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AI Models in Interpreting Basic Design Elements and Principles

Temel Tasarım Ögelerini ve İlkelerini Yorumlamada Yapay Zekâ Modelleri

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ABSTRACT

This study addresses the challenge of evaluating how effectively artificial intelligence (AI) models can interpret and visualize basic design principles and elements—a skill essential in creative disciplines such as art and design education. The core aim is to examine whether AI-generated visual outputs can reflect a deliberate understanding of design concepts, particularly within abstract symmetrical and asymmetrical compositions. To explore this, the study analyzes the performance of 18 widely used text-to-image AI models, based on five design principles—rhythm, movement, contrast, emphasis, and balance—and five design elements—dot, line, shape, color, and texture. Each model was prompted to generate compositions aligned with these criteria, and the outputs were evaluated based on three primary criteria: understanding the design elements, understanding the design principles, and understanding the balance. Scores ranged from 1 (least accurate) to 5 (most accurate), and averages were calculated for comparative analysis. The results revealed that while models like Microsoft Designer and DALL-E occasionally produced strong outputs, they lacked consistency across different balance types. In contrast, models such as Craiyon and Flux.ai consistently underperformed. Notably, high scores in asymmetrical balance often inflated overall averages, masking deficiencies in design comprehension. The study concludes that symmetrical balance serves as a more reliable indicator of AI proficiency and emphasizes the need for holistic evaluation frameworks. These findings offer valuable insights for integrating AI tools into design education and assessing their pedagogical potential.

Keywords: Artificial intelligence models, design elements, design principles, visual composition.

ÖZ

Bu çalışma, yapay zekâ (YZ) modellerinin temel tasarım ilkeleri ve öğelerini yorumlama ve görselleştirme becerilerini değerlendirme sorunsalına odaklanmaktadır. Araştırmanın temel amacı, YZ modellerinin ürettiği görsel çıktılarda tasarım kavramlarını bilinçli biçimde yansıtıp yansıtamadığını incelemektir; özellikle soyut, simetrik ve asimetrik kompozisyonlar bağlamında. Bu kapsamda, çalışma kapsamında ritim, hareket, kontrast, vurgu ve denge gibi beş tasarım ilkesi ile nokta, çizgi, şekil, renk ve doku gibi beş tasarım öğesine dayalı olarak 18 yaygın metinden-görüntüye YZ modeli değerlendirilmiştir. Her modele yapılandırılmış yönergeler verilmiş, modellerin ürettiği görseller şu üç temel kritere göre değerlendirilmiştir: tasarım öğelerini anlama, tasarım ilkelerini anlama ve dengeyi anlama. Her çıktı 1 (en düşük) ile 5 (en yüksek) arasında puanlanmış ve ortalamalar alınarak model performansı analiz edilmiştir. Bulgular, Microsoft Designer ve DALL-E gibi modellerin zaman zaman başarılı çıktılar ürettiğini, ancak bu başarıların dengeli ve tutarlı olmadığını ortaya koymuştur. Craiyon ve Flux.ai gibi modeller ise çoğunlukla düşük performans sergilemiştir. Özellikle asimetrik denge üzerinden alınan yüksek puanlar, bazı modellerin tasarım anlayışındaki eksiklikleri maskelemektedir. Çalışma, simetrik dengenin gerçek yeterliliği ölçmede daha güvenilir bir kriter olduğunu vurgulamakta ve YZ modellerinin tasarımsal değerlendirmelerinde bütüncül bir yaklaşıma ihtiyaç duyulduğunu önermektedir. Bu sonuçlar, YZ araçlarının tasarım eğitimi süreçlerine entegrasyonu ve pedagojik açıdan değerlendirilmesi için önemli bir zemin sunmaktadır.

Anahtar Kelimeler: Yapay zekâ modelleri, tasarım öğeleri, tasarım ilkeleri, görsel kompozisyon.

Introduction

Basic design, also known as the fundamentals of design, forms the foundation of any visual composition. It encompasses essential principles and elements that guide the creation of aesthetically pleasing and functionally effective designs. The elements of design include line, shape, form, space, texture, value, and color (Ching, 1979), which serve as the building blocks of any visual representation. The principles of design, such as balance, contrast, emphasis, movement, pattern, rhythm, and unity (Ching, 1979), are the guidelines that determine how these elements are combined to create a cohesive and harmonious composition. These principles and elements are integral to the design process, providing structure and ensuring that the outcome communicates the intended message effectively.

In design education, particularly at the foundational level, abstract compositions are widely employed to introduce students to core principles and elements. Scholars have emphasized that such exercises not only provide a formal visual language but also cultivate essential skills such as observation, decision-making, and aesthetic judgment (Boucharenc, 2006; Öztuna, 2007). Over time, these explorations evolve into more complex outputs including architectural layouts, interior environments, graphic systems, and textile patterns, thereby underscoring the central role of the basic design course as a formative stage in creative training (Birlik, 2012; Esen et al., 2018).

In recent years, artificial intelligence (AI) has begun to reshape both design education and production. Studies note that AI tools are increasingly tested in studio environments not only as generators of visual outcomes but also as potential collaborators in the ideation process (Meron & Araci, 2023; Ringvold et al., 2023). One of the most prominent developments in this area is the use of text-to-image models, where designers input descriptive language and receive visual compositions in return (Oppenlaender, 2022). While these systems perform relatively well in producing representational or figurative content, their capacity to engage with abstract prompts grounded in basic design principles remains underexplored and warrants systematic investigation (Bekhta, 2024; Farrokhnia et al., 2024).

This study addresses that gap by evaluating how effectively AI models can interpret and represent fundamental design principles and elements within abstract compositions, particularly in symmetrical and asymmetrical layouts. In doing so, it asks a core pedagogical question: can AI simulate the kind of formal sensitivity and intentionality that students are expected to develop through basic design education?

To explore this, 18 different text-to-image AI models were prompted with structured descriptions combining design elements and principles. Their outputs were assessed using three criteria: understanding the design elements, understanding the design principles, and understanding the balance. The findings are interpreted not only in terms of model performance but also in terms of the broader implications for creative education.

The remainder of this paper is structured as follows: the next section provides a review of basic design and its educational role, followed by a discussion on abstract art as a conceptual framework. This is followed by a methodological explanation of how AI outputs were evaluated, the presentation of findings, and a final section offering a critical discussion and conclusions for both practice and pedagogy.

Basic Design: Elements and Principles

Basic design is an essential course taught during the initial years of art and design education. In German, it is referred to as “Grund Gestaltungslehre” and holds a significant place in art education (Güngör, 1983). The primary aim of this course is to enhance students’ design abilities and help them translate artistic thought into practice (Ertok Atmaca, 2014). It was first defined as a systematic educational program by Walter Gropius at the Bauhaus School in 1919 (Gök, 2019). Bauhaus aimed to merge art and craft to produce more functional and aesthetic products (Birlik, 2012). The Industrial Revolution in the 18th century marked a shift in the understanding of art and design, combining aesthetic concerns with functionality to create new design approaches. Bauhaus became the most concrete example of this transformation, laying the foundation for modern design. Over the years, basic design education has spread worldwide, becoming an indispensable part of art education (Atalayer, 2004).

Basic design education not only develops students' perception, observation, and creativity skills but also equips them with a design language. It also involves learning various practical techniques (Aytekin, 2008). Students learn to create compositions by using the basic elements and principles of design, a process that includes both theoretical and practical education (Çetin, 2002). Basic design courses not only enhance students’ creativity but also improve their material usage, technical knowledge, and aesthetic understanding. As such, it is a cornerstone of art and design education (Ertok Atmaca, 2014).

The elements of basic design are the building blocks of a composition (Bal, 2023). These elements form the foundation of visual organization in art and design. Key elements include dot, line, shape, color, texture, tone, and scale (Güngör, 1983). By utilizing these elements, designers create compositions that embody the principles of design.

Dot is the simplest and most fundamental unit of design. Everything begins with a dot, serving as the first step of a design. A dot can create a sense of stillness or movement within a composition. When in motion, it transforms into a line (Atalayer, 1994a). In the initial stages of design, the impact of the dot is significant, as lines form from dots, surfaces from lines, and volumes from surfaces.

Line emerges from the movement of a dot and is a fundamental design element. It is used to convey direction, motion, and form in a composition. Straight, curved, dashed, or wavy lines create different emotional and visual effects (Öztuna, 2007).

Shape defines the outer boundaries of an object. Geometric shapes provide an organized and systematic appearance, while free shapes evoke a more natural and organic perception (Susmuş, 1999). Shapes in design enhance the visual impact of objects, and combining different shapes creates dynamic compositions.

Color strengthens the emotional dimension of a design. According to Doğan (2020), color is perceived based on the wavelength of light reflected from an object. Colors also have various psychological effects on individuals (Tepecik, 2002). For example, warm colors evoke energy and vitality, while cool colors bring calmness and tranquility. The harmonious or contrasting use of colors enhances the aesthetic value of a composition.

Texture describes the visual or tactile characteristics of a surface. According to Çınar and Çınar (2020), natural textures are perceived through touch, while artificial textures are grasped visually. Rough, smooth, soft, or slippery surfaces contribute to the unique textural qualities of objects (Ertok Atmaca, 2014).

Direction refers to the orientation of lines or forms in space (Demircioğlu, 2016). It plays a crucial role in creating movement and dynamism in design. Horizontal directions indicate calmness, vertical directions suggest strength and stability, and diagonal directions represent motion. Combining different directions in a composition prevents stagnation and adds dynamism while enhancing visual interest (Güngör, 1983).

Space defines the distance between elements in a design. Close spacing creates a sense of order, while varied spacing adds dynamism and movement (Araz Ustaömeroğlu, 1998). Proper spacing helps prevent monotony in a design and contributes to visual depth. For example, in an interior space, arranging furniture with specific spacing can create both a sense of order and spaciousness.

Basic design principles provide guidelines for organizing design elements. These principles ensure that a design achieves unity and aesthetic appeal. Principles like rhythm, movement, contrast, emphasis, unity, balance, and harmony bring coherence and meaning to a composition.

