

DESIGN GENERATION BASED ON ARTIFICIAL INTELLIGENCE: A COMPARATIVE ANALYSIS OF METHODOLOGICAL APPROACHES

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Abstract: This article explores four methods of generating architectural and interior design using artificial intelligence — zero-shot, one-shot, few-shot, and prompt chaining — from both theoretical and experimental perspectives. Practical experiments were conducted based on real design tasks to compare output quality, user control, technical complexity, and generation speed. Particular focus is given to the prompt chaining approach, which was used to develop a step-by-step landscape design concept for the Shorkul reservoir area in Bukhara. The article outlines the advantages and limitations of each method and offers recommendations for effective integration of AI tools into the design process.

Keywords: artificial intelligence, design generation, prompt chaining, zero-shot, one-shot, few-shot, architectural design, landscape project, ChatGPT, Midjourney, AI-powered interior design

Introduction: Artificial Intelligence (AI) is fundamentally transforming design processes. In traditional design workflows, engineers and architects are often limited to exploring only a few alternatives due to constraints in time and resources. In contrast, generative AI models are capable of rapidly producing countless design solutions [1]. Research shows that AI not only enhances technical optimization in architecture and design, but also improves creative processes — enabling designers to explore multiple alternative solutions through decision-support and generative systems, all while maintaining creative control in the hands of the human designer [1].

Using AI tools, designers can quickly generate, evaluate, and revise multiple design alternatives, which facilitates better-informed decisions at early stages of the design process [1]. Currently, AI-generated solutions are gaining critical importance in fields such as interior design, architecture, and landscape design. Designers frequently need to consider a wide range of options in terms of materials, colors, and forms — a process that can be time-consuming. AI helps accelerate this process and expands the scope of creative exploration.

For instance, in a 2024 study by Gallega and Sumi, ChatGPT and DALL·E 2 were tested to streamline the selection of materials and textures in 3D interior scenes [2]. In this experiment, professional designers rated AI tools 72.8 out of 100 on a creativity support index and 47.3 out of 100 on task workload — acknowledging the usefulness of AI in their workflows [2]. At the same time, participants noted that although AI-generated suggestions were meaningful and contextually relevant, they still required fine-tuning based on domain-specific knowledge bases [2].

In conclusion, while the potential of AI in design generation is considerable, its implementation in practice still faces certain limitations and challenges.

Theoretical Background. Prompt engineering is the science and craft of constructing prompts — textual inputs given to an AI model — with the aim of eliciting desired outputs. With the emergence of large language models (LLMs), prompt engineering has gained particular importance, as precise and well-formulated instructions can significantly influence the model's responses [3]. In this approach, we formulate natural language instructions for the model, guiding it to extract and generate internal knowledge in a targeted direction [3]. Importantly, prompt engineering does not require altering the model's parameters or architecture — it leverages the model's pre-trained knowledge base [3]. For example, in the study by Gallega and Sumi, specially constructed prompts were used to obtain design

suggestions from ChatGPT regarding interior materials, resulting in relevant and useful recommendations [2]. Well-structured prompts unlock the model's full potential, while vague or poorly phrased prompts may lead to subpar outcomes.

Zero-shot, one-shot, and few-shot prompting are strategies that differ in the number of examples provided to the LLM (or other generative models) to guide its output.

- Zero-shot prompting provides only a task description, with no example responses. The model must rely entirely on its pre-trained knowledge to perform the task [3][4]. For instance, asking ChatGPT "Give me an idea for a bedroom design" constitutes zero-shot prompting — the model generates an idea based solely on general knowledge acquired during training. While this approach is simple and widely used, it may lack accuracy since the model must "infer" how to perform the task on its own [4].

- One-shot prompting involves providing one example in addition to the task description [4]. This helps clarify the expected output. For example: "Design a rector's office like this: [description of an example]. Now generate a similar design." This allows the model to consider stylistic cues from the sample. In the famous GPT-3 experiments by Brown et al., one-shot prompting often yielded significantly better results than zero-shot, as it offered context and direction — though still limited in generalization [3].

- Few-shot prompting refers to providing two or more examples. This is also known as in-context learning, where the model is given several demonstrations and asked to generate a new response in a similar fashion [4]. For instance, one may present several example interior project descriptions and then ask for a new design that aligns with the patterns in those examples. Few-shot prompting often results in more accurate and consistent outputs, as the model adapts to the structure of the given samples [3]. However, this approach requires careful selection and formatting of examples, as inappropriate samples may introduce unintended bias or reduce performance [3].

