AI VS. HUMAN: THE PUBLIC'S PERCEPTIONS OF THE DESIGN ABILITIES OF ARTIFICIAL INTELLIGENCE

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ABSTRACT

With the increasing implementation of artificial intelligence (AI) in the design process, it is crucial to understand how users will accept AI-designed products. This work studies how the public currently perceives an AI's design capability as compared to a human designer's capability by conducting an online survey of 205 people via Amazon Mechanical Turk. The survey collects the respondents' perception on 16 specific bicycle design goals, demographic information, and self-reported level of design and AI/ML knowledge. Findings reveal that people think an AI would perform worse than a human designer on most design goals, particularly the goals that are user-dependent. This work also shows that the higher people's self-reported level of knowledge in design and the older they are, the more likely they are to think an AI's design capability would exceed a human designer's capability. The insights from this work add to the understanding of user acceptance of AI-designed products, as well as human designers' acceptance of AI input in human-AI teams.

Keywords: Artificial intelligence, Collaborative design, Market implications

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1 INTRODUCTION

Successful products often possess multiple desirable characteristics, such as usefulness, aesthetics, and durability. To help design teams to deliver these characteristics, a body of design literature exists to understand how human designers design and to innovate on the methods that they can use to achieve "good" products. However, human designers can have many limitations in performing these individual design tasks. On an individual task level, for instance, human designers are susceptible to limiting their creative potential because of a tendency to fixate on pre-existing designs (Jansson and Smith, 1991). On a greater scale, human designers alone or even as a team do not have the capacity to effectively consider and optimise the design for all of its goals at the same time (Eppinger et al., 1991; Maier and Fadel, 2006). Therefore, there is still much room for improvement in the current design practice and its outcomes.

With the advance in data-driven methods in design, artificial intelligence (AI) systems have increasingly been implemented to replace or supplement human designers in specific stages of the design process (Camburn et al., 2020; Chen et al., 2022; Nie et al., 2021; Raina et al., 2019; Regenwetter et al., 2022; Song et al., 2022; Williams et al., 2019). Specific AI algorithms are often developed to target and achieve a specific design goal by extracting insights from large datasets. Most prevalent are generative design algorithms that utilise a large dataset of existing designs to generate new designs (Alcaide-Marzal et al., 2020; Mazé and Ahmed, 2022; Oh et al., 2019; Shu et al., 2020; Zhang et al., 2019). These generative design AIs are deployed to state-of-the-art computer-aided design (CAD) software, such as Autodesk Fusion 360, to help human designers efficiently search the solution space, as well as prevent design fixation by offering unique, unexplored ideas. In addition to these AIs that help in the early stages of the design process, there are many others that assist throughout or at the later stages of the design process, such as data-driven topology optimization, simulation, or process management AIs (Gyory et al., 2022; Jang et al., 2022; Pan et al., 2022). Such incorporation of AIs in the design process raises promising opportunities for creating better designs via human-AI teaming by leveraging the strengths of both human designers and AI systems.

Human-AI teaming in design has critical implications for users' acceptance of designed products. The same product may be accepted differently depending on users' expectations of the designer's design ability. Even a well-designed product by a hybrid human-AI team may be accepted less than a product by a human-only team if users have a low trust in AI's design abilities, and vice versa. Unfortunately, despite the high rate at which AIs for design are advancing, there are very few physical products that are commercially available and popular, leaving most laypeople unfamiliar with such AIs. As a result, it is likely that the public (users) has inaccurate knowledge, expectations, and trust in AIs for design. Therefore, this work conducts an online survey of 205 people to understand people's current perceptions of AIs' design abilities in comparison to those of human designers. There are many different factors that may influence people's perceptions of AIs' design abilities, such as their personality traits like propensity to trust others, prior experience with AI, expertise, and demography (Hoffman et al., 2013; Lee and See, 2004). Therefore, the survey collects information specifically about the respondents' prior knowledge and demography. The results presented in this work focus on the answering the following research questions:

1. *Does the general public perceive AI or humans as performing better or worse on achieving specific design goals?*

It can be hypothesised that the public perceives human designers to be better at achieving design goals that require more consideration of human preferences and needs, such as aesthetics and comfortability (Lan et al., 2008; McDonald and McLaughlin, 2021), and AIs to be better at those that are more quantitative, such as creating a large quantity of designs.