Rhythm involves the repetition of design elements in an orderly manner (Ching, 1979). This repetition creates a sense of flow and movement in a composition (Korniienko, 2017). According to Çolak (2004), repetition can take various forms, such as full repetition, variation, or interval repetition. For instance, a symmetrical arrangement of windows on a building's facade establishes rhythm and visual harmony.

Movement adds a dynamic quality to a design. It guides the viewer's gaze through lines, shapes, and colors (Erim, 2011). Movement transforms a design from static to engaging, drawing the viewer into the composition (Demircioğlu, 2016).

Contrast introduces a balance of opposites within a design. The contrast between color, texture, direction, or form grabs attention and enhances visual interest. For instance, using dark and light colors together emphasizes the composition's contrast.

Emphasis creates a focal point in a design. Highlighting one element over others directs the viewer's attention to a specific area, making the design more compelling (Çeken et al., 2018).

Unity ensures that all design elements work together to form a cohesive whole. Harmony among elements enhances the visual order and aesthetic values, creating a unified composition.

Balance ensures that a design appears visually stable and aesthetically pleasing. It is achieved by evenly distributing the visual weight of elements. Balance can be symmetrical or asymmetrical (Araz Ustaömeroğlu, 1998). Symmetrical balance involves equal distribution along a central axis, while asymmetrical balance uses varied elements to create dynamic equilibrium.

Harmony allows design elements to work together seamlessly. Similarities in shape, color, texture, or scale create harmony, resulting in a visually soothing and cohesive design (Bigali, 1999).

Instead of elaborating each concept in lengthy paragraphs, the fundamental elements and principles of basic design are summarized in Table 1. This allows the subsequent sections to focus more clearly on the study's objectives, especially in the influence of abstract art within basic design education.

Table 1.
The fundamental elements and principles of basic design

Category	Concept	Definition / Description
Elements	Dot	The most basic unit in design; creates stillness or initiates movement. Forms the foundation for lines, surfaces, and volumes.
	Line	Emerges from the movement of a dot. Conveys direction, motion, and form (e.g., straight, curved, wavy).
	Shape	Defines object boundaries. Geometric shapes are systematic; organic shapes are natural and expressive.
	Color	Based on light wavelengths. Affects emotional responses; warm colors evoke energy, cool colors suggest calmness.
	Texture	Visual or tactile surface quality. Can be natural (tactile) or artificial (visual).
	Direction	Orientation of forms in space. Horizontal = calm, vertical = strength, diagonal = motion.
	Space	Distance between elements. Impacts order, depth, and visual rhythm in a composition.
Principles	Rhythm	Repetition of elements to create flow and continuity. Can be regular, variable, or interval-based.
	Movement	Guides viewer's eye across the design. Adds visual dynamism.
	Contrast	Juxtaposition of opposites (light/dark, rough/smooth) to enhance attention and visual impact.
	Emphasis	Creates a focal point to highlight an important area of the composition.
	Unity	Ensures all elements contribute to a cohesive whole. Supports visual integrity.
	Balance	Distributes visual weight evenly. Can be symmetrical (formal) or asymmetrical (informal).
	Harmony	Achieved through similarity in shape, color, or texture. Produces a pleasing, consistent composition.

The elements and principles of basic design play a vital role in laying the foundation for artistic creation and providing designers with a method of self-expression. Combining elements like dot, line, shape, and color with principles such as rhythm, movement, contrast, emphasis, and balance results in a visually integrated whole.

The integration of these basic design elements and principles not only shapes the visual language of design but also constitutes the foundation of formal art and design education. As such, understanding how these concepts are introduced and practiced in educational settings is essential. The next section focuses on basic design education, examining how these foundational training is structured pedagogically and how it supports students' development in art and design disciplines.

Basic Design Education

Basic design education serves as the pedagogical extension of fundamental design principles, transitioning abstract concepts into structured learning experiences. Often referred to as *"introductory education"*, *"basic art"*, or *"foundation course"* in international contexts, this stage forms the cornerstone of creative disciplines such as architecture, interior design, and visual arts (Atalayer, 1994b; Boucharenc, 2006).

Introduced in Turkey in the mid-20th century, basic design education emerged as a transformative response to traditional, skill-based instruction, shifting the focus toward visual perception, intuition, and experimentation. Pioneering institutions such as the Istanbul State Academy of Applied Fine Arts (now Marmara University) and Mimar Sinan Fine Arts University institutionalized this pedagogical model by establishing foundational design courses as core components of first-year design curricula (Esen et al., 2018; Marmara University, 2015).

At its core, basic design education aims to cultivate aesthetic sensitivity, develop visual thinking, and enhance students' creative capacities. These goals are pursued through a combination of theoretical instruction and experiential learning. Students engage with design elements such as line, shape, texture, and color through hands-on studio work, gradually developing their ability to construct visual relationships and explore spatial concepts (Besgen et al., 2014; Gürer, 1990). This active process of discovery also fosters cognitive and emotional growth, encouraging learners to articulate their thoughts visually and intuitively.

Beyond the acquisition of technical skills, the pedagogical approach emphasizes the development of individual expression and critical judgment. As Gokaydın (1990) notes, the studio environment provides students with a secure space to test their perceptions and exercise autonomy. This aligns with Matisse's assertion that "creation begins with seeing," reinforcing the idea that artistic production is rooted in perceptual clarity and personal insight.

In interior architecture and related spatial disciplines, basic design courses function as a preparatory framework. Students learn to transfer two-dimensional abstract thinking into three-dimensional design strategies. Studio-based education, which forms the backbone of this process, not only strengthens students' material and formal understanding but also instills foundational habits necessary for professional practice (Denel, 1979; Kaptan, 2003).

The historical lineage of basic design education can be traced back to the Bauhaus School, where Johannes Itten's *Vorkurs* laid the foundation for a systemic and multi-layered pedagogical model. This approach, which integrates material exploration with form-based problem solving, remains influential in contemporary curricula (Boucharenc, 2006; Özkar, 2004). It is within this lineage that modern design programs continue to locate the philosophical and methodological basis of their foundation courses.

Here, art is not only considered as a source of inspiration but also as a pedagogical tool that enhances perceptual skills, conceptual thinking, and expressive freedom. Among the many art forms integrated into design education, abstract art holds particular importance. Its emphasis on visual language, compositional structure, and emotional resonance parallels the goals of basic design training. For this reason, the following section explores the nature and historical development of abstract art, identifying its relevance to foundational design education and its significance in the evaluation framework used in this study.

In sum, basic design education is not merely a technical orientation but a pedagogical philosophy that prioritizes process over product. It gives students the freedom to explore ideas, make mistakes and try again. These abilities are not only essential for learning how to design but also increasingly important for keeping up with evolving technologies such as artificial intelligence. The next section expands this discussion by examining the relationship between foundational art education and the emergence of abstract art practices, situating basic design pedagogy within a broader aesthetic and historical framework.

Art and Abstract Art

Basic design education is not only about form and technique but also about fostering artistic awareness and visual thinking. In this context, art, particularly abstract art, functions as both a conceptual and aesthetic resource. Scholars have emphasized that abstract compositions play a crucial role in foundation studios by enabling students to internalize non-figurative thinking, explore visual balance, and engage with fundamental elements such as color, line, and form beyond representational boundaries (Boucharenc, 2006; Robinson & Pallasmaa, 2015). Historical accounts of abstract art also demonstrate its pedagogical value. Kandinsky (1911/2012) argued that abstraction evokes an "inner necessity" that connects perceptual structures with emotional experience, and Mondrian's neoplasticism highlighted how the reduction to pure lines and colors generates universal compositional harmony (Pippin, 2002). Understanding abstract art and its historical evolution therefore contributes not only to the comprehension of creative processes but also to the cultivation of perceptual sensitivity and aesthetic intentionality in foundational design training.

Art has been a tool for human expression throughout history (Ayas & Dalkılıç, 2023). Humans have developed various creative methods to understand their surroundings and convey this understanding to others. In this context, abstract art stands out as an approach that not only reflects the external appearance of nature but also aims to express the inner world of the individual (Atalay, 2023). Abstract art rejects realistic depictions of objects and instead focuses on creating meaning through elements such as color, form, and line. Michel Souphor defines abstract art as a completely unique form of expression that does not directly mirror reality (Timuroğlu, 2013). Thus, abstract art provides an aesthetic experience while encouraging viewers to engage in personal interpretations.

The relationship between abstract art and other art forms is also significant. This genre is not limited to painting; it has influenced fields such as music, literature, dance, and sculpture (Atalay, 2023). For instance, abstract figures and movements in a dance performance can create an aesthetic experience for the audience. Similarly, abstract poetry can evoke emotions and thoughts independently of the literal meanings of words (Tunalı, 2008). These characteristics, which affect various branches of art, contribute to the recognition of abstract art as a universal language of art.

Abstract art does not aim to represent objects as they are but seeks to convey their essence to reflect emotions and thoughts. Wassily Kandinsky emphasized the connection between music and painting in abstract art, highlighting the impact of colors on individuals. According to him, abstract art creates a vibration in the viewer, which reflects the inner world of the artist (Sezer &

Sezer, 2020). Tunalı (2008) stated that abstract art is grounded in elements like geometry and plasticity and serves as a vital tool for artists to express their ideas. This movement offers an aesthetic experience by distancing viewers from perceptions of reality.

At the core of abstract art lies the freedom of thought. Michel Souphor explained that abstract art does not compel viewers toward a specific interpretation but instead provides a structure open to individual perceptions and emotions (Timuroğlu, 2013). This approach allows abstract art to be interpreted differently by various individuals. Additionally, the components of abstract art include plastic elements such as color, line, form, and composition. These elements are utilized to express the artist's emotions and evoke diverse emotional responses in viewers.

The history of abstract art covers a wide time period, from early human drawings to modern art movements. In prehistoric times, people expressed their environment through simplified shapes and patterns (Kaido, 2021). The abstraction seen in cave paintings demonstrates how people in those eras tried to interpret nature and events around them through a symbolic language. For instance, the drawings in the Lascaux Cave provide insights into the lifestyle and beliefs of prehistoric people.

