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THE AUGMENTED DESIGNER: A RESEARCH AGENDA FOR GENERATIVE AI-ENABLED DESIGN

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ABSTRACT

Generative AI algorithms that are able to generate creative output are progressing at tremendous speed. This paper presents a research agenda for Generative AI-based support for designers. We present examples of existing applications and thus illustrate the possible application space of Generative AI reflecting the current state of this technology. Furthermore, we provide a theoretical foundation for AI-supported design, based on a typology of design knowledge and the concept of evolutionary creativity. Both concepts are discussed in relation to the changing roles of AI and the human designer. The outlined research agenda presents 10 research opportunities for possible AI-support to augment the designer of the future. The results presented in this paper provide researchers with an introduction to and overview of Generative AI, as well as the theoretical understanding of potential implications for the future of the design discipline.

Keywords: Artificial intelligence, Creativity, Computational design methods, Design knowledge, Generative AI

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1 INTRODUCTION

Designers have always used tools: from pencil to CAD to 3D printing. The availability and transformative power of these tools have in turn impacted designers' work processes and their creative output – the design. Now, there is a new tool: Generative Artificial Intelligence (AI). Generative AI, sometimes also referred to as "creative AI" or "synthetic media", is a rather new concept that uses deep learning algorithms to generate a creative output (e.g., image, text, video, sound) based on a given input (so-called "prompt"). For example, the prompt "create an image of an alien in the style of van Gogh", would result in a variety of computer-generated images of aliens that look like an artwork by Dutch painter Vincent van Gogh. Even though AI and parametric generative design has a decade-long tradition (Gero and Kazakov, 1996; Kicinger et al., 2005a), recently, this technology has improved enormously These technologies can generate, for example, realistic videos, high-resolution scalable patterns, and furniture designs. The question arises, how this new type of tool will influence designers' work processes and their design output, which is also the research question that guides this conceptual paper.

In this paper, we introduce a framework outlining the conceptual space of Generative AI with a particular focus on the characteristics of design knowledge and creativity. We present an overview of Generative AI including selected examples (Section 2). In Section 3, we discuss different types of design knowledge to identify potential connecting points between Generative AI and the generation of design knowledge. In Section 4, we introduce the concept of evolutionary creativity and discuss potential opportunities for Generative AI to enhance creativity. The first concept outlines possible representations, while the second one addresses the creation of design ideas. Both concepts and their possible interrelationships with Generative AI are then summarised in a framework, outlining a research agenda for generative AI-supported design, which is presented in Section 5. As a consequence, this paper offers the following contributions: (1) It provides an overview of the application space of Generative AI for the design discipline; (2) it explains and positions Generative AI on a theoretical and philosophical level; (3), it provides an outlook to the future role of the designer when "augmented" by Generative AI, and (4) it outlines a research agenda with opportunities for further research in this emerging field.

2 GENERATIVE AI

Generative AI is a recent development in the field of AI. In the following subsections we explore the concept's origins and current research on AI's impact on design processes including an overview of the application space for this technology along with exemplary tools.

2.1 Generative AI origins

AI is an umbrella term that relates to machines with the ability to perceive, synthesise, and infer information. In science fiction movies, AI is often depicted as an all-knowing consciousness that outperforms humans in almost any task. Although today's technology is still far from artificially re-creating a human brain, AI applications often already surpass human intelligence in designated tasks, such as image diagnosis, natural language translation or chess.

Machine Learning is a sub-discipline of Artificial Intelligence where algorithms are trained with examples to make predictions. Early machine learning models were able to perform dedicated classification and regression tasks, such as image classification or price prediction with high accuracy. An algorithm could for instance be trained with sales data from past years to predict future revenue. The underlying mathematics are decades old, but at the time, the necessary computing power was either not available or too expensive. Over the last twenty years, computing capabilities of affordable hardware increased drastically, essentially enabling the computation of complex machine learning models on consumer laptops.