2. *How are these perceptions related to what they think of their own level of design or AI/machine learning (ML) knowledge?*

The above perceptions are expected to correlate their self-reported level of design or AI/ML knowledge. For example, self-reported experts may be aware of data-driven generative design or topology optimization methods, therefore perceiving AIs to be very proficient at creating a large quantity of designs, or light-weight designs.

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3. How are these perceptions related to their age?

If general opinions about AI systems extend to AIs for design, depending on their experiences with AI systems, younger people may hold more positive or more negative perceptions of AI abilities than older people.

2 METHODS

An online survey about peoples' expectations for AIs' design abilities is conducted via Qualtrics and Amazon Mechanical Turk, popular online platforms to design surveys and recruit respondents respectively for crowdsourced work. The survey collects respondents' demographic information, their self-reported knowledge level about design and AI/ML, and their expectations of AI abilities (in comparison to human abilities) in achieving various design goals.

2.1 Survey design

The survey contains six to nine questions (depending on respondents' answers) about respondent's demographics, two questions about their level of design and AI/ML knowledge, a bank of questions about their expectations for human versus AI's ability to design a bicycle, an open comment box, and a CAPTCHA verification. The survey is designed to take about 10 minutes to complete, and once completed, each respondent receives a unique six-digit completion code to enter into Amazon Mechanical Turk to successfully submit their response. Each respondent is compensated $2 for completing the survey. No identifiable information about the respondents is collected, and the survey was determined to be exempt by MIT's Institutional Review Board.

2.1.1 Questions

The survey collects demographic information about the respondents, including age, gender, ethnicity/race, culture, English-speaking ability, highest level of education, major (if they earned a Bachelor's degree or above), current student status (if they earned a Bachelor's degree or above), and current level in school (if they are current in school). Some of this information will be used in future studies, while this paper mainly focuses on the results from the following questions.

Two questions about the respondents' knowledge about design or AI/ML are included in the survey to understand whether their expectations for AIs' design abilities are dependent on their perception of their own knowledge. The questions ask the respondents to self-report how much they know about design or AI/ML compared to the average adult. It is important to note the answers to these questions do not reveal the respondents' actual knowledge level but provide insights into their perception and confidence in the knowledge level.

The question about the expectations for AIs' design abilities provides a context for the respondents to provide clarity in what the question is asking: "A design company is designing a new bicycle for its customer. There is a human designer who has trained for many years to design bicycles. And there is a computer-based artificial intelligence (AI) that is trained on a large dataset to automatically design bicycles.". This clarification is essential because many people, especially those that do not know much about design and/or AI, may not be familiar with AI systems that design. Then, the question asks for the respondents' opinions on which of the two (human or AI) can better create bicycle designs that meet various design goals (a large number, variety, high quality, unique, functional, safe, stylish, easy–to-use, long-lasting, environmentally friendly, comfortable, easily repairable, light-weight, customer likes, useful, and easily manufacturable). The answer choices are "Human", "Equally well", and "AI". The 16 design goals are an amalgam of standard design characteristics and metrics (Homburg et al., 2015; Kudrowitz and Wallace, 2013; Lan et al., 2008; Paramasivam and Senthil, 2009; Shah et al., 2003). For example, the first four goals (i.e., a large number of, a variety of, high quality, and unique bicycle designs) correspond to the four measures of effectiveness of ideation that are widely used in design literature (Shah et al., 2003). The wordings of the design goals in the survey are tested and selected through several rounds of pilot studies with non-experts of varying ages. Finally, two validation rows are added to this question to identify fraudulent data.

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2.1.2 Data validation

To ensure survey data quality, several methods have been implemented. Multiple responses are prevented by Qualtrics survey settings, as well as requiring the respondents to submit a unique survey completion code created by Qualtrics. Furthermore, CAPTCHA verification is used to protect automated bots from filling out the survey. Then, two validation questions are added among the bank of questions (16 goals) about the expectations for AIs' design abilities to identify fraudulent data. These two questions ask the respondents to select the predetermined answers, and if either of the two questions are not answered correctly, their data is removed. A total of 220 respondents have completed the survey, and after filtering out the data that do not meet the requirements, 205 of those responses are included in the results.