However, the emergence of abstract art in its modern sense occurred in the early 20th century with pioneering artists such as Kandinsky, Malevich, and Mondrian. Kandinsky's 1911 work "Composition 5" is considered one of the earliest examples of abstract art (Atalay, 2023). This movement prioritized individual creativity and freedom of expression, moving away from figurative representations. In the second half of the 20th century, new movements like abstract expressionism emerged, offering different interpretations of abstract art. For example, Jackson Pollock's action paintings represent a dynamic and energetic side of abstract art.

The historical development of abstract art has manifested differently across geographies and cultures. While geometric and lyrical abstraction flourished in Europe, abstract expressionism gained prominence in America. Additionally, abstract art's influence is evident in Islamic culture, where geometric patterns and abstract forms created an aesthetic language due to the prohibition of figurative representations (Kaido, 2021).

Pioneers like Wassily Kandinsky, Piet Mondrian, and Kazimir Malevich played a critical role in the evolution of abstract art (Pippin, 2002). Kandinsky used color and line as spiritual tools for expression, emphasizing the sensory effects of art on viewers. Malevich initiated the suprematism movement, highlighting the aesthetic power of geometric forms and aiming to construct art on a logical foundation. Mondrian focused on creating pure aesthetics with limited color palettes and vertical-horizontal lines through his neo-plasticism movement (Kaido, 2021). These artists established the fundamental principles of abstract art, inspiring both their contemporaries and future generations.

Other significant representatives of abstract art include Joan Miró, Paul Klee, and Jackson Pollock. Miró combined organic forms and vibrant colors in his works, showcasing the playful side of abstract art. Klee expanded the boundaries of abstract art with his innovative use of line and color. Pollock presented the energetic and dynamic expression of abstract art through his action paintings. These artists share a common characteristic: they prioritize individual creativity and freedom of expression in abstract art.

Additionally, local representatives of abstract art demonstrate its universality. In Turkey, Mübin Orhon emerged as a pioneer of abstract art, producing works in the lyrical abstraction style (Erden, 2013). Orhon's paintings stood out with their mastery of color and light and made significant contributions to the development of Turkish abstract art.

By examining the origins and development of abstract art, as well as its major figures and stylistic directions, we can better understand the visual language that informs basic design education. Abstract art's emphasis on intuition, composition, and individual expression aligns closely with the pedagogical goals of foundation studios. In the context of this research, abstract art provides a conceptual lens for evaluating whether AI models can grasp and generate compositions that mirror the formal and expressive qualities nurtured through early design education.

AI and Text-to-Image

Artificial intelligence (AI) is a field that has its origins in ancient myths but became a formal academic discipline with the development of computer technologies in the 20th century (Haenlein & Kaplan, 2019). AI was first defined at the Dartmouth Conference in 1956, and it started with rule-based systems. It evolved from expert systems seen in the 1980s to deep learning algorithms in the 2010s (Delipetrev et al., 2020). With subfields like machine learning and deep learning, AI has enabled computers to learn from data and perform tasks that would usually require humans (Shaveta, 2023).

AI keeps advancing, and recent technologies like Generative Adversarial Networks (GANs) and diffusion models have produced impressive results. GANs, created by Ian Goodfellow, use two neural networks: one generates images, and the other evaluates them (Goodfellow et al., 2014). These models analyze data patterns and create realistic visuals. Some variants, like StackGAN and AttnGAN, use text inputs for a layered creation process (Zhang et al., 2017; Xu et al., 2018). Diffusion models start with noise and then reverse the process to create detailed features (Dhariwal & Nichol, 2021).

GANs and diffusion models have made a huge impact, especially in creative areas like art and design. GANs can speed up and automate artistic processes by working with pre-trained datasets (Elgammal, 2019). This has allowed artists to explore new creative directions. Techniques like Neural Style Transfer (NST) apply one artist's style to another image, opening up more ways to express art (So, 2018). These systems don't just help human creativity; they can also produce entirely new visual outcomes.

Text-to-image technology is one of the areas where AI has taken creativity and aesthetics to the next level. Systems like CLIP and DALL-E pair text inputs with meaningful visuals (Radford et al., 2021). These models are trained on large datasets from the internet and can generate photorealistic images (Ramesh et al., 2021). Additionally, open-source platforms like Stable Diffusion have made this technology more accessible to a wider audience (Rombach et al., 2022).

These systems have brought new perspectives to artistic creation. Their ability to learn has improved the quality of artistic outputs and challenged traditional ideas of creativity (Elgammal, 2019). NST transfers an artist's style to another image, while DALL-E can create completely new and original designs, pushing creativity further (Russo, 2022; So, 2018). However, the ethical and legal aspects of these technologies are still debated. Critics argue that while some artists' works are used to train these systems, they don't receive any financial compensation (Ghosh & Fossas, 2022).

Today, the most popular AI models for text-to-image generation include DALL-E, Midjourney, and Stable Diffusion. DALL-E stands out for creating impressive images with photorealistic detail from text inputs (Ramesh et al., 2021). Models like Midjourney and OpenAI's DALL-E 3 let users guide the results by using specific terms to change the style or format (Ringvold et al., 2023). Stable Diffusion has gained popularity among both commercial and individual users due to its open-source nature and continues to be developed by a large community (Rombach et al., 2022). While these models allow users to create stunning visuals, concerns about data biases and ethical issues have emerged (Dehouche, 2021).

These systems also have significant social impacts. For instance, text-to-image models have made digital art more accessible to a wider audience (Oppenlaender, 2022). However, issues like dataset biases and ethical concerns force us to rethink the balance between creativity and consumption (Dehouche, 2021). The interaction between artists and these technologies has added new layers to both creative processes and the commercial side of art.

Beyond their technical capabilities, these systems are increasingly being integrated into design education, prompting both opportunities and concerns. As AI tools become more accessible, educators face the challenge of incorporating them meaningfully into curricula while preserving the pedagogical goals of creative training (Meron & Araci, 2023). Several studies have highlighted that while AI platforms like ChatGPT or text-to-image models offer support in ideation and content generation, they still require careful human guidance to produce context-aware and discipline-specific outputs (Farrokhnia et al., 2024). Similarly, Kahraman et al. (2024) observed that in interior design studios, AI can assist in concept development by helping students visualize different material and form combinations, yet it cannot replace the critical and problem-solving skills that design training seeks to cultivate. From an instructional perspective, AI-based platforms have also led to the emergence of new educational strategies such as online design studios, which combine adaptive technologies with interactive learning environments (Tang et al., 2022). These approaches not only remove spatial and temporal constraints but also enhance collaborative and personalized learning. However, scholars caution against overreliance on AI-generated templates, emphasizing the need for educators to maintain creative flexibility and ethical responsibility (Meron & Araci, 2023). In this evolving context, understanding the role of AI in design education becomes essential—not only for evaluating its technical performance but also for assessing its impact on creative development, teaching practices, and the future of design pedagogy.

In conclusion, text-to-image generation technologies are some of the most exciting AI applications today. They have transformed visual production and design, opening new possibilities in creativity, storytelling, and aesthetics. However, ethical concerns and questions about artists' rights require us to think more broadly about these technologies.

Material and Methods

The methodology of this study was systematically designed to ensure a systematic and balanced approach to examining design principles and elements within the constraints of 5 fundamental prompts. These 5 prompts guided the selection of 5 design principles—rhythm, movement, contrast, emphasis, and balance—and 5 design elements—dot, line, shape, color, and texture (Tables 2 and 3). Each principle and element is represented exactly twice across the 5 prompts, and each prompt was then duplicated in both symmetrical and asymmetrical balance versions, resulting in a total of 10 prompts for analysis. This duality ensures a comprehensive examination of balance types, allowing for comparative insights into how symmetrical and asymmetrical layouts impact the representation of design principles and elements in the visual outputs.

The decision to limit the study to exactly 5 principles and 5 elements was made to preserve methodological clarity and rigor. Introducing a sixth design principle would have disrupted the systematic pairing and repetition essential to the study's structure, complicating the balance and diluting the study's focus. By restricting the study to 5 principles and 5 elements, we could ensure that each was consistently represented across the 10 total prompts—5 in symmetrical balance and five in asymmetrical balance—establishing an internal control for reliable comparisons and analysis. This limitation was therefore a deliberate and necessary choice to maintain clarity within the study's parameters, ensuring that the framework remained both manageable and scientifically valid.

Each of the 5 fundamental prompts was designed to explore unique combinations of design principles and elements. By pairing each design principle and element in a distinctive configuration, the prompts avoid redundancy and enhance the visual complexity and analytical depth of each composition. In addition, the symmetrical and asymmetrical versions of each prompt isolate balance as a variable, allowing researchers to observe how different layouts impact the AI's interpretation of design principles and elements. The repetition of each principle and element twice within the five prompts means that they each appear a total of four times across the 10 prompts, creating a type of internal control within the study.

This systematic pairing and repetition not only diversifies the visual outputs but also enhances the scientific rigor of the study. Each instance serves as a comparison point for its counterpart, ensuring that any accurate representation of design concepts is not merely coincidental but supported by repeated results. By providing multiple opportunities for each principle and element to be represented correctly, this structure increases the reliability of conclusions. If the AI accurately interprets a design principle or element in both instances, it strengthens the evidence that the model reliably understands these concepts, which in turn enhances the validity of the study.

