatial constraints	Annotated 2D layout with labeled zones and circulation paths

To ensure clarity and methodological transparency, the overall research workflow is structured as a comparative design framework consisting of two parallel scenarios and a unified evaluation stage. The study compares an architect-led conceptual design process (Scenario A) with an AI-informed generative process (Scenario B) for identical design principles. A comparative framework of Architect-led and AI-informed conceptual design processes is presented in Figure 1. The figure synthesizes the sequential stages of design development, from initial input formulation to layout generation and subsequent comparative evaluation based on defined spatial performance criteria.

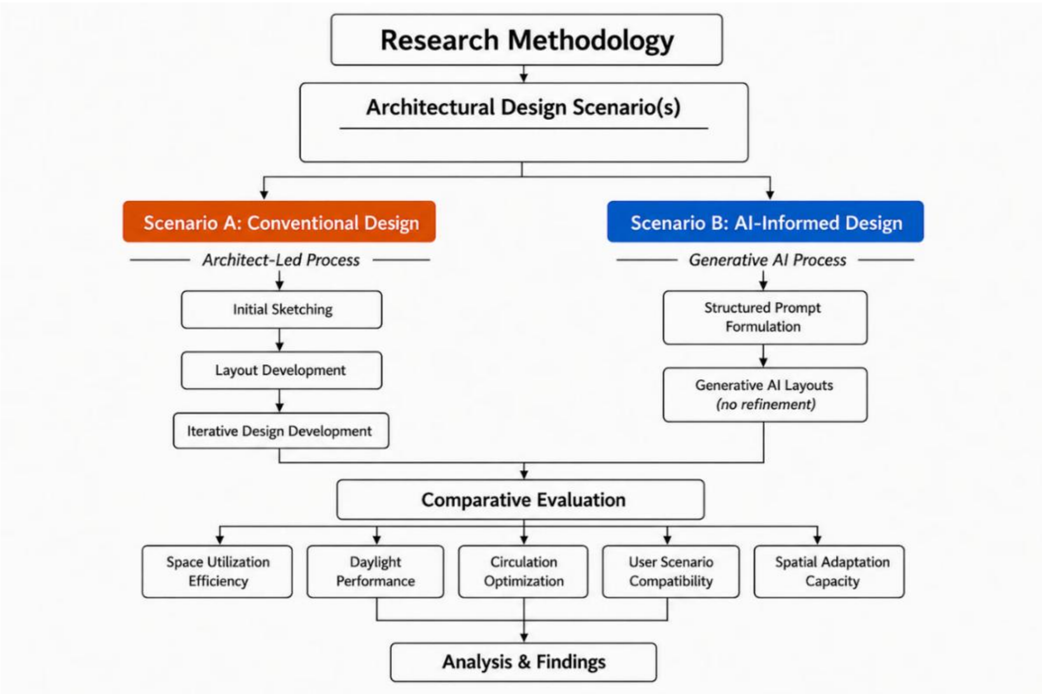

Figure 1. Comparative framework of Architect-led and AI-informed conceptual design processes (Developed by the Authors).

3.4 Evaluation Framework

Architect -led and AI-informed conceptual design layouts are evaluated based on a structured five-criteria framework for conceptual spatial performance assessment. The framework is synthesized from recurring evaluation indicators identified across recent architectural design studies. (Jang et al., 2025; Park et al., 2024; Yan et al., 2025).

To ensure methodological consistency, relevant studies were selected based on the following criteria:

- focus on early-stage architectural design,
- inclusion of spatial or performance-based evaluation metrics,

Through this process, frequently recurring evaluation indicators were identified and grouped into five dominant categories. These categories were selected based on their repetition across multiple sources and their relevance to conceptual spatial decision-making.
The final selection of five criteria reflects the minimum set of non-overlapping indicators required to capture both structured spatial organization and performance-oriented aspects of conceptual design.

