EXPLORING THE ROLE OF TEXT-TO-IMAGE AI IN CONCEPT GENERATION

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ABSTRACT

Artificial intelligence (AI) capable of generating images from a text prompt are becoming increasingly prevalent in society and design. The general public can use their computers and mobile devices to ask a complex text-to-image AI to create an image which is in some cases indistinguishable from that which a human could create using a computer graphics package. These images are shared on social media and have been used in the creation of art projects, documents and publications. This exploratory study aimed to identify if modern text-to-image AI (Midjourney, DALL-E 2, and Disco Diffusion) could be used to replace the designer in the concept generation stage of the design process. Teams of design students were asked to evaluate AI generated concepts from 15 to a final concept. The outcomes of this research are a first of its kind for the field of engineering design, in the identification of barriers in the use of current text-to-image AI for the purpose of engineering design. The discussion suggests how this can be overcome in the short term and what knowledge the research community needs to build to overcome these barriers in the long term.

Keywords: Artificial intelligence, Conceptual design, text-to-image, Design process, Concept Generation

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Cite this article: Brisco, R., Hay, L., Dhami, S. (2023) 'Exploring the Role of Text-to-Image AI in Concept Generation', in *Proceedings of the International Conference on Engineering Design (ICED23),* Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.184

1 INTRODUCTION

Artificial intelligence (AI) has become something of a societal buzzword in recent years. However, research on AI in design has a long history and a well-established community including journals such as AI EDAM[1] and conferences such as DCC[2]. Researchers have explored a variety of potential roles that AI systems can play in the design process (Ayele & Juell-Skielse, 2021; Gero & Kannengiesser, 2014; Karimi et al., 2019), but a key focus has been on computational creativity. That is, the ability of computational systems to support creative thinking and the development of ideas (Sosa & Gero, 2016). This work has often treated AI as a kind of co-creative assistant. However, there has long been debate around the extent to which AI can be considered to be itself a 'creator', versus simply supporting a human's creative process (Cornock & Edmonds, 1973).

The recent rise of openly available generative text-to-image AI that is accessible to non-specialist users has sparked huge public interest in this topic. Systems such as Midjourney, DALL-E and Disco Diffusion and more recently Stable Diffusion, combine generative algorithms with an intuitive interface, allowing the user to enter natural language prompts and receive a range of generated images conveying concept(s) identifiable in the text. There has recently been a sharp increase in the awareness and accessibility of these systems which are capable of generating high resolution images in varied aesthetic styles that match text prompts with a apparent high accuracy rate. This naturally leads to questions regarding the role that text-to-image AI could play in conceptual engineering design. There has been an explosion in the production of generative art in the public discourse[3], and examples of designers in other domains beginning to incorporate text-to-image AI into their workflows for Magazine cover generation[4] or storyboarding[5]. However, the use of text-to-image AI as a design activity has yet to be extensively explored in an engineering design context.

One promising application of text-to-image AI systems in a conceptual engineering design is as a representational tool to support rapid visualisation of concept ideas and variants during concept generation, to efficiently produce high quality images that can then support interpretation and decision making about concept selection and development. This could have a number of advantages including increased productivity to capitalise on a competitive advantage by reducing the time spent on visualisation and enabling rapid exploration of larger numbers of alternatives (Torkkeli & Tuominen, 2002). The images generated could spark ideas that would not have been discovered by human designers alone exploring a smaller portion of the design space. It could also provide a way for non-designers without training in design sketching and CAD to more easily express their ideas, increasing the accessibility of the design process. However, examining the approaches currently used to generate images in commercially available text-to-image systems highlights several issues that may limit their effectiveness including creativity and appropriateness of these tools in an engineering design context and warrant further investigation.

The text-to-image AI models discussed in this paper use a method of machine learning where an AI model is firstly trained on sets of millions of real-world image-text pairs, essentially learning associations between natural language and visual attributes. New images are generated with a technique named diffusion where random noise is used as a starting point to generate new images based on the knowledge of the model. The recent proliferation of text-to-image AI models is attributed to the development of new learning techniques such as generative adversarial networks (GANs) and diffusion models using Contrastive Language–Image Pre-training (CLIP) (Ramesh et al., 2022) making the time to train and therefore cost significantly less. The difference between text-to-image AI systems is the method of training the systems, the database of images used to train the images, the method of image generation and the user interface.