Table 2.
Prompts, design elements, design principles, and balances

Prompts	**Design Elements**	**Design Principles**	**Balance**
Generate an abstract square composition in grayscale with **symmetrical** balance, creating **movement** and **rhythm** using **dots** and **lines**. To create the **movement**, use a gradual sequence of increasingly larger dots along diagonal lines that guide the eye across the composition. To create the **rhythm**, arrange different rows of small and large dots along parallel horizontal lines, mirroring these rows symmetrically on either side of the axis.	Dot Line	Movement Rhythm	Symmetrical
Generate an abstract square composition with **symmetrical** balance, creating **emphasis** and **unity** using **shapes** and **colors**. To create the emphasis, use orange color to fill a circle shape with a group of identical purple squares colored in different shades on a light green surface. To create the unity, group the different shaded purple squares and the orange circle right in the middle in a radial symmetry.	Shape Color	Emphasis Unity	Symmetrical
Generate an abstract square composition with **symmetrical** balance, creating **emphasis** and **contrast** using **textures** and **colors**. To create the **emphasis**, position a dense arrangement of large **dots** at the **center** of the composition. To create the **contrast**, place contrasting layers of rough and smooth **textures symmetrically** around the **dots**, increasing the **contrast**.	Texture Color	Emphasis Contrast	Symmetrical
Generate an abstract square composition in grayscale with **symmetrical** balance, creating **movement** and **unity** using **lines** and **shapes**. To create the **movement**, arrange diagonal lines that vary subtly in thickness as they extend across the composition, directing the eye outward. To create the **unity**, repeat geometric shapes, like circles and squares, placed symmetrically along these lines to form.	Line Shape	Movement Unity	Symmetrical
Generate an abstract square composition in grayscale with **symmetrical** balance, creating **rhythm** and **contrast** using **dots** and **textures**. To create the **rhythm**, arrange rows of dots in alternating sizes along horizontal lines, repeating this pattern symmetrically across the composition. To create the **contrast**, use distinct textures, such as rough and smooth surfaces, placed in alternating sections around the dotted areas to increase the visual contrast.	Dot Texture	Rhythm Contrast	Symmetrical
Generate an abstract square composition in grayscale with **asymmetrical** balance, creating **movement** and **rhythm** using **dots** and **lines**. To create the **movement**, position a series of dots that gradually increase in size, placed along non-uniform diagonal lines to lead the eye across the composition in an unpredictable path. To create the **rhythm**, arrange alternating rows of small and large dots along irregularly spaced horizontal lines, varying the density of dots across different areas to establish a dynamic, uneven rhythm.	Dot Line	Movement Rhythm	Asymmetrical
Generate an abstract square composition with **asymmetrical** balance, creating **emphasis** and **unity** using **shapes** and **colors**. To create the emphasis, use orange color to fill a circle shape with a group of identical purple squares colored in different shades on a light green surface. To create the unity, group the different shaded purple squares and the orange circle as if they were parts of a whole.	Shape Color	Emphasis Unity	Asymmetrical
Generate an abstract square composition with **asymmetrical** balance, creating **emphasis** and **contrast** using **textures** and **colors**. To create the **emphasis**, position a bold, dark **textured** area in deep red slightly off-center to draw immediate attention. To create the **contrast**, arrange surrounding zones with different smooth textures in muted beige and rough textures in dark brown.	Texture Color	Emphasis Contrast	Asymmetrical
Generate an abstract square composition in grayscale with **asymmetrical** balance, creating **movement** and **unity** using **lines** and **shapes**. To create the **movement**, arrange diagonal lines of varying thicknesses in an irregular pattern, guiding the eye across different areas of the composition. To create the **unity**, repeat geometric shapes, like circles and squares, positioned unevenly along these lines to create a dynamic structure.	Line Shape	Movement Unity	Asymmetrical
Generate an abstract square composition in grayscale with **asymmetrical** balance, creating **rhythm** and **contrast** using **dots** and **textures**. To create the **rhythm**, arrange rows of dots in alternating sizes along irregular, unevenly spaced horizontal lines, establishing a rhythmic pattern across the composition. To create the **contrast**, use distinct textures, such as rough and smooth surfaces, placed in irregular sections around the dotted areas to increase the contrast.	Dot Texture	Rhythm Contrast	Asymmetrical

Table 3.
Design elements' and design principles' count in prompts

Balance	Design Elements	Count	Design Principles	Count
Symmetrical	Dot	2	Rhythm	2
	Line	2	Movement	2
	Shape	2	Contrast	2
	Color	2	Unity	2
	Texture	2	Emphasis	2
Asymmetrical	Dot	2	Rhythm	2
	Line	2	Movement	2
	Shape	2	Contrast	2
	Color	2	Balance	2
	Texture	2	Emphasis	2

Visual Outputs

In this study, AI models such as MidJourney, DALL-E, and Adobe Firefly are capable of generating multiple visual outputs for a single prompt. To ensure consistency and accuracy in the evaluation, the research team selected the most accurate visual output based on the criteria of "understanding the elements," "understanding the principles," and "understanding the balance." Each selected visual output was deemed the most representative of the corresponding design elements and principles.

Table 4 presents the selected visual outputs for each model for symmetrical balance. Table 5 presents the selected visual outputs for each model for asymmetrical balance.

Table 4.
Visual outputs in different AI models - symmetrical balance

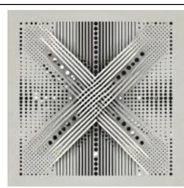
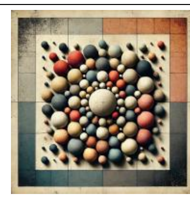
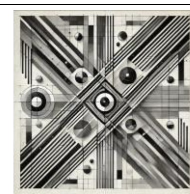
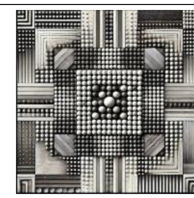
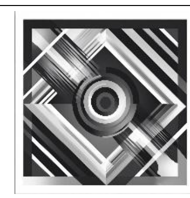
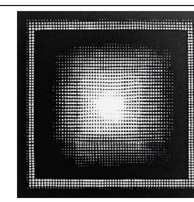
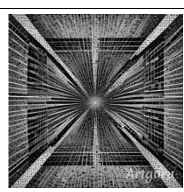
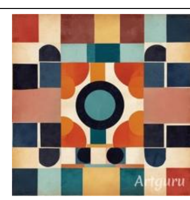
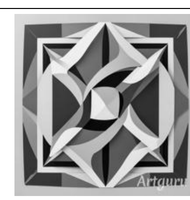
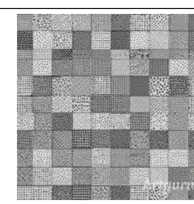
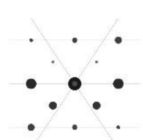
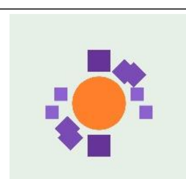
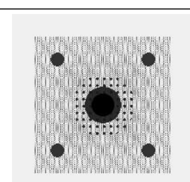
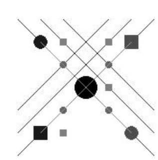
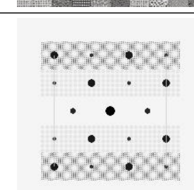
AI Model	Visual Output 1	Visual Output 2	Visual Output 3	Visual Output 4	Visual Output 5
DALL-E					
MidJourney					
Artguru					
Claude					

Table 4.
Visual outputs in different AI models - symmetrical balance (Continued)

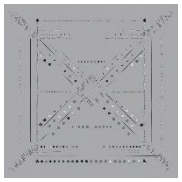
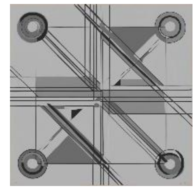
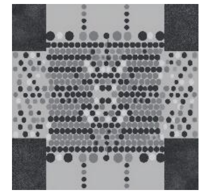
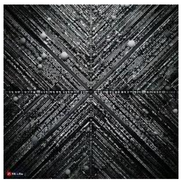
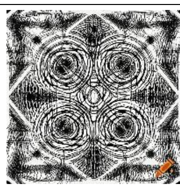
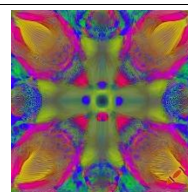
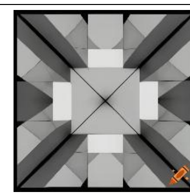
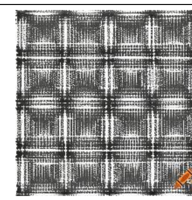
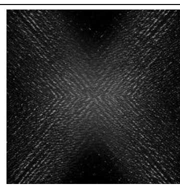
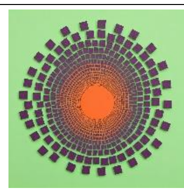
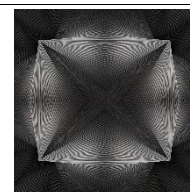
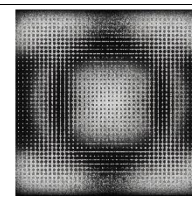
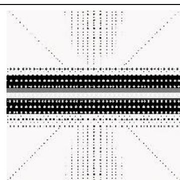
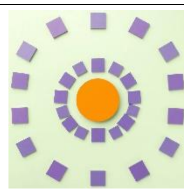
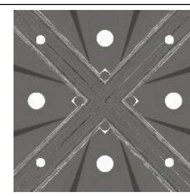
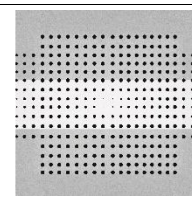
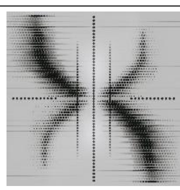
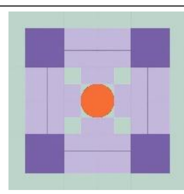
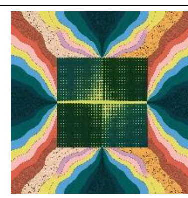
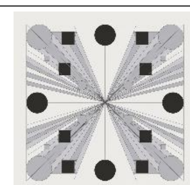
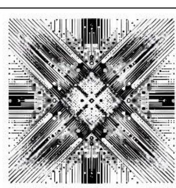
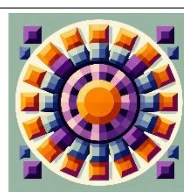
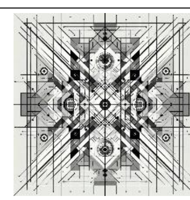
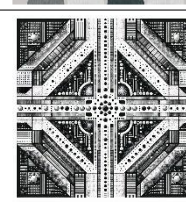
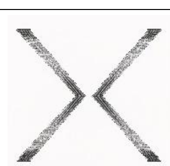
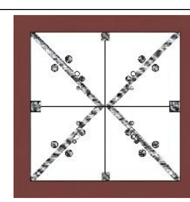
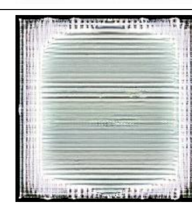
Leonardo.ai					
Adobe Firefly					
Craiyon					
Gemini					
Gencraft					
Ideogram					
Microsoft Designer (Dall-E 3)					
Openart (Stable Diffusion 3.0)					

