

Are Confident Designers Good Teammates to Artificial Intelligence?: A Study of Self-Confidence, Competence, and Collaborative Performance

L. Chong, K. Kotovsky and J. Cagan 

Carnegie Mellon University, United States of America

 cagan@cmu.edu

Abstract

For successful human-artificial intelligence (AI) collaboration in design, human designers must properly use AI input. Some factors affecting that use are designers' self-confidence and competence and those variables' impact on reliance on AI. This work studies how designers' self-confidence before and during teamwork and overall competence are associated with their performance as teammates, measured by AI reliance and overall team score. Results show that designers' self-confidence and competence have very different impacts on their collaborative performance depending on the accuracy of AI.

Keywords: artificial intelligence (AI), teamwork, collaborative design, decision making, design cognition

1. Introduction

With the advance of artificial intelligence (AI) systems, AI has increasingly been proving its usefulness in engineering design, including areas such as customer preference identification (Chen et al., 2013), concept evaluation (Camburn et al., 2020), and manufacturing (Williams et al., 2019). As of now, however, human designers remain in the loop as their creativity and agility are yet to be reproduced by an AI and are still crucial in the design process (Song et al., 2020). Human-AI collaboration may even bring about synergy, accomplishing tasks that neither an AI nor human can solve alone (James Wilson and Daugherty, 2018). Therefore, AI agents are progressively deployed in human-AI design teams to achieve better joint performance, especially by assisting human designers to make better design decisions (Gyory et al., 2022; Zhang et al., 2021).

Despite the promise of AI systems, their assistance is only effective when designers appropriately utilize the help offered by AI. However, there are many factors that may affect and even hinder designers' collaboration with AI agents, especially those that affect their perception of themselves and of the AI. One of these factors is designers' self-confidence. Individuals' beliefs about their skills impact various aspects of teamwork such as their effort provision and team production (Vialle et al., 2011). Similarly, in human-AI teams, Lee and Moray (1994) discovered a strong relationship between the difference in human trust and self-confidence and their reliance on the automated teammate. Furthermore, Chong et al. (2022) presented the trial-by-trial effect of self-confidence on and by AI use. It is evident that self-confidence plays a crucial role in any collaboration settings. Therefore, this work investigates the relationship between designers' self-confidence and their collaborative performance.

Research in psychology have repeatedly shown that people often overestimate their abilities. For example, people are overly confident in their driving skills (Svenson, 1981), their managerial skills

(Larwood and Whittaker, 1977), their job performance (Myers and Twenge, 2018), and in their general knowledge (Fischhoff et al., 1977). On the one hand, there are some costs to such over-confidence including distrust in teammates (Lee and See, 2004) and risky decisions such as value-destroying mergers by CEOs (Malmendier and Tate, 2005). These behaviours can be a serious setback for human-AI design collaboration if it affects designers' decision to rely on AI's input. On the other hand, over-confidence has been shown to benefit teamwork by increasing motivation and reducing free-riding behaviours (Vialle et al., 2011), which can improve collaboration in design settings as well. Therefore, along with self-confidence, this work examines the role of designers' task competence in their collaborative performance. Additionally, the relationship between self-confidence (i.e., perceived competence, in this work) and competence is studied.

The current work utilizes experimental data from Chong et al. (2022). The main goal of Chong et al. (2022) was to study the evolution of two different types of human confidence, confidence in AI and self-confidence, during human-AI collaborative decision-making and their impact on the decisions. Regarding self-confidence, they showed how it changes over the course of collaboration and tracked its trial-by-trial influence on design decisions. The purpose of the current study is to understand how designers' self-confidence at different points of human-AI collaboration, as well as their competence, is correlated with their overall collaborative performance. The data from Chong et al. (2022), particularly designers' reported self-confidence, scores of unassisted actions (i.e., competence), scores of assisted actions (i.e., team performance), and their decisions to accept or reject AI suggestions, present an opportunity to achieve this purpose. Considering the available data from Chong et al. (2022), in this work, designers' overall acceptance of AI teammate's input (reliance on AI) and the final scores (overall team performance) are used to measure designers' collaborative performance. Furthermore, leveraging the experimental conditions in Chong et al. (2022) that include AIs with differing performance levels, this work conducts its analysis in two different collaboration settings: one where designers are working with a high-performing AI and another where they are working with a low-performing AI.

2. Methods

As mentioned, this work takes advantage of the data from a previous study by Chong et al. (2022). The relevant data for this work were collected during that human subject experiment. This section describes the areas of the experiment that are pertinent to the research goals here.