It captures five complementary and non-overlapping aspects required to assess architectural layouts at the conceptual stage: spatial efficiency, environmental performance, circulation logic, user-oriented spatial organization, and spatial adaptability.

Specifically, space utilization efficiency is derived from studies on layout optimization and spatial organization, where indicators such as proportion, functional grouping, and zoning clarity are used to assess plan efficiency (Park et al., 2024; Cudzik & Nessel, 2025).

Daylight performance is derived from early-stage environmental design research, where orientation, façade exposure, window placement, and spatial depth are commonly used as plan-level indicators influencing daylight access (Deng et al., 2022; Mohammed, 2026; Çelik, 2025).

Circulation optimization is based on established spatial configuration principles addressing continuity, hierarchy, and directness of movement paths, which are widely used to evaluate circulation efficiency and spatial connectivity (Wang et al., 2025; Yuan & Zhou, 2025).

User scenario compatibility is derived from user-centered spatial evaluation approaches, where spatial adjacencies, privacy relationships, and functional connectivity are used to assess how layouts support patterns of daily use (Tafti et al., 2026; Mohammadi et al., 2025).

Spatial adaptation capacity is informed by research on adaptable and flexible architecture, where spatial openness and the potential for reconfiguration are key indicators of long-term usability (Kassem et al., 2025; Hasani & Riggio, 2025).

Based on this synthesis, each indicator is translated into observable plan-based indicators, forming the evaluation structure presented in Table 2. This approach allows a consistent comparison between AI-informed and architect-led layouts by linking theoretical evaluation indicators to measurable spatial characteristics.

Table 2. Presents the criteria and plan-based indicators used for the comparative evaluation.

Criteria	Indicators			
Space Utilization Efficiency	Proportion	Functional-Circulation-Residual Organization,	Spatial Zoning Clarity	
Daylight Performance	Orientation	Façade Exposure	Window Placement	Envelope-Relative Interior Depth
Circulation Optimization	Continuity	Hierarchy	Directness of Movement Paths	
User Scenario Compatibility	User-Aligned Spatial Adjacencies	Privacy Hierarchy	functional connectivity	
Spatial Adaptation Capacity	Spatial Openness	Modular Organization	Flexibility for Reconfiguration	

The defined metrics capture two complementary types of conceptual design reasoning. Rather than representing a strict binary classification derived from a single source, this distinction is employed here as an analytical lens to differentiate between structured and performance-oriented aspects of spatial evaluation.
'Space Utilization Efficiency' and 'Circulation Optimization' reflect structured spatial organization, focusing on geometric configuration, adjacency relationships, and program distribution in early-stage layout generation, as commonly addressed in generative and computational design research (Yan et al., 2025; Jang et al., 2025).
Conversely, Daylight Performance, User Scenario Compatibility, and Spatial Adaptation Capacity relate to performance-oriented and user-centred considerations, including environmental responsiveness, spatial experience, and adaptability over time. These aspects are widely examined in building performance analysis (Reinhart & Fitz, 2021).

The framework differentiates between computationally tractable layout generation and higher-order architectural reasoning, which relies on tacit knowledge and contextual judgment. Consequently, the framework evaluates how different design approaches embed structured logic alongside interpretive decision-making within a shared architectural problem. Ultimately, the framework serves as a tool for interrogating how each approach encodes spatial logic and design reasoning at the conceptual level."

4. Results

The key findings of a comparative analysis of Nano Banana 2 and C. Dalle-E 3 AI-informed design layouts and human-designed layouts are presented in Figure 2. This visual comparison highlights the similarities and differences in spatial organization, functional distribution, circulation patterns, and overall design coherence between the two approaches. Visual representations uncover that AI and human design processes differ not only in their output forms but also in the logic of spatial organization, offering insights into the potential of algorithmic design and the role of human intuition. The analysis reveals both the distinct characteristics and commonalities within the defined criteria.
Authors evaluate the layouts based on five multidimensional criteria: Space Utilization Efficiency, Daylight Performance, Circulation Optimization, User Scenario Compatibility, and Spatial Adaptation Capacity, whose dimensions are defined through literature. This study employs a comparative table, based on defined criteria and their dimensions, to systematically evaluate AI and human-designed layouts. This structure facilitates a clear and objective assessment of key design parameters, allowing for consistent comparisons across all examples. The detailed interpretation of the findings with the dimensions of the criteria is presented in Table 3.