Table 4.
Visual outputs in different AI models - symmetrical balance (Continued)

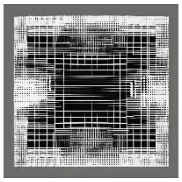
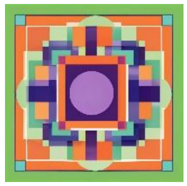
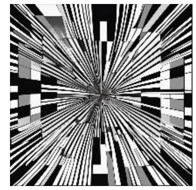
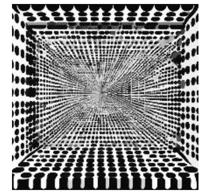
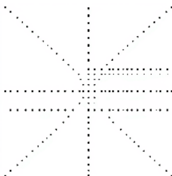
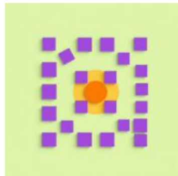
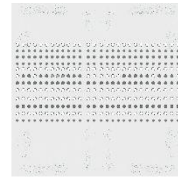
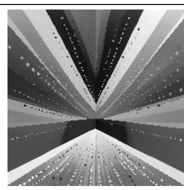
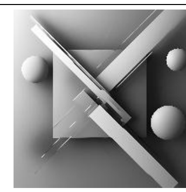
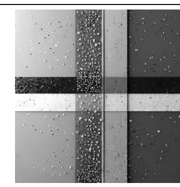
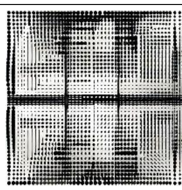
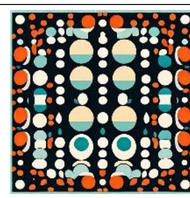
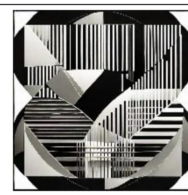
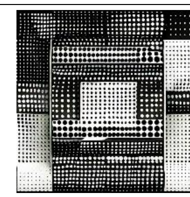
Pixlr					
Flux.ai					
Kling.ai					
Runway					

Table 5.
Visual outputs in different AI models - asymmetrical balance

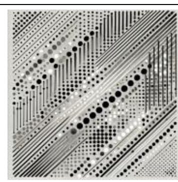
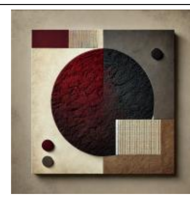
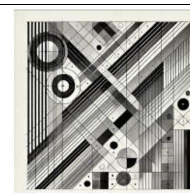
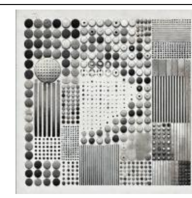
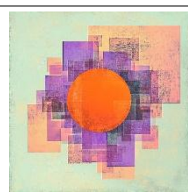
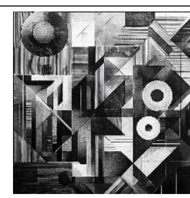
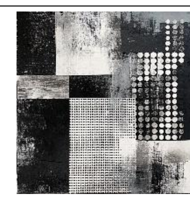
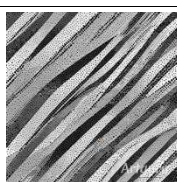
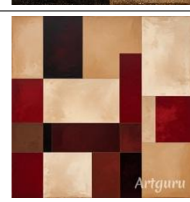
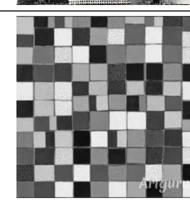
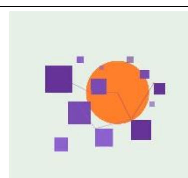
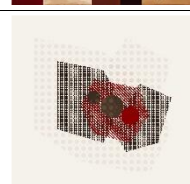
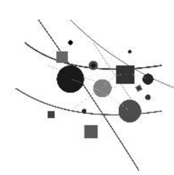
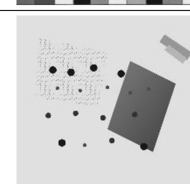
AI Model	Visual Output 1	Visual Output 2	Visual Output 3	Visual Output 4	Visual Output 5
DALL-E					
MidJourney					
Artguru					
Claude					

Table 5.
Visual outputs in different AI models - asymmetrical balance (Continued)

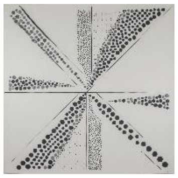
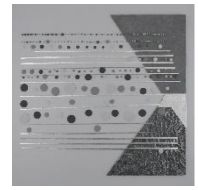
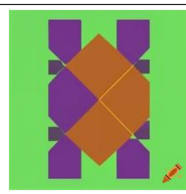
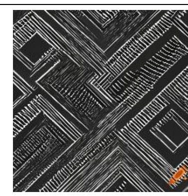
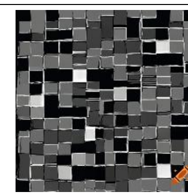
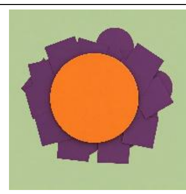
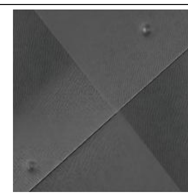
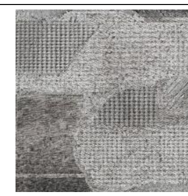
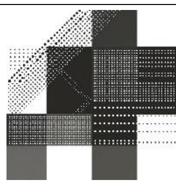
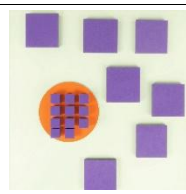
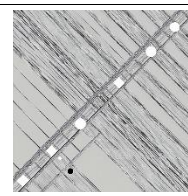
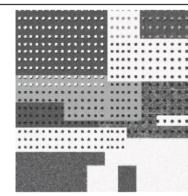
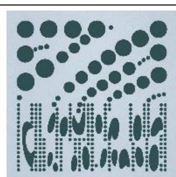
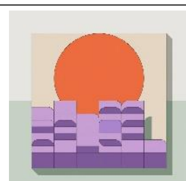
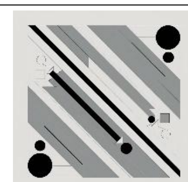
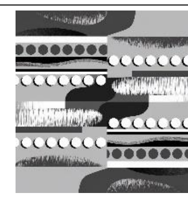
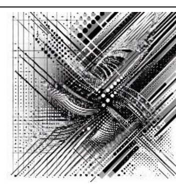
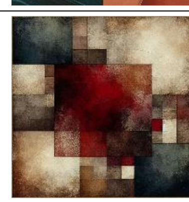
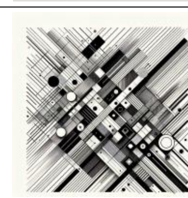
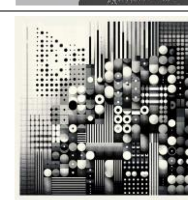
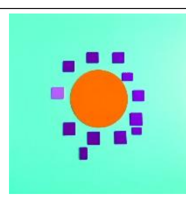
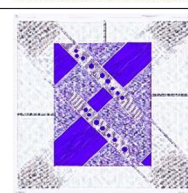
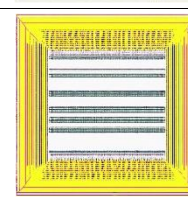
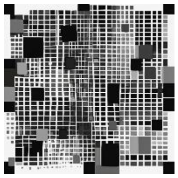
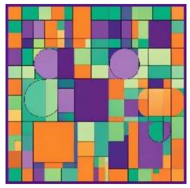
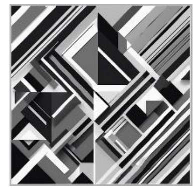
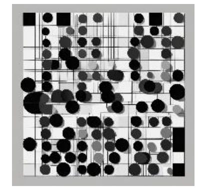
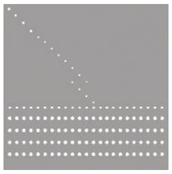
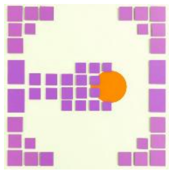
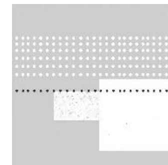
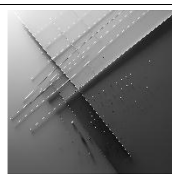
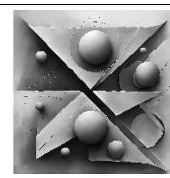
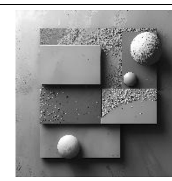
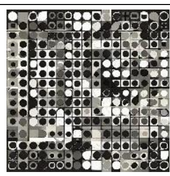
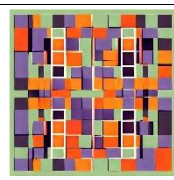
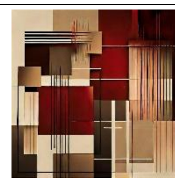
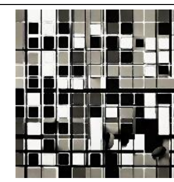
Leonardo.ai					
Adobe Firefly					
Craiyon					
Gemini					
Gencraft					
Ideogram					
Microsoft Designer (Dall-E 3)					
Openart (Stable Diffusion 3.0)					

Table 5.
Visual outputs in different AI models - asymmetrical balance (Continued)

Pixlr					
Flux.ai					
Kling.ai					
Runway					

Evaluation Method and Criteria

The evaluation of the AI-generated visual outputs was conducted based on three primary criteria: "understanding the elements," "understanding the principles," and "understanding the balance." These criteria were drawn from widely accepted pedagogical frameworks in basic design education, where students are assessed based on their ability to use visual elements (e.g. line, color, shape), apply compositional principles (e.g., rhythm, emphasis, harmony), and achieve visual coherence, especially through balance (Kahraman et al., 2024; Tang et al., 2022). This triadic structure reflects the common evaluative dimensions used in design studios, particularly in foundation-level courses where conceptual clarity and visual reasoning are prioritized. For each prompt, the AI models produced multiple visual outputs, and the research team carefully assessed these outputs to select the most accurate representation for further analysis.