Prompt chaining is a technique used to break down a complex task into a sequence of smaller subtasks, each guided by a separate prompt [5]. Instead of asking the model to complete a compound instruction all at once — such as "Translate a text from Spanish to English, extract the facts, and translate them back into Spanish" — the process is broken down: first reading the Spanish text, then translating, then identifying key points, and so on [5]. This method, popularized in part by IBM researchers, improves model control and response quality [5]. In prompt chaining, each step's output becomes the context for the next prompt, creating a coherent logical flow throughout the process [5].

Prompt chaining has proven particularly useful in multifaceted tasks such as design. For example, a user may first ask the model to generate a list of design requirements, then create individual solutions for each requirement, and finally combine them into a cohesive project proposal. This layered approach enhances the user's control over model outputs and allows for iterative review and refinement at each stage [5].

Method	Definition	Advantage	Limitation	When to Use
Zero-shot	The AI model is given a task without any examples.	Fast, simple, good for general ideas.	Vague, lacks control.	For open-ended conceptual generation.
One-shot	A task is given with one example.	More targeted output, greater control.	May still lack sufficient context.	When generating ideas in a specific format.
Few-shot	The model is guided with 2–5 examples.	Context-aware, more accurate results.	Prompts become complex.	When copying a style or structure is necessary.

Prompt chaining	Each subsequent prompt builds on the previous one.	Iterative control, refined visual outputs.	Time-consuming, requires experience.	For complex design tasks and decision-making processes.
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Table 1. Comparative Analysis of Design Generation Methods and Methodologies

Research Methodology. This experimental study utilized several advanced artificial intelligence (AI) tools and platforms. For text generation, the ChatGPT model developed by OpenAI was selected. This model proved effective in constructing prompts, generating design recommendations, and analyzing intermediate outputs during prompt chaining processes, as well as developing interactive design scenarios [12], [13].

Image generation was conducted using the Midjourney platform. Midjourney is a cutting-edge generative AI system designed to produce high-quality and stylistically rich visual compositions based on user prompts. It is particularly popular in interior, landscape, and conceptual architectural design projects [14].

Additionally, the experimental design process was supported by practical platforms such as Planner 5D and ReRoom AI. Planner 5D is an AI-enhanced design environment that enables users to draw room layouts in 2D and 3D formats, automatically arrange furniture, and explore multiple design alternatives. Its built-in tools, such as the Design Generator and Smart Wizard, generate design suggestions automatically based on user-provided parameters [6].

ReRoom AI, on the other hand, allows users to create photorealistic interior renders in over 20 different design styles based on an uploaded photo or 3D model of an existing space. The platform prompts users to upload an image of their room and select a desired style, after which it produces a new interior variant within a short time frame [7]. This tool is particularly well-suited for applying few-shot and prompt chaining techniques in practice, as it enables users to supply an existing example and generate a new design through AI assistance [15].

Zero-shot Approach (Bedroom Design)

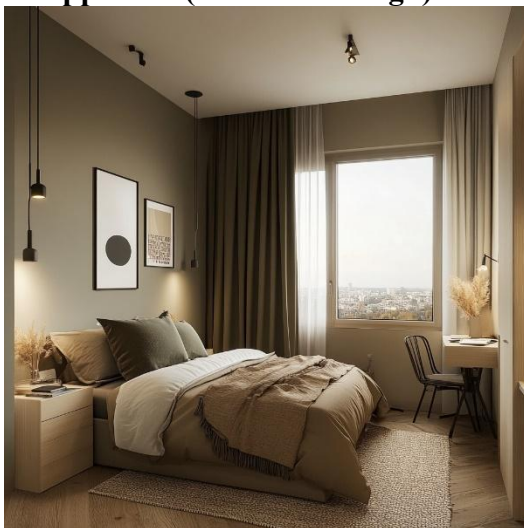




Figure 1. Bedroom interior concept generated by the Midjourney model using the zero-shot approach.

