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Inspiration or indication? Evaluating the qualities of design inspiration boards created using text to image generative AI

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Abstract

This study explores the application of image generative AI to support design process by creating inspiration boards. Through an evaluative study, we compare the diversity, quantity, fidelity, and ambiguity of boards generated by image generative AI and traditional methods. The results highlight how generative AI produces a quantity of images, it exhibits limited diversity compared to traditional methods. This suggests a tendency for supporting interpolation rather than extrapolation of ideas, in turn providing insights on best practice and into the optimal stage for its application.

Keywords: *inspiration boards, artificial intelligence (AI), design creativity, industrial design, visualisation*

1. Introduction

Text to image generation AI (image GenAI) has generated substantial societal interest since widespread availability to the public in 2022. At the same time, there has been a boom in the design industry and research fields interest in this topic, concerning how it might be used to support the design process but also potential impacts. For designers, the prospect of massive time and resource savings by using AI to automate time consuming design tasks (such as creating inspiration boards) enabling greater search over a spread of ideas, with faster iteration, is extremely compelling.

Designers work extensively with visual material to be inspired and iteratively problem solve. Logically platforms that can generate visual material that can embody such inspiration are of interest in terms how they could support designers. Inspiration boards are the focus of our study, used in industrial design during the concept development phase of the design process to inspire, guide and communicate aesthetic qualities of a product such as forms, materials, colours, finishes, interfaces (Velasquez-Posada 2019). Emerging research on the use image GenAI in design indicates a viable avenue to support inspiration via provision of inspirational image content (Koch (2017) that can be the basis of AI supported inspiration boards that stimulate design inspiration on the above-mentioned qualities of a product. (Brisco et al. 2023; Mikkonen 2023). Inspiration boards are interesting as the subject matter in our exploration of image GenAI supporting inspiration as we contend they are a formal embodiment of inspirational material. This is noted as we acknowledge that inspiration can occur subconsciously and from any manner of stimuli. Critically we view the inspiration board as a deliberate collection of visual material deemed by the designer as offering inspiration.

The goal of our study is to extend emerging research in image GenAI supporting inspiration by understanding 'what' image GenAI can produce in terms of inspiration boards. Our specific research aim is to conduct an evaluative study assessing the qualities of image GenAI inspiration boards. These include manifest qualities such as number of images and content, but also qualities connected to the creative/inspirational potential of images and considerations of efficiency in terms of the number of images created. As such we contribute an initial implementation of its use and subsequent guidance on how image GenAI might be best applied in the context of industrial design inspiration boards.

The remainder of the paper is set out as follows, section 2 surveys relevant literature framing the use of AI to support design activity (2.1) and exploring relevant variables for researching inspirational material in design (2.2). Section 3 sets out our application of GenAI for design inspiration boards, followed by a description of our research method (section 4). Results are given in 5 and discussed in 6, with conclusions drawn in 7.

2. Background

This section provides an overview of key recent literature framing the value proposition of GenAI to support designers and outlining the specific qualities of inspiration boards that will be studied.

2.1. Generative AI in conceptual design - proposed ways of working and benefits.

Recent research frames the designer's role as transitioning from creating designs, generating knowledge, and refining, to a role focused on selecting supported by creation and refinement by GenAI (Thoring et al. 2023). The AI supported role involves the designer creating the prompts that guide the AI and evolving the design via means usually supported within the AI platform (mutating, recombining, interpolating, extrapolating), all of which are driven by designers' reflection on GenAI creations. The key potential in this shift is that the designer can become supported in terms of the AI quickly generating a range of designs. In turn this potentially supports both a broader and deeper exploration of the solution space. This shift is echoed in Koch (2017) McComb et al. (2023), highlighting how AI has potential to make design teams more creative and productive. This is argued from the time savings associated by less time spent in generating designs/visualisations, and creativity since using AI can stimulate the creation and exploration of more concepts (a potentially broader solution space). Doing so enables the designer to spend more time and cognitive resources towards tasks such as selection and decision making. For example, existing AI applications in generative design demonstrate how designers are now able to set parameters and leave the task of digital modelling and optimising to an AI platform enabling faster creation of design variations. This can be framed as using AI to "interpolate" ideas/solutions within parameters (Thoring et al. 2023). However, in the context of inspiration, such parameters either don't exist or are qualitative. We can frame inspiration as "extrapolating" ideas/solutions whereby the designer must analogise potential solutions from an external source (Thoring et al. 2023).