3 RESULTS

3.1 Respondent demographics

Among the 205 respondents, 63 are between the age of 18-29, 93 are between 30-39, 27 are between 40-49, 17 are between 50-59, four are between 60-69, and one is over 70. 130 (63.4%) of the respondents identified their gender as male, and 75 (36.6%) as female. None of the respondents identified as transgender, non-binary, or other. The respondents are majority white or Caucasian (74.7%), followed by Asian or Pacific Islander (11.5%), Black or African American (6.0%), American Indian or Alaska Native (4.6%), Hispanic or Latino (2.8%), and other (0.5%). The respondents' cultural background is 50.9% North America, 22.0% South America, 12.5% Central America, 7.0% Asia, 3.9% Europe, 1.7% Africa, 1.3% Caribbean or Pacific Islands, and 0.9% Australia. All respondents except six of them are native English speakers. Finally, their highest level of school includes one respondent with less than a high school degree, 21 with a high school degree or equivalent, 142 with a bachelor's, 36 with a graduate, and five others (associate or vocational degree). Among the 178 respondents with a bachelor's degree or more, majors vary widely with Engineering and Technology (27.8%) and Health and Medicine (18.9%) being the two most common ones. 40 of the 178 are currently in school when taking the survey with majority (52.5%) being Master's students. Although the respondents are randomly recruited via Amazon Mechanical Turk, it is important to note that the results in this work are generally representative of the perceptions of the majority groups (e.g., male, white or Caucasian, or cultural background from the Americas).

3.2 Perception of specific design abilities of AI versus human

Figure 1 shows the average results of all responses to the question comparing the specific design abilities of a human designer and an AI. "Human", "Equally well", and "AI" responses are quantified as -1, 0 and 1 respectively to calculate the average of the responses. The results demonstrate that the respondents tend to perceive the design abilities of an expert human designer to be better than those of a well-trained AI. The respondents expect eight of the 16 bicycle design goals (high quality, safe, stylish, easy-to-use, environmentally friendly, comfortable, customer likes, useful) would be better achieved by a human designer (one sample t-test, $p<0.05$). Interestingly, five of these eight goals that show greater significance (one sample t-test, $p<0.01$) (safe, stylish, easy-to-use, comfortable, and customer likes) are highly subjective or user-dependent goals (Davis, 1989; Lan et al., 2008; McDonald and McLaughlin, 2021).

There are two design goals that the respondents expect an AI to perform better than a human designer (one sample t-test, $p<0.05$): generating a large number of designs and creating easily manufacturable bicycle designs. It should be noted that unlike the subjective goals discussed above, creating a large number of designs is an easily quantifiable objective that does not require any user evaluation.

The responses do not show a strong inclination toward either a human or an AI for six of the design goals (one sample t-test, $p>0.05$): variety, unique, functional, long-lasting, easily repairable, and light-weight. These results can be interpreted as 1) the respondents expect a human designer and an AI to be equally good at achieving the goals or 2) the respondents are not sure which of them are better. The latter interpretation is possible because the question does not have an "Unsure" answer option.

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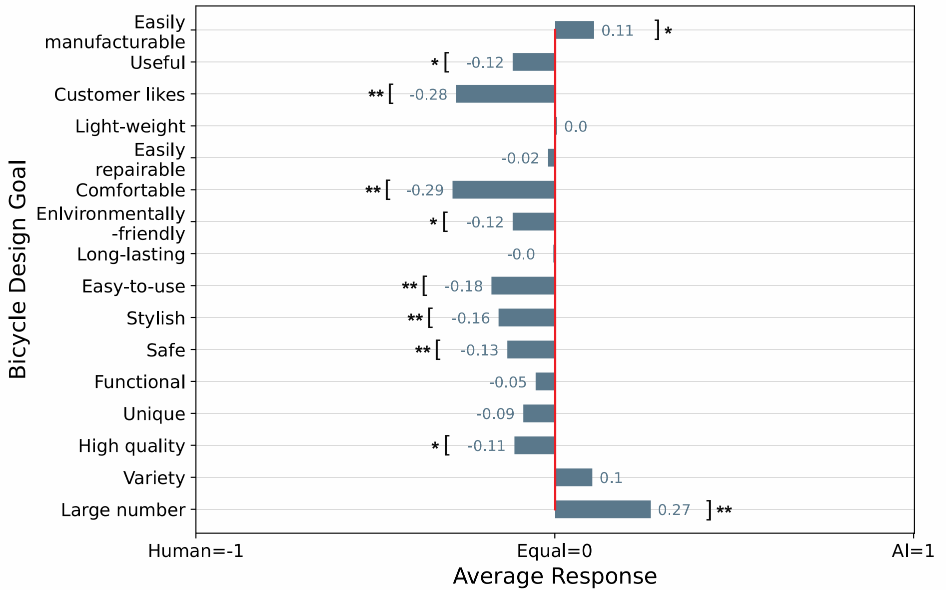