Human-Designed Layout	AI-informed Layout. Nano Banana 2	AI-informed Layout. DALL·E 3

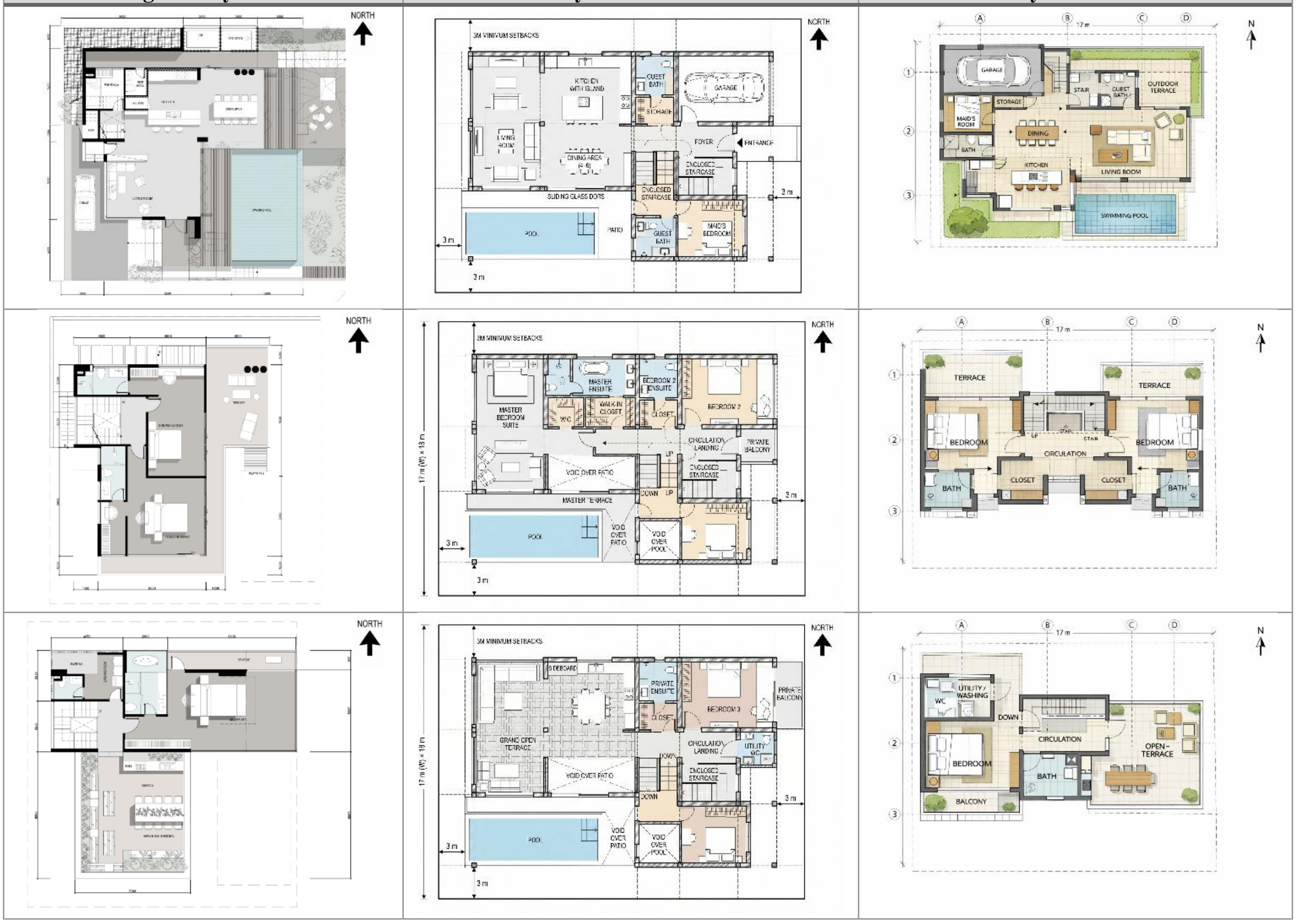

Figure 2. Comparative analysis of Architect -led and two AI-informed conceptual design layouts.

