...::KENT AKADEMİSİ | URBAN ACADEMY

Volume: 18 Issue: 4 - 2025 | Cilt: 18 Sayı 4 - 2025

ARTICLE INFO | MAKALE KUNYESI

Article Type: Research Article | Araştırma Makalesi
Submission Date | Gönderilme Tarihi: 20.11.2024
Admission Date | Kabul Tarihi: 25.03.2025

CITATION INFO | ATIF KÜNYESİ

Kahvecioğlu, C., Ast, M. C., Sağlık, A. (2025). Text to Image in Landscape Architecture: Artificial Intelligence Approaches, *Kent Akademisi Dergisi*, *18*(4):1824-1844. https://doi.org/10.35674/kent.1588484

Text to Image in Landscape Architecture: Artificial Intelligence Approaches

Peyzaj Mimarlığında Metinden Görüntüye: Yapay Zekâ Yaklaşımları

Ceren KAHVECİOĞLU[1], Mahmut Can AST[2], Alper SAĞLIK[3]

ÖZ

Peyzaj mimarlığı tasarım çalışmalarında, yaratıcı ve farklı konseptlere sahip mekânların yaratılmasında fikir geliştirme süreci, uzun zamanlar gerektiren bir süreçtir. Teknolojik gelişmelerle birlikte zamanın etkin kullanımı önem kazanmakta ve yapay zekâ (AI) alanında yaratıcı, gerçekçi ve detaylı metinden görsel üreten uygulamalar dikkat çekmektedir. Text-to-Image (T2I) yöntemi ile tasarım fikirlerinin hızlı ve doğru bir şekilde geliştirilmesi açısından, peyzaj mimarlığında AI uygulamalarının kullanımı, akıllara birçok soru getirmektedir. AI tarafından üretilen görseller, mesleki doğruluk ve estetik açıdan ne kadar tatmin edicidir? Mesleki terimlerini doğru bir şekilde algılayabilmekte midir? AI ve peyzaj mimarlığı arasındaki genel ilişki durumu nedir? gibi sorulara bu çalışmada cevap aranmaktadır. Bu çalışmada; yazarlar tarafından tasarım alanında kullanılan 50 mesleki terim belirlenmiş ve bu terimler doğrultusunda 6 farklı tasarım konsepti ile 70 kelimelik promptlar oluşturulmuştur. Oluşturulan promptlar kullanılarak yazarlar, T2I özelliğine sahip Dall-E, MidJourney, LookX ve mnml uygulamalarından görseller üretilmiştir. Üretilen görseller; mesleki uygunluk, görsel estetik, yaratıcılık ve teknik detaylar açısından değerlendirilmiştir. Çalışma sonucunda, seçilen terimler arasında bazı mesleki terimlerin soyut, ileri teknik ve kapsam alanın geniş kavramlar olduğu tespit edilmiştir. AI uygulamalarında mesleki terimlerin doğru bir şekilde algılanabilmekte, peyzaj tasarımında farklı ve yaratıcı konseptlerin geliştirilmesinde tatmin edici görseller elde edebilmektedir. Bu bağlamda, peyzaj mimarlığı ve AI alanında iş birliği yapılarak uygulamaların geliştirilmesine katkı sağlanabilir. Aynı zamanda, bu çalışma; T2I uygulamaları ve peyzaj mimarlığı arasındaki mevcut durumu ortaya koyarak, daha yaratıcı, kaliteli ve detaylı konsept görsellerin üretilmesi açısından geliştirilebilir bir potansiyel olduğunu göstermektedir.

Anahtar Kelimeler: Konsept, Metinden Görsele, Peyzaj Mimarlığı, Peyzaj Tasarımı, Yapay Zekâ

ABSTRACT

Generating ideas for designing spaces with creative and diverse concepts in landscape architecture design is a time-consuming process. With technological advancements, effective use of time has become increasingly significant, and applications that produce creative, realistic, and elaborate visuals from text in the field of artificial intelligence (AI) have attracted attention. However, the use of AI applications in landscape architecture raises many questions regarding the rapid and accurate development of design ideas through the Text-to-Image (T2I) method: how satisfying are AI-generated visuals in terms of professional accuracy and aesthetics? Can AI accurately perceive professional terms? What is the general relationship between AI and landscape architecture? Apart from coming up with an answer to these questions, this study aims to investigate the potential of text-to-image (T2I) models in generating design concepts for landscape architecture. In this study, the authors identified fifty professional terms used in the field of design and created 70-word prompts with six different design concepts in line with these terms. Using the created prompts, the authors generated visuals from Dall-E, MidJourney, LookX and mnml applications with T2I feature. The images generated were evaluated based on their adherence to professional standards, aesthetic appeal, creativity, and technical accuracy. Results indicated that while AI models could effectively interpret a wide range of professional terms, including abstract and highly technical concepts, there were limitations in capturing the nuanced details of landscape design. This study highlights the potential of AI to assist landscape architects in the early stages of the design process, but also underscores the need for human expertise to refine and optimize AI-generated designs. Future research should explore ways to improve the accuracy and specificity of AI-generated landscape designs, as well as investigate the potential of integrating AI with other design tools and techniques.

[1] **Corresponding Author:** Çanakkale Onsekiz Mart University, crnkahvecioglu@gmail.com, ORCID: 0000-0002-2290-4356
[2] Çanakkale Onsekiz Mart University, mahmutcanast@gmail.com, ORCID: 0009-0005-7628-1093
[3] Çanakkale Onsekiz Mart University, alpersaglik@gmail.com, ORCID: 0000-0003-1156-1201

Keywords: Artificial Intelligence, Text-to-Image, Landscape Architecture, Landscape Design, Concept

INTRODUCTION:

Landscape architecture is a discipline encompassing art and science that shapes and manages the physical world and natural systems by creating spaces with economic, environmental, social, and cultural perspectives (Waterman, 2009, pp. 8-11). Landscape design, on the other hand, is defined as the arrangement and modification of spaces, ranging from large-scale urban areas to small-scale gardens, based on the characteristics of these spaces (Ardhianto et al., 2023). The design process can be defined as the time required for generating design ideas to achieve the final solution by means of drawing tools, the only way that allows the designer to convey their thoughts concretely. Traditionally, designers have relied heavily on hand-drawn representations to visualize and communicate their ideas throughout the design process. As a result of these developments, computer-aided design tools, which play an important role in the landscape design process, provide convenience to designers (Denerel & Birişçi, 2019).

The widespread adoption of computer-aided design (CAD) tools by designers has made digital processes more efficient than analog methods in landscape and architectural design. Employing artificial intelligence to determine a concept with a long design process in landscape design offers a paperless solution. Therefore, with the advent of programs that can yield high-quality outputs requiring less time and skill compared to CAD programs, artificial intelligence (AI) is the next frontier in digital design technology. Although there is limited research on the potential use of AI in landscape architecture, AI is an emerging technology in this field (Ardhianto et al., 2023; Li & Amoroso, 2023).

AI systems serve a wide range of purposes in our everyday life. AI systems, which could initially offer limited solutions, appear to push the boundaries of technological developments in the field of machine learning (ML) and perform similarly to the human mindset. It is difficult to forecast what the future holds for various AI applications, particularly in the fields of art and design; that said, their use is becoming popular over time. It is apparent that the number of users that benefit from AI software generating images from text is rapidly increasing thanks to its convenience (Aslan & Aydın, 2023). That text-to-image systems have a simple and intuitive basis helps the user direct the system through a text, and the system responds by generating a new image. By using words, the user can determine the simplicity, complexity, and style of the prompt on the system, which can either imitate anything the user dictates or create imaginary ideas. AI applications allow users to control the final image to improve outputs or use specific terminology to make adjustments, enabling users to interact with AI applications with unlimited possibilities in T2I (Fernandez, 2022). Hanafy (2023) argues that the application of T2I in architecture is utilized in the earliest stages of design, allowing the architect to quickly create a visual representation of design concepts with a text-based prompt. It is also noted that this situation allows the architect to explore a wide range of possibilities and iterate on different design approaches.