*Figure 1. Average responses of all respondents. The average values range from -1 (human) to 1 (AI), where 0 means a human designer and an AI are perceived to perform equally well. * indicates significance at 5% level, and ** indicates significance at 1% level.*

3.3 Perception by self-reported design knowledge

Figure 2 shows how the respondents' expectations for design abilities of AI are different based on their perception of their own design knowledge. The respondents are divided into three groups based on what they reported their level of design knowledge to be compared to an average adult: 31 respondents below average (reported "Far below average to none" or "Below average"), 88 respondents at average (reported "Average"), and 84 respondents above average (reported "Above average" or "Far above average"). Combining the responses to all design goals, the respondents' perception of human versus AI design ability is positively correlated to their self-reported level of design knowledge (Spearman's Rho, p<0.01). This result means the more expert the respondents think they are in design, the more they perceive AI to be better at designing than human designers. This can be observed in Figure 2 where the diamond points (below average group) tend to be on the left of the other two groups, while the triangle points (above average group) tend to be on the right.

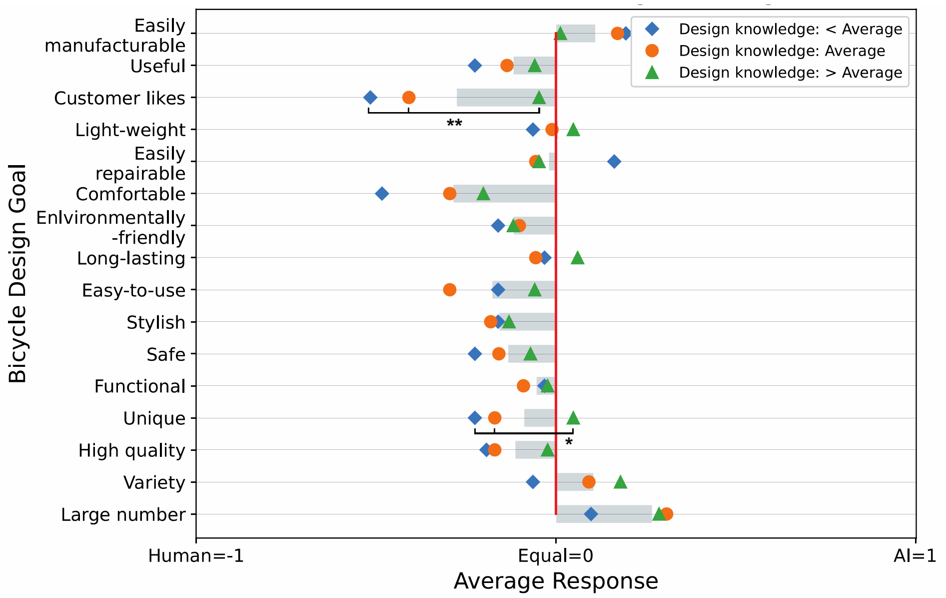

*Figure 2. Average responses by self-reported level of design knowledge. The average values range from -1 (human) to 1 (AI), where 0 means a human designer and an AI are perceived to perform equally well. * indicates significance at 5% level, and ** indicates significance at 1% level.*

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Interestingly, the respondents' perceptions of human versus AI's ability in each design goal are mostly independent of self-reported design knowledge. Strong positive correlation to self-reported design knowledge is observed in the responses for two design goals: creating a unique bicycle and creating a bicycle that a customer likes (Spearman's Rho, $p<0.05$ and <0.01 respectively). The lower the respondents' self-reported design knowledge, the more likely they are going to expect a human designer to be better at meeting those two design goals than an AI.