Developing concepts with particular structural and behavioural attributes is important in engineering design in order to address functional requirements (Gero & Kannengiesser, 2014). These kinds of attributes and their relationships are not understood by current commercial text-to-image AI systems. This is reflected to some extent in the 'surreal' and 'dreamy' quality often ascribed to AI-generated images, that break real-world conventions and expectations. Whilst this aspect of text-to-image

1 https://www.cambridge.org/core/journals/ai-edam
2 http://www.dccconferences.org/dcc22
3 https://boringcrypto.medium.com/ai-generated-art-looks-unreal-now-what-88b703eed579
4 https://www.cosmopolitan.com/author/219341/gloria-liu/
5 https://sarahdrummond.medium.com/the-future-is-what-you-think-it-is-d7a54369ea32

https://doi.org/10.1017/pds.2023.184 Published online by Cambridge University Press

generation can be leveraged to produce novel aesthetics, it is not necessarily conducive to generating images of novel functional concepts, or images that support the interpretation and development of functionality during designing. This creates challenges if text-to-image AI is to be used in conceptual engineering design, as the design process is heavily geared towards the specification of concept functionality (Umeda & Tomiyama, 1997).

Text-to-image AI models are only aware of things that exist in the real world (based on the images they have been trained on) and can only generate images that are derivations of known things. The AI will also be biased towards the visual characteristics of frequently occurring everyday objects, because these are likely to appear more frequently in the training sets. Overall, therefore, it might be expected that concept development supported by text-to-image AI runs the risk of being highly derivative and lacking in novelty, particularly when it comes to developing new products with no analogue.

2 AIM OF THE STUDY

There is a lack of research on the application of text-to-image AI in engineering design within the literature. Image generation approaches used in commercial systems potentially create some unique challenges in this context as is the motivation for this research. To provide insight in this area, this paper reports an initial exploratory study seeking answers to two key research questions:

- RQ1: To what extent can publicly available text-to-image AI systems generate images of concepts that support the interpretation of concept ideas to inform decisions about concept selection in engineering design?
- RQ2: What are designers' perceptions of the generated concept images and the potential role of text-to-image AI in the design process?

To answer these questions, the results of the initial exploratory study are discussed with the use case of text-to-image AI in engineering design. The outcomes of this research are intended to position the current understanding of text-to-image AI tools for researchers and designers.

In this paper, recent literature is briefly reviewed in Section 3 to summarise current knowledge about AI use in conceptual engineering design to provide context for the study. The study methods are outlined in Sections 4, and the results with respect to each research question are presented in Section 5. A discussion of the findings and recommendations for the application of text-to-image AI in engineering design is provided in Section 6, with limitations, Section 7 and conclusions summarised in Section 8.

3 LITERATURE REVIEW

AI in engineering is currently a novel concept as it comes to maturity, however there are pockets of the field that are more established in the development of solutions. At the 2022 Design Computing and Cognition conference held at the University of Strathclyde, Alymani et al., (2022) published on a node-based learning approach to classify architectural building to ground relationships, Deprez et al., (2022) presented an approach to the generation of residential floorplans using neural networks, and Koh, (2022) on generative machine learning for architectural design to create automated layouts of stairs and rooms. The architecture research field appears to have a long history (at least since 1995) in creating demonstrations from AI theory that engineering design can learn from, with 2D and 3D concepts generated (Castro Pena et al., 2021) and an understanding of the role of the conceptual design phase in exploring solutions to requirements. Perhaps it is the nature of architecture researchers to be more accepting of AI to support their concept generation, or perhaps it is the nature of that which they are generating. Yet it seems conceivable that if an AI can generate configurations of building layouts, then an AI can be built that can generate configurations of components of a product e.g. a chair with three main components, legs, a seat and a back.