Li and Amoroso (2023) state that digital design technologies play a dominant role in visual communication in landscape architecture, and technological advancements in AI, along with graphic software, represent the next frontier in digital image creation. However, they emphasize that little information is available about the potential of AI in generating visuals in the field of landscape architecture. Additionally, they compared images produced by AI applications such as DALL-E 2 and NVIDIA GauGAN2 and evaluated them by landscape architecture experts to investigate whether they can compete with visualization methods used in the education process and by professionals. Fernberg and colleagues (2023) mention that creating 2D assets for design renderings in landscape architecture and generating only a few images with minimal customization is a very time-consuming task. In the study conducted by these researchers, a comparative evaluation of applications was performed using generative AI applications such as DALL-E 2, MidJourney, and Stable Diffusion to create a 2D asset library.

Concept development, which is the beginning of the design process, is a sub-process where important details are determined to be included in the design and followed from the start to the end of the design process. In this process, the design approaches to be developed according to the requests involve a time-consuming process depending on the competencies of the designer. Employing text-to-image AI applications in carrying out the process quickly and accurately raises many questions. How professionally accurate and aesthetically satisfying are the visuals produced by AI? Can it comprehend the professional terminology of landscape architecture properly? And how does it relate to the overall situation in landscape architecture? The current study addresses these questions, aiming to evaluate the images created by T2I-producing AI applications such as DALL-E, MidJourney, LookX, and mnml from the perspective of the landscape architecture profession.

1. What is Artificial Intelligence (AI) and What Are Its Types?

In recent years, AI has garnered significant attention due to advancements in computer hardware, the amount of available data, computer network speed, and processing algorithms. However, there is considerable ambiguity regarding what AI conceptually means as well as its scope (Enholm et al., 2022). In the general sense, the reference point for the definition of AI is the functionality of the human brain.

Intelligence can be defined as an individual's ability to reason, understand concepts, solve problems, and learn effectively. Mental and emotional abilities allow an individual to adapt to their environment, adjust to changes, and make informed decisions using existing knowledge (Morandin-Ahuerma, 2022). AI, on the other hand, is a field of science and engineering concerned with developing systems that exhibit characteristics of human intelligence such as natural language processing, problem-solving, planning, learning, perception, adaptation, and responding to the environment (Tecuci, 2012).

The search for an artificial copy of man is not a new idea. The history of artificial intelligence dates back to Ancient Greek period before Crist. In ancient Greece, Daedelus, who ruled the wind in mythology, was seen developing the idea of creating artificial humans and ideas about humanoid robots. In addition, the definition of the human thought system by philosophers and Charles Babbage's work on a mechanical machine that exhibits human-like intelligent behavior in 1884 is an important work in terms of taking the first steps for modern artificial intelligence. However, as a result of these studies, Babbage decided that a machine that could exhibit human-like intelligent behavior could not be produced and stopped his work (Mijwel, 2015).

In 1950, the question raised by Alan Turing, "can machines think?" had a significant impact on computer science and other scientific fields. The concept of AI was first used in a research workshop held at Dartmouth College in New Hampshire in 1956 (Howard, 2019). Twice in the field of AI, financial shortcomings resulted in a period of stagnation known as "AI Winter", during which investment and interest in AI research were reduced. However, in subsequent periods, success achieved in machine learning, the increase in the quality, scale, and the computational power of data sets led to the successful performance of AI systems that were able to impress humans, which increased interest and confidence in this field (Jiang et al., 2022).

In the past few years, machine learning (ML), a subclass of AI, has garnered significant interest due to increased data accessibility and advancements in computational power, making it one of the most widely used methods. ML is built and trained based on mathematical models to have the ability to learn from a specific data set, produce predictions, determine relationships, and make inferences; this informed training aims to enhance machine intelligence, which means systems can operate without being explicitly programmed to automatically produce predictions for test examples (Enholm et al., 2022; Minh et al., 2022). ML systems can be categorized into four groups: supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning (Enholm et al., 2022).

Supervised learning involves training data with target values and is based on comparing the calculated output with the expected output. This type of learning identifies patterns based on the training data and derives its own rules from the labeled data. Unsupervised learning, on the other hand, does not include a target training pattern. In fact, the system learns autonomously by exploring and adapting based on the input pattern (Das et al., 2015; Enholm et al., 2022). Semi-supervised learning uses both labeled and unlabeled data together, whereas reinforcement learning does not learn from past data but from feedback obtained through interactions with an external environment (Enholm et al., 2022). Deep learning (DL), the most popular subset of ML, mimics the human brain's ability to process data and patterns to make decisions (Minh et al., 2022).

Deep neural networks, following the neural network architecture, are neuron network models consisting of several parameters and layers between input and output. DL is, therefore, referred to as deep neural networks. DL automatically learns data features and represents them hierarchically. This powerful structure provides superiority over traditional ML methods. The initial layers simply process the input data, and this first output then goes to the upper layer where more complex features are learned. Therefore, DL is well-suited for handling larger data and complexity (Sharma et al., 2021). DL is increasingly used in fields such as computer vision (CV), the Internet of Things (IoT), and natural language processing (NLP) (Minh et al., 2022).

2. Text-to-Image Generation (T2I)

Visual content provides more comprehensive, accurate, and understandable ways of sharing and understanding information compared to written texts, offering efficient, effective, and original methods of communication (Agnese et al., 2019). Through hearing or reading, people visualize stories, creating mental images. Visualizing and making sense of the complex relationship between the visual world and language is a natural process for humans. Inspired by the human mind's visualization ability, creating a system that understands the relationship between vision and language and can generate visuals that reflect the meaning of text descriptions is a significant leap toward creating intelligence similar to human intelligence (Frolov et al., 2021).

Although T2I, which aims to create images from text, is an emerging field, it is a part of computer vision and machine learning that has seen significant progress in recent years within the AI domain. The goal here is to create an automatic model that can understand the representation of words and produce image outputs accordingly by defining visual elements with rich text descriptions (Agnese et al., 2019; Tan et al., 2023). Large-scale AI models are gaining increasing attention due to the success of T2I generation through data sets (Gafni et al., 2022).

Generative models developed in the field of machine learning have become significant and popular due to their applicability in various fields. These models can be utilized in natural language, music, video, image processing, and other academic areas due to their ability to represent sophisticated and high-dimensional data (Hong et al., 2019). In particular, text-to-image AI applications such as Disco Diffusion, OpenAI's DALL-E, MidJourney, Stable Diffusion, and Google's Imagen (Figure 1) have generated great interest. In AI systems, a language-vision model is employed to understand the '*prompt*' text that guides users in producing high-quality outputs (Lyu et al., 2022). Image generation modeling, which had been a fundamental problem in the field of computer vision, has made significant advancements with the emergence of DL techniques. Variational Autoencoders (VAEs) are probabilistic models used to maximize the lower bound of data likelihood. Autoregressive models, on the other hand, have produced attractive synthetic images by modeling the conditional distribution in the pixel space (Zhang et al., 2017).