With the emergence of Deep Learning technologies, early machine learning methods were outperformed in most tasks. Deep Learning refers to the creation of artificial neural networks where inputs are processed in various layers of neurons trying to mimic the learning process of the human brain. Today, such algorithms define the state of the art in many disciplines, e.g., computer vision and speech recognition.

In the field of computer vision, Kingma and Welling (2013) introduced Variational Autoencoders as a generative model, enabling the generation of high-quality images. Goodfellow et al. (2020) introduced Generative Adversarial Networks. Based on Deep Learning and Game Theory, image generation capabilities of these algorithms could be significantly improved over time and are for instance used in medical image enhancement and speech recognition. In 2017, the landmark article *Attention is All You Need* (Vaswani et al., 2017) introduced Transformer based models that increased the semantic understanding of text for machines. Based on this technology, large language models such as GPT-2, GPT-3 (OpenAI, 2022) and more recently GPT-4 (OpenAI, 2023) were developed, being able to interpret and generate text, e.g., a blog entry from selected keywords. Those algorithms can be regarded as the foundation for Generative AI.

Generative AI tools allow users to provide a set of initial requirements or examples, such as keywords, images, or videos, that are processed with neural networks. The outcome can be a synthesis or an optimization. Figure 1 shows an example from Nvidia Canvas (NVIDIA, 2022a). The left side shows the input where a designer created an abstract painting of a landscape, and the right side shows the computational result of a Generative AI algorithm that interprets the painting and renders a detailed realistic representation. The designer does not paint with colours but with semantically aware materials like mountains, grass, or clouds.

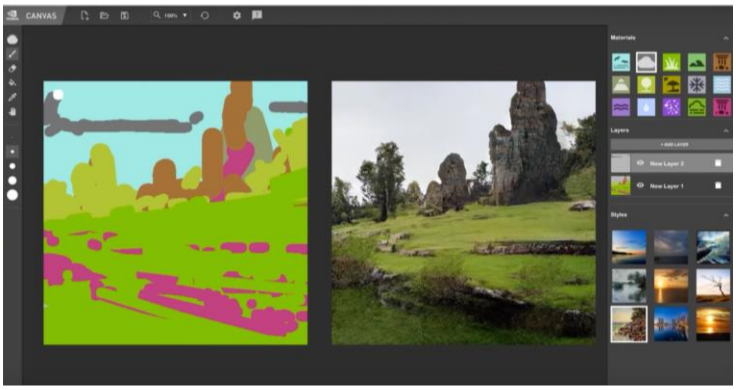

Figure 1: Example: Nvidia Canvas (NVIDIA, 2022a)

ChatGPT, an AI-chatbot developed by OpenAI, is one of the most popular examples for Generative AI tools. Based on OpenAI's GPT-4 model, it can generate texts and interpret images according to user prompts. One of the reasons for its popularity lies in its versatility and the ability to provide human-like responses. ChatGPT demonstrates a high degree of semantic understanding enabling various use cases, such as explaining, summarizing, and generating text, but also writing computer code in various programming languages. Although ChatGPT generates high quality output, it comes with limitations where sometimes, the model "hallucinates" facts and makes reasoning errors (OpenAI, 2023).

2.2 Generative AI in design processes

The possible impact of Artificial Intelligence (AI) on design processes and design activities has gained significant interest within the design community since the past decades. Generative and parametric methods to support the design process have been developed already in the 1990s. For example, Gunaratman and Gero (1994) compared and combined neural and symbolic representations for generating and optimizing engineering structures. Kicinger (2005b) used cellular automata for representing and generating steel structures in combination with evolutionary algorithmic optimization. Sarica et al. (2019) discussed the symbolic representation of design knowledge and automatic creation of ontologies from patent documents based on text mining methods. Others investigated more specific use cases for AI-support in design. For example, Siemon et al. (2022) explored the potentials of AI as a teammate in creative collaboration, Nobari et al. (2021) explored how generative adversarial networks can be used to create innovative designs for bicycles, and Hwang (2022) reports on a literature review revealing that AI-driven tools are mostly used to support the generation and execution of ideas. Several authors provided overviews giving the reader an idea about the developments and potentials of AI in relation to the design field, see, e.g., Verganti et al. (2020) and Gero (2007).