Specific to GenAI applied in inspiration activities for industrial designers, Mikkonen (2023) explore how inspiration boards (also known as mood boards and vision boards) can be supported via GenAI, however fall short from actually testing the approach. Brisco et al. (2023) find from early explorations with image GenAI that designers see a clear potential for its use to support inspiration finding activities. At the same time, they highlight a current limitation of image GenAI alone to create viable/functional solutions. Ultimately both researchers identify the strength of image GenAI to quickly create a wide variance of imagery to inspire aesthetic qualities of a product such as forms, materials, colours, finishes, interfaces.

In summary literature highlights an opportunity for AI support for iteration and breadth of solution as advantages where the designer reviews, rationalises, and decides. At the same time, the ability to convert this content into 3d geometry is presently limited, likewise the capacity for image GenAI to perform technical or functional analysis on results is limited too. Hence our focus on the use of image GenAI to support industrial designers' inspiration board creation during concept generation.

2.2. Existing concerns in inspiration and visualisation - fixation, fidelity and ambiguity

Visualisation is a key mechanism within design thinking, where designers create, respond to, and communicate visual stimuli whether the stimuli is an emergent design or an external inspiration (Goldschmidt and Smolkov 2006; Vasconcelos and Crilly 2016). While visualisation is an essential

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element of the design process, research shows how key qualities of visualisation can be connected to negative effects and may then influence their inspirational or creative potential.

With respect to inspiration, there is the potential for premature design fixation. Previous research shows how higher levels of fidelity in inspirational material leads to less novel ideas being created (Cardoso and Badke-Schaub 2011; Cheng et al. 2014). This follows research in prototyping where higher fidelity in physical representations (prototypes) can lead to fixation (Viswanathan et al. 2014) and reduced idea fluency (Ranscombe et al. 2020). It is thought the fixation arises via sunk cost effects where time and effort expended to create a given fidelity of prototype are a cause (Viswanathan et al. 2014). Nevertheless, some degree of fidelity is essential to communicate various attributes of a design fully and explicitly. Thus, fidelity can be viewed as a kind of "necessary evil" where it is required at some level to provide inspiration, but too much can be problematic. The speed of creating, and volume of high-fidelity imagery that can be produced via image GenAI is especially worth noting as time and effort expended are reduced and could therefore mitigate sunk cost. At the same time effort could be redistributed from creating images to prompting and reviewing a large amount of created content, potentially shifting the cause of sunk cost effects. As such the quantity of images generated are interesting to explore alongside fidelity and fixation.

A further lens to view fixation is the similarity of stimuli to problem and project. Researchers have shown that similarity or 'closeness' of inspiration to the project brief or design space can support innovation and/or lead to fixation (Cardoso and Badke-Schaub 2011; Fu et al. 2013). Namely that there is theoretically a closeness/distance of inspiration to avoid fixation and best support innovation by supporting designers to extrapolate from diverse domains of the inspiration to the domain of the project in question. It follows that an inspiration board is expected to comprise diverse content reflecting the way that inspiration should balance similarity or closeness to the brief with distance to support innovation. A typical inspiration board will include a range of images that communicate inspiration in terms of; overall forms and geometry that the product could adopt (Forms), appearance of materials and applicability in your project (Materials), specific colours and colour combinations that might suit the user and brief, details of material textures, material breaks, finishes and accents (Finishes), format style and location of any interfaces or touchpoints (Interface) (Velasquez-Posada 2019; Mikkonen 2023). We contend this type of diversity represents a designer's "rule of thumb" approach to achieve the balance of 'distance' described in Cardoso and Badke-Schaub (2011) and Fu et al. (2013). Thus, diversity of images within inspiration boards is worth analysing.