3.4 Perception by self-reported AI/ML knowledge

Figure 3 demonstrates the same type of results as Figure 2 but now the difference in the respondents' expectations based on their perception of their own AI/ML knowledge. The respondents are divided into three groups according to what they reported their AI/ML knowledge level to be compared to an average adult: 21 respondents below average (reported "Far below average to none" or "Below average"), 94 respondents at average (reported "Average"), and 89 respondents above average (reported "Above average" or "Far above average"). Combining the responses to all design goals, the respondents' perception of human versus AI design ability is not correlated to their self-reported level of AI/ML knowledge (Spearman's Rho, $p>0.05$). The responses to the specific design goals are also not affected by their self-reported AI/ML knowledge level (Spearman's Rho, $p>0.05$).

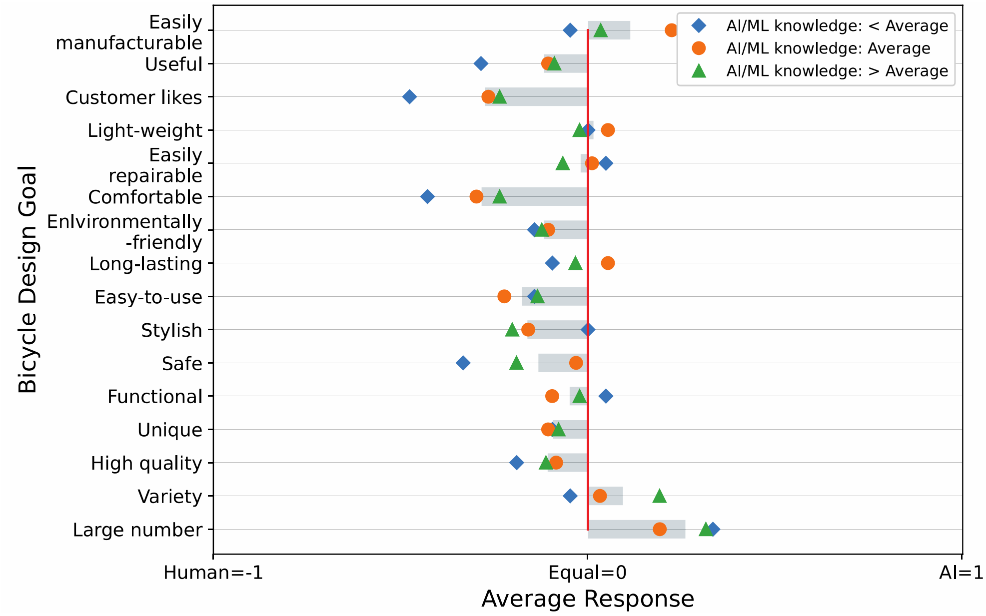

*Figure 3. Average responses by self-reported level of AI/ML knowledge. The average values range from -1 (human) to 1 (AI), where 0 means a human designer and an AI are perceived to perform equally well. * indicates significance at 5% level, and ** indicates significance at 1% level.*

3.5 Perception by age

Figure 4 shows the differences in the respondents' perception of human versus AI's specific design abilities based on their age. The three age groups are 18-29, 30-39, and over 40, each consisting of 63, 93, and 49 respondents respectively. The overall average of the responses is positively correlated to the respondents' age (Spearman's Rho, $p<0.01$); the younger the respondents, the more they perceive a human designer to be more proficient at designing a bicycle than an AI. Focusing in on the specific design goals, the perception of human versus AI's ability in generating a large number of bicycle designs is the only one that is positively correlated to the respondents' age (Spearman's Rho, $p<0.05$). Older people are more likely than younger people to think that a well-trained AI can produce a large quantity of designs better than a human design expert.