4.1 Zero-shot Approach (Bedroom Design)

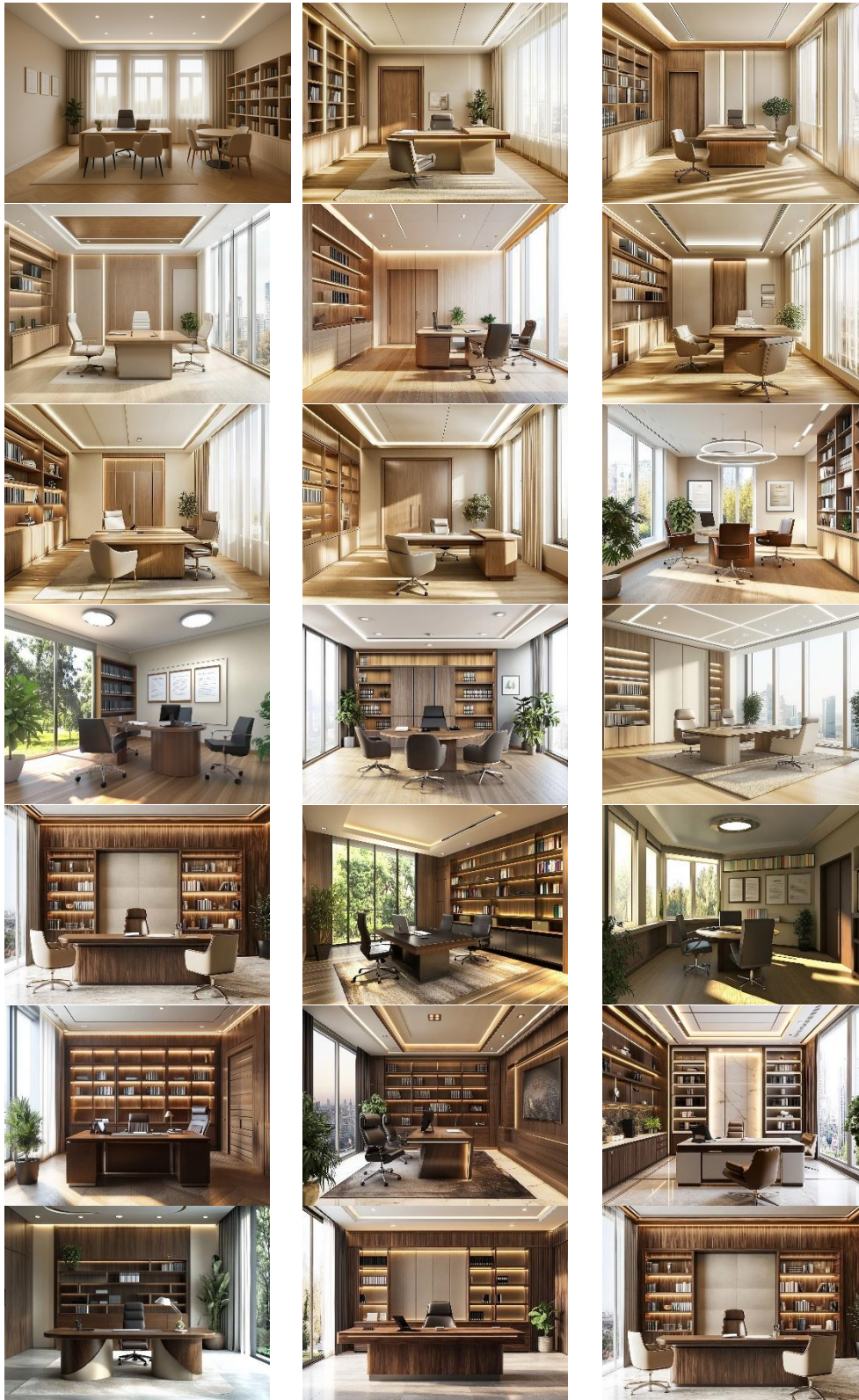
In this experiment, no examples were included in the prompt — the model generated a design based solely on the textual description provided (Figure 1). To test the zero-shot approach, bedroom design was selected as the first experimental task. Using ChatGPT, a concise prompt was formulated to define the design requirements, such as: “A 20 sq.m. bedroom, bright and modern style, with a large window and blue accent details.” This description, without any visual reference or sample, was then submitted to the Midjourney model. The resulting images (Figure 1) depict an interior concept generated solely based on the model’s internal knowledge. That is, Midjourney drew upon thousands of bedroom designs and visual patterns it had previously encountered during training to synthesize a new and original variation.