Research also shows how the ambiguity in inspirational material and visualisations can have positive impacts on creativity and collaboration. For example, Gonçalves et al. (2012) show that levels of ambiguity in the form of presenting designers with partial images as inspiration has a positive influence on generating more innovative designs. It is also known that preserving ambiguity in visualisation can support divergent thinking as the visualisation can be interpreted in multiple ways stimulating more ideas (Bresciani 2019). Likewise lower levels of realism and detail can be advantageous in stakeholder engagement in terms of eliciting and sharing knowledge (Kuys et al. 2023).

In summary, while the design process aims to resolve nebulous ideas towards concrete solutions, it is important to balance fidelity and ambiguity in both inspiration and visualisation to maintain creativity and iteration towards the ideal solution. It follows that fidelity and ambiguity will be key qualities explored in the application of image GenAI in generating inspirational material. Likewise diversity in images is flagged as potentially important with respect to facilitating innovation. Finally, quantity is also interesting to review as a manifestation of the labour the AI supports, but also as potentially influential with respect to sunk cost effects. It follows that results from analysing these qualities can form the basis of guidance on practice with image GenAI inspiration boards and how these might be adapted to improve the application.

3. Application of generative image AI for design inspiration boards

This section proposes our application of image GenAI to create industrial design inspiration boards, stating precise use of the boards, process of creation, and our project context in which they are implemented and analysed.

3.1. Inspiration board contents and context of use

Inspiration boards used by industrial designers during the concept development phase of the design process aim to inspire, guide, and communicate aesthetic qualities of a product such as forms, materials, colours, finishes, interfaces. They are typically used when the fundamental concept for the design is defined in terms its purpose and function, but the design is not finalised in terms of precise form/geometry, materiality, interface. The approach is implemented in the context of 4th year undergraduate industrial design 1-year long "capstone" project on a self-determined brief. The timing within student projects echoes the typical industry use, i.e. where students had defined overall product function or typology. For example, in the project to design "a micro-mobility electric scooter", the overall function and purpose of the product is defined. The goal of the inspiration board is to inspire and define ideas for how the scooter will be embodied in terms of form language, materials, colours, finishes. All students in the cohort completed inspiration boards at this same phase of their project. However, not all students used the image GenAI approach, opting for traditional approach instead. Total participation was 21 students with 12 using the image GenAI approach and 9 using the traditional approach representing the control in our comparison. Participants that used image GenAI had little or no experience with the platform but were all offered basic training.

3.2. Implementation, image GenAI versus traditionally created inspiration boards

The traditional approach to creating inspiration boards involves searching for image content (usually browsing the internet or magazines) for inspiring images which are collaged into an inspiration board(s). Our GenAI supported approach differs by prompting the GenAI platform to generate original images which are compiled/collaged to form the inspiration board. Participants using both GenAI and traditional techniques were encouraged to strike a balance between levels of fidelity and ambiguity in images used to maximise inspirational potential. This should be balanced in terms providing appropriate fidelity to perceive the design and potentially become inspired. At the same time fidelity shouldn't be too great to avoid the fixation effects. Inspiration boards should embody a degree of ambiguity to facilitate reinterpretation or analogising how qualities of the image can inspire and manifest in the emerging design. This is also flagged as potentially important to avoid IP infringement concerns whereby the designer is forced to reimagine the inspiration for their context. Examples of traditional and image GenAI inspiration boards can be seen in Figure 2 and Figure 3 respectively.

3.3. Generative image AI platform

Midjourney was selected as the specific Image Gen AI platform to be used. The selection was based on its capacity at the time of conducting the study (July 2023) to produce the most varied generations based on the same text prompts, when compared to other GenAI tools. At the same time, it is capable to produce realistic/high fidelity images equivalent to the type of images collected using traditional approaches. This is a critical factor in choosing Midjourney to enable analysis of fidelity of traditional and GenAI inspiration boards.