2.1. Truss Design Experiment

The experiment was an online human subject study, conducted via Amazon Workspaces, with 100 participants recruited from Carnegie Mellon University (CMU) and University of California at Berkeley, in accordance with a protocol approved by CMU's Institutional Review Board. All participants were Mechanical Engineering undergraduate and graduate students who have had taken a mechanics course prior to the study. All participants worked on 33 truss design problems (3 for practice and 30 for the experiment), where given a truss state, they must make the most advantageous action towards maximizing the strength-to-weight ratio (SWR). Each problem provides a unique truss state that is possible under the defined design condition with three supporting joints and two additional joints with forces acting on them (see Figure 1 for an example problem). Each participant collaborated with an AI agent (developed by Chong et al. (2022)) that provided an action suggestion for each problem, which is the AI agent's selection of the next design action for the given problem. The accuracy of the AI agent differentiated the two experimental conditions in this study. The participants were randomly assigned to one of these conditions (50 per condition). The AI agent in Condition 1 changed its accuracy from 80% to 20% after 20 problems, while that in Condition 2 changed from 20% to 80%. In the current study, only the data from the first 20 problems (before the change in AI accuracy) are used for analysis because the aim of the study is not to examine the effect of the change in AI accuracy.

Each truss design problem (see Figure 1 for an example) followed the same procedure. First, given a truss state, the participants selected their best action before receiving an AI suggestion (see Figure 1A). Once they have made this unassisted action, they received an AI suggestion. Then, the

participants could either select this AI-suggested action as the final decision (i.e., accept the AI suggestion) or make any other action (i.e., reject the AI suggestion) (see Figure 1B). After the final decision, the participants received positive or negative feedback depending on whether the action was advantageous or disadvantageous for the goal of the task and gained or lost 5 points accordingly. The participants had been informed at the start of the experiment that those with a final score above a given threshold will earn an additional monetary prize. Finally, the participants reported their confidence in the AI's ability to design trusses and confidence in their own ability. The confidence questions asked: How good are you (or the AI) at designing trusses?, and the answers were in a 5-point Likert scale: very good, good, neutral, bad, and very bad.

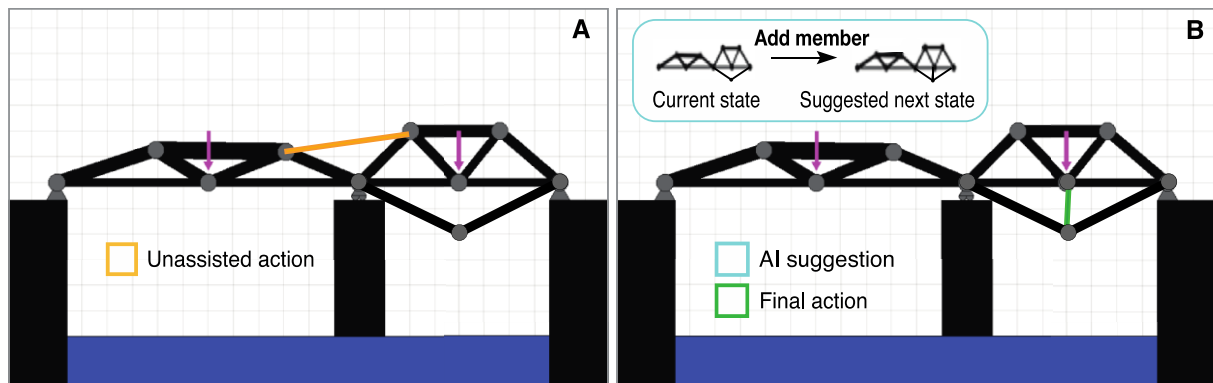


Figure 1. Example truss design problem (A) before and (B) after AI suggestion is given to the participants

The data from this experiment include information about the participants' self-confidence before and during the experiment, consisting of reported self-confidence immediately before the first problem and reported self-confidence after each of the 30 problems. In addition, the participants' unassisted action scores, final (assisted action) scores and their AI acceptance decisions respectively provide information about their competence, team performance, and reliance on AI.

3. Results

The main results of this work show how designers' self-confidence at different points of collaboration correlates with their overall reliance on AI, overall team performance, and competence. The correlation results in two different settings are illustrated: one with a high-performing AI of 80% accuracy and another with a low-performing AI of 20% accuracy. These settings are from the first 20 problems of Chong et al. (2022)'s study. Self-confidence shows how good the participants think they are at designing trusses at five different intervals of time: before the first problem and during each of the four sequential 5-problem intervals making up the 20 problems. Competence demonstrates how good the participants actually are at designing trusses. In this work, designers' overall collaborative performance (i.e., how good designers are as a teammate) is represented by their reliance on the AI and team performance scores.