Research regarding the impact of Generative AI on design processes can be found in various disciplines. In digital manufacturing, Buonamici et al. (2020) describe how a generative AI system can

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be used to find alternative designs for a robot arm component with the objective of limiting weight. McClelland (2022) shows how AI technologies can be applied to optimise the manufacturing process of spaceflight optical instruments. In architecture, Zhao et al. (2021) demonstrate how Generative AI can support the generation of plane functional layouts for operating departments in hospitals with innovative designs. Karadag et al. (2022) propose an AI system that generates classroom layout designs for educational buildings. In fashion, Särmäkari and Vänskä (2022) analysed two case studies illustrating how Generative AI alters the design process of fashion designers. In user experience design, Houde et al. (2022) analysed the process of user experience modernization towards opportunities for Generative AI technologies to support individual process steps.

2.3 Generative AI application space

We researched state of the art Generative AI tools and technologies to provide an overview of the technology's capabilities. Table 1 shows the application space of Generative AI where each cell contains examples of tools and technologies that are further explained below. The table can be read in an input-to-output manner indicating potential use cases for Generative AI in the design space, e.g., Sound/Speech-to-text: Sonix (7). For some input-to-output combinations, we did not find related technologies which might indicate potentials for future work.

Table 1. Application space of generative AI

Output / Input	Text	Sound/Speech	Image	Video	3D
Text	ChatGPT (1) Jasper (2)	Replica Studios (3)	Dall-E (4), Midjourney (5)	Synthesia (6), Make-A-Video (7)	DreamFusion (8)
Sound/ Speech	Sonix (9)	Aiva (10)	Deepsing (11)	WZRD (12)	Audio2Face (13)
Image	ChatGPT (1), Image Description Generator (14)	Melobytes (15)	Artbreeder (16)	Transframer (17), Endless Loops (18)	3D Photos (19)
Video	Video Reasoning (20)	AutoFoley (21)	-	Video-to-Video Synthesis (22)	3D Video Generation (23)
3D	-	-	-	-	3D Generative Models (24)

1. ChatGPT is an AI-chatbot based on GPT-4, enabling a variety of use cases, e.g., generating and interpreting texts or computer code, writing song-lyrics, and composing music (OpenAI, 2023).
2. Jasper is a content platform based on GPT-3 that helps users to automatically create social media content such as blog posts from initial text snippets describing the intended use case (Jasper, 2022).
3. Replica Studios takes a short vocal performance as input to create AI voice actors for games and films that can be used via a text-to-speech interface (Replica Studios, 2022).
4. Dall-E creates artistic illustrations from natural language descriptions (DALL-E 2, 2022).
5. Midjourney is an AI-tool that generates images based on natural language descriptions via text prompts (Midjourney, 2023). Compared to Dall-E which aims for a highly realistic look, Midjourney focuses more on incorporating different art styles.
6. Synthesia is an AI platform that enables users to create videos from text where AI avatars can for instance act as trainers or presenters depending on individual use cases (Synthesia, 2022).
7. Make-A-Video, developed by Meta, creates videos from textual descriptions (Singer et al., 2022).
8. DreamFusion creates 3D images from textual descriptions (Poole et al., 2022).
9. Sonix provides AI-generated transcriptions from audio or video files (Sonix, 2022).
10. Aiva generates music from uploaded examples (AIVA, 2022).
11. Deepsing is a deep learning technology that translates music to images and visual stories (Passalis and Doropoulos, 2021).
12. WZRD uses generative adversarial networks to create videos from music (WZRD, 2022).
13. Audio2Face takes a voice track as an input and renders the facial expressions of 3D characters including emotional expressions (NVIDIA, 2022b).
14. Karpathy and Fei-Fei (2015) present a deep learning model that generates natural language descriptions of images.