Each selected visual output was scored independently by the authors according to the following scale:

1: The visual output is the least accurate representation of the criterion.

5: The visual output is the most accurate representation of the criterion.

The evaluation process was applied to both symmetrical and asymmetrical balance compositions. For each visual output, the scores provided by the authors were averaged to obtain a final score for each criterion. This scoring method ensured consistency in the assessment and allowed for a more objective comparison of the AI models' performance across different prompts and balance types.

The resulting scores, presented in the evaluation tables, reflect the models' capabilities in accurately interpreting and visualizing the design elements, principles, and balance within the generated compositions.

Results

Symmetrical Balance

1. **Understanding of Design Elements and the Application**

The evaluation of AI models (Table 6) revealed no clear frontrunner with consistently strong performance in understanding and applying design elements. While Microsoft Designer (DALL-E 3) and DALL-E achieved the highest average scores of 3.6, their individual visual outputs showed significant variability, ranging from 2 to 5. This inconsistency suggests that their high averages are not reflective of uniformly strong capabilities but rather occasional excellence interspersed with lower-quality results. Adobe Firefly and Craiyon followed with moderately high averages of 3.2, yet they also exhibited similar inconsistencies across prompts. On the lower end of the spectrum, Runway and Flux.ai recorded the weakest average score of 2.0, though even these models sporadically managed to produce outputs rated as 3, indicating isolated moments of moderate success amidst overall poor performance.

Both Microsoft Designer (DALL-E 3) and DALL-E, despite their higher averages, failed to maintain consistent results, suggesting that their ability to interpret design elements fluctuates significantly depending on the prompt.

In conclusion, the study found no AI model with consistently high performance in understanding and applying design elements. Most models exhibited notable fluctuations in quality, underscoring areas for improvement in their ability to interpret and represent these fundamental concepts. While higher-scoring models like Microsoft Designer (DALL-E 3) and DALL-E showed potential, their inconsistency detracts from their reliability. These findings emphasize the importance of considering both average scores and performance variability when assessing the effectiveness of AI models in design applications.

2. Understanding of Design Principles and the Application

The evaluation of AI models in understanding and applying design principles (Table 5), such as rhythm, contrast, emphasis, movement, and balance, highlighted significant variability in performance. Microsoft Designer (DALL-E 3) achieved the highest average score of 4.2, demonstrating strong capabilities in interpreting and applying these principles effectively. This was followed by DALL-E, which scored an average of 3.8, indicating a solid but slightly less consistent performance. Adobe Firefly and Craiyon ranked next, each with an average score of 3.2, showing moderate proficiency in integrating design principles into their outputs. On the other hand, Runway and Flux.ai recorded the lowest average scores of 1.6 and 2.2, respectively, reflecting notable struggles in this area.

Consistency across visual outputs was again a critical factor. Microsoft Designer (DALL-E 3). Similarly, DALL-E exhibited a range of results, Craiyon and Adobe Firefly showed steadier but unremarkable performance, with their scores generally clustered around the middle of the scale. By contrast, Runway consistently underperformed. Flux.ai, while also weak overall, demonstrated slightly more variation.

These findings suggest that no model consistently excelled in understanding and applying design principles. While Microsoft Designer (DALL-E 3) and DALL-E produced several high-quality outputs. Craiyon and Adobe Firefly maintained average performance without substantial deviations, positioning them as moderately capable yet uninspired options. Conversely, Runway and Flux.ai were predictably weak.

In summary, the evaluation underscores the challenges faced by AI models in reliably interpreting and applying design principles. Although some models achieved high average scores. These findings reinforce the importance of assessing both average performance and consistency when evaluating AI models in design contexts.

3. Understanding of Balance and the Application

The evaluation of AI models in understanding and applying balance (Table 5), both symmetrical and asymmetrical, revealed considerable variability in their performance. Craiyon and Microsoft Designer (DALL-E 3) achieved the highest average score of 4.4, reflecting a strong ability to interpret and represent balance effectively. These models consistently produced outputs that demonstrated an understanding of how visual weight and harmony are distributed within a composition. DALL-E followed with an average score of 3.2, showing a decent capability to understand balance. Adobe Firefly and Ideogram also scored 3.4, indicating a moderate but reliable grasp of balance. At the lower end of the spectrum, Runway recorded the weakest performance with an average score of 1.8, followed closely by Flux.ai with an average score of 2.6, suggesting significant challenges in achieving visually stable compositions.

When consistency was analyzed, the results revealed notable differences among models. Craiyon and Microsoft Designer (DALL-E 3), despite their high average scores, displayed occasional variability in their outputs, with scores ranging from 3 to 5. This suggests that while these models are capable of generating excellent results, their performance is not entirely reliable. DALL-E, on the other hand, showed a wider range of scores from 2 to 5. Models like Adobe Firefly and Ideogram performed steadily in the mid-range, maintaining moderate scores without significant deviations. Conversely, Runway and Flux.ai not only struggled to produce high-quality outputs but also exhibited limited variability, consistently scoring between 1 and 2 with rare instances of moderate success.

Overall, no model demonstrated flawless or entirely consistent performance in understanding and applying balance. Craiyon and Microsoft Designer (DALL-E 3) stood out as the most capable models, yet their occasional variability limits their reliability. DALL-E, while showing potential with some high-scoring outputs, requires improvement in achieving steadier performance. In contrast, Runway and Flux.ai were predictably weak, consistently failing to produce visually balanced compositions. These results highlight the ongoing challenges AI models face in mastering balance as a fundamental design principle.

In conclusion, the findings emphasize the importance of both average scores and consistency in evaluating AI models' ability to understand and apply balance. While some models showed promising results.

4. Overall Performance Analysis

The overall average scores (Table 6) show that Microsoft Designer (DALL-E 3) and DALL-E performed strongest in symmetrical balance tasks, with averages above 4.0 and 3.5 respectively. Their outputs frequently demonstrated accurate use of design elements and proportional distribution, though consistency across prompts remained a challenge. Adobe Firefly and Ideogram followed with mid-range averages around 3.3, offering stable but unremarkable results. Craiyon achieved a similar score yet displayed greater variability, alternating between effective and ineffective interpretations. Runway and Flux.ai remained the weakest performers, with averages below 2.6 and recurring difficulties in grasping core principles of balance.

Taken together, these results indicate that AI models are generally more reliable when dealing with symmetrical compositions, where proportionality provides clearer algorithmic cues. However, even the strongest performers were unable to sustain uniform quality across all outputs, suggesting that current systems excel in isolated cases rather than consistently. For design education, this implies that while symmetrical balance may be a more accessible entry point for AI-assisted exploration, critical reflection is still required to address the models' fluctuating reliability.

Table 6.
Evaluation of AI Models' Interpretation of Basic Design Principles and Elements for Symmetrical Balance

Symmetrical Balance					
Model	**Visual Output No**	**Understanding The Design Elements**	**Understanding The Design Principles**	**Understanding The Balance**	**Average**
AI DALL-E	**1**	4	4	3	4.06
	2	5	5	5	
	3	4	4	2	
	4	3	4	2	
	5	2	2	4	
Average	**1-2-3-4-5**	3.6	3.8	4.4	
MidJourney	**1**	3	3	1	3.06
	2	5	5	5	
	3	2	2	2	
	4	4	4	2	
	5	3	3	2	
Average	**1-2-3-4-5**	3.4	3.4	2.4	
Artguru	**1**	4	4	4	3.13
	2	4	4	5	
	3	2	2	2	
	4	3	3	3	
	5	3	3	1	
Average	**1-2-3-4-5**	3.2	3.2	3.0	
Claude	**1**	2	2	4	2.46
	2	3	3	1	
	3	1	2	5	
	4	3	3	1	
	5	2	2	2	
Average	**1-2-3-4-5**	2.2	2.6	2.6	
Leonardo.ai	**1**	2	2	2	3.19
	2	5	4	5	
	3	3	3	4	
	4	3	3	2	
	5	2	2	4	
Average	**1-2-3-4-5**	3.0	3.2	3.4	
Adobe Firefly	**1**	3	4	2	3.26
	2	5	4	3	
	3	2	2	4	
	4	3	3	4	
	5	3	2	4	
Average	**1-2-3-4-5**	3.2	3.2	3.4	
Craiyon	**1**	2	2	4	3.53
	2	3	3	5	
	3	3	3	4	
	4	4	4	5	
	5	3	3	4	
Average	**1-2-3-4-5**	3.0	3.2	4.4	
Gemini	**1**	3	2	4	3.0
	2	4	4	1	
	3	3	3	4	
	4	1	1	5	
	5	3	3	4	
Average	**1-2-3-4-5**	2.8	2.6	3.6	
Gencraft	**1**	2	2	2	3.06
	2	3	3	3	
	3	4	4	4	
	4	3	3	4	
	5	3	3	3	
Average	**1-2-3-4-5**	3.0	3.0	3.2	
Ideogram	**1**	2	2	1	3.26
	2	5	5	5	
	3	2	2	2	
	4	3	3	4	
	5	3	3	2	
Average	**1-2-3-4-5**	3.0	3.4	3.4	

Table 6.
Evaluation of AI Models' Interpretation of Basic Design Principles and Elements for Symmetrical Balance (Continued)

Symmetrical Balance					
Model	Visual Output No	Understanding The Design Elements	Understanding The Design Principles	Understanding The Balance	Average
Microsoft Designer (DALL-E 3)	1	4	4	4	4.06
	2	5	5	5	
	3	3	3	4	
	4	4	4	4	
	5	2	2	4	
Average	1-2-3-4-5	3.6	4.2	4.4	
Openart (Stable Diffusion 3.0)	1	2	3	4	2.8
	2	4	4	5	
	3	2	2	2	
	4	3	3	3	
	5	1	1	3	
Average	1-2-3-4-5	2.4	2.6	3.4	
Pixlr	1	3	3	1	2.46
	2	4	4	5	
	3	2	2	2	
	4	2	2	2	
	5	1	1	2	
Average	1-2-3-4-5	2.4	2.4	2.6	
Flux.ai	1	2	2	1	2.26
	2	3	3	3	
	3	2	3	4	
	4	1	1	4	
	5	2	2	2	
Average	1-2-3-4-5	2.0	2.2	2.6	
Kling.ai	1	4	4	3	2.93
	2	4	4	3	
	3	4	4	4	
	4	2	2	1	
	5	2	2	1	
Average	1-2-3-4-5	3.2	3.2	2.4	
Runway	1	3	2	2	1.8
	2	2	2	2	
	3	2	2	4	
	4	1	1	1	
	5	2	2	1	
Average	1-2-3-4-5	2.0	1.6	1.8	

Asymmetrical Balance

1. Understanding of Design Elements and the Application

The evaluation of AI models in understanding and applying design elements (Table 7), such as dots, lines, shapes, colors, and textures, revealed considerable variability in performance. DALL-E achieved the highest average score of 3.6, making it relatively successful compared to other models. However, its performance was inconsistent. This variability suggests that while DALL-E shows potential, it lacks the ability to consistently deliver high-quality results in applying design elements.