These differences are reflected in Table 3, particularly in circulation and daylight-related indicators.

Table 3. Constitutes the core analytical material of this study.

Criterion	Indicator	Scenario A (Architect-Led)	Scenario B (AI-informed)
Space Utilization Efficiency	Proportion	Moderate	Strong
	Functional–circulation–residual organization	Strong	Moderate
	Spatial zoning clarity	Strong	Moderate
Daylight Performance	Orientation	Strong	Limited
	Façade exposure	Strong	Limited
	Window placement	Strong	Moderate
	Envelope-relative interior depth	Strong	Limited
Circulation Optimization	Continuity	Moderate	Strong
	Hierarchy	Strong	Limited
	Directness of movement paths	Moderate	Strong
User Scenario Compatibility Limited	User-aligned spatial adjacencies	Strong	Limited
	Privacy hierarchy	Strong	Limited
	Functional connectivity	Strong	Moderate
Spatial Adaptation Capacity	Spatial openness	Strong	Limited
	Modular organization	Moderate	Limited
	Flexibility for reconfiguration	Strong	Limited

Following Table 3, the comparative evaluation of the AI-informed and architect-led layouts reveals observable differences across five criteria.

Space Utilization Efficiency: The AI-informed layout arranges the living room, kitchen, and service spaces in direct adjacency, forming a continuous cluster of enclosed functions. Circulation connects these spaces through a single path without intermediate zones. In contrast, the architect-led layout introduces a semi-open courtyard and transitional areas between enclosed functions, creating multiple spatial layers and separating interior zones.

Daylight Performance: The AI-informed layout places the pool along the south-west edge and positions the primary living spaces within the building mass, with limited direct adjacency to external edges.

By contrast, the architect-led layout organizes the main living areas around a south-east-facing courtyard, positioning these spaces directly along open edges and establishing spatial continuity with exterior zones.
Circulation Optimization: In the AI-informed layout, movement between the entrance, living room, kitchen, and service areas occurs along a single uninterrupted path without changes in direction.
In the architect-led layout, circulation is distributed across multiple segments, with movement passing through transitional zones and involving directional changes between interior and semi-open spaces.
User Scenario Compatibility: In the architect-led layout, the pool is positioned as a central outdoor element directly accessible from both living and dining areas. The kitchen and dining spaces are aligned with the outdoor terrace, and service spaces are located separately from primary living zones.
In the AI-informed layout, access to the pool occurs through the service zone, the dining area is not directly connected to the outdoor terrace, and service and living functions are placed in closer proximity.
Spatial Adaptation Capacity: The architect-led layout includes larger open areas within the main living zones, with fewer fixed internal partitions and greater spatial continuity between functions.
In contrast, the AI-informed layout defines most functions through enclosed rooms with fixed boundaries and more explicit internal divisions.

5. Discussion

AI-informed layouts(generated by Dall-E 3 and Nano Banana 2) demonstrate stronger performance in space utilization efficiency and circulation optimization, particularly in indicators such as proportion, continuity, and directness of movement paths. This pattern is consistent with prior studies showing that GenAI systems are effectively applied in layout generation and evaluated using quantifiable spatial and performance-based metrics, such as spatial distribution, connectivity, and daylight performance (Hu et al., 2024; Park et al., 2024; Jang et al., 2025; Li et al., 2024). These findings suggest that the higher performance of AI-informed layouts in this study is closely linked to the rule-based and quantifiable nature of these criteria.