4. Method to analyse image GenAI supported inspiration boards

The method to evaluate qualities of inspiration boards resulting from our application of image GenAI is now described. The method follows visual content analysis approaches used by Brown and Tiggemann (2016) and applied in the context of design visualisation by Kuys et al. (2023). The objective of visual content analysis is to identify and code manifest qualities of the boards such as diversity of content and quantity of images alongside qualities of fidelity and ambiguity that literature shows can influence the creative and inspirational potential of the boards. Following coding trends in these qualities are identified and compared between image GenAI and traditional inspiration boards. The following scheme is used to code the above-mentioned qualities via 5-point Likert scales.

Fidelity – Defined following Vasconcelos and Crilly (2016) as aesthetic/visual level of detail. Specifically, level of detail towards a real object. For example, an image showing a product interface feature represented as a product photograph showing realistic materials is high fidelity. Oppositely an

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image showing an ambiguous line sketch with little product detail would be deemed low fidelity. Fidelity is rated on a 5-point Likert scale from 1 "very low fidelity' to 5 – "very high fidelity".
Ambiguity – The specific interpretation of ambiguity for the purpose of coding follows Cheng et al. (2014) concept of partial images. The rationale is that the more an image is zoomed or cropped, the more ambiguous its content becomes thus increasing ambiguity in the image. Thus, it is defined by ambiguity from complete image via zooming or cropping to create a "partial" image (Cheng et al. (2014)). Note this is distinct from ambiguity in sketching where ambiguity can be defined by less detail and precision (Self 2019). We follow the definition of (Cheng et al. 2014) since most of the content code is photograph rather than sketch. Following the example above for fidelity, low ambiguity is an image including the whole object or product, high ambiguity of the same image would mean zooming such that only forms and material can be seen, and the overall product is not clear. Ambiguity is rated on a 5-point Likert scale from 1 "very zoomed" to 5 – "entire product". The points on the scale are defined by the extent that the entire product that is visible, 2 – 25% of the product is visible, 3- 50% of the product is visible, 4 - 75% of the product is visible.
Diversity – For our study we follow Goldschmidt and Smolkov (2006) who define diversity in inspirational material as a diversity of media and content such as images, sketches, objects of a diverse subject matter. Highly diverse would be an inspiration board that shows a diversity of products categories and subjects e.g. a range of different products, plus images of people, food, landscapes, and artwork. A low diversity would be an inspiration board focused entirely on products from a specific product category. Diversity is rated on a 5-point Likert scale from 1 "very uniform" to 5 – "very diverse".
Quantity – The quantity of images included in the inspiration boards and is recorded as the total number distinct images identified in each board.
Reliability of coding is established by using two coders coding in isolation before meeting to compare results. Coder 1 was familiar with the projects while Coder 2 was detached from the students' design projects, to ensure the coding was not informed by on prior knowledge of the projects. Results are then compared to check alignment. 8 of the 84 ratings differed by more than 1 point. These were revisited and discussed to achieve agreeance within 1 point on the respective Likert scales. Following alignment discussion 60/84 ratings aligned with the same rating, 27/84 are within 1-point rating on the respective Likert scales. Finally scores from both coders are averaged (mean) to provide final ratings used in analysis.

5. Results

Figure 1 below provides an overview of data from coding the qualities of inspiration boards. Table 1 presents statistics for median ratings and mean absolute deviation (MAD) comparing qualities of traditional inspiration boards (the control) and the boards created with GenAI. One tailed T-tests are used to understand whether differences in GenAI vs traditional inspiration boards are statistically significant. The reader should refer to figures 2, 3 and 4 to see examples of how trends in the two kinds of inspiration boards manifest.