Similarly, Microsoft Designer (DALL-E 3) and Ideogram, with average scores of 3.4 and 3.2, respectively, performed better than most models but did not demonstrate a consistent ability to achieve high scores. MidJourney and Leonardo.ai, both averaging 3.0, delivered moderate results, showing an acceptable but unremarkable understanding of design elements.

In contrast, models such as Craiyon and Flux.ai, with average scores of 1.6 and 2.0, consistently struggled to effectively interpret and apply design elements. Claude, with an average score of 1.2, exhibited the weakest performance, indicating severe limitations in understanding and representing design elements. This highlights a general need for improvement across all AI tools in achieving stability and reliability in applying design elements.

In conclusion, DALL-E and Microsoft Designer (DALL-E 3) were comparatively better at applying design elements, but their inconsistent performance prevents them from being deemed truly successful. Lower-performing models like Craiyon, Flux.ai, and Claude require significant development to address their evident deficiencies.

2. Understanding of Design Principles and the Application

The evaluation of AI models in understanding and applying design principles (Table 7), such as rhythm, contrast, emphasis, and movement, revealed a similar pattern of variability and inconsistency. Adobe Firefly and Ideogram achieved the highest average scores of 3.4, indicating relative success compared to other models. However, neither consistently maintained high scores across outputs. Microsoft Designer (DALL-E 3) and Leonardo.ai followed closely with average scores of 3.0 and 3.2, respectively, reflecting a decent but inconsistent ability to apply design principles effectively.

DALL-E, while achieving an average score of 3.0, demonstrated significant variability across outputs. This highlights occasional success but an overall inability to consistently apply design principles across all scenarios. Similarly, MidJourney, with an average score of 3.0, showed moderate proficiency.

On the lower end, Craiyon, Flux.ai, and Claude consistently underperformed, with average scores ranging between 1.6 and 2.2. These models frequently failed to effectively apply key design principles, often producing outputs that lacked coherence and failed to meet evaluation standards.

In summary, no AI model demonstrated consistent excellence in understanding and applying design principles. While Adobe Firefly and Ideogram were relatively stronger performers, their lack of consistency prevents them from being considered fully successful. DALL-E and Microsoft Designer (DALL-E 3) showed potential but were hampered by fluctuating performance. Lower-performing models such as Craiyon and Claude continue to face significant challenges.

3. Understanding of Balance and the Application

The evaluation of AI models in understanding and applying balance for asymmetrical compositions (Table 7) revealed consistently high scores across models. DALL-E, Microsoft Designer (DALL-E 3), Ideogram, and Pixlr achieved the highest average scores, all receiving 5.0 or close to it in their understanding of balance. However, asymmetrical balance, by nature, requires less rigid precision than symmetrical balance.

To assess true proficiency in balance, it is crucial to consider performance in both symmetrical and asymmetrical balance. Models that consistently performed well across both categories demonstrate a deeper understanding and capability. For instance, Microsoft Designer (DALL-E 3) and DALL-E showed relatively strong results in symmetrical balance, complementing their high scores in asymmetrical balance.

On the other hand, models like Craiyon, Flux.ai, and Claude, despite achieving high scores in asymmetrical balance, consistently underperformed in symmetrical balance.

In conclusion, while asymmetrical balance results show high average scores, these alone are insufficient to determine true proficiency. Models like Microsoft Designer (DALL-E 3) and DALL-E, which performed well in both symmetrical and asymmetrical balance, are more likely to possess a genuine understanding of balance. Conversely, models that excelled only in asymmetrical balance demonstrate potential weaknesses.

4. Overall Performance Analysis

The overall average scores for asymmetrical balance (Table 7) reflect notable variability across models. DALL-E and Microsoft Designer (DALL-E 3) obtained the highest averages, yet their results were strongly boosted by high scores in the balance criterion rather than by consistently strong performance in design elements or principles. Craiyon and Flux.ai displayed a similar pattern: their overall averages appeared inflated by balance scores, masking broader weaknesses in applying fundamental design concepts.

These outcomes suggest that success in asymmetrical tasks often stemmed from isolated or incidental alignments with balance rather than a systematic understanding of underlying principles. As a result, overall averages must be interpreted with caution, as they risk overstating the capabilities of models that performed unevenly across criteria. For design education, this finding highlights that while AI can occasionally approximate asymmetrical balance, its limitations in sustaining coherence across prompts make it an unreliable substitute for critical human judgment.

Table 7.
Evaluation of AI Models' Interpretation of Basic Design Principles and Elements for Asymmetrical Balance

Asymmetrical Balance					
AI Model	**Visual Output No**	**Understanding The Design Elements**	**Understanding The Design Principles**	**Understanding The Balance**	**Average**
DALL-E	1	4	4	5	3.86
	2	4	3	5	
	3	4	4	5	
	4	4	2	5	
	5	2	2	5	
Average	**1-2-3-4-5**	3.6	3.0	5.0	
MidJourney	1	3	4	5	3.66
	2	4	5	5	
	3	2	2	5	
	4	3	2	5	
	5	3	2	5	
Average	**1-2-3-4-5**	3.0	3.0	5.0	
Artguru	1	4	4	5	3.13
	2	2	2	5	
	3	3	3	5	
	4	1	1	5	
	5	1	1	5	
Average	**1-2-3-4-5**	2.2	2.2	5.0	
Claude	1	2	2	5	2.66
	2	1	4	5	
	3	1	1	5	
	4	1	1	5	
	5	1	2	5	
Average	**1-2-3-4-5**	1.2	1.8	5.0	

Table 7.
Evaluation of AI Models' Interpretation of Basic Design Principles and Elements for Asymmetrical Balance (Continued)

Asymmetrical Balance					
AI Model	**Visual Output No**	**Understanding The Design Elements**	**Understanding The Design Principles**	**Understanding The Balance**	**Average**
Leonardo.ai	1	3	3	5	3.66
	2	4	4	5	
	3	3	3	5	
	4	2	1	4	
	5	3	3	5	
Average	**1-2-3-4-5**	3.0	3.2	4.8	
Adobe Firefly	1	3	4	5	3.53
	2	4	5	2	
	3	4	4	5	
	4	2	1	5	
	5	1	3	5	
Average	**1-2-3-4-5**	2.8	3.4	4.4	
Craiyon	1	2	2	4	2.66
	2	2	2	5	
	3	2	2	5	
	4	1	1	5	
	5	1	1	5	
Average	**1-2-3-4-5**	1.6	1.6	4.8	
Gemini	1	1	1	5	2.8
	2	4	4	5	
	3	2	2	5	
	4	1	1	4	
	5	1	1	5	
Average	**1-2-3-4-5**	1.8	1.8	4.8	
Gencraft	1	3	2	5	3.0
	2	2	2	5	
	3	3	3	5	
	4	1	1	3	
	5	2	3	5	
Average	**1-2-3-4-5**	2.2	2.2	4.6	
Ideogram	1	3	3	5	3.8
	2	4	4	5	
	3	3	3	5	
	4	3	1	4	
	5	3	4	5	
Average	**1-2-3-4-5**	3.2	3.4	4.8	
Microsoft Designer (Dall-E 3)	1	4	5	5	3.86
	2	4	4	5	
	3	3	3	5	
	4	3	1	5	
	5	3	2	5	
Average	**1-2-3-4-5**	3.4	3.0	5.0	
Openart (Stable Diffusion 3.0)	1	3	2	5	3.0
	2	3	3	5	
	3	2	2	5	
	4	1	1	4	
	5	1	1	2	
Average	**1-2-3-4-5**	2.2	2.2	4.6	
Pixlr	1	4	2	5	3.6
	2	2	2	5	
	3	3	3	5	
	4	4	2	5	
	5	3	3	5	
Average	**1-2-3-4-5**	3.2	2.6	5.0	
Flux.ai	1	3	3	5	2.73
	2	2	2	2	
	3	2	2	5	
	4	1	1	3	
	5	2	3	5	
Average	**1-2-3-4-5**	2.0	2.2	4.0	

Table 7.
Evaluation of AI Models' Interpretation of Basic Design Principles and Elements for Asymmetrical Balance (Continued)

Asymmetrical Balance					
AI Model	**Visual Output No**	**Understanding The Design Elements**	**Understanding The Design Principles**	**Understanding The Balance**	**Average**
Kling.ai	1	4	3	5	3.0
	2	2	2	5	
	3	2	2	5	
	4	1	1	4	
	5	1	1	5	
Average	**1-2-3-4-5**	2.0	2.4	4.6	
Runway	1	3	3	5	3.0
	2	2	2	5	
	3	2	2	5	
	4	2	1	5	
	5	2	1	5	
Average	**1-2-3-4-5**	2.2	2.0	4.8	

Symmetrical and Asymmetrical Balance

1. Understanding of Design Elements and the Application

When considering both symmetrical and asymmetrical balance together, the evaluation of AI models in understanding and applying design elements revealed consistent challenges across the board. DALL-E emerged as one of the better-performing models, with an average score of 3.6 in both balance categories combined. However, its performance varied significantly across visual outputs. This inconsistency suggests that while DALL-E demonstrates potential in applying design elements, it lacks the ability to reliably produce high-quality results across different scenarios.