The key advantage of this approach lies in its simplicity — minimal input is required from the user: a clear description is enough. For example, in the study by Gallega and Sumi, designers provided their requirements to ChatGPT without examples, and the model successfully generated useful textual recommendations — a classic case of zero-shot interaction [2]. In our test, Midjourney’s visual output was of notably high quality. The model independently resolved aspects such as lighting, furniture layout, and harmony of wall and floor colors. However, the limitation of this method is that the outcome is less predictable: the user has limited control over the specific style or focus the model may choose. In fact, zero-shot prompting is often an exploratory and iterative technique — users may need to generate multiple versions and refine prompts with constraints in subsequent iterations [4].

In our trial, the first image aligned well with expectations: modern and bright, yet with certain unexpected decorative interpretations not specified in the prompt — a product of the model’s “creative inference.”

Overall, the zero-shot approach represents the simplest form of design generation, allowing rapid exploration of multiple ideas. However, the alignment between output and user intent may be weaker, due to the absence of guiding examples. As we will see in the next section, including even a single example (one-shot) improves output precision significantly.

One-shot Approach (Rector’s Office Design)



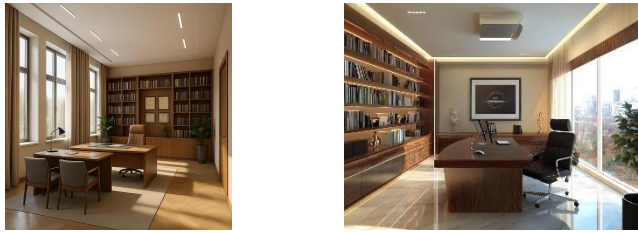


Figure 2. Office interior generated using the one-shot approach.

In this experiment, a sample layout was provided to the model as a reference for generating a design of a "rector's office." As a result, the AI generated a formal and modern office interior aligned with the sample's style (Figure 2).

As the second test, the one-shot prompting method was applied. The design task involved creating an office space for a university rector — a setting that demands a specific formal style and high functionality. To formulate the prompt, ChatGPT was first used to compile a list of design requirements for a rector's office (e.g., "Small office size, classic-style furniture, bookshelf units, a meeting table, and windows allowing good natural lighting").

According to the one-shot methodology, a single reference example was then added. This included a description such as: "Example: A classic office with dark wooden furniture and green walls." Additionally, Midjourney's image prompt feature enabled us to upload a small photo of an existing rector's office as a visual sample. Once the task description and one visual/textual example were submitted, the model generated the output shown in Figure 2.

The analysis of this one-shot approach revealed several improvements over zero-shot prompting. Firstly, the design style was more consistent: classic stylistic features shown in the example — such as wooden tones and a formal ambiance — were clearly reflected in the generated result. While the zero-shot approach gave the model full creative freedom, the one-shot prompt guided it to follow the reference. As highlighted in the literature, providing even a single example can significantly improve the model's task understanding [4]. For instance, Brown et al. (2020) demonstrated that GPT-3's outputs became substantially more accurate with one-shot prompting [3]. Our visual experiment confirmed this observation: the office interior generated in one-shot mode better met the functional and aesthetic expectations.

However, the one-shot method has its limitations — the model adapts strictly to the single given example. If the reference is of low quality or deviates from the intended direction, the model's output may follow that undesired trajectory. In our case, the sample office was well-chosen, but had we provided a highly futuristic office example, the result could have diverged stylistically. Thus, one-shot prompting requires careful and skillful example selection by the user.

In summary, one-shot prompting offers the user greater control compared to zero-shot and improves the alignment between output and intent. This method allows the designer to "teach" the model a preferred style or reference, shaping the generation process accordingly. However, a single example may not always suffice — especially when the task is complex or has multiple layered requirements.

Few-shot + Platform Integration (Planner 5D + ReRoom)