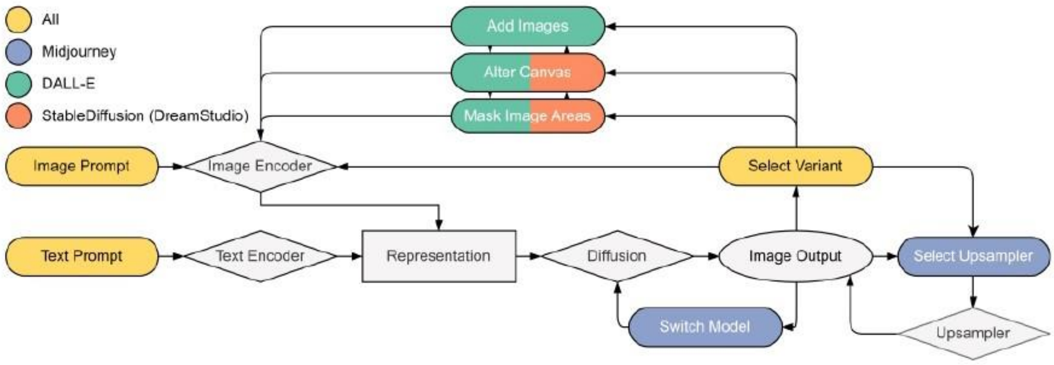

Figure 1. T2I Architecture of Different AI Models (Tanugraha, 2023)

The significant advancements in DL are not confined to classification-based problems. Generative models, a broad research area, stand out with new technical achievements. The idea of using encoder/decoder architecture has regained importance with Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs). They are followed by diffusion models, which have recently emerged (Żelaszczyk & Mańdziuk, 2024).

Researchers employ generative models in developing unsupervised learning to reduce the human supervision and the number of samples required for the system to learn. The most popular approach in generative modeling is GANs, which typically rely on the relationship between two machine learning models (Goodfellow et al., 2020). GANs are among the powerful generative models capable of producing realistic-looking samples with a random z vector, and they do not require knowing an explicit real data distribution or any prior mathematical assumptions (Gui et al., 2023). Relying on a wide range of applications including text-to-image generation, image completion, future prediction, 3D models, and videos, GANs provide a cutting edge in fields such as computer vision, image processing, and sequential data, making them the most successful models in image processing and computer vision (Zhu et al., 2017; Gui et al., 2023).

Diffusion models based on text embedding sequences, which do not contain classifiers, are a class of generative models that sample from a learned data distribution by denoising Gaussian noise conditionally on class labels, text, or low-resolution images (Saharia et al., 2022). VAE defines data generation using a probabilistic distribution through Variational Bayesian Inference. Unlike traditional autoencoders, VAEs have an additional sampling layer, along with an encoder and a decoder layer (Bengesi et al., 2023). Although GANs, VAEs, and Diffusion are some of the most popular options for text-to-image generation, it is also possible to create models that do not rely on these methods (Żelaszczyk & Mańdziuk, 2024).

In 2021, the release of OpenAI's CLIP marked a significant technical advancement in the field of text-to-image generation. CLIP, as a pre-trained language-vision model, allows for zero-shot image manipulation guided by text prompts. When used as a discriminator in a generative system, CLIP directs the generator to synthesize digital images. Currently, many programs such as DALL-E 2 and Stable Diffusion use CLIP for text encodings (Lyu et al., 2022).

In the field of computer vision, pre-trained visual models, trained on large-scale image datasets, are able to extract rich semantic information and understand the content of images (Wang et al., 2023). Advances in deep learning have significantly contributed to computer vision applications and image processing techniques. One of these advancements has emerged in the field of image synthesis, which involves the creation and manipulation of images. Inspired by visualizations envisioned in the human mind, conditional image synthesis can be achieved using an intuitive interface and text descriptions (Frolov et al., 2021). The development of purpose-built systems in the field of AI over the years and the discovery of new techniques are bringing a new dimension to the T2I field. Additionally, it facilitates direct communication and interaction between humans and AI, offering the possibility of use for various purposes in many professional disciplines as well as daily life. AI provides time-saving applications that users can benefit from, such as simplifying daily life and making effective use of time.

3. Artificial Intelligence Applications from Text-to-Image

With advancements in AI technology, the T2I production technique is expected to become a more important tool in the field of architecture. Through T2I production, AI is significantly transforming the function of visualizing people's ideas (Hanafy, 2023). Alongside advancements in AI, various systems have been introduced and continue to be developed. The applications used in this study for text-to-image generation include DALL-E, MidJourney, LookX, and mnml, and this section discusses the features of the systems used.

3.1. DALL-E

Generative Artificial Intelligence (GAI) programs have become a trend with text-based image generators, particularly in 2022. After the release of the AI tool called DALL-E by OpenAI research laboratory, AI technology has enabled users to automatically generate images within seconds using text commands, which has garnered significant interest from users (Enjellina et al., 2023). One of the remarkable features of DALL-E is its ability to produce a wide range of representations, from photorealistic depictions of objects and environments to more abstract, stylized images. Therefore, it can yield results in creative fields such as design, art, and illustration (Hanafy, 2023).

3.2. MidJourney

MidJourney offers an independent research domain aimed at exploring new realms of thought and expanding human imagination. Established by developers with a focus on design, humans, and AI, MidJourney has its own website but uses the Discord application to obtain results (Tanugraha, 2023).

3.3. LookX

LookX, as a highly advanced AI rendering tool for early concept work, assists architects in creating initial design ideas by uploading reference images or samples (Makarouni, 2024). The LookX AI company, utilizing its expertise in advanced technologies, aims to facilitate the use of AI technology by architectural design practitioners by addressing human-computer interaction with its approach to architectural design (LookX, 2024). LookX, with the aid of deep learning, allows users to generate visuals for projects with parameters including style, cost, requirements, and arrangements (Anonymous, 2023).

3.4. Mnml

Mnml offers many features that transform creative concepts and sketches into remarkable designs in the field of architecture. With its powerful AI algorithms, mnml allows users to easily redesign interior or exterior spaces and create different design variations within seconds (Graff, 2023). Offering various AI rendering tools in the architecture discipline, mnml also facilitates the production of architectural visuals using T2I.

4. Prompt Engineering in Artificial Intelligence

Developments in deep generative systems have made it possible to create high-quality media such as music, images, and text. These advancements are becoming increasingly important for creative fields by enhancing the potential for collaborative and dynamic co-creative processes between AI systems and humans (Dang et al., 2022). Prompt engineering, the process of adapting text-based inputs to AI models, plays a crucial role in this process. The quality of the prompt entered in AI tools like ChatGPT is of great importance for obtaining relevant, accurate, and detailed responses. As the importance of studies in this field increases, it is evident that the skills and expertise in prompt engineering are not confined to any specific discipline or profession (Lund, 2023). Prompt engineering, the practice of writing text for generative systems, is also known as prompting, prompt design, or prompt programming (Oppenlaender, 2023).

Prompt engineering emerges as a crucial technique by combining inputs with additional context to provide parameter efficiency and enhance the capabilities of pre-trained visual-language models (VLMs) and large language models (LLMs) (Wang et al., 2023; Sahoo et al., 2024). It involves the strategic and systematic design and optimization of prompts that give instructions to guide AI models for task-specific outputs without altering their parameters. This technique ensures accuracy, relevance, and consistency in model outputs through carefully crafted instructions. Consequently, it enables models to specialize in various tasks and fields, unlocking the full potential of AI models and making them accessible and applicable across diverse areas, thereby opening doors to a future filled with possibilities (Chen et al., 2023; Sahoo et al., 2024).