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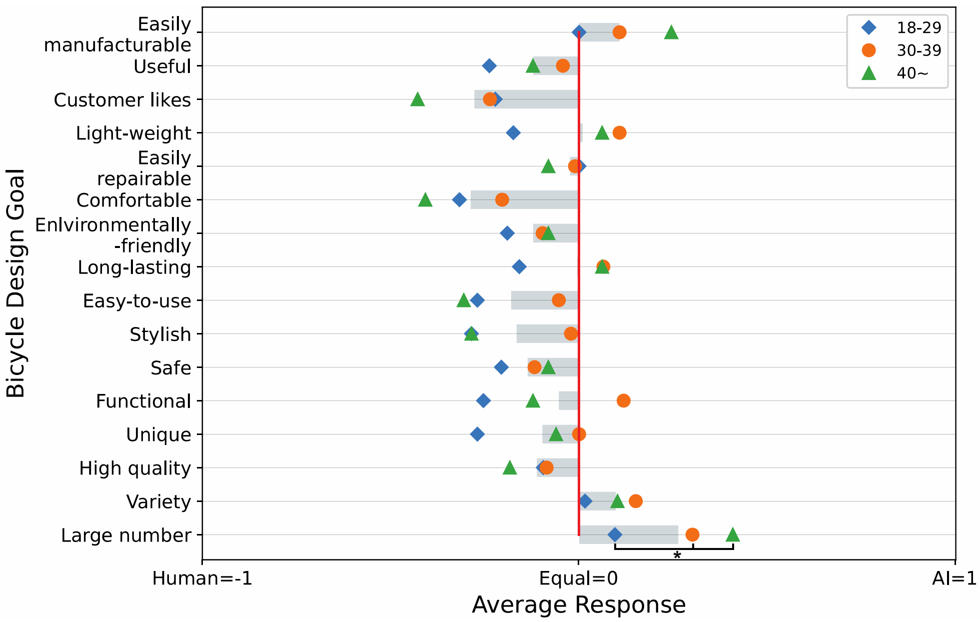

*Figure 4. Average responses by age. The average values range from -1 (human) to 1 (AI), where 0 means a human designer and an AI are perceived to perform equally well. * indicates significance at 5% level, and ** indicates significance at 1% level.*

4 DISCUSSION

The results first show how the public perceives AI or humans as performing better or worse on achieving specific design characteristics. As shown in Figure 1, the respondents lean towards a human designer as better performing for eight out of the 16 goals and towards an AI for only two. Therefore, people tend to perceive that a human designer is more proficient at achieving most design characteristics. This favoured opinion for human designers over AIs may be because the public does not know very well yet about AIs for design. Despite the rapid advance of AIs for design in research, real-world design practice is still mainly executed by human designers. Even with the recent implementation of data-driven CAD tools in design practice, such as Autodesk Fusion 360, laypeople are unlikely to be aware of these tools. It is also important to recognize that people could think a human designer is better at designing a bicycle than an AI because of the user-centred characteristic of product design. Most product design tasks, including the bicycle design example that this survey uses, are creating products for *human* users, consisting of many user-specific goals (Giacomin, 2015; Lee et al., 2017; Miaskiewicz and Kozar, 2011, Landauer, 1996). This characteristic of product design may influence people to perceive that *human* designers will interpret and meet these goals better than a *machine* (AI) designer.

This explanation about user-centred design is consistent with more specific findings about the public's perceptions of human versus AI's design ability. In Figure 1, the design goals people think can be reached significantly better ($p<0.01$) by a human designer than an AI are creating bicycles that are safe, stylish, easy-to-use, comfortable, and customer likes. As hypothesised earlier in this paper, these goals are all very subjective characteristics that demand more consideration of human preferences and needs (Davis, 1989; Lan et al., 2008; McDonald and McLaughlin, 2021), which people may not believe an AI can understand and design for. Contrastingly, the respondents perceive an AI to exceed a human designer in generating a large number of designs and creating easily manufacturable designs, which are both quantitative and user-independent goals.

The second set of results in this work reveal how people's comparison of human and AI's design abilities is correlated to their perception of their own design or AI/ML knowledge. First, people who perceive themselves to know a lot about design are more likely to think that an AI can generally design better than a human designer ($p<0.05$). If the self-reported level of design knowledge is in any way indicative of their actual design knowledge, this result may be explained that self-reported design experts are more well-informed about the shortcomings of human designers, as well as the invention of high-performing

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AIs for design. However, further results demonstrate that the self-reported design experts are not so much aware of the AI tools in design, but rather, aware of the shortcomings of human designers. Observing the responses for each design goal in Figure 2, the self-reported design knowledge is only correlated to the respondents' perception of AI and human's performance on designing a bicycle that a customer likes and is unique ($p<0.01$). These design characteristics are not what AIs in design are popular for achieving, such as light-weight (Mazé and Ahmed, 2022; Nie et al., 2021; Oh et al., 2019), but are what human designers struggle to achieve (Hsu et al., 2000; Jansson and Smith, 1991).