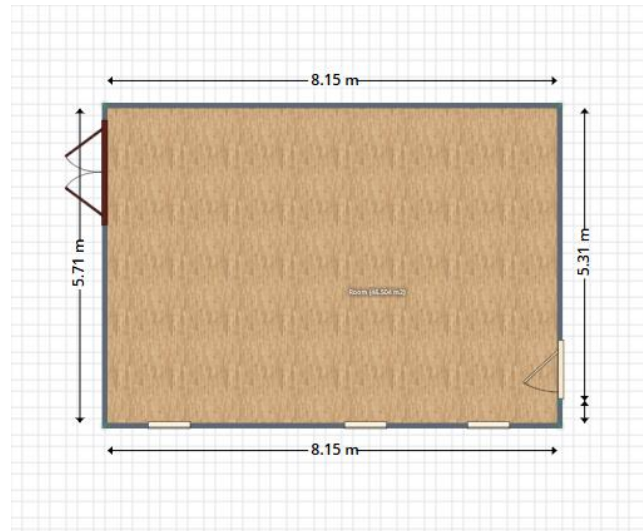
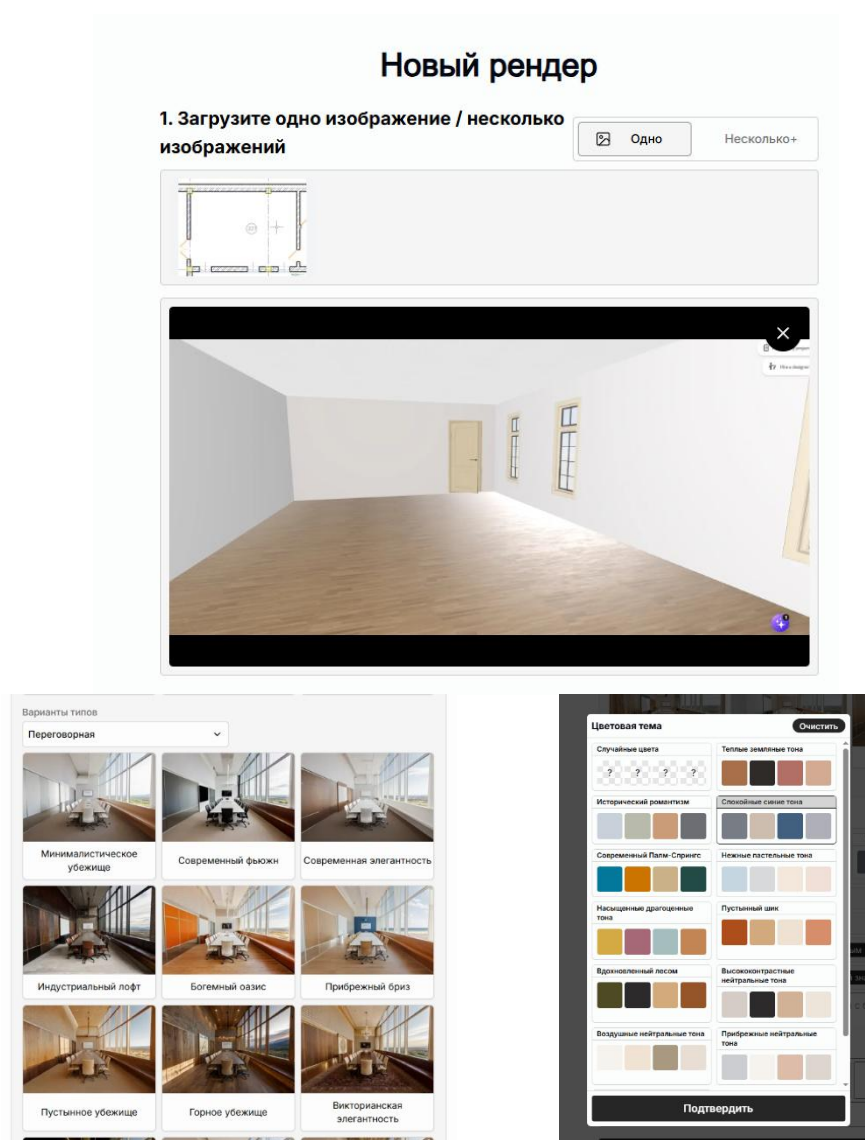




Figure 3. 3D visualizations created in Planner 5D based on the layout.



