Designing AI-driven Inspiration for Design Professions

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Abstract. In design professions like architectural design, engineering, product design, urban design, or systems design, it is important for business to innovate and solve problems creatively. However, peoples` creativity is not naturally inexhaustible and personal traits, biological conditions and several other external influences determine human ability to solve problems creatively. That makes it hard for professions whose necessity to exist on the markets depends on creative problem solving. Artificial Intelligence (AI) offers new possibilities to design creativity support systems (CSS). We design an AI-based CSS for architects that delivers stimuli by using generative adversarial networks (GANs) trained with a high-quality dataset. The kernel theoretical assumptions are based on the concepts of fixation and mental representation abilities. Based on design principles, general requirements, and a trained GAN, we design instantiations to test our hypotheses. We further suggest an online experiment to evaluate our designs.

Keywords: Creativity, Design Science Research, Artificial Intelligence (AI).

1 Introduction

In today's world, we are often faced with wicked problems. Therefore, we need new digital solutions that allow for a better tomorrow. Creativity is a crucial pillar in this regard to tackle those problems and innovate [1]. From that practical point of view, the practice of design is based on creativity, and further competitive advantage calls out for creative problem solving. In the realm of design practice and design professions like architectural design, engineering, product design, urban design, or systems design, it is important for business to solve problems and make decisions creatively. However, peoples` creativity is not naturally inexhaustible. For example, personal traits, biological conditions, and several other external influences determine human ability to solve problems creatively [2]. Especially for design practice it is important to understand creativity as a resource that is never complete and perfect. According to Baskerville et al. [3], "bounded creativity (the amalgamation of Simon's bounded rationality in design and bounded creativity in engineering) means that humans are limited in their ability to make perfectly creative designs" [3]. An exemplary phenomenon is fixation, which is an undesirable condition for professionals who rely on creative problem solving and try to generate variations in their designs. Such an issue makes it hard for professions whose raison d'être depends on creative problem solving. We understand fixation as "the inability to overcome a bias in the representation of a situation by transferring knowledge from prior experience in an inappropriate manner" [4]. To prevent or solve the inability to generate new and useful ideas or concepts, stimuli can be a means to foster the idea generation [5]. Delivering technology-based stimuli to support creativity of individuals or groups and the exploration of the systems (i.e., creativity support systems; CSS) has a long history in information systems research (e.g., [6]). Technological progress is constantly creating new needs and opportunities to design these systems [7]. For example, AI offers new possibilities to design CSS. Especially adversarial learning, or more specifically GANs, are an exciting approach for the data-based generation of stimuli as they try to mimic cognitive capabilities. However, GANs rely on probabilistic instead of deterministic calculation. This implies that CSS building on this technology derive their results based on complex statistical models that incorporate many contextual factors without the knowledge of developers and users. Hence, outcomes are hard to comprehend and research on design is needed. We design an AI-based CSS for architects that delivers stimuli based on a high-quality dataset by using a GAN. Therefore, we build on the work of [7], who already suggested a general AI-based CSS, which we applied to the context of architectural design. In this work, we apply the general requirements and principles of AI-driven CSS to a specific context (i.e., architectural design). For this purpose, we apply them without exploring further requirements and principles to investigate their robustness in the research-in-progress status of our work. We will further iteratively deploy the prescriptive knowledge from the unspecific CSS and improve, adapt, and exploit the requirements and principles of AI-driven CSS, which is a relevant design contribution in DSR [8]. The kernel theoretical assumptions are based on the concepts of fixation and mental representation abilities. Based on the derived design principles [7] and a trained GAN, we design instantiations to test the design principles. We further suggest an online experiment to evaluate our designs.