Within engineering design, proposals of how best to implement generative design algorithms are beginning to emerge and focus on specific aspects of design e.g. human-centered (Urquhart et al., 2022) or artifact recall (using linkography) to support decision making (Le & Jung, 2020).

There are also advances in text-to-3D model AI (Poole et al., 2022) in the CAD space that appear promising for bridging the gap between those without 3D CAD modelling skills and customisation of concepts e.g., for 3D printing. And this could also increase productivity in the design process without the need for the designer to model, at least, the initial main form of the concept. This has been

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demonstrated in a product design context by Yoo et al., (2021) who present a framework to generate and evaluate 3D CAD concepts with the product example of a car wheel, and with CAD generative design and stress analysis optimisation of a gear and pinion (Wu et al., 2018).
Within educational communities, Figoli et al., (2022), investigated perceptions of students towards AI technologies. Students were accepting of AI in the design process during a pre and post project survey, however those who were most welcoming were also those who re-evaluated their position during the post project survey meaning their experiences with AI had strongly influenced their views against the use of AI in future projects, indicating that current AI systems are perhaps without consideration if they are appropriate or not to be used in education (Beetham & Sharpe, 2019) or in practice.
Maher & Fisher, (2012) discuss an AI approach for judging creative design. The approach focused on measures of novelty, value, and surprise and was evaluated using student laptop computer concepts against those made by Apple. The method of evaluation appears appropriate in terms of a machine learning approach and the decisions made. However, this study was highly context dependent meaning there is a great amount of work to enable universal evaluation.

4 METHODOLOGY

To better understand the use of publicly available text-to-image AI as a substitute for designers during the conceptual design process and initial exploratory study was devised asking participants, students of the Research Studies class at DMEM, University of Strathclyde, Glasgow, UK, to take part in a concept evaluation experiment. The product chosen for the experiment was a chair based on its simplicity and familiarity. 20 participants took part in the study in six teams (four teams of three participants and two teams of four participants). Participants were 55% male and 45% female of ages between 21 and 24 (Mean 22). Participants were final year (5th year) Masters students studying Product Design Engineering, Product Design and Innovation, and Sports Engineering.

Figure 1 - Worksheet for the experiment with all 15 chair concepts presented.

Participants were presented with 15 chair concepts and asked to evaluate these as initial concepts. Working in teams, the participants used any method they consider suitable to evaluate the 15 chair concepts to a final chosen concept. Participants were supplied with a worksheet (Figure 1) featuring each chair concept. Participants were given 30 minutes to agree on a final chosen concept.
Chair concepts were generated using three different text-to-image AI; Midjourney (images 1, 4, 10, 14, 15), DALL-E 2 (images 3, 5, 6, 8, 11) and Disco Diffusion (images 2, 7, 9, 12, 13). Images were generated using the text prompt "chair" on the 13th September 2022. Midjourney generated images in batches of four with the first batch included with the first image of the second batch. It is recognised that this approach may have limited the conceptual variance yet replicated how a designer would generate images in practice.

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Participants responded to a survey collecting data on the process the students followed to select a final concept and their reflections on the experience of concept evaluation towards research questions.
The questionnaire was prepared online using Microsoft Forms as is the universities recommendation for data protection. The questions created are as follows:
RQ1
1. Which image was selected by your team as the final concept?
2. Which Design Activity(s) did the team use to select a final concept?

RQ2
3. Can you identify a pattern in the 15 initial designs? What do you think this might be?
4. Do you think that the final concept is a suitable chair? and why?
5. Do you think these pre-generated images could replace a team's concept generation activities?
6. How might the pre-generated images be improved to make them suitable for concept selection?
7. How might the design activity be improved to support the concept selection?

NVIVO 2020 software was used to code the survey responses and create quantifiable data. Coding was required as students used their own language to respond to questions and certain criteria had similar meanings e.g., "not stable", "lacking stability", "lack of stability" etc.