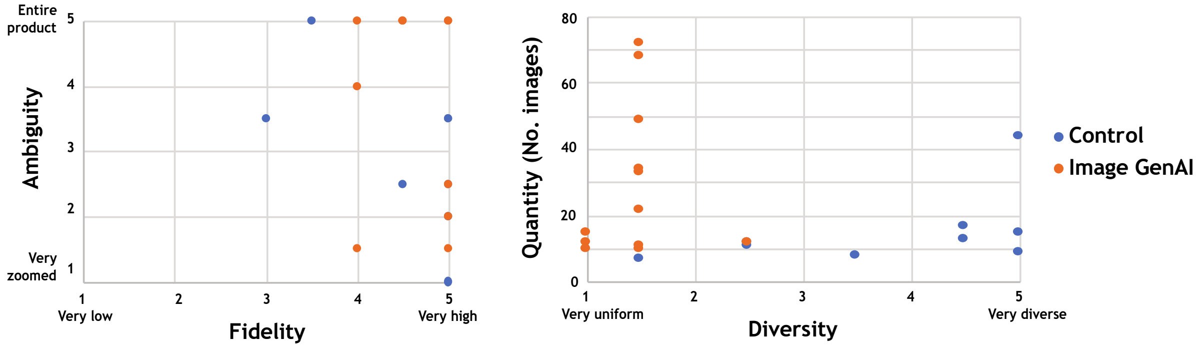

Figure 1. Scatter plots summarising the spread of data on qualities of image GenAI versus traditional inspiration boards

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With respect to fidelity, we see little difference between the control and GenAI inspiration boards. Both typically include high fidelity representations. Both control and GenAI inspiration boards are rated on average as between "high fidelity" and "very high fidelity" fidelity due to their almost exclusive use of photographs (or photograph levels of fidelity). This is highly consistent across GenAI group where mean average deviation (MAD) is 0.59 i.e. all outcomes are high fidelity. The T-test shows the fidelity of images in the traditional inspiration boards is not significantly greater than GenAI images (P value > R).

Table 1. Summarising data comparing qualities of traditional versus image GenAI inspiration boards

	Fidelity		Ambiguity		Diversity		Quantity	
	Control	*GenAI*	*Control*	*GenAI*	*Control*	*GenAI*	*Control*	*GenAI*
Median	5.00	4.75	2.50	5.00	4.50	1.50	12.00	18.50
MAD	0.59	0.38	0.93	1.33	1.14	0.23	6.89	17.43
T-Test P-value (R = 0.05)	0.4458		0.1454		0.0015		0.0090	

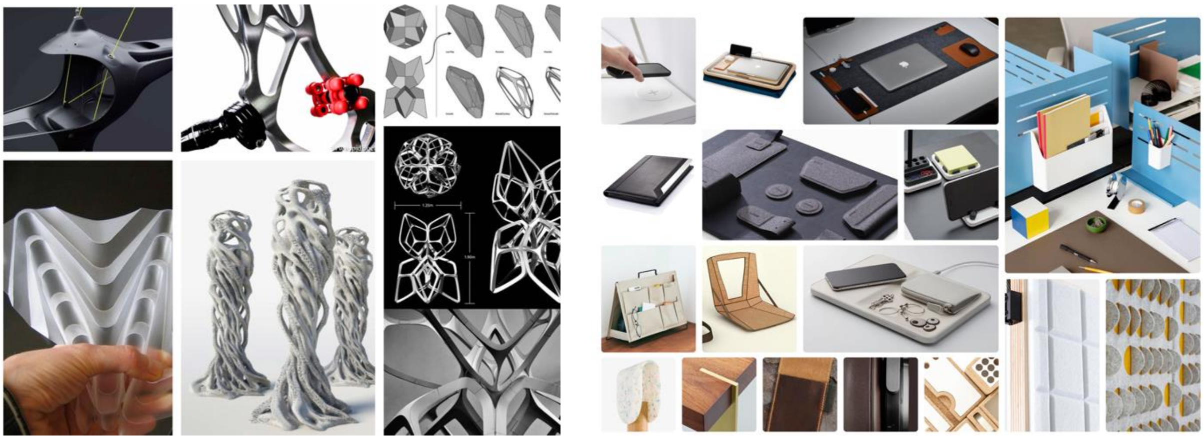

Figure 2. Examples of traditional inspiration boards; left panel project ID - 4 "crutches for amputee sports"; right panel project ID- 18 "mobile workstation"