A prompt is a set of instructions provided to a large language model (LLM) that allows for its customization, capability enhancement, or improvement. By providing specific rules and guidelines, a prompt can influence the interaction with the LLM and the generated output. It establishes the context of the conversation, informing the LLM of what information is important and how the form or content of the desired output should be. Although a prompt can be defined in many different ways, creating a language that accurately and comprehensively defines all the nuanced ways a prompt can be constructed is challenging (White et al., 2023). Therefore, it is crucial for users to understand the impact of prompts.

In an AI model, the practitioner typically runs a prompt and, after observing the results, adapts the prompt to improve the output. Therefore, prompt engineering is an iterative process. The emerging community in this field has discovered that adding specific keywords to text input prompts can enhance the aesthetic quality and appeal of images. These terms can be referred to as 'style phrases,' 'clarifying keywords,' 'vitamin phrases,' or 'prompt modifiers.' By adding these prompt modifiers to the text input, the goal is to steer the text-to-image synthesis in a particular direction and modify the output (Oppenlaender, 2023).

In AI models, prompt engineering is based on several key principles for effectively guiding the processing and production of prompts. These principles include clarity and precision, contextual information, the desired format, and controlling the length of the words. These principles directly impact the performance of generative AI models and form the basis of effective prompt engineering. Understanding and applying the technical foundations of these principles can optimize human-AI interaction (Lo, 2023). Therefore, it is essential to know the nuances of prompt writing within the context of prompt engineering for establishing proper interaction between humans and AI (Table 1).

Table 1. Shaping the Requests (Chen et al., 2023; Lin, 2024)

Giving Instructions	Comprehensive prompts should be created to obtain more precise and relevant outputs. Providing clear and step-by-step instructions in large-scale tasks reduces ambiguity and indecisiveness in the model.
Being Open and Clear	To produce the desired output, clear and specific prompts need to be provided. Clearly stating the objectives and constraints helps guide the model in the right direction.
Role-prompting	Assigning a specific role, such as that of an assistant or expert, allows the model to provide specialized feedback and different perspectives by mimicking these roles.
Use of Symbols to Distinguish	Dividing different sections of a prompt or using multi-line sequences allows the model to better understand the instructions.
Trying a few times / Resampling	Running the model multiple times with the same instructions helps reduce natural variability in the responses, leading to higher quality outputs.
Zero-Shot and Few-Shot Prompting	A one-shot prompt involves providing a single example for the model to learn from, whereas a few-shot prompt provides multiple examples. Giving instructions with concrete examples is an effective approach.
Specify The Preferred Response Format	Specifying the desired formatting (such as meter, tone, etc.) helps limit the possible outputs and enhances the connection to the instructions.
Requesting A Large Number of Options	Requesting multiple options from the models increases diversity in the outputs.

Korzynski et al. (2023) have stated that prompt engineering is a competency similar in structure to digital literacy and is necessary for success in the field of modern technology. Many researchers emphasize that competence in prompt engineering could be a significant area that can distinguish experts in different fields (as cited in, Lund, 2023).

5. Materials and Method

AI, with its relatively recent history, is evolving by establishing relationships with various professions. AI's innovative approaches in the professional domain have revolutionized workflows, adding new dimensions to areas such as data analysis, problem-solving, recommendation systems, and media production. This study examines questions such as the professional accuracy and aesthetic satisfaction of AI-generated images, whether AI applications correctly understand landscape architecture terms, and the overall relationship between AI and landscape architecture.

This is a qualitative study aiming to evaluate text-to-image AI applications from the perspective of the landscape architecture profession. The research has investigated how AI perceives and visualizes professional terms used in landscape architecture. The study consists of four phases (Figure 2). In the first phase, an extensive literature review was conducted on the concept of AI, visual production with Text-to-Image, techniques for generating visuals from text using AI, and prompt writing. In the stages following this point, the authors seek answers to the research questions put forward as the subject of the study. In the second phase, professional terms used in landscape architecture were identified. In the third phase, prompts were written, input were entered into AI applications, and outputs were obtained. In the final phase, the obtained visuals were evaluated. To identify the professional terms, 50 terms were selected based on Pouya (2020)'s book 'Technical English for Landscape Architects', and six different prompt texts were prepared: green roof, coastal landscape area, wetland, residential garden, cultural landscape area, and public space.

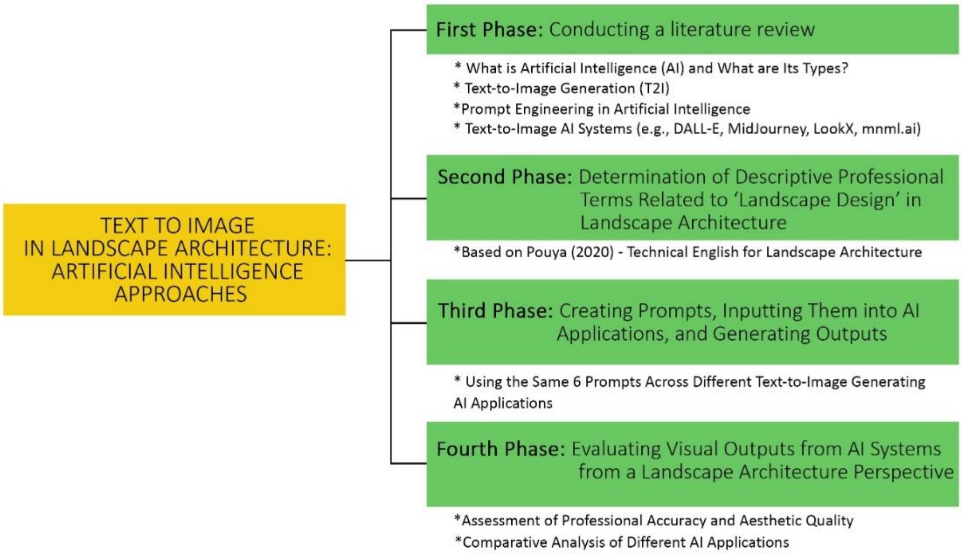

Figure 2. Text to Image in Landscape Architecture: Artificial Intelligence Approaches Study Scheme

After completing the preparation phases, the AI applications DALL-E, MidJourney, LookX, and mnml were purchased as full versions to obtain and evaluate the text-to-image outputs. The outputs obtained from the same prompt input were evaluated in terms of their success in understanding and visualizing landscape architecture terms, which was followed by the evaluation of the integration of text-to-image AI systems into the landscape design process and the more effective use of this technology in the professional field.

6. Determining Descriptive Professional Terms Related to "Landscape Design" in Landscape Architecture

One of the most critical aspects of text-to-image generation, a field with high human-AI interaction, is the prompts created by the designer or user. This section focuses on the creation of the necessary prompts to obtain outputs from AI applications. Using Pouya (2020)'s book "Technical English for Landscape Architects," 50 professional terms were identified (Figure 3) and six different concept prompts were prepared (Table 2). The terms identified are key concepts in shaping landscape design projects.

Figure 3. Professional Terms Shaping Designs in Landscape Architecture (Created by the author using Pouya, 2020)

There are various and comprehensive study topics in the field of design within landscape architecture. Therefore, six topics were selected for the creation of prompts on specific subjects: green roof (P1), coastal landscape area (P2), wetland (P3), residential garden (P4), cultural landscape area (P5), and public space (P6). Using the identified professional terms (Figure 3), prompts specific to these topics were created. While preparing the prompts, Table 1 was utilized, specific terminologies were used for detailing, and texts (Table 2) were prepared to guide the AI. The texts were prepared in a comprehensive, clear, and precise manner, with the professional terms used indicated in bold.