5 RESULTS

In this section, the results of each of the questions of the survey are presented. Question one asked: Which image was selected by the team as the final concept? Outcomes are summarised as Figure 2. The most popular concept selected by 50% of teams was image 8. Images 3, 6, and 14 were selected once.

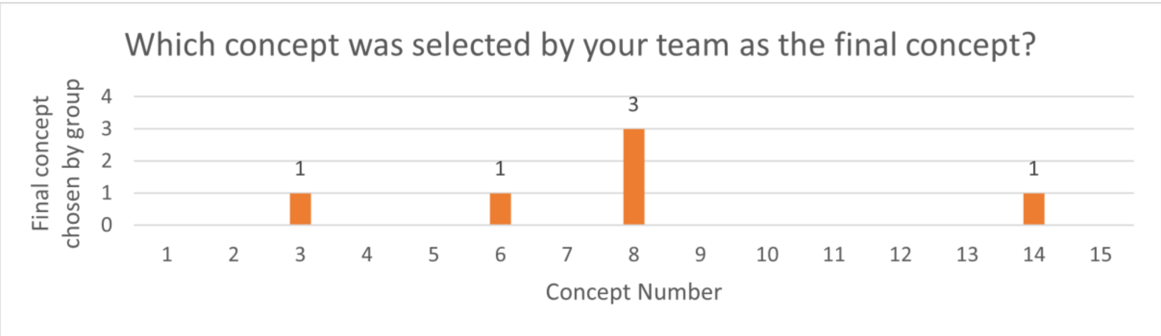

Figure 2 - Final concepts selected by teams

Question two asked: Which Design Activity(s) did the team use to select a final concept? Outcomes are summarised as Table 1. Team 1 selected image 3 and used dot sticking to narrow down to six concepts based on personal preference (3, 5, 6, 7, 8, 15) and a weighting matrix based on categories of aesthetics, function and comfort to a final concept. Team 2 selected image 6 conducting dot sticking to narrow down to four concepts (1, 3, 5, 6) and Plus, Minus, Interesting (PMI) to support discussion towards a final concept. Teams 3 and 4 selected image 8 using dot sticking on categories of: team 3 - practicality, stability, ease of use, aesthetic, ergonomics, conceptual and ease of manufacturing, and team 4 functionality, comfort, aesthetic, safety and personal preference respectively. Team 5 who selected image 8 split the concepts between the team members and then thematically analysed the concepts into stability, comfort, and aesthetic. The team then conducted discussions around these themes to select a final concept which met these criteria. Team 6 who selected image 14 used dot sticking based on categories of comfort, creative and practical.
Question three asked: Can you identify a pattern in the 15 initial designs? Of the 20 participants, eight identified that the images were created using AI. One respondent identified "computer generated" which could also be interpreted as created by AI. Other answers included criticisms of the designs themselves including: "designed by someone who has never sat on a chair", "each concept has at least one design flaw", "otherworldly", "Could be chairs from movies", "charity shop vibe" and "similar colours".
Question four asked: Do you think that the final concept is a suitable chair? and why? Of the 20 participants 17 responded they the final concept selected was a suitable chair. Of these positive responses there were two types of response. Yes - justified because of specific criteria typical of a chair (9 respondents), or Yes - as it is the most appropriate (8 respondents) indicating there is a belief that none of the initial images are particularly suitable. One respondent said that the final concept was

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not suitable due to the need for modification, and two respondents said they were unsure as they required more information that the image could not provide.

Table 1 - Evaluation process chosen by participants.

Team	Concept	Approach	Criteria used to evaluate
1	3	Dot sticking > six concepts. Weighted matrix > final concept.	Personal preference. Aesthetics, function and comfort.
2	6	Dot sticking > four concepts. PMI > final concept.	Personal preference. Personal preference.
3	8	Dot sticking > final concept.	Practicality, stability, ease of use, aesthetic, ergonomics, conceptual and ease of manufacturing.
4	8	Dot sticking > final concept.	Functionality, comfort, aesthetic, safety and personal preference.
5	8	Thematic analysis > final concept.	Stability, comfort, and aesthetic.
6	14	Dot sticking > final concept.	Comfort, creative, practical.