Median ambiguity in the control group is 2.5 corresponding to "25% - 50% of the entire product". The median rating for GenAI boards is 5 corresponding to "entire product" but with greater average distribution than the control (1.33 versus 0.93 respectively). Despite the difference in median rating, results from the T-test show differences in ambiguity are not statistically significant (P value > R). Manifestation of ambiguity is similar in both control and GenAI. I.e. zooming or cropping specific elements of images. As indicated by the MAD, the control group have greater variation in ambiguity within boards (some partial some whole). Where GenAI boards show ambiguity, it is comprehensively zoomed (see Figure 3 right panel, and Figure 4 right panel). It should be noted with respect to this quality that zooming to add ambiguity was encouraged, thus it is interesting that many participants using image GenAI did not follow this advice.

Diversity in images within GenAI inspiration boards is less compared with the control. The median rating for GenAI inspiration boards was 1.5 – corresponding to between "very uniform" and "uniform" while control inspiration boards were rated as 4.5 corresponding to between "diverse" and "very diverse". Deviation shows high consistency in both GenAI and control groups (MAD = 0.23 and 1.14 respectively), i.e. control is uniformly diverse or very diverse. GenAI boards are "uniform" or "very uniform". The T-test shows greater diversity in traditional inspiration boards is statistically significant (P value < R).

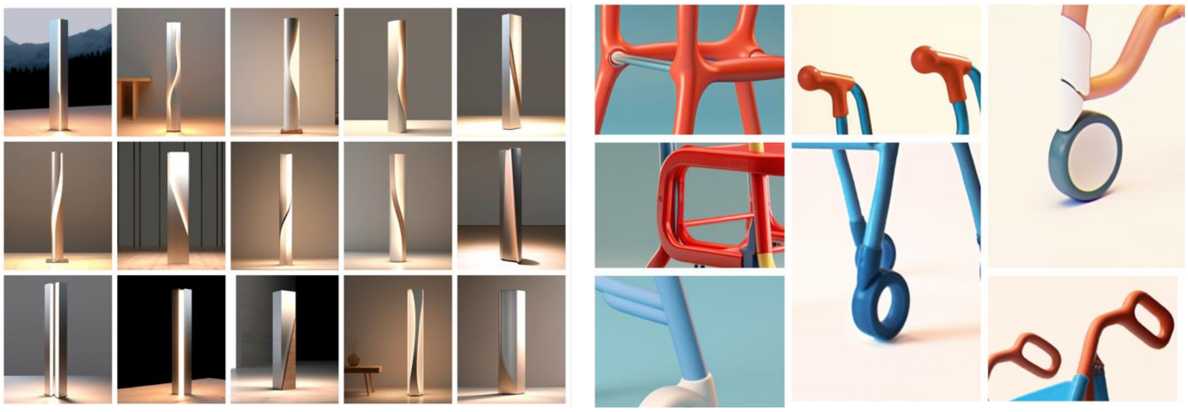

Figure 3. Examples of image GenAI inspiration boards; Left panel is project ID - 8 "smart lamp"; Right panel is project ID- 15 "walking aid for kids"