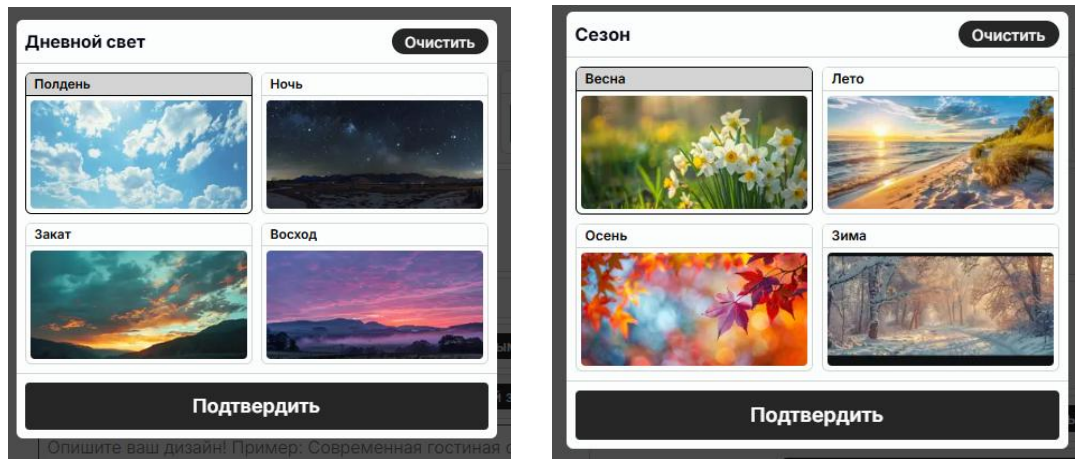


Figure 4. ReRoom AI interface.



Figure 5. Interior design stages generated using ReRoom AI.

In the few-shot approach, the model is guided through several examples before generating the final design output via an AI-powered platform.

In the third experiment, the few-shot method was integrated with specialized design platforms. The task remained the same as before: to generate an interior design for a university rector's office. First, the office floor plan, originally drafted in AutoCAD, was uploaded into **Planner 5D** (Figure 3). The software then produced a 3D visualization of an empty room layout (Figure 4). These 3D visualizations were subsequently uploaded into **ReRoom AI** for style transformation.

In ReRoom AI, the few-shot process unfolded as follows: a 3D model of the interior was provided as input, and then the user selected a new target style from the platform's interface [8]. For instance, we asked the system to transform a “loft-style” interior into a “Scandinavian” style. This was achieved by selecting the corresponding style option from ReRoom’s menu (Figure 4). Internally, ReRoom likely uses Generative Adversarial Networks (GANs) or Diffusion Models to analyze the original image and generate a stylistically transformed render within seconds. The outcome of this transformation is shown in Figure 5.

So where is the few-shot element here?

First, multiple design variants produced in Planner 5D can serve as examples for ReRoom AI — in our specific test, a single 3D layout was selected, but the platform had previously been tested with other styles as well.

Second, ReRoom AI is pre-trained on more than 20 interior design styles, meaning that the model has already learned from multiple examples per style [8]. When a user selects “Scandinavian,” for example, the platform leverages numerous embedded references to generate the new result. Although the process appears seamless to the user, internally it draws upon a rich set of style-specific data — a modeled form of few-shot learning.

The results of this experiment demonstrated that the few-shot approach produced the most accurate and user-aligned outcomes. For instance, when the room was transformed into a Scandinavian style, the model replaced the exposed brick wall texture with white paint and wooden panels, and substituted furniture with simple, light-colored alternatives — all typical of Scandinavian interiors. Achieving such specific stylistic shifts through zero-shot or one-shot methods would have been significantly more difficult, as these would require detailed textual explanations that the model may or may not interpret accurately. In contrast, few-shot prompting allows the model to learn from context, resulting in more reliable outputs [3].

Scientific literature also supports this: LLMs trained with multiple examples tend to commit fewer errors and adapt more precisely to new instructions [3]. Our visual experiment confirmed this claim.

Of course, the few-shot + platform method is not without its challenges. This approach requires the most user involvement: the user must first create or select several variants, upload them to the platform, and then configure the necessary style parameters. In short, the process is more time- and attention-intensive.

However, in terms of quality, this method produced the highest-rated outputs — the generated interiors were stylistically coherent, rich in detail, and well-aligned with functional requirements. The degree of user control was also significantly higher, as designers could influence the process at multiple stages (creating variants, selecting the best option, and defining the final style).

In conclusion, the few-shot approach — especially when integrated with specialized platforms — delivers highly effective results in design generation. It mirrors real-world design workflows, where designers often review several options before selecting a final solution. AI-enhanced few-shot techniques are well-suited to accelerating this process in professional design contexts.