Microsoft Designer (DALL-E 3) similarly performed well in combined evaluations, with an average score of 3.4. Although it exhibited moments of excellence. Ideogram, with a combined average of 3.2, showed relative stability compared to its peers but did not consistently achieve high scores, further reinforcing the observation that none of the models excelled consistently in understanding and applying design elements.

Lower-performing models like Craiyon, Flux.ai, and Claude consistently struggled in both symmetrical and asymmetrical balance contexts. Their combined average scores ranged from 1.2 to 2.0, highlighting significant limitations in comprehending and integrating design elements into their outputs.

One notable trend is that higher average scores in asymmetrical balance often compensated for weaker performance in symmetrical balance, particularly for models like Craiyon and Flux.ai. This underscores the importance of assessing symmetrical balance more critically, as it requires greater precision and deliberate control over design elements. Asymmetrical balance, by contrast, is less demanding and more susceptible to incidental success.

In conclusion, no AI model demonstrated consistent excellence in understanding and applying design elements across both balance categories. DALL-E and Microsoft Designer (DALL-E 3) showed relative strength but were hindered by variability. Lower-performing models like Craiyon and Claude exhibited consistent weaknesses, emphasizing the need for significant development.

2. Understanding of Design Principles and the Application

When analyzing the application of design principles, including rhythm, contrast, emphasis, and movement, across both symmetrical and asymmetrical balance, the performance of AI models was similarly inconsistent. Adobe Firefly and Ideogram achieved relatively higher average scores of 3.4, indicating some ability to apply these principles effectively.

Microsoft Designer (DALL-E 3) and Leonardo.ai, with combined average scores of 3.0 and 3.2 respectively, showed moderate capability but struggled to consistently integrate design principles into their outputs.

DALL-E, another relatively stronger model, achieved a combined average score of 3.0. This further underscores the challenge of achieving consistent excellence in the application of design principles.

In contrast, lower-performing models like Craiyon, Flux.ai, and Claude consistently struggled, with combined average scores between 1.6 and 2.2. Their inability to effectively apply key design principles across both balance contexts highlights fundamental deficiencies in their capabilities.

One critical observation is that high scores in asymmetrical balance often inflated the averages for some models, masking their weaker performance in symmetrical contexts. This was particularly evident for models like Craiyon and Flux.ai, which benefitted from the less structured requirements of asymmetry.

In conclusion, while Adobe Firefly and Ideogram showed relative promise in applying design principles, their lack of consistency prevents them from being deemed truly proficient. DALL-E and Microsoft Designer (DALL-E 3) demonstrated moderate capability. Lower-performing models like Craiyon and Claude exhibited clear deficiencies, emphasizing the need for further development.

3. Understanding of Balance and the Application

The evaluation of balance—a core criterion encompassing both symmetrical and asymmetrical compositions—revealed significant discrepancies in performance and interpretation. Models such as DALL-E, Microsoft Designer (DALL-E 3), and Pixlr scored highly in asymmetrical balance, with averages of 5.0 or close to it.

Symmetrical balance demands precision and intentionality. A single misplaced element can disrupt the entire composition, making consistent success in symmetrical balance a stronger indicator of true mastery. In this regard, only a few models demonstrated relative capability. For instance, Microsoft Designer (DALL-E 3) and DALL-E achieved moderate success in symmetrical balance, suggesting a certain level of comprehension.

On the other hand, models like Craiyon and Flux.ai scored consistently high in asymmetrical balance but underperformed in symmetrical balance. Claude, similarly, exhibited weak performance in symmetrical contexts despite achieving some success in asymmetry.

In conclusion, while asymmetrical balance results often reflect high scores, they should not be taken as definitive proof of a model's capability in understanding balance. True proficiency can only be inferred when a model demonstrates consistent performance across both symmetrical and asymmetrical contexts. Models like Microsoft Designer (DALL-E 3) and DALL-E, which achieved relative success in both categories, show potential but require significant refinement to achieve true consistency. Conversely, models like Craiyon and Flux.ai, despite their strong asymmetrical scores, remain fundamentally limited in their understanding of balance.

4. Overall Performance Analysis

The combined evaluation of symmetrical and asymmetrical balance (see Tables 6–7) highlights the uneven proficiency of current AI models. DALL-E and Microsoft Designer (DALL-E 3) achieved the highest averages, yet their results fluctuated considerably: strong outcomes in asymmetry often compensated for weaker performances in symmetry. Adobe Firefly and Ideogram produced moderate results, showing stability in some criteria without achieving consistently high standards. Craiyon, Flux.ai, and Claude also benefited from inflated asymmetry scores, which concealed persistent difficulties in applying design elements and principles effectively.

Symmetry emerged as the more demanding condition, requiring deliberate control and precision. Models that performed poorly in symmetry but relatively well in asymmetry likely achieved the latter through incidental alignments rather than intentional mastery. This contrast underscores the importance of symmetry tasks as a more reliable indicator of true proficiency.

Overall, while higher-scoring models such as DALL-E and Microsoft Designer (DALL-E 3) show potential, their inconsistency points to the need for refinement. Lower-performing systems require fundamental improvement to address gaps in understanding design principles. For design education, these results emphasize that AI tools may stimulate critique and discussion but cannot yet replace the intentional decision-making skills developed through human-centered training.

Conclusion

This study evaluated the capabilities of AI models in applying design elements, principles, and balance across symmetrical and asymmetrical compositions. The findings revealed significant variability in performance, highlighting both potential strengths and critical limitations across the models assessed.

Microsoft Designer (DALL-E 3) and DALL-E emerged as comparatively better-performing models, demonstrating relative proficiency in applying design elements and principles, particularly in balance-related tasks. However, their inconsistent performance across symmetrical and asymmetrical contexts underscores the need for further refinement. The high scores achieved in asymmetrical balance often compensated for weaker performance in symmetrical balance, raising questions about the depth of these models' understanding and their ability to apply design concepts deliberately rather than incidentally.

Moderate performers like Adobe Firefly and Ideogram showed stability in certain areas but fell short of achieving consistent high performance. These models exhibited potential in applying design principles but lacked the precision and reliability required for broader success. Conversely, lower-performing models such as Craiyon, Flux.ai, and Claude consistently struggled across all criteria, demonstrating fundamental deficiencies in their ability to comprehend and integrate design concepts into visual outputs.

A key insight from the study is the critical importance of symmetrical balance as a test of true proficiency. Unlike asymmetrical balance, which is more forgiving and susceptible to randomness, symmetrical balance requires intentional control and precision. Models that excelled only in asymmetrical contexts often relied on incidental success rather than a deliberate understanding of balance.

The results emphasize the need for a holistic evaluation framework that considers both symmetrical and asymmetrical contexts, as well as all design criteria, to accurately assess the capabilities of AI tools in design applications. While the study identified promising directions for improvement, particularly for models like Microsoft Designer (DALL-E 3) and DALL-E, it also highlighted substantial gaps that need to be addressed for AI tools to achieve consistent and intentional design performance.

From an educational perspective, these findings offer valuable implications for basic design pedagogy. The inconsistent yet discussion-provoking outputs of AI models can be used as teaching tools, encouraging students to critically evaluate design principles, detect flaws, and articulate what constitutes successful application of balance, elements, and principles. In this way, AI-generated outputs serve not as replacements for traditional studio exercises but as supplementary materials that foster reflective learning and visual literacy.

Furthermore, integrating AI tools into studio environments may provide students with opportunities to compare human and machine interpretations of design concepts. This comparative approach can strengthen their analytical skills and highlight the importance of intentionality, creativity, and contextual sensitivity in design education.

In conclusion, while AI models exhibit potential in generating designs, their current limitations underscore the need for further development to achieve greater consistency, intentionality, and depth in understanding and applying design elements, principles, and balance. Future research should focus on refining these tools to enhance their reliability and their ability to support designers in creative and technical tasks.

Limitations

This study, while systematically designed to explore the capabilities of AI in interpreting and representing foundational design principles, is bound by certain limitations. One of the primary constraints is the deliberate restriction to five design principles—rhythm, movement, contrast, emphasis, and balance—and five design elements—dot, line, shape, color, and texture. This choice was made to maintain methodological clarity and control, ensuring balanced representation across a manageable number of variables. However, this restriction excludes other potential design principles and elements that might also contribute to a comprehensive understanding of visual composition, thus narrowing the scope of the study.

Furthermore, each design principle and element appear only four times across the ten total prompts (five fundamental prompts in both symmetrical and asymmetrical versions). While this repetition offers some level of internal validation, additional prompts or alternative configurations could further substantiate the AI's interpretation capabilities. Thus, the reliance on a limited set of prompts may restrict the generalizability of the findings to a broader array of design scenarios.

The use of symmetrical and asymmetrical balance as the only balance types analyzed in this study also presents a limitation. Although this dichotomy provides valuable insights into the effects of balance, other forms, such as radial or dynamic balance, are not explored. These alternative balance types could potentially reveal different aspects of AI interpretation that remain unexplored within the current framework.

Another limitation is inherent to the specific AI model(s) used, which may have unique biases or strengths that affect their interpretation of design principles and elements. The findings of this study may therefore be limited in applicability to other AI models, as the interpretations of design concepts could vary depending on the underlying algorithms and training data.

Lastly, while this controlled approach aids in isolating specific design variables, it also imposes an artificial structure that may not fully capture the organic or intuitive nature of human design processes. The structured prompts are designed to produce predictable outputs for analysis, but this may limit the AI's ability to generate compositions that are complex, spontaneous, or contextually adaptive in ways human designers might produce.

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