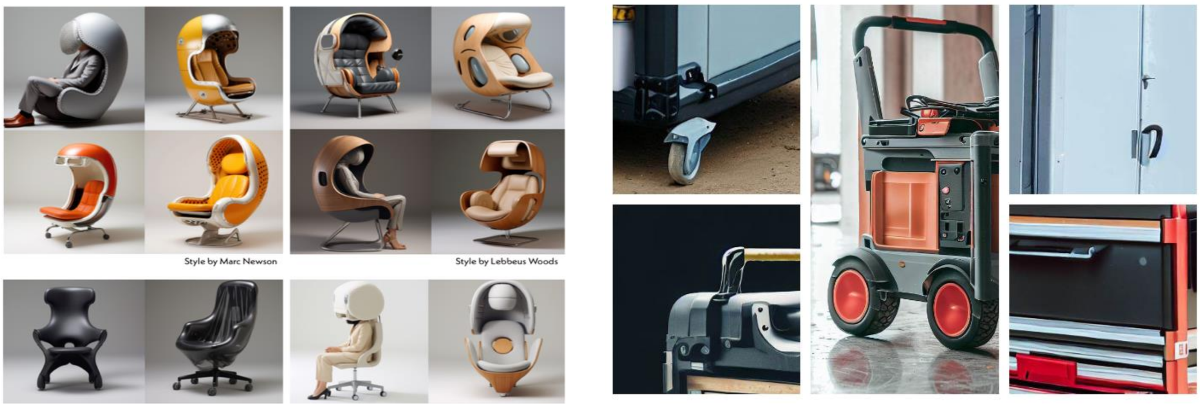

Figure 4. Examples of image GenAI inspiration boards; Left panel is project ID - 3 "chair"; Right panel is project ID -6 "tool trolley"

For the control group the diversity manifests in the inclusion of a variety of product types/categories, likewise a diversity in material and media (artworks, structures, and products) (see Figure 2). For GenAI – “very uniform” manifests in subtle stylistic variations on what is essentially the same design (see Figure 3 left "smart lamp"). Where GenAI boards show “uniform” we see some repeated forms, materials, and design language that arise from extracting from the product whole (see Figure 3 right 'walking aid for kids"). Where we occasionally see some greater diversity in GenAI boards, it manifests in stylistic diversity in the same product category (see Figure 4, variations of the product category “chairs” (left) and “tool trolleys” (right)).
There is a clear difference in terms of quantity of images included in inspiration boards. The median for GenAI boards is approximately 50% greater than for the control. The T-test shows the greater quantity of images in inspiration boards created using GenAI is statistically significant (P value < R) Traditional inspiration boards tended to be single page with approx. 15 images. With GenAI we see a median of 18.5 images with some boards including 49, 72 and 68 images. The smallest quantity is 10, close to the median for the control.

6. Discussion

The significant differences observed in the qualities of traditional and GenAI supported inspiration boards (diversity and quantity) suggest two slightly different manifestations of inspiration. Thoring et al. (2023) highlight “interpolation” and “extrapolation” in outlining possible use/roles for Gen AI to support design. The trend for GenAI boards to be less diverse but greater in number images suggests the image GenAI leads to interpolating, whereby the designer is using the GenAI to generate inspiration within the bounds of the predefined product category. For example, project ID 8 to design a lamp has an inspiration board comprising many configurations of a lamp (see Figure 3 left panel). Or, project ID

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3 to design a chair has an inspiration board comprising many stylistic variations of chairs (see Figure 4 left panel).

Conversely the control group exhibit extrapolating whereby the inspiration board captures a more diverse range of inspiration drawn from outside the product category. As such we contend traditional inspiration boards represent greater support for inspiration in terms of supporting analogising potential solutions from different products and beyond. For example, project ID 4 to design a crutch for amputee sports created an inspiration board comprising a range of product categories and abstract forms (Figure 2 left panel).