Prompt chaining

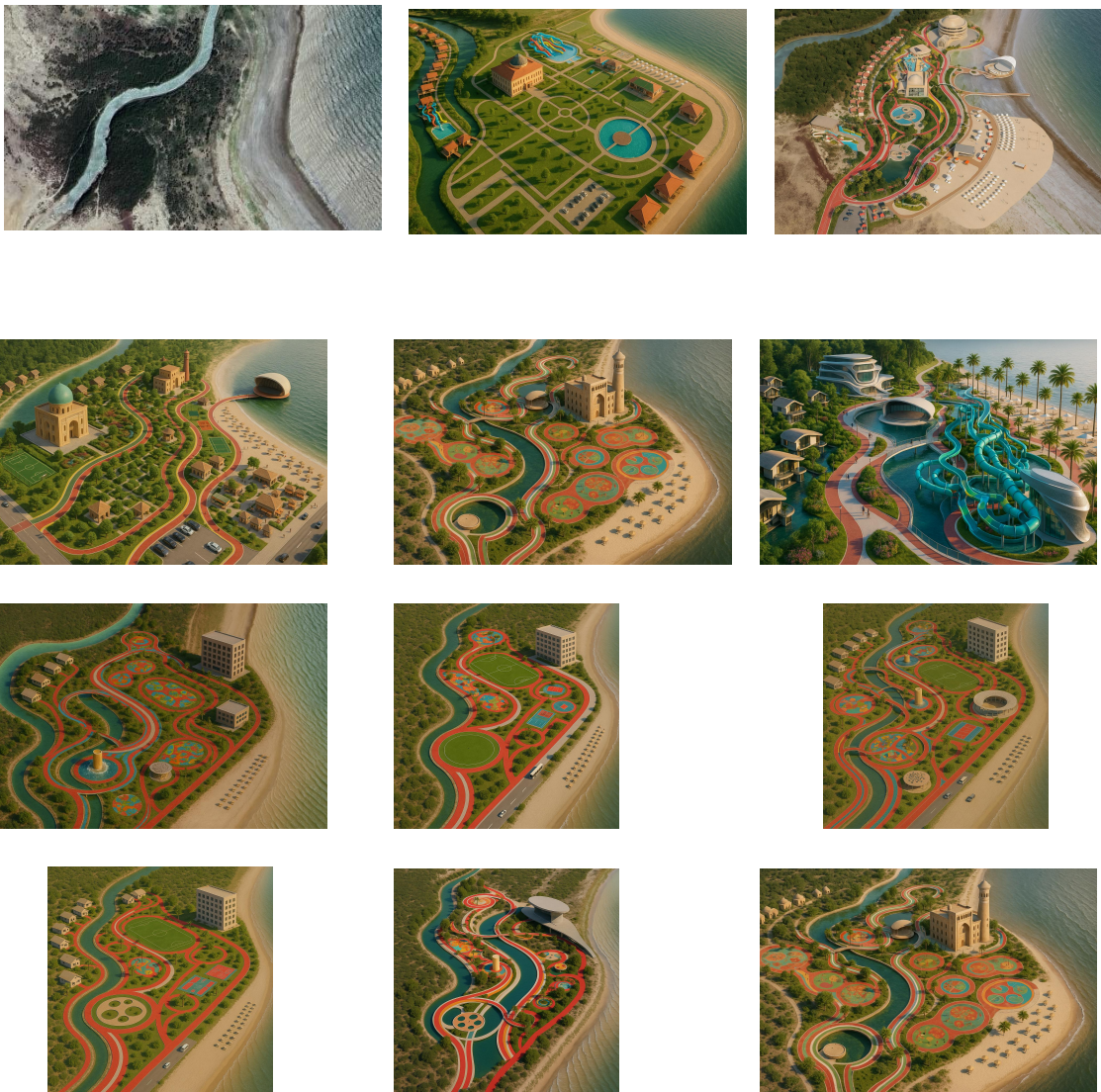


Figure 6. Landscape design concept generated using the prompt chaining approach.

In this example, the task of designing a recreational landscape for the surroundings of the Sho'rko'l Reservoir, located in Bukhara, was carried out step-by-step with the support of artificial intelligence. Unlike previous zero-shot experiments, this scenario involved describing a complex design problem through a sequence of prompts — a methodology known as **prompt chaining** (Figure 6).

Step 1: Defining Requirements and Establishing Context

The first prompt given to ChatGPT was:

“List the key geographic and social factors to consider when designing the landscape around the Sho'rko'l Reservoir.”

The model recommended the following considerations:

- Ecological and topographic features near the water (e.g., sandy shores, lowland canal networks);

- Potential for recreation, sports, and eco-tourism (e.g., beach zones, walking and running paths, playgrounds, sports areas);
- Integration of traditional and modern architecture (e.g., towers, mausoleum-style buildings, open-air stage);
- Visual harmony (e.g., circular and biomorphic forms, colorful walkways).

These recommendations were reviewed, and the most relevant ones were retained to match the site's location and needs.