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15. Melobytes detects objects, concepts, scenes and texts in uploaded images and uses an AI to generate music (Melobytes, 2022).
16. Artbreeder uses generative adversarial networks to remix and synthesise uploaded images into new artistic image compositions (Artbreeder, 2022).
17. Transframer uses generative models to create short videos from a single image (Nash et al., 2022).
18. Endless Loops takes an image as input and creates animated loops, turning images into videos (Halperin et al., 2021).
19. Kopf et al. (2020) present a system that creates 3D photos from single mobile phone pictures.
20. Yi et al. (2020) developed an approach comprising several neural networks for neuro-symbolic dynamic reasoning on videos that is able to understand and explain 3D animations.
21. AutoFoley is a deep learning-based technology that automatically creates soundtracks for silent movies (Ghose and Prevost, 2021).
22. Video-to-Video Synthesis generates realistic videos from animated edge maps (Wang et al., 2018).
23. 3D video generation takes a 2D video as an input and generates 3D videos where content can be viewed from different angles (Bahmani et al., 2022).
24. Sutherland et al. (2022) developed an approach to build 3D generative models from minimal data where 3D morphable models are generated from single 3D meshes.

Additional examples indicate that the field of Generative AI continuously generates more use cases and will potentially continue to grow in the future. GitHub developed for instance an AI copilot that generates functions in computer code where programmers only have to provide a comment regarding their purpose in natural language (GitHub, 2022). Yang (2022) developed a tool for translating speech to animated drawings and Uizard (2022) takes hand-drawn user interface sketches as an input to create complete smartphone app designs.

3 DESIGN KNOWLEDGE

Designing means creating something new and useful. To understand the possible impact of Generative AI on this task, we take a look at the characteristics of design-specific knowledge and search for possible interaction points for Generative AI. For this purpose, we refer to a framework of design knowledge (Thoring et al., 2022). The authors distinguish four levels of design knowledge, building up on each other. The base level (A) is called “Artefact Knowledge” implying knowledge is “frozen” in a physical instantiation (like knowledge about construction and ergonomics is frozen into a chair (Müller and Thoring, 2011)). “Design Intuition” (level B) describes the designer’s tacit knowledge, for example the intuition for what is a good form or a balanced colour scheme. Level C is called “Design Language”. This type of knowledge is externalised. It includes – among written and spoken language – design-specific visualisation skills and design terminology. On the top level, we find “Design Theories”, which represent formalised models, such as generalisable and transferable design principles. In between these four levels are “Transitions” that indicate how one type of knowledge transforms to the next (in both directions; up and down). Figure 2 (left) illustrates the four levels and three transitions.