Question five asked: Do you think these pre-generated images could replace a team's concept generation activities? Of the 20 respondents, only one respondent was positive towards the potential of AI to replace concept generation activities. Three respondents said no, and the remaining 16 said they were unsure as they recognised the potential in the future. Unsure respondents commented of the ethics of AI in concept generation or using the concepts as inspiration supplementing ideas of the design team. Two respondents identified the potential for AI to support in aesthetics or as inspiration, but not for functionality and structure of the chairs.

Table 2 (left) & Table 3 (right)- Ideas for concept development and ideas for process improvement and the number of participants who identified the ideas.

Ideas for concept development	Numbers of respondents who identified ideas
Clearer image	4
Improved realism	4
Pre-evaluation by a human	2
Improved keywords	2
Improved AI	2
As aesthetic inspiration	1
Pre-defined Specification	1
3D	1

Ideas for process improvement	Numbers of respondents who identified ideas
Pre-defined Specification	4
Improved realism	2
Fewer initial concepts	2
3D	2
As aesthetic inspiration	1
Clearer image	1
Comparison with a datum concept	1

Question six asked: How might the pre-generated images be improved to make them suitable for concept evaluation? Outcomes are summarised as Table 2. Respondents summarised issues with the presented concept images including: the need for a clearer image and improved realism of the image. This could be improved through an improved text-to-image AI or perhaps 3D outputs of the AI. Other ideas were procedural including, pre-evaluation of concepts by a human (to remove any unrealistic solutions), improved keywords to create images, use of a specification to create keywords, and use of images as aesthetic inspiration rather than as initial concepts.

Question seven asked: How might the design activity be improved to support the concept evaluation? Outcomes are summarised as Table 3. Respondents summarised ideas for the improvement of the design activity including defining a specification ahead of the evaluation, fewer initial concepts to evaluate, 3D concepts and using a datum or control concept for comparison. Respondents also identified that improved realism and clearer image would support the design activity. Respondents also identified that a restructuring to use AI as aesthetic inspiration than functional would improve the design activity.

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6 DISCUSSION

The motivation of this research was to understand the role that text-to-image AI could play in conceptual engineering design. All teams who took part in the research activity were successful in evaluating the 15 concepts to a final concept. However, there were complexities caused by the use of AI images that have the potential to be alleviated through change in design process and/or change in future text-to-image AI systems.

6.1 Support the interpretation of concept ideas

Concepts selected by teams were 3, 6 and 8 generated by DALL-E 2, and 14 generated by Midjourney. Certainly, the students had an attraction towards the concepts generated by DALL-E 2 perhaps indicating that the stye of image was most appropriate for the concept evaluation task. No team selected those generated by Disco Diffusion suggesting that the lack of distinct form was inappropriate. Surprisingly, the most popular concept, 8, is one where the full design is not totally visible as the image is cut off on top, however, this did not deter from the selection.

All teams, excluding one, chose to use dot sticking as the method of concept evaluation, perhaps supplementing this with another method requiring negotiation. It was interesting to learn that all teams choose to identify their own criteria for evaluation and did not search for established categorisations such as Pugh PDS. Participants did identify that a pre-defined specification for evaluation would have supported the activity. If integrated into a full design project, the role of AI may change to supplement concept generation of the team using the specifications most important to the design outcomes.

6.2 Perceptions of the generated concept images

40% of students who took part in the study were able to identify that the initial concepts were created using AI. This indicates that a minority of the students were familiar with the style of an AI image to identify them. This perhaps indicates the prominence of awareness of AI image generation tools in the public discourse for this group of participants. Other responses provide an insight into the reflections of the suitability of the images as concepts. One student responded they believed the chairs were "designed by someone who has never sat on a chair", and this is correct. Another responded that "each concept has at least one design flaw" indicates that this student didn’t not identify the concepts as robust and usable.