Step 2: Developing Compositional Concepts

Next, we asked the model:

“Based on the criteria above, generate a conceptual landscape design.”

The AI proposed the following compositional elements:

- A traditional domed building (e.g., historical madrasa or cultural center) as the central anchor;
- Symmetrically arranged walkways and oriental-style gardens surrounding it;
- Elongated recreational zones along the beach: shaded areas, picnic spaces, and an open-air amphitheater;
- A large water feature (fountain or canal) with surrounding circular colored pathways.

Step 3: Expanding the Concept with Functional Additions

The subsequent prompt requested:

“Add features like water slides, sports areas, and residential cottages to the above design.”

ChatGPT responded with:

- Various types of aquapark slides;
- Flat-roof or brick-roof vacation cottages;
- Aesthetically integrated football, basketball, and tennis courts;
- Decorative circular landscaping elements.

Step 4: Refining Details, Textures, and Lighting

To further enhance the visualization, a final prompt was submitted:

“Mark the pathways with colorful pavement, add more palm trees, include sunset lighting effects, and render the view from a drone-like aerial perspective.”

This final step produced a highly realistic composition, capturing natural lighting, shading, and overall visual balance.

This experiment demonstrated that working in sequential prompt chaining mode — rather than giving a single general prompt — significantly improved the quality of visual results. Each new prompt served as a logical continuation of the previous one, enabling conceptual evolution and refinement. The user's inputs were gradually refined based on social, cultural, and technical criteria, resulting in a coherent, adaptive, and visually compelling landscape design.

Prompt chaining not only enhances visual output quality but also supports the development of design thinking, models decision-making sequences, and activates the creative potential of artificial intelligence.

Summary of Findings. The four experiments conducted demonstrate that each AI-based design generation approach has its unique strengths and limitations. They can be comparatively evaluated based on the following key criteria:

- Visual quality (accuracy and relevance),
- Flexibility (ability to vary in style and concept),
- Control level (extent of user influence over the process),
- Prompt sensitivity (output responsiveness to input),
- User involvement (level of creative and functional input required).

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Zero-shot	Average: low precision in overall compositions	Low: ideas remain vague	Very low: user cannot predict results	Moderate: output is broadly related to the prompt	Minimal: only initial prompt input
One-shot	Good: clear form and concept	Moderate: limited to one example	Moderate: some control within narrow scope	High: accurate response to specific prompt details	Medium: based on a single input
Few-shot	High: strong coherence in style, tone, and form	Good: guided by multiple examples	Moderate: adaptable but pre-defined	High: deep alignment with prompt context	Active: user provides structured context
Prompt chaining	Very high: increasing accuracy at each step	Very high: editable at any stage	High: user influences each step	Very high: highly responsive to each prompt	Maximum: ongoing interaction, refinement, and analysis

Table 2. Analysis of Experimental Approaches

Conclusion. This analysis demonstrates that the prompt chaining method provides the highest level of user engagement and control. As a result, it serves as the most suitable approach for developing complex and conceptually rich design projects. In contrast, the zero-shot approach remains the least controllable but is highly efficient for rapid prototyping. The one-shot and few-shot methods present more balanced alternatives, particularly effective for generating stylistically coherent design solutions. In this study, four methodological approaches to AI-driven design generation—zero-shot, one-shot, few-shot, and prompt chaining—were explored through experimental trials. Each method was evaluated individually, and the results were compared based on criteria such as visual quality, user control, creative supervision, complexity, and interactivity.

The zero-shot approach, while offering quick conceptual outputs, proved limited in accuracy and user control. The one-shot and few-shot methods allowed for greater contextual and stylistic precision by incorporating examples, but they exhibited constraints in prompt sensitivity. Among all, prompt chaining emerged as the most effective method. It enabled users to participate in each stage of the process, allowing for iterative refinement and structured decision-making in complex design development.

The landscape design case study at the Sho'rko'l reservoir demonstrated that advanced tools such as ChatGPT, Midjourney, Planner 5D, and ReRoom AI can be successfully integrated through an iterative prompt chaining approach to yield high-quality conceptual and visual design results. This approach has proven effective in maintaining a balance between AI automation and user-driven creativity in the design workflow.

Based on these findings, the prompt chaining methodology is proposed as one of the most promising approaches for establishing a collaborative, flexible, and creative interaction between designers and artificial intelligence systems. It holds particular potential for addressing complex, multi-stage challenges in contemporary architectural and design practices.

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