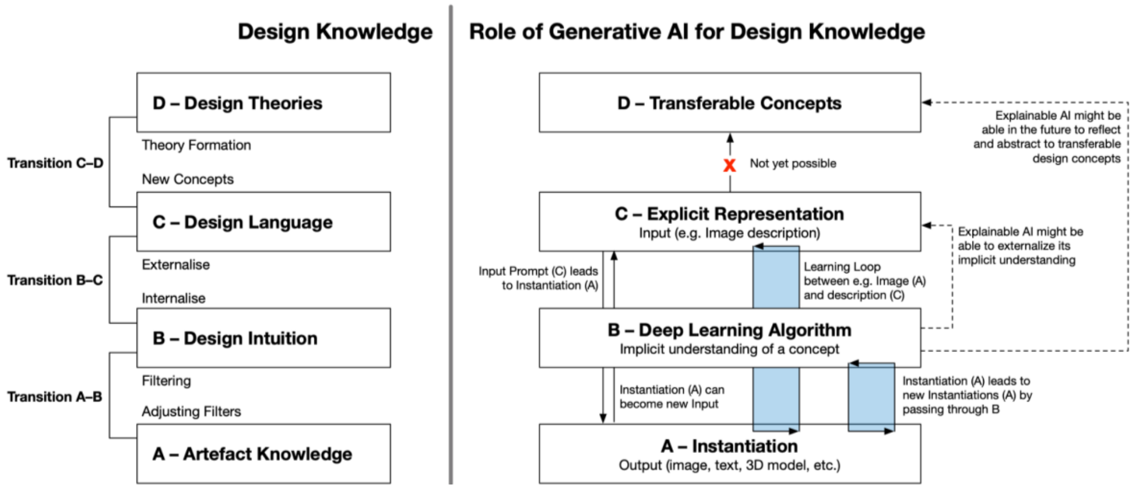

Figure 2: Left: Model of design knowledge, based on Thoring et al (2022); Right: Adapted knowledge model with relation to generative AI.

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We identified several relations between the different types of design knowledge and the capabilities of Generative AI, illustrated in Figure 2 (right). The Artefact level (A) includes design "Instantiations", either created by a human designer or by the AI, for example images (sketches, artworks), texts (design requirements, idea descriptions), or 3D models (physical prototypes, digital models), etc. The Intuition level (B) contains the "Deep Learning Algorithm", which develops an implicit representation of specific concepts (for example, the concept of a "car" or the concept of "van Gogh style"). This implicit representation is based on embedding the instantiation in an appropriate latent space. A latent space is a compressed mathematical representation which was trained on many prior examples so that points that are semantically similar to each other are also close to each other (Arvanitidis et al., 2018). On level C we can find "Explicit Representations" of a concept, for example, the textual description of a car depicted on an image. The top level (D) refers to "Transferable Concepts", that represent the capability to understand, reflect, abstract, and derive design principles based on the concepts of the lower levels.

Typically, a human designer would provide a prompt (level C) to the algorithm (B), which would then create a tangible instantiation (A) as a creative output. This prompt is usually text-based, but could also have other explicit forms, for example, a sketch. Vice versa, the tangible instantiation (A) could be used as a new input (C). For example, a sketch that is created by the algorithm could be fed back as a prompt (together with additional instructions) for a new round of generative design creation.

The back-and-forth iteration between levels A, B, and C, results in two loops within the framework: one learning loop between level C and level A, where the algorithm (on level B) learns/internalises concepts to develop an intuition. This can happen, for example, by training the algorithm with a multitude of images (A) and related textual descriptions (C). The second loop takes place between level A and level B. Through recombination and variation, the algorithm (B) creates variations of a given image (A). These two loops are the main areas for AI-interventions within this framework. This is in line with the explicit–implicit interaction theory (Hélie and Sun, 2010), arguing that creativity can be understood through the iterative integration and transformation of implicit and explicit knowledge.

Knowledge on Level D related to "Transferable Concepts" allowing for abstraction, generalisation, and transfer of design principles cannot yet be created by Generative AI. "Explainable AI" (Samek et al., 2019) tries to make an AI model more transparent and understandable by explaining why specific decisions were made. The learned and internalised patterns of simple machine learning models, like linear regressions or decision tree algorithms, are easier to understand for a human. However, the millions of learned weights in a deep neural network are opaque for any human, even for the developer of the network. There are some Explainable AI approaches that try to make the tacit representation of a deep learning model more accessible. A deep learning model might be able to tell that a picture depicts a "cat", where the cat is located on the picture, or that the picture is painted in a "van Gogh style". However, to the best of our knowledge, there is no AI-based method that could explain what the essence (i.e. the distinguishing characteristics) of a "van Gogh style" is and teach a designer how to apply this knowledge as a transferable concept.