Table 2. Prompts Generated for Selected Topics

Prompt Code	Written Prompts
P_1	A modern, creative, innovative **green roof**, **urban landscape design** with high **visual aesthetics and quality**. Use **formal form walkways** and **hard landscape** elements. Recreational areas with **urban furniture** appropriate to the **human scale**. Create **attractive** and colourful **children's playgrounds**, **sports areas**, **recreation areas** and **rest areas**. Creative, colourful, **planting designs** in **natural forms**. **In vegetation design**, design with **evergreen shrubs**, **deciduous trees** with effective habitus appearance. High quality, realistic visuals.
Terms used	*Green roof, urban design, visual quality, aesthetics, formal form, walkway, hardscape, recreation area, urban furniture, human-scale, visual appeal (attractive), playground, sports area, naturalistic form, evergreen, shrub, deciduous tree.*
P_2	A modern, creative, innovative, **urban space** **landscape architecture** project with high **visual aesthetics and quality** along the **coastal landscape area** with a **sustainable and ecological design** approach. **Pedestrian roads** and **outdoor designs** in **informal and symmetrical form**. Use **permeable paving materials granite cube stone** for paths. Modern, grey, medium and dwarf scale **lighting design**. In **green areas**, create creative and eye-catching **rain gardens** that **manage rainwater**. High quality, realistic visuals.
Terms used	*Urban design, urban space, visual quality, aesthetics, coastal landscape, sustainable landscape design, ecological, pedestrian roads, outdoor design, informal form, symmetrical design, permeable floor, lighting design, green space, rain garden, rainwater management.*
P_3	A creative, **high visual aesthetic and quality** **landscape design** in an ecologically important **wetland** and **rural area**. Design **aquatic plants** in and around the **pond**, wooden **pedestrian paths** surrounding the pond, resting areas on wooden pedestrian paths and **urban furniture** in these areas. Design lines should be created with **natural forms**. **Shade trees**, **evergreen shrubs** and herbal designs should be created. A natural, calming, nature-integrated environment. High quality, realistic visuals.
Terms used	*Aesthetic, visual quality, landscape design, wetland, rural, aquatic plant, pond, pedestrian path, furniture design, natural form, tree, evergreen, shrub.*
P_4	A modern, aesthetically, creatively designed villa and **garden landscape design** on the **high slopes of the mountain**, in the forest. On the lowest floor of the house there will be a terrace and **a large garden**. Let the **soft landscape area** be more than the **hard landscape area**. **A water feature** created with **natural forms**, **walkways** in **formal form**. **Arid landscape** design, **ornamental plants**, natural environment. High quality, realistic visuals.
Terms Used	*Garden, landscape design, softscape, hardscape, water element, naturalistic form, walkway, arid landscape, ornamental plant.*

P_5	**Cultural area**, **rural area**, **historical ruins**. **Cultural landscape design**, **walkway paths**, **planted green spaces**, resting areas, high modern observation terraces surrounding the area with historical ruins. **Landscape design** in harmony with the historical texture. Creative, **aesthetic**, accentuating **rain gardens**, **green infrastructure** design in **green areas**, in harmony with the historical texture. Colourful herbal design. **Lighting and urban furniture design**, high **visual aesthetics and quality** in design. *High quality, realistic visuals.*
Terms Used	*Cultural area, cultural landscape, rural area, walkway, planted space, landscape design, aesthetic, rain garden, green infrastructure, green area, lighting design, furniture design, visual quality.*
P_6	A creative, aesthetic and modern design of a **pedestrian path** in a **city park** **a natural form** of medium width, **allee design** with **palm trees** along the path. **Deciduous plants and ornamental plants**. Wooden seating areas suitable for **human scale** along the path. Around **water element** and **aquatic plants**. A built environment, **aesthetic and high quality** area with a high artistic approach, suitable for **public space**. *High quality, realistic visuals.*
Terms Used	*Pedestrian road, park, natural form, allee, deciduous plant, ornamental plant, human scale, water element, aquatic plant, aesthetic, visual quality, public space.*

The thoughts desired or envisioned by the designer for each topic are provided in detail within the prompts. Unlike the LookX and mnml applications, there is no word limit for prompt texts in the AI applications DALL-E and MidJourney. The mnml application allows for a prompt entry of 70 words. Therefore, to obtain accurate data and enable comparison of the programs, all prompts were created with a limit of 70 words.

In the designs to be created by AI applications, it is desired to generate creative ideas for landscape design projects and produce visually high-quality and realistic outputs. In the coastal area landscape design (P2), the use of 'granite cobblestone' as a permeable surface in the design was specifically requested. When it comes to the public space landscape design (P6), the use of the plant 'palm tree (Washington filifera)' was particularly requested in the planting design.

7. Artificial Intelligence from Text-to-Image (T2I) in Landscape Architecture

In this section of the study, the prompts generated for six different design topics in landscape architecture (Table 2) were used to produce images for landscape design through the T2I method in AI applications such as DALL-E, MidJourney, LookX, and mnml. The images generated were evaluated in terms of professional accuracy, visual aesthetics, creativity, and the technical details of the AI application. Additionally, the images produced by different AI applications were compared and analyzed.

The prompts created in Table 2 were sequentially entered into the AI applications, and outputs were obtained. When examining the images created with Prompt 1 (P1) (Figure 4) in terms of scale, the spatial and linear values of the landscape design were clearly readable in the outputs obtained from the DALL-E and mnml applications. In the prompts and prompt texts entered, DALL-E was the application that clearly responded to the prompts "use formal form walkways and hard landscape elements" and "create attractive and colorful children’s playgrounds, sports areas, recreation areas, and rest areas"; this was not fully observed in the other applications.

Figure 4. Visuals of AI applications with Prompt 1 (P1)

The general concept of "green roof" in the images was clearly perceived by DALL-E (12.21 sec) and mnml (19.91 sec). However, this concept was not clearly perceived in MidJourney (40.67 sec) and LookX (1 min 55 sec) due to the visual perspective created by these applications. In terms of plant design, the prompts were correctly reflected in the images produced by DALL-E, MidJourney, and LookX. While these AI applications provided visual aesthetics in plant design, the mnml application fell behind in this aspect.

Having examined the visuals generated with Prompt 2 (P2) (Figure 5) and the requests in the given prompt, it was observed that the visuals produced by LookX (1 min 1 sec) and mnml (19.59 sec) applications did not fully meet the desired outputs; therefore, they were excluded from the evaluation. When it comes to the visuals produced by DALL-E (11.65 sec) and MidJourney (40.18 sec) in terms of scale, it was observed that the spatial and linear values of the landscape design project produced by DALL-E were clearly readable.

Figure 5. Visuals of AI Applications with Prompt 2 (P2)

The terms used and the prompt texts entered showed that the 'coastal landscape area' prompt had slight impact on the generated visuals; however, terms like 'granite cube stone', 'informal and symmetrical form', and 'lighting design' were clearly visible in both visuals. The 'rain gardens' prompt was addressed in the visual created by DALL-E but not in the one created by MidJourney. There was no specific request regarding the planting design. However, the use of plants in the design approach, such as 'rain gardens', was creatively implemented by the AI applications in both visuals. Particularly, the visual created by MidJourney stood out in terms of design and detail for the paving element 'granite cube stone' as well as other materials.

As for the visuals created using Prompt 3 (P3) (Figure 6) within the wetland concept framework, all AI applications perceived requests such as 'wooden pedestrian paths surrounding the pond', 'rural area', and 'aquatic plants' accurately. The visuals produced by DALL-E (18.52 sec) and MidJourney (39.19 sec) included representations responding to the 'resting area' and 'urban furniture design' prompts, whereas these prompts were not addressed in the visuals produced by LookX (55.30 sec) and mnml (20.13 sec). In all visuals, the 'aquatic plants' prompt was met with the use of the Nymphaea sp. (Lotus) plant.