The majority of respondents (85%) indicated that their chosen chair concept was suitable. This indicates that the activity was successful and modern text-to-image AI could be used to replace the designer in the concept generation stage. However, there are improvements that could be made to the process, and genuine concerns over the quality and suitability of all images generated. This sentiment is reflected in the response to question seven, where only one participant was confident in AI's ability to support the design process similar to the outcomes of Figoli et al., (2022).

To become more confident, there are some improvements that would need to be implemented as identified by the respondents. A clearer image, i.e., higher quality/resolution would be achievable perhaps with longer image generation times, or a change in the technology. This is complemented with the suggestion that 3D would overcome some of the challenges of interpretation by allowing multiple views of the concept alleviating misinterpretation. This may be possible with novel text-to-image AI such as DreamFusion capable of 3D or may ne negated with 'smarter' text-to-image AI such as Stable Diffusion or future AI systems.

Concept three is a good example of where the AI was uncertain on the seat of the chair and the resultant definition is low resembling a soft fluffy material, such as candyfloss or clouds. This is perhaps an unexpected outcome that students would interpret the materials of the initial images in unusual ways. One team agreed that concept 14 was made out of cheese, rather than looking like cheese but made from a more robust material. This highlights the inconsistency in interpretation when the concepts have been generated outside the design team. This may also explain why so many students reported that an improved realism of the concepts would help to improve the text-to-image AI.

Two students identified that an initial review to remove certain concepts and to generate more relevant ones would help with the design activity. Perhaps a process or method could be designed to support the AI in designing more appropriate concepts, related to the ideas of improving the keywords, the engine itself or the selection criteria. Another unexpected outcome was the suggestion that the text-to-image AI would be suitable in generating aesthetic inspiration. Rather than creating the initial concepts directly, AI could influence the design teams methodology and may be better suited in populating a mood board or vision board. Research is investigating how many generative steps are required to suitably inspire a designer based on AI generated chairs (Wang et al., 2021).

It is unclear why participants felt that less concepts would help with their evaluation. Typically, a larger number of concepts means more ideas to consider. However, this may be related to the comment on relevance where participants felt that certain ideas were not suitable and required a pre-screening.

Reflecting on process, respondents shared some ideas to improve the design experience including the definition of specifications. Within a typical product design process, before generating and selecting concepts there would generally be an extensive market research stage culminating in the development of a specifications document. This would help to affix criteria for evaluation than relying on the students subjective opinions. Related is the suggestion that a datum or control would be useful to compare the initial concepts against. This is typically facilitated with a competitor product to support decision making using a weighting and rating matrix. One team chose to conduct a weighted matrix with a smaller number of concepts, however they did not use a datum concept.

6.3 Research challenges for text-to-image AI in engineering design?

In the same way that those creating AI define specific criteria tailored to the needs of the systems development, engineering designers must consider this to support the development of text-to-image AI to best support engineering design activities. The survey questions were intended to explore theories about the ways in which designers wish to interact with AI during the design process i.e., how the process of designing changes when each of the design team do not have ownership of the concepts; and which aspects of the design process do the designers want to have control over. Designers have a high influence over the design process towards design development and AI has the potential to reduce that level of control. An analogy to the inclusion of AI in the design process can come from research in collaboration. It is understood that designers experience anxiety about lack of control which is a major factor in the design process. Therefore, there is a need to consider the level of control that is appropriate when implementing AI as a 'design team member'. Perhaps this means greater control over the inputs of the text-to-image AI system or processes.

In this initial exploratory study, a simple prompt of chair was selected. This text prompt was selected with the reasonable assumption that the images used to train the AI would include many variations as it is an abundant product in the world and the images would be suitably labelled. However, in the case of disco diffusion the concepts are highly similar. In the diffusion process, all aim for the colour brown and for a weaved or wooden pattern (Figure 3). This perhaps suggests the training was not as extensive for this category of product. Then it can be assumed that to develop an AI that is trained on chairs only, with variety in the training images would produce further creative outcomes. Perhaps specific AI for specific concepts is the answer.