4 EVOLUTIONARY CREATIVITY

As outlined in the previous sections, Generative AI is capable of "generating" creative output. If we consider this a creative act, we need to understand how this relates to creativity theory. Among the manifold creativity theories, the one of particular interest is the concept of evolutionary creativity (Simonton, 1999a, 1999b). We decided to refer to this concept because it can be applied to any system (including AI), whereas most other creativity theories stem from Psychology, and hence, apply only to human behaviour. A detailed description of evolutionary creativity in relation to the design process can be found in Thoring and Müller (2011).

Evolutionary creativity distinguishes between "Variation" and "Selection", which can be mapped to the distinction between "generative models" and "discriminative models" in AI. In Variation, new concepts are created through either "mutation" or "recombination". As outlined in the previous section, the creation of design knowledge through Generative AI happens in large parts through iterations between level A and B: An algorithm creates variations of a design by what is called mutation and recombination in evolutionary theory. This could happen, for example, through interpolation in the latent space of known concepts (i.e., creating new designs in between existing designs). At its current state, the technology is well capable of creating thousands of variations of a particular design, based on random mutation and interpolation. By contrast, extrapolation out of the latent space (i.e., continuation of a series

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of concepts into unknown territory) or bridging to another latent space is not yet possible for the technology. However, extrapolation might lead to novel, original concepts and hence is more desired than interpolation. At the same time, an AI can perform recombinations and mutations based on provided prompts (provided by a human designer). These prompts serve as a guidance for an AI to prevent mutations and recombinations that are completely out of scope.

In a discriminative model, the "Selection" of a variant must be made. While an AI can generate thousands of variants of a design, the difficult part is then to decide which one to choose. This crucial step is still done by a human designer, who is able to judge the created design regarding the quality (e.g., aesthetics), and the fit to the context and its requirements. Selected designs can be used as new prompts for the variation step, leading to iterations between variation and selection.

Figure 3 outlines the interplay of Variation and Selection. The AI is mainly involved in the Variation process, whereas the human designer is responsible for selecting designs based on the fit to the context and requirements and based on the design quality. The designer also typically provides the prompts either for the initial variation or for the iteration of selected designs.

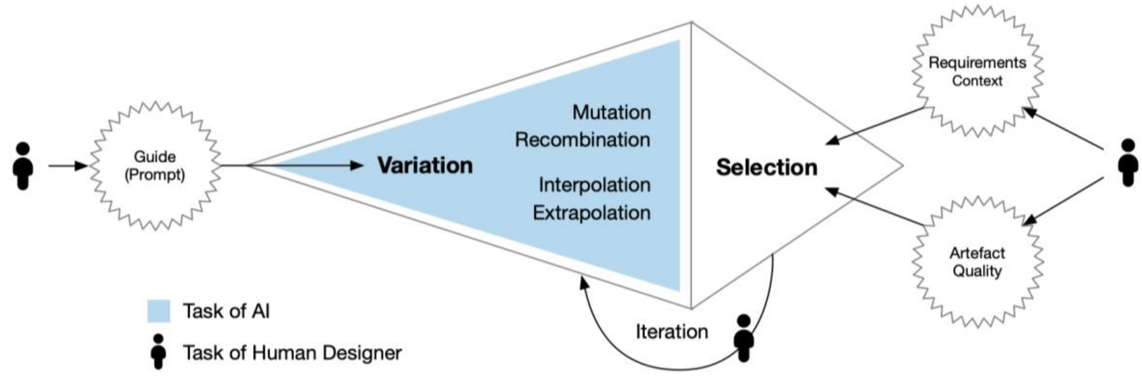

Figure 3: Interplay of human and AI tasks related to evolutionary creativity

5 THE AUGMENTED DESIGNER – ENHANCED BY GENERATIVE AI

As outlined in the previous sections, there are some tasks where an AI can provide significant support for a designer, for example, by generating numerous variations of a design. The question arises, what additional opportunities might emerge from this fast-developing technology, which would augment the designer even further. To motivate further research in this direction, we suggest a research agenda that is outlined below. When looking at the two frameworks introduced in the previous sections, several areas for further research can be identified:

1. **Guided Prompts:** The task of generating prompts to "guide" Generative AI is typically done by a human designer. There are marketplaces that sell prompts, such as PromptBase (PromptBase, 2022). However, the development of prompts could be further facilitated through AI. To ensure guided variation, we need more controlled and targeted prompts (see points 2 and 3). One possibility could be a tangible interface which allows designers to see the immediate impact of their prompts, similar to the interface depicted in Fig 1. The challenge of creating appropriate prompts is to capture the design context and requirements. Prompt engineering might also be a future skill for designers.
2. **Mutation**: Variation can be created by "mutation" of existing concepts. A research question in this realm would be how to control and steer mutation in a desired or unexpected direction, and how to control the results in the sense of being still within a reasonable range of application.
3. **Recombination**: Another mechanism to create variation is the "recombination" of existing concepts. Here, it is important to ensure semantically controlled combinations in different dimensions (colour, shape, function). An AI needs to be trained accordingly and a designer needs ways to guide an AI to the dimensions it should be using.
4. **Interpolation**. As outlined earlier, interpolation is relatively easy to accomplish for an AI. Potentials for improvement can be found in the interface for human designers controlling the direction and degree of the interpolation, e.g., through slide controllers, like the example in Fig. 1. Furthermore, an AI could be trained to better create reasonable interpolations that make sense in the given context.

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5. **Extrapolation**. At its current state, Generative AI is not yet capable of extrapolating explicit design knowledge. However, in this step lies the true potential of innovation. How can we find ways to train the AI to think outside of the latent space box, to generate truly innovative solutions that are beyond the existing design options?
6. **Selection** based on **Context**. The question arises, whether an AI could also build an intuition (level B in our knowledge model) that would allow for selecting the most appropriate design solution. To enable this step, an AI would need to develop a deep understanding of the world to evaluate the fit of the design to the context and requirements. Also, designers need ways to encode their domain requirements.
7. **Selection** based on **Artefact Quality**. Future efforts could focus on training an AI to assess the quality of a design, for example, based on aesthetic parameters or by creating large sets of training data based on human designers' assessments.
8. **Iteration.** When design educators give students feedback for iterating their design, they are not just selecting promising design ideas, but giving them guidance and direction on how to iterate. How can we translate this to the interaction with a Generative AI? Especially the Q&A capabilities of tools such as ChatGPT could be further explored in this context.
9. **Transferable Concepts.** How can we further generalise explicit representations to transferable concepts, such as design principles or design patterns?
10. **Externalisation.** Can an AI externalise more nuanced conceptual dimensions from the latent space, such as aesthetic properties? Are there conceptual dimensions in the latent space that have no appropriate words in the English language, but should be named?

6 DISCUSSION AND CONCLUSIONS

As demonstrated in the previous sections, there are some design tasks that can be well performed with the support of Generative AI, such as generating variations, and others that still need to be performed by human designers, such as selecting designs or transferring abstracted concepts to, e.g., students. While Generative AI technology is evolving at an enormous speed, its potentials for and impact on the designer and the design process are yet unclear. The technology might become simply another tool to support the designer, but it could also replace some of their traditional tools and skills. How should the design discipline adapt to these developments? Where are the boundaries of this technology? Will an AI at some point be able to distinguish good designs from bad ones? Will it be able not only to generate options, but also to make choices? If an AI learns to externalise and explain its decisions and to convert those to "transferable concepts", will it supersede the design teacher?

With the present paper we provide a theoretical foundation for a research agenda aiming to answer such questions. We argue that the two presented perspectives – design knowledge and evolutionary creativity – provide a solid foundation for the theoretical understanding and the practical application of Generative AI to the design field. More specifically, we consider the interplay of internalising and externalising design knowledge and the interplay of variations and selection the core aspects of the AI-supported "augmented designer". We acknowledge, though, that there might be more aspects to consider, other than knowledge creation and creativity. For example, future work could focus on the relation of Generative AI to the design *process*.

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