AI-informed layouts also achieve higher spatial efficiency, particularly in proportion and functional–circulation organization (Table 3). This result is consistent with Li et al.'s (2025) report, which shows that GenAI models demonstrate strong performance in layout generation tasks driven by programmatic logic. However, as noted by Zhang et al. (2025), such data-driven approaches tend to reproduce spatial logic derived from existing datasets rather than incorporating design intentions or contextual considerations.

In contrast, the architect-led design outperforms the AI-informed layouts in daylight performance, particularly in orientation, façade exposure, and envelope-relative interior depth, where greater efficiency is observed. The architect-led layout integrates these indicators into a coherent spatial configuration, while the AI-informed layout shows reduced performance across them. This finding aligns with Çelik (2025), which highlights that current AI models do not reliably incorporate solar orientation and daylight-related spatial logic.

The most significant performance difference between the two approaches is observed in user scenario compatibility. The AI-informed layout shows limited performance on indicators such as privacy hierarchy and functional connectivity, suggesting that spatial organization is based on proximity rather than on user-centered spatial relationships. In contrast, the architect-led layout establishes clearer relationships between spaces, supporting patterns of daily use and functional organization. This finding aligns with Mostafavi et al.'s (2025) study, which states that spatial adjacency alone is insufficient to represent user-based movement patterns and social organization.

Moreover, the architect-led design also demonstrates greater performance in spatial adaptation capacity, particularly in spatial openness and flexibility for reconfiguration. The architect-led layout employs adaptable spatial boundaries, allowing spaces to be reinterpreted or reconfigured over time. In contrast, the AI-informed layout consists of more rigid and enclosed spatial divisions, limiting flexibility. This result aligns with Cocho-Bermejo's (2025) study, which notes that image-based generative systems often rely on fixed spatial representations rather than flexible geometric relationships.

In terms of circulation, the AI-informed layout demonstrates stronger performance in continuity and directness of movement paths. However, the architect-led layout shows clearer hierarchical organization, distinguishing between different types of movement such as public, private, and service access. This observation aligns with Mostafavi et al. (2025), who highlight the difference between spatial adjacency and user-oriented spatial organization.

The findings indicate that AI-informed layouts are effective at organizing spatial configurations under explicit rules and constraints, particularly for efficiency-related criteria. However, they show limited performance in environmental integration, user-centered spatial reasoning, and adaptability. Architect-led design, in contrast, demonstrates enhanced performance in these interpretive and context-dependent aspects of spatial organization.

At the end the current study offers two main contributions to previous work on the topic. On the one hand, it applies a comparative methodology that evaluates both AI-informed and architect-designed conceptual processes using the same design challenge and evaluation framework. This is important because, rather than comparing the results of the use of artificial intelligence techniques in architecture separately from the rest of the design process, the comparative analysis offered by the present research makes it feasible to compare the performance of both systems in terms of spatial and spatial reasoning as well as decision-making.

On the other hand, the study provides a novel evaluation framework that enables the assessment of various conceptual designs according to several performance criteria related to space utilization efficiency, daylighting performance, circulation optimization, user scenarios, and spatial adaptability.

6. Conclusion

This study examines how AI-informed conceptual design produces spatial configurations that differ from those developed through architect-led processes. By applying a comparative framework based on two parallel design scenarios and evaluating their outcomes using a five-criteria model, the study provides insight into how spatial configurations support different patterns of user-centered design and interaction at the conceptual stage.

The findings indicate that AI-informed and architect-led layouts do not demonstrate a consistent dominance across all evaluated criteria. Instead, each approach shows relative strengths across different dimensions of spatial evaluation.

AI-informed layouts perform better for Space Utilization Efficiency and Circulation Optimization, particularly through indicators such as proportion, spatial zoning clarity, continuity, and directness of movement paths. In contrast, architect-led layouts perform better in Daylight Performance, User Scenario Compatibility, and Spatial Adaptation Capacity, particularly through indicators such as orientation, façade exposure, privacy hierarchy, functional connectivity, spatial openness, and flexibility for reconfiguration.