We contend the different manifestations of inspiration may well arise from the fundamental difference between generating visual content via text prompt (GenAI), versus searching through visual material for inspiration (traditional). In the instance of GenAI designers are required to input text prompts to create visual material that may be inspirational. It is not surprising that they begin with prompts including the product category they are designing for which implicitly leads the designer towards interpolating many ideas within the single product category. The subsequent question for further research is how to better support designers to harness generative creative power of image GenAI when prompting to produce material with greater potential for extrapolating and thus analogising. There is a suggestion of an optimal "distance" for extrapolating (Fu et al. 2013). Future research would follow ideas raised in (Gonçalves et al. 2012) regarding textual stimuli to investigate how the idea of distance could manifest in terms of verbal prompts. A key takeaway for future use of image GenAI in inspiration boards is then need for attention paid to prompting. This could involve similes and synonyms (e.g. "illumination", "radiating device" for the lamp project) for inspiration that is somewhat close, then injecting prompts from more distant concepts, or even using exclusion prompts (NOT a "lamp"). We contend that manipulating ambiguity could also assist in promoting extrapolating. The cropping or manipulation of images may conceptually move the image from the product category or make its association with the category more ambiguous.

It is also worth considering the low diversity in image GenAI inspiration boards with respect to fixation. It is difficult to establish whether fixation did or did not occur. However, it is fair to say that interpolating is suggestive of convergent design behaviour, which could be viewed as less support for more creative/innovative inspiration. Here it is also worth noting the fidelity with which inspiration is generated. Literature suggests greater fidelity of inspiration can be problematic. In the GenAI group inspiration created is closely aligned to the design under development, to what extent could this level of fidelity and lack of diversity lead to fixation? Another perspective could be that lower diversity in greater quantities embody exhaustive convergent exploration towards a specific outcome, a kind on 'indication board'. Conversely the more diverse boards (generated by traditional means) are more process driven (the process of seeking inspiration) likely most useful earlier in the design process during ideation due to greater analogising potential. A takeaway for future use is how the advantages of using GenAI to create many variations of inspirational content with minimal effort is potentially most useful in later concept generation phases. Whereas traditional inspiration boards are better placed in earlier concept generation phases of the design process.

The finding of image GenAI inspiration boards typically having a greater quantity of images is notable with respect to the paradigm shift in designers being supported in creating but having greater responsibility in deciding and reasoning on work created (Thoring et al. 2023). It is possible the quantity of inspiration is so great that synthesising specific or actionable inspiration from the board is challenging. Further research should interrogate in more detail how to manage the volume of ideas/visualisations that can be created with respect to how inspiration is translated and even reinterpreted by members of a design team.

Several limitations to our findings should be acknowledged. While we were able to characterise differences between boards created, but the extent of understanding influence on design process is limited. By studying the use of image GenAI within live design projects that occur over a substantial period of time, we acknowledge that inspiration can occur or be caused by any manner of activities. Likewise given the diversity of projects and participants, the intervention may have occurred at relatively different progression through the design process for each participant. Thus, we cannot establish any causality from the use of image GenAI and influence on the design process and final design

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outcome without further research. As such our findings are limited to understanding how its use manifests when applied to inspiration board creation. Finally, we acknowledge the limitation of our sample size and influence on the reliability of statistical significance.

7. Conclusion

This paper reports the development and preliminary testing of an approach to apply generative image AI for design inspiration boards. The resulting approach adopts Midjourney to generate and collect inspirational images and was tested against traditional inspiration boards. Characterising the image GenAI boards against the control (traditional) highlighted how image GenAI boards were typically less diverse in image content but included a higher quantity of images. We contend this trend speaks to the tendency for image GenAI inspiration being used to support “interpolating” rather than “extrapolating” and analogising. Ultimately, we conclude that the promise of AI to support inspiration only partially holds as it supports creation of a large volume of imagery but with tendency for designers to generate inspiration within a specific object/product category. Key guidance for future use of image GenAI in inspiration boards includes; using greater diversity of prompting terminology, manipulating ambiguity to enhance diversity and potentially conceptual distance between project and inspiration source, and locating their use in later concept generation phases of the design process. Further research is required to understand how to better harness the potential of image GenAI including prompting behaviour to support extrapolating and in turn support in earlier stages of design process. At the same time research is also needed to understand the implications for designers having a greater volume of inspiration to decide on and curate.

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