Figure 6. Visuals of AI Applications with Prompt 3 (P3)

In the visuals created within the framework of the residential garden concept using Prompt 4 (P4) (Figure 7), a landscape design in a sloped forest area was requested, and all AI applications created outputs compatible with this request. However, none of the applications generated visuals that adequately represented the specified natural water forms. Specifically, the 'arid landscape' approach was requested for the plant design, and while strong plant design outputs were obtained from the DALL-E (11.28 sec), MidJourney (40.50 sec), and LookX (1 min 59 sec) applications, weak plant design outputs were obtained from the mnml (20.58 sec) application.

Figure 7. Visuals of witApplications with Prompt 4 (P4)

It is important to properly interpret and resolve terrain plasticity in landscape design. Therefore, DALL-E and MidJourney offer high-level terrain solutions in sloped areas, while LookX and mnml offer low-level solutions. Furthermore, regarding the responses to the concepts of 'softscape' and 'hardscape,' the desired proportions in the visuals according to the prompt 4 text are not clearly perceived in the MidJourney and mnml applications.

The visuals created using Prompt 5 (P5) are provided in Figure 8 below. The DALL-E (11.05 sec) application produced a visual that reflected all the requested concepts. In MidJourney (42.68 sec), despite the inclusion of the 'historical ruins' request, the generated visuals did not display the remnants of historical structures. However, technical landscape solutions for a sloped area were provided. In the LookX (2 min 12 sec) and mnml (19.47 sec) applications, historical ruins were depicted as restored and open for use. Overall, the visuals generally used structural materials and compatible plants suitable for the historical context. The 'lighting design and furniture design' requests were not included in the visuals produced by applications other than DALL-E.

Figure 8. Visuals of AI Applications with Prompt 5 (P5)

As for Prompt 6 (P6), all AI applications were requested to create visuals (Figure 9) of a pedestrian path in a public park area using natural forms. However, the visuals produced by the applications except for LookX (1 min 01 sec) showed the paths in a formal form. Regarding the seating elements requested along the path, only a single seating element was present in the visual produced by mnml (20.26 sec). The concepts of 'water element' and 'aquatic plant' mentioned in the text were fully understood and accurately rendered by DALL-E (12.98 sec); the other applications, however, did not produce accurate outputs for these concepts.

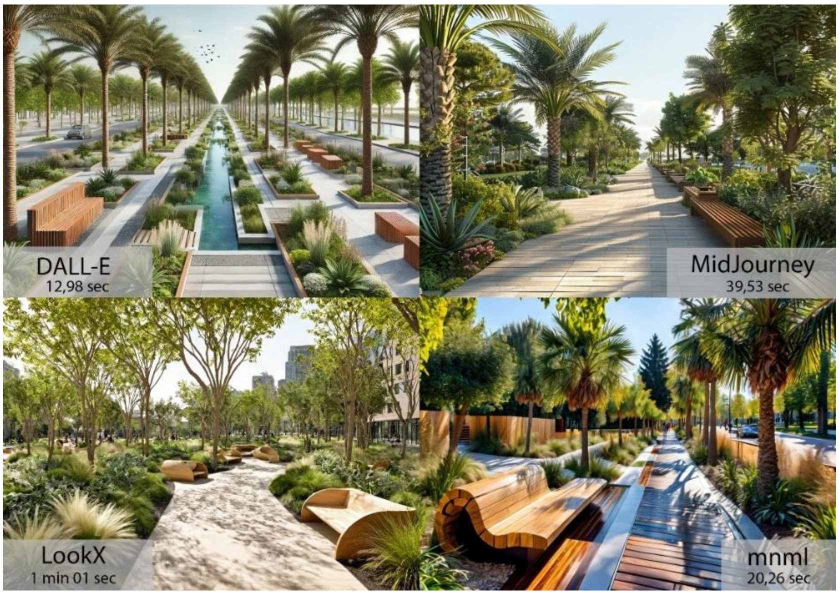

Figure 9. Visuals of AI Applications with Prompt 6 (P6)

In terms of landscape design, an 'allee' design with the use of the same type of trees opposite each other was requested to support structural line values and create emphasis. The Washington filifera (Palm) plant was particularly specified for this design. In line with these requests, accurate outputs were obtained from the DALL-E, MidJourney, and mnml applications, whereas the LookX application did not produce an accurate output.

Landscape designs were created using Text-to-Image methods in AI applications with prompt texts formed using landscape architecture professional terms, as visually presented above. DALL-E, MidJourney, LookX, and mnml stand out respectively considering the visuals obtained in terms of visual creativity. From a technical standpoint, MidJourney and LookX provide the highest quality and most realistic visuals. However, regarding the production times of the prompts (Table 2) across the AI applications, the order from fastest to slowest is DALL-E, mnml, MidJourney, and LookX.

8. Discussion

It is critical for designers to keep up to date with the developments in the field of design. Recently, artificial intelligence has emerged as a very interesting topic in academic and professional studies. Especially the creation of the desired designs by AI tools in a short time by providing inputs with text prompts has attracted attention. In this study, the functioning process of the process of generating images from text with artificial intelligence in the professional discipline of landscape architecture was investigated. At the same time, the correct understanding of the terms in the professional framework by AI tools was investigated. Within the scope of the research, prompt texts were created over different spatial concepts with professional terms determined by the authors. The created prompts were visualized by the authors using DALL-E, Midjourney, LookX and mnml tools that produce images with T2I method.

The success of the material obtained from AI tools depends on the appropriate transfer and interpretation of the values associated with the professional discipline (Sağlık and Minkara, 2024). Since there is no exact consistency of the language spoken in AI tools, there is a possibility that the algorithm may make mistakes in understanding the architectural description and generating visuals (Hanafy, 2023). Accordingly, the keywords in the developed prompt texts were associated with the images. The findings of the study showed that the terms in the professional discipline of landscape architecture are not fully understood by AI tools. Although this result differs from the results of Li (2023)'s study on AI and landscape architecture, it supports this finding obtained within the scope of the study. Li (2023) stated that terms such as 'biodiversity' and 'mixed-use development' are not fully understood by AI tools.

In addition, Li (2023) stated that although the visuals produced with DALL-E 2 received high scores from the participants in the surveys conducted within the scope of the study, it could not produce a landscape project plan at the scale of a park or neighborhood. This was clearly seen when the visuals produced within the scope of this study examined. If terms such as 'plan' or 'bird's eye view' were not used in the prompts, it was seen that projects were produced from different perspectives in the visuals obtained from the AI tools used.

When creating prompts, it is of great to use text that is purposeful, precise and fully reflects the content (Benliay and Kılıç, 2024). However, in order to accurately evaluate the responses of AI tools to the same text, the AI tool named 'mnml' was created with a limit of 70 words. While this situation constitutes the limitation of the study; in future studies, the quality of the outputs produced by AI tools that produce images from text in line with this limitation should be questioned.

The role of AI tools in landscape architecture design processes should be examined in more detail in the future. In particular, its integration with human creativity, the stages of design and the contribution of AI-generated visuals to decision-making processes are important.

The findings show that AI-based tools are not yet sufficiently developed in landscape architecture. However, with the right guidance and advanced algorithms, it is possible for these tools to contribute more to design. Specific datasets and training materials can help AI to interpret professional terms more accurately. Furthermore, new methods to improve the interaction between landscape architects and AI systems should be explored and training processes for the use of AI-based tools should be strengthened.