These findings underscore that AI-informed design is effective in structuring spatial relationships based on explicit organizational logic, whereas architect-led design demonstrates a stronger capacity to support user-centered and adaptive spatial conditions. This distinction highlights a fundamental difference between rule-based spatial generation and experience-informed spatial reasoning.

7. Limitations of the Study and future work

This study's findings should be interpreted within the following limitations. Firstly, the single residential prototype restricts generalizability to complex building types. Therefore, future research should focus on testing the framework across different building typologies to assess generalizability. Since the image-based AI outputs (DALL·E 3/Nano Banana) lack the geometric precision needed for rigorous spatial analysis, future research may explore CAD/BIM-integrated workflows, which were not included in the present study. Thirdly, the plan-only evaluation limits objective environmental performance assessment, so future studies may integrate simulation-based environmental metrics with qualitative spatial evaluation methods. Finally, the study compares only one AI-informed layout and one architect-led layout, which may not fully represent the iterative and collaborative nature of real-world human–AI design processes. Future studies may further examine the role of interaction, refinement, and design control within hybrid design workflows.

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Conflicts of Interest

The authors report no conflicts of interest.

Data Availability Statement

The data supporting the findings of this study are derived from the experimental design scenarios and comparative spatial evaluations conducted by the authors. No external datasets were used. All relevant data are available from the corresponding author upon reasonable request**.**

Institutional Review Board Statement

Not applicable. This study does not involve human participants or animal subjects.

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Appendix B

Design the ground floor of a contemporary residential villa on a 17 m × 18 m site.

The site boundary and north orientation are provided. The design must incorporate the north direction as part of the spatial configuration.
The building must comply with the following constraints:
The total built area of the ground floor must not exceed 106.22 m².
The footprint must be clearly L-shaped and positioned in relation to the pool.
A minimum setback of 3 m must be maintained from the site boundaries.
The staircase must be enclosed, connected to a circulation space, and consistently positioned across all floors.
The spatial program includes:
Living room with seating elements
Dining area for 4–6 people
Kitchen with an island in an open-plan configuration
Maid’s bedroom
Storage/service space
Guest bathroom
Garage for one vehicle with direct access to the entrance
The layout should define spatial arrangement, adjacency between functions, and circulation paths based on the given constraints.
The output should be a 2D architectural floor layout including furniture layout, circulation paths, zoning indication, structural grid, and column system. The north direction must be indicated.

Design the FIRST FLOOR of the same residential villa. The layout must align with the ground floor configuration.
CRITICAL REQUIREMENT – STAIRCASE CONTINUITY:
The staircase must remain in the same position as in the ground floor.
The staircase must connect to a circulation space.
Indicate vertical movement using “UP” and “DOWN”.
Program requirements:
2 bedrooms (each including sleeping area and closet with bathroom
The layout should define spatial arrangement, adjacency between spaces, and circulation paths based on the given constraints.
Output:
2D floor plan aligned with the ground floor layout
Indication of furniture elements
Clear identification of the staircase and circulation connections

Design the SECOND FLOOR of the same residential villa, maintaining alignment with the lower floors.
CRITICAL REQUIREMENT – STAIRCASE CONTINUITY:
The staircase must remain in the same position as in the lower floors.
Indicate stair arrival with “DOWN”.
The staircase must connect to a landing or circulation space.
Program requirements:
1 bedroom including sleeping area and private bathroom and private balcony
1 open terrace space including outdoor seating and dining elements
1 utility/washing space include wc
The layout should define spatial arrangement, adjacency between spaces, and circulation paths based on the given constraints.
Output:
2D floor plan aligned with lower floors
Indication of built and open areas
Inclusion of furniture elements
Clear identification of the staircase and circulation connections