2 Designing inspAIred

Designers' repertoire. While some cognitive explanations of creativity focus on phenomena like *eureka moments,* which explain creative problem solving that emerges from *nothing*, this explanation alone is not sufficient for the case of designers and the case of architects. Their personal experience is important to generate new designs [9]. In this case, experience does not mean that old solutions are simply reinvented and used for the new situation at hand. It is more about investigating the new situation by using previous procedures, forms, practices, and bodies of knowledge to create a new solution. The so-called repertoires of a designer are "[...] not rules, but thousands of examples, comparative, directly and intuitively based on experience[...]" [10, 11]. **Representational abilities of humans**. Representational abilities are important for creative problem solving to prevent fixation, and thereby deal with bounded creativity. There are three different representational abilities [12]: i.e., primary representation, secondary representation, and meta-representation. To better understand and to visualize the different representational abilities, we present Maier's [13] study. In a room two cords are hanging from the ceiling and subjects are placed in the room. The task is to tie the two cords together. However, the tow cords are placed too far away from each other to reach them with open arms. Additionally, there are several objects placed in the room (e.g., pliers) that can be used. Most subjects were not able to solve the problem. The solution is that the pliers can be used as weight and pendulum to reach one of the cords, while holding the other one. Primary representation led the subjects to see the pliers as what they semantically mean. Primary representation means a direct relation to the reality, where the individuals only see the actual meaning (i.e., pliers are pliers). The ability of secondary representation led the subjects see the pliers as weights. Individuals` ability of secondary representation helps to see the real world in another way [4]. Further, the third ability of representation, the meta-representation helps to solve the problem and understand the pliers/weights as inspiration and part of the solution. In summary, secondary representation and meta-representation can help to change the perspective and leave the problem space to enter the solution space, which is shown in Maier's study. **Training the GAN.** While traditionally designers and in our particular case architects rely on heuristics, and we stressed out the problem of individual experience and overall the concept of bounded creativity (i.e., fixation), AI as a statistical and data-based concept seems to be promising [14, 15]. Machine Learning can help to enrich the individuals' repertoire and complement individuals' intuition based on countless previous solutions [16]. Neural networks are a new approach in the field of adversarial learning through which the algorithms mimic human capabilities. GANs are a special form of neural networks, which can generate data themselves [17]. A GAN consists of two competing neural networks: a generative model G that aims to create results of a certain distribution out of training data, and a discriminative model D that estimates the probability of whether these results came from G or from the training data. As such, G aims to maximize the errors of D to create realistic results that cannot be distinguished from real data. With this methodology, GANs are capable of, e.g., creating realistic images [18]. Particular fields of application have been face aging, image inpainting, and building footprint recognition and generation [14, 17]. Thus, the ability of GANs to recognise patterns and reproduce them opens new windows of opportunity for AI as an "expert system for design diagnosis and design synthesis" [16]. **General Requirements and Design Principles.** While GANs can generate realistic images, the illustration as stimuli has the potential to strengthen different representational abilities. Realistic images will tend to stimulate primary representation, more abstract representation in turn will tend to stimulate secondary and meta-representation and help the viewer to look beyond the obvious. Based on kernel theory and justification knowledge [19], we apply the general requirements and design principles [20] from Klein et al. [7]. The general requirements help to link the design principles with theoretical and conceptual underpinnings. According to Klein et al. [7], the general requirements are: "(1) The system must support iterative combination of frames. (2) The system must activate secondary representation and meta-representation. (3) Overall Requirement: The system must help the participants to interpret the given stimuli and objects (e.g., by asking "What else could the object be?")". We apply the "command variables" [20] as general componentsv (GPs) and : "Design Principle 1; the system must deliver stimuli, which are more generic rather than detailed and realistic. Design Principle 2; the system must deliver stimuli, which make relations between different objects visible." as design principles (DPs) [7]. **Construction and Instantiation.** According to the DPs and GRs, we present an expository instantiation [19] (Outcome D) to suggest an evaluation strategy [22]. The construction consists of three different activities: data acquisition, data annotation, and algorithm training. We collected site plans of already published competition-winning results. For data annotation, we considered the following elements of the site plans: surrounding buildings, existing buildings on the site, the site, the building, access to the building, and access to the site. We trained the algorithm with 460 images. Based on the trained GAN, we were able to generate stimuli for new architectural design tasks. In the following, we present two different representation variants that have different normative characteristics with respect to our requirements and thus allow a "systematic manipulation of artefact design variables" [23]. Figure 1 shows four different conditions to evaluate the instantiation. A: abstract and information high; B: detailed and information high; C: abstract and information low; D: detailed and information low.

Fig. 1. Instantiations

3 Evaluation / Further Research

Approach. As this research is intended for design, we want to contribute to descriptive and prescriptive knowledge base. Accordingly, we aim at constructing an IT artifact and develop prescriptive knowledge on how to design the IT artefact (e.g., methods, techniques, principles of form and function) [24]. The two perspectives (i.e., interior mode and exterior mode) define our research: 1. interior mode, "theorize prescriptively for artifact construction"; 2. exterior mode, "theorize about artifacts in use" [25].We "provide theory-driven design guidelines and prescriptions for IS design, and the generation of hypotheses that are testable" [26], in order to contribute to the knowledge base in both, the rigor and the relevance cycle [27]. Against that background, our research activity will ensure to derive and implement explanatory design principles of form and function [28] of an AI-driven CSS to inspire design-oriented profession during creative problem solving. Our design decisions in this project are continuously informed by evaluation, and in this first phase, the evaluation will be explanatory, because it "prescribes principles that relate requirements to an incomplete description of an object" [20]. The process of our research activity will consist of two core activities: It consists of (a) building and (b) evaluation (i.e., (a) theory and artifact building and (b) evaluation of design principles and hypotheses) [29]. **Model (Figure 2).** According to kernel theory, it is important to enable secondary and meta-representation. The stimuli should enable interpretation of the shown stimulus. Thus, abstract illustration of the information will lead to a higher evaluation of the possible inspiration and a more detailed illustration will lead to a lower evaluation (DP1). Additionally, more information contextual and relational information regarding the design task, will lead to a higher evaluation and low degree of information will lead to a lower evaluation (DP2).

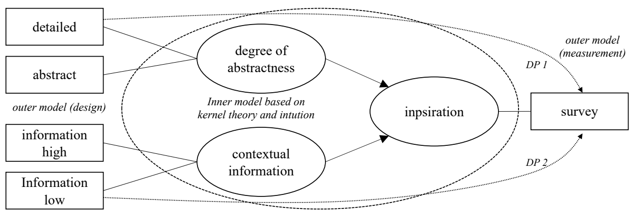

Fig. 2. Design Theory for AI-driven inspiration

Evaluation. We will conduct an online experiment following a two-step approach (i.e., ex-ante, ex-post). The design model will be tested in a 2x2 setting (ex-ante). Participants are architects with professional experience. Participants will get instructed to a fictive creative problem-solving task. After the instruction, the participants will get the stimuli. Then, participants will evaluate the usefulness of the shown stimuli regarding their potential inspiration. Additionally demographic variables and information about their professional context will be requested. In the ex-post evaluation, we will test the credibility of our GAN. Therefore, the participants will rate different designs (n=40) as to whether they are designed by a GAN or if they are contributions from architects. With our research we want to show, that AI-driven systems are potentially able to inspire professionals during creative problem-solving tasks and contribute by identifying explanatory variables, why they do inspire. The relevance for practice is high, as designers and architects` demand for unique solutions are high. The findings can be seen as a first step and the transfer for other professions would be beneficial. Our theoretical contribution is high, because we build theoretical elements and derive design principles, which are based on kernel theory.

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