CONCLUSION:

In a continuously developing and transforming world, it is crucial to keep up with technology and adapt to changes. The concept of 'artificial intelligence,' which has gained increasing popularity in recent years, has come to the forefront in many professional disciplines. One of the advancements in the field of AI is Text-to-Image (T2I) generation, which offers 'highly captivating' and intriguing visuals in the fields of art and design. Therefore, the main objective of this study is to reveal the relationship between T2I and the profession of landscape architecture. Four different AI applications with T2I capability were selected to do so. While the DALL-E and MidJourney applications stand out in art and visual production, the LookX and mnml applications offer different architectural visualization methods.

Seventy-word prompts containing professional terms regarding landscape architecture were created for the selected AI applications. The outputs obtained from the AI applications were analyzed in terms of professional suitability, visual aesthetics, creativity, and technical details of the AI applications. As a result of these analyses:

- When evaluating the generated landscape design visuals in terms of creativity, the DALL-E application stands out. This is followed, in decreasing order, by MidJourney, LookX, and mnml.
- In terms of technical quality and authenticity, the MidJourney and LookX applications offer high-quality and realistic visuals. Although DALL-E outweighs these two applications in producing creative outputs, MidJourney and LookX outperform DALL-E in visual quality and authenticity. Mnml, on the other hand, has yielded he lowest performance in this aspect.
- Regarding the time required to generate the visuals, the applications have been ranked from fastest to slowest as follows: DALL-E, mnml, MidJourney, and LookX.
- As a result of the analyses, it would be improper to suggest that the AI applications do not precisely perceive the selected professional terms. The AI applications visualized abstract concepts such as 'visual quality', 'aesthetics', 'sustainable landscape design', and 'ecological'. However, they failed to clearly visualize advanced technical terms like 'rain management', 'rain garden', and 'green infrastructure'.
- DALL-E stands out in lighting and furniture design, while these details are less prominent in other AI applications. The LookX and mnml applications, in particular, lack such details.
- When a specific plant is not specified in the plant design, it is difficult to make precise identifications of the plant species used in the visuals. However, the usage areas of some plants, their habitus appearance, flowers, etc., can help identify the plant species through their dendrological features.

In the applications and analyses conducted, when terms like 'plan' or 'bird's eye view' were not used in the prompts entered into the AI applications, the generated visuals showed a specific point of the project. An exception to this is DALL-E, which presents landscape projects on a larger scale among the applications included in this study. However, it should be noted that prompts are open to development. In this study, single-time text entries were employed to obtain outputs from the AI applications. Moreover, the LookX and mnml applications have word limits for prompt texts, whereas DALL-E and MidJourney do not have such restrictions. Therefore, more detailed visuals can be produced by elaborating on the prompt texts.

In conclusion, the visuals obtained from AI applications are satisfactory in terms of professional accuracy and aesthetics, and they can greatly assist in creative concept studies in landscape projects. Along with the technical solutions included in the visuals, they provide designers with many details such as color, texture, and form of the materials used in structural and plant landscape design, thus providing the pathways to follow in the design process. However, it has been observed that some terms did not yield clear responses. In this context, landscape architects can improve prompts to produce desired visuals and contribute to the development of applications by collaborating with professionals working in the AI field. Based on the findings in this study, it is evident that the relationship between T2I applications and landscape architecture is still in its early stages and there is significant potential for development in producing more creative, high-quality, and elaborate visuals.

Compliance with the Ethical Standard

Conflict of Interest: *The author(s) declare that they do not have a conflict of interest with themselves and/or other third parties and institutions, or if so, how this conflict of interest arose and will be resolved, and author contribution declaration forms are added to the article process files with wet signatures.*

Ethics Committee Approval: *Ethics committee approval is not required for this study.*

Financial Support: No financial support has been received for this article.

Acknowledgments: *There is no person or organization to thank.*

REFERENCES:

Agnese, J., Herrera, J., Tao, H. & Zhu, X. (2019). A survey and Taxonomy of Adversarial Neural Networks for Text-to-image Synthesis. *WIREs Data Mining and Knowledge Discovery.* https://doi.org/10.1002/widm.1345.

Anonymous (2023, August). *Mimarların ve Tasarımcıların Bilmesi Gereken 10 Yapay Zeka Uygulaması*. XXI. https://xxi.com.tr/i/mimarlarin-ve-tasarimcilarin-bilmesi-gereken-10-yapay-zeka-uygulamasi.

Ardhianto, P., Santosa, Y. P., Moniaga, C., Utami, M. P., Dewi, C., Christanto, H. J., Chen, A. P. S. (2023). Generative Deep Learning for Visual Animation in Landscape Design. *Hindawi Scientific Programming*. https://doi.org/10.1155/2023/9443704

Aslan, T. & Aydın, K. (2023). Metinden Görüntü Üretme Potansiyeli Olan Yapay Zekâ Sistemleri Sanat ve Tasarım Performanslarının İncelenmesi. *Ondokuz Mayıs University Journal of Faculty of Education, 42*(2), 1149-1198. https://doi.org/10.7822/omuefd.1293657.

Benliay, A. & Kılıç, A. (2024). Peyzaj Tasarımı Sunum Tekniklerinde Yapay Zeka Uygulamalarının Değerlendirilmesi*. PEYZAJ – Eğitim, Bilim, Kültür ve Sanat Dergisi. 6*(1), 1-14. DOI: 10.53784/peyzaj.1490265

Bengesi, S., El-Sayed, H., Sarker, M., Houkpati, Y., Irungu, J., & Oladunni, T. (2023). Advancements in Generative AI: A Comprehensive Review of GANs, GPT, Autoencoders, Diffusion Model, and Transformers. *IEEE Access, 12*, 69812-69837.

Chen, B., Zhang, Z., Langrene, N., & Zhu, S. (2023). Unleashing the Potential of Prompt Engineering in Large Language Models: A Comprehensive Review. *ArXiv.*

Dang, H., Mecke, L., Lehmann, F., Goller, S., & Buschek, D. (2022). How to Prompt? Opportunities and Challenges of Zero- and Few-Shot Learning for Human-AI Interaction in Creative Applications of Generative Models. *ArXiv*.

Das, S., Dey, A., Pal, A. & Roy, N. (2015). Applications of Artificial Intelligence in Machine Learning: Review and Prospect. *International Journal of Computer Applications, 115*(9), 31-41.

Denerel, S. B. & Birişçi, T. (2019). A Research on Landscape Architecture Student Use of Traditional and Computer-aided Drawing Tools. *Amazonia Investiga, 8*(24), 373-385.

Enholm, I. D., Papagiannidis, E., Mikalef, P. & Krogstie, J. (2022). Artificial Intelligence and Business Value: a Literature Review. *Information Systems Frontiers. 24*, 1709-1734. https://doi.org/10.1007/s10796-021-10186-w

Enjellina, Beyan, E. V. P. & Rossy A. G. C. (2023). A Review of AI Image Generator: Influences, Challenges, and Future Prospects for Architectural Field. *Journal of Artificial Intelligence in Architecture, 2*(1), 53–65. https://doi.org/10.24002/jarina.v2i1.6662

Fernandez, P. (2022). Technology Behind Text to Image Generators. *Library Hi Tech News*, *10*, 1-4. http://dx.doi.org/10.1108/LHTN-10-2022-0116

Fernberg, P., George, B. H. & Chamberlain, B. (2023). Producing 2D Asset Libraries with AI-powered Image Generators. *Journal of Digital Landscape Architecture, 8*, 186-194. 10.14627/537740020

Frolov, S., Hinz, T., Raue, F., Hees, J. & Dengel, A. (2021). Adversarial Text-to-Image Synthesis: A Review. *Neural Networks, 144*, 187 – 209. https://doi.org/10.1016/j.neunet.2021.07.019

Gafni, O., Polyak, A., Ashual, O., Sheynin, S., Parikh, D., & Taigman, Y. (2022). Make-A-Scene: Scene-Based Text-to-Image Generation with Human Priors. *ArXiv*.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. & Bengio, Y. (2020). Generative Adversarial Networks. *Communications of the ACM*, *63*(11), 139-144. http://dx.doi.org/10.1145/3422622

Graff, D. (2023, 6 November). *"mnml.ai: Redefining Architectural Design with AI-Powered Innovation"*. Artificial Intelligencepedia. https://artificialintelligencepedia.com/mnml-ai-redefining-architectural-design-with-ai-powered-innovation/.