As reported by Maher & Fisher, (2012) the evaluation process undertaken by the students is highly context dependent. To develop a more generalised AI would require greater learning in niche product areas rather than a more generalised learning experience. Using the example of a chair, there would need to be multiple variations of each component, and a balance between the freedom and restrictions of the configuration. The benefits are perhaps then questionable. A traditional design brief approach would require a specification which may influence the designers' approach and a pre-evaluation of concepts by researchers which would not represent the expected designers workflow. The approach using the text-to-image AI like those currently publicly available as described in this paper, enables more complex outcomes and arguably more creative outcomes, however, this is yet to be tested. The contrary point is that many of the concepts generated were not appropriate to function as a chair, and the current methods of teaching AI are not suitable in teaching AI about affordances.

Figure 3 - Example of disco diffusion generative image creation

Whilst the current methods of image generation highlight some issues, Berisha & Lobov, (2021) define five 'schools of thought' for machine learning in the context of AI-based methods for product

https://doi.org/10.1017/pds.2023.184 Published online by Cambridge University Press

design. These different AI methods can help to solve different challenges in the product design process. By identifying papers in the research field, the authors report the most common combinations of these school of thought are genetic algorithm and neural networks, and genetic algorithm and fuzzy logic. This identifies that there are other combinations of AI training and executing to explore which may bring benefits for engineering design specifically.

In the future, there will certainly be examples of AI engines in product/industrial design that are successful in generating highly specific concepts within a context. However, at this time it appears there is a need to manage this process and for human intuition to play a part in evaluation and making design decisions. AI may certainly support designers, but it is not yet foreseen if they can replace the creative process of designing a chair desirable for humans.

7 LIMITATIONS

Limitations of this initial exploratory study include the sample size of 20 participants and the bias of the experiences of students all being from the same university, department, and year group. If the study can be repeated in collaboration with other engineering design educators the results can be generalised, or differences in education and practice may reveal new insights. The study may also develop to include established design practitioners. This study was limited to include the AI technology available at the time which is not specialise to the product category of chair or to the task of developing products. Such developments may support the appropriate generation of images appropriate to the task.

8 CONCLUSIONS

This research investigated the application of text-to-image AI within an engineering design context. Examples of designers using text-to-image AI have begun to appear in the public discourse without consideration if the outcomes are suitable and appropriate. This exploratory study aimed to answer two questions on the extent to which publicly available text-to-image AI systems can be used to generate images of concepts for concept selection in engineering design, and what are designers' perceptions of this. A literature review revealed a lack of practical examples of the development of text-to-image AI in field such as product design and industrial design where other design field such as Architecture have established fields of study. There is much knowledge that can be transferred and practices to consider adopting. However, there has been long established research in areas such as machine learning, human cognition and AI that can help to bridge the gap between these cross-discipline research efforts.

The exploratory study revealed that student teams demonstrated a preference towards criteria-based evaluation techniques with this experimental setup that may be an appropriate technique for future research studies. If chosen, there are some recommendations from the participants of this study including pre-define the specification and use this in image generation and pre-selection. However, there was also an identification of improvements for the development of the text-to-image AI systems that may be used to generate these images including: clearer image (meaning defined form), improved realism and 3D. And finally, there were some suggestions to the process including: the use of the images as aesthetic inspiration, fewer concepts and comparison with a datum.

The participants shared a mixed responded on their perception of AI in the conceptual design phase. The design activity was successful in using AI for the selection of a final concept, however, the technology should not be used in its current maturity to replace the abilities of a design team to generate concepts.

Future studies should investigate where it is appropriate to integrate text-to-image AI within the design methodology perhaps towards a new design methodology using AI as a stakeholder in the design process. It can also be beneficial to establish a baseline for this technology in the design process either through a comparison with real world products as a datum, or with other concepts designed by a design team. This initial study brings into question how the community of engineering design researchers should collaborate on research in this area. Should specific AI tools for conceptual design be developed, or do we require a text-to-image AI engine for every product category? Can a methodology be designed to best use AI in the design process for conceptual design and beyond?

ACKNOWLEDGMENTS

Thanks to the students and staff of the Research Studies class 2023 at DMEM, University of Strathclyde for taking part in the study.

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