Secondly, people's beliefs about AI versus human design ability, both generally and in each design goal, are not correlated to their self-reported AI/ML knowledge ($p>0.05$), as shown in Figure 3. This result is unexpected because the more AI/ML knowledge people have, the more likely they are educated about AIs for design and their functions and abilities, which can affect their responses in the survey. Such lack of correlation with self-reported AI/ML knowledge may mean that 1) the respondents' self-report is not accurate and/or 2) AI/ML experts may not know about AIs for design. Considering the widespread everyday discussions about AI/ML in the media, it is likely that many people perceive themselves to be knowledgeable in the domain when they are not. Also, because AIs for design is still relatively a recent advancement, even the real experts of AI/ML may not know about them.

This work lastly examines the relationship between people's age and their views on AI's design ability in comparison to that of a human designer. Overall, the results show that older people tend to think AIs will perform better than humans ($p<0.01$). Such difference in perception by age may be because of the recent increase in the everyday use of AI technology. Younger people who may have more first-hand experience with AI technology may have realised that AIs do not always perform well, while older people are more oblivious and have positive views on AI. Unfortunately, there are inconsistent results in literature about the relationship between people's age and their technology acceptance (Arning and Ziefle, 2009; Hauk et al., 2018), therefore further research is needed to confirm the finding from this work.

Overall, this work shows that the public's current perception of how AI's design ability compares to that of a human designer is that an AI would perform worse on most design goals, especially the user-specific goals. However, there is a clear trend in which the better people think they know about design or the older they are, the more likely they are to expect an AI to perform better in design than a human designer, while people's perception of their own AI/ML knowledge does not demonstrate this relationship. These results provide crucial insights into users' acceptance of AI-designed products as AIs are increasingly being implemented into various steps of the design process. The insights can help market the products more effectively to the public by informing where people's expectations of AIs' performance do or do not align with AIs' actual performance. Furthermore, with the rapid development of AIs for design, many practising human designers may not be up-to-speed, and therefore the results from this survey could also be applicable to human-AI teaming scenarios. Although this application should be made carefully, this work can offer insights into human designers' trust for their AI teammates and help improve the effectiveness of human-AI teaming in design.

There are many opportunities for future work that can help further understand both laypeople and experts' current and changing perceptions of AIs for design and successfully integrate AIs into the design process. First, this work focuses on the variations in people's perceptions in terms of self-reported design knowledge, AI/ML knowledge, and age. However, there are many other factors that may affect their perceptions, such as their actual level of knowledge in design and AI/ML, cultural background, gender, and the difficulty of the design task. Examining the influences of other factors can help achieve a more comprehensive understanding of people's expectations of AIs for design. Additionally, the results in this work most likely present the perceptions of the majority groups in the United States (e.g., white or Caucasian or cultural background from the Americas) due to the random recruiting of the respondents from Amazon Mechanical Turk. For more specific understanding, future works may run the survey with intentional recruiting of specific demographic groups. Third, people's perceptions of the design ability of a designer (human or AI) may not be a sufficient indication of whether they will trust or accept products. Therefore, controlled experiments or case studies exploring this relationship will be a great supplement to this work. Moreover, a survey only with expert human

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designers can expand this study beyond users' perceptions and directly inform human-AI teaming scenarios. Finally, it would be interesting to conduct a long-term study by repeating this survey every few years to investigate how people's perceptions of AIs and human designers change over time.

5 CONCLUSIONS

This work studies how the public currently perceives an AI's design ability as compared to a human designer's ability. An online survey is conducted to collect respondents' perception on 16 specific bicycle design goals, demographic information, and self-reported level of design and AI/ML knowledge. The results show that people expect an AI to perform worse than a human designer on most design goals, particularly those that demand consideration of user-specific needs and preferences. This work also finds that the more people judge themselves to be knowledgeable in design and the older they are, the more likely they are to think an AI's design ability would exceed a human designer's ability. The insights from this work are useful in understanding user acceptance of AI-designed products, as well as human designers' acceptance of AI help in human-AI teams, as more AIs are deployed into the design process.

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