Gui, J., Sun, Z., Wen, Y., Tao, D. & Ye, J. (2023). A Review on Generative Adversarial Networks: Algorithms, Theory, and Applications. *IEEE Transactions on Knowledge and Data Engineering*, *35*(4), 3313- 3332. 10.1109/TKDE.2021.3130191

Hanafy, N. O. (2023). Artificial Intelligence's Effects on Design Process Creavitiy: "A Study on Used A.I. Text-to-Image in Architecture". *Journal of Building Engineering, 80*, 107999. https://doi.org/10.1016/j.jobe.2023.107999

Hong, Y., Hwang, U., Yoo, J., & Yoon, S. (2017). How Generative Adversarial Networks and Their Variants Work. *ACM Computing Surveys (CSUR), 52*, 1 - 43.

Howard, J. (2019). Artificial Intelligence: Implications for the Future of Work. *American Journal of Industrial Medicine*, *62*: 917-926. 10.1002/ajim.23037

Jiang, Y., Li, X., Luo, H., Yin, S. & Kaynak, O. (2022). Quo Vadis Artificial Intelligence?. *Discover Artificial Intelligence*, *2*, 4. https://doi.org/10.1007/s44163-022-00022-8

Li, M. (2023). Designer Robots: An Early Look at Applications for Artificial Intelligence Visualization Software in Landscape Architecture. *Master Thesis*. The University of Guelph, Canada.

Li, M. & Amoroso, N. (2023). An Early Look at Applications for Artificial Intelligence Visualization Software in Landscape Architecture. *Journal of Digital Landscape Architecture*, 543 – 553. 10.14627/537740057.

Lin, Z. (2024). How to write Effective Prompts for Large Language Models. *Nature Human Behaviour 2024*(8), 611–615. https://doi.org/10.1038/s41562-024-01847-2.

Lo, L. S. (2023). The Art and Science of Prompt Engineering: A New Literacy in the Information Age. *Internet Reference Services Quarterly*, *27*(4), 203–210. https://doi.org/10.1080/10875301.2023.2227621

LookX (2024, 18 June). *About Us*. URL: https://www.lookx.ai/about.html

Lund, B. (2023). The Prompt Engineering Librarian. *Library Hi Tech News, 8*(40), 6-8. https://doi.org/10.1108/LHTN-10-2023-0189.

Lyu, Y., Wang, X., Lin, R. & Wu, J. (2022). Communication in Human–AI Co-Creation: Perceptual Analysis of Paintings Generated by Text-to-Image System. *Applied Sciences, 12*(22), 11312. https://doi.org/10.3390/app122211312.

Makarouni, E. (2024, 18 June). *Tech for Architects: 7 Top AI Tools for Architectural Rendering and Visualization. Architizer.* https://architizer.com/blog/practice/tools/top-ai-tools-for-architectural-rendering-visualization/.

Minh, D., Wang, H. X., Li, Y. F. & Nguyen, T. N. (2022). Explainable Artificial Intelligence: A Comprehensive Review. *Artificial Intelligence Review*, (55), 3503-3568. https://doi.org/10.1007/s10462-021-10088-y.

Mijwel, M. M. (2015). History of Artificial Intelligence. *Computer Science,(April 2015)*, 3-5.

Morandin-Ahuerma, F. (2022). What is Artificial Intelligence? *International Journal of Research Publication and Reviews, 3*(12), 1947 – 1951.

Oppenlaender, J. (2023). A Taxonomy of Prompt Modifiers for Text-to-Image Generation. *Behaviour & Information Technology*, 1–14. https://doi.org/10.1080/0144929X.2023.2286532

Pouya, S. (2020). *Technical English for Students of Landscape Architecture*. Malatya: İnönü University Publisher.

Sağlık, A. & Minkara, E. B. (2024). Perception in Human Pyschology and Landscape Prioritised Visualisation of Space with Artificial Intelligence*. Journal of Architectural Sciences and Applications, 9*(2), 831 – 843. https://doi.org/10.30785/mbud.xxxxx

Saharia, C., Chan, W., Saxena, S., Li, L., Whang, J., Denton, E.L., Ghasemipour, S.K., Ayan, B.K., Mahdavi, S.S., Lopes, R.G., Salimans, T., Ho, J., Fleet, D.J., & Norouzi, M. (2022). Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding*. ArXiv*.

Sahoo, P., Sahoo, P., Singh, A. K., Saha, S., Jain, V., Mondal, S., & Chadha, A. (2024). A Systematic Survey of Prompt Engineering in Large Language Models: Techniques and Applications. *ArXiv*.

Sharma, N., Sharma, R. & Jindal, N. (2021). Machine Learning and Deep Learning Appliacations-A Vision. *Global Transitions Proceedings*, *2*, 24-28. https://doi.org/10.1016/j.gltp.2021.01.004

Tan, Y.X., Lee, C.P., Neo, M., Lim, K.M., Lim, J.Y., & Alqahtani, A. (2023). Recent Advances in Text-to-Image Synthesis: Approaches, Datasets and Future Research Prospects. *IEEE Access*, 11, 88099-88115.

Tanugraha, S. (2023). A Review Using Artificial Intelligence-Generating Images: Exploring Material Ideas from MidJourney to Improve Vernacular Designs. *JARINA – Journal of Artificial Intelligence in Architecture*, *2*(1), 48 – 57.

Tecuci, G. (2012). Artificial Intelligence. *WIREs Comput Stat, 2012*; 4: 168-180. 10.1002/wics.200

Wang, J., Liu, Z., Zhao, L., Wu, Z., Ma, C., Yu, S., Dai, H., Yang, Q., Liu, Y., Zhang, S., Shi, E., Pan, Y., Zhang, T., Zhu, D., Li, X., Jiang, X., Ge, B., Yuan, Y., Shen, D., Liu, T. & Zhang, S. (2023). Review of large vision models and visual prompt engineering. *Meta-Radiology*, *2023*(1), 100047. https://doi.org/10.1016/j.metrad.2023.100047.

Waterman, T. (2009). *The Fundamentals of Landscape Architecture*. AVA Academia the Environment of Learning.

White, J., Quchen, F., Hays, S., Sandborn, M., Olea, C., Gilbert, H., Elnashar, A., Spencer-Smith, J. & Schmidt, D. C. (2023). A Prompt Pattern Catalog to Enhance Prompt Engineering with ChatGPT. ArXiv. https://doi.org/10.48550/arXiv.2302.11382.

Żelaszczyk, M., & Ma'ndziuk, J. (2024). Text-to-Image Cross-Modal Generation: A Systematic Review. ArXiv.

Zhang, H., Xu, T., Li, H., Zhang, S., Wang, X., Huang, X., & Metaxas, D.N. (2017). StackGAN: Text to Photo-Realistic Image Synthesis with Stacked Generative Adversarial Networks. *2017 IEEE International Conference on Computer Vision (ICCV),* 5908-5916.

Zhu, J., Park, T., Isola, P., & Efros, A.A. (2017). Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks. *2017 IEEE International Conference on Computer Vision (ICCV)*, 2242-2251.