All data in this analysis are in ordinal variables, meaning that they are categorical or discrete variables with natural ordering. For example, self-confidence before the experiment is reported in a 5-point Likert scale with corresponding values 0, 0.25, 0.5, 0.75, and 1. Self-confidence during the experiment is a variable that averages 5-point Likert scale values in each 5-problem interval, thus ranging from 0 to 1. Competence is the sum of the 20 action scores (i.e., 5 or -5 for advantageous or disadvantageous action respectively in each problem) given to the participants' unassisted actions and therefore ranges between a possible -100 and 100. Reliance is a variable that measures how often the participants relied on the AI teammate by averaging 20 binary values (i.e., 0 or 1) that represent whether the participants accepted or rejected the AI suggestion for the 20 problems. Therefore, like self-confidence, reliance ranges between 0 and 1. Finally, overall team performance is the sum of the 20 action scores (i.e., 5 or -5) given to the participants' assisted actions (final decisions), ranging from -100 to 100.

3.1. Self-Confidence

This section examines the correlation results between designers' self-confidence at various points of the experiment and their overall collaborative performance, represented by reliance on AI and team performance in this work. The analysis is conducted using self-confidence values at five different times of the experiment (initial, problems 1-5, 6-10, 11-15, and 16-20) to identify the change in the correlation.

3.1.1. Correlation with Overall Reliance on AI

Figure 2 presents correlation results that indicate how designers' self-confidence at various times of human-AI design collaboration relates to their overall reliance on the AI teammate. Because all variables in the analysis are ordinal and each have five or more levels, Spearman's Rho is used to measure the association between them. For Spearman's Rho analysis, correlation coefficient rho ranges between -1 and 1, where 0 means no correlation, and positive and negative values correspond to positive and negative correlation respectively.

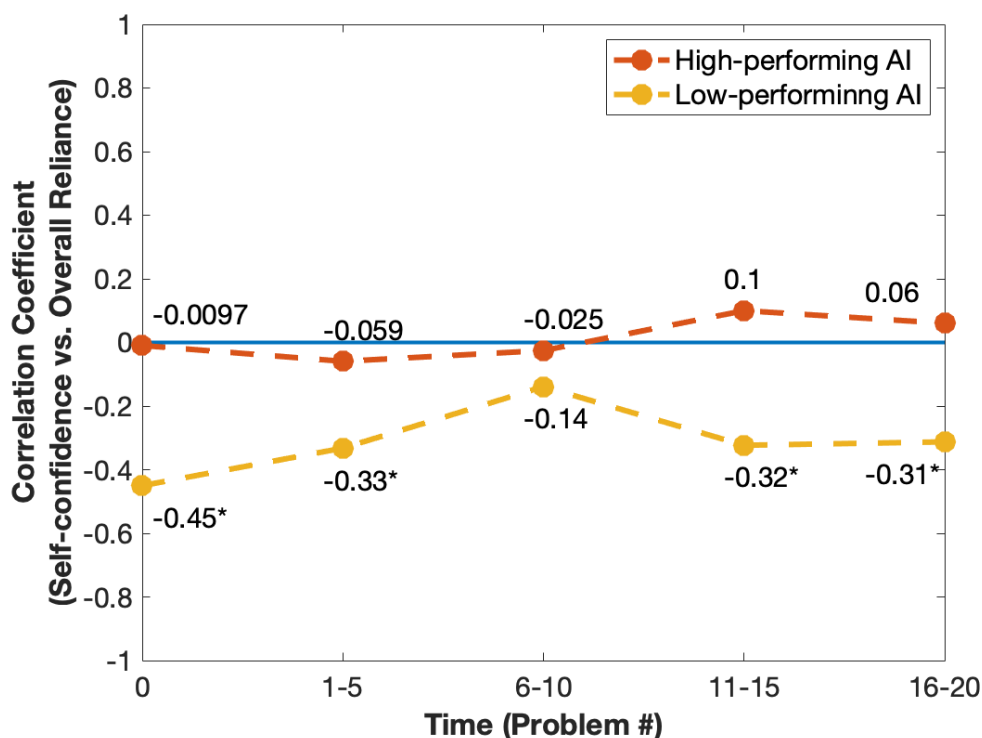


Figure 2. Spearman's Rho results between designers' self-confidence at different points of collaboration and their overall reliance on AI. * indicates significance at 95% level

Observing the rho values in Figure 2, when the participants are working with a high-performing AI, their self-confidence does not show a significant relationship with their overall reliance on the AI. However, with a low-performing AI, the participants' self-confidence is negatively correlated (below the blue line) with their overall reliance on the AI throughout the collaboration process, except during problems 6-10. This means that when working with a low-performing AI, designers who are highly reliant on the AI tend to show low self-confidence in the early and late stages of collaboration and vice versa. In addition, it is important to pay attention to the trend in the strength of the correlation in the low-performing AI condition. The results suggest that the strength of the correlation weakens over time (approaching the blue line) until halfway through the experiment where it ends up insignificant. Then, the relationship strengthens again till the end. Therefore, with a low accuracy AI, designers' self-confidence closer to the start or the end of the collaboration is more correlated with their reliance on AI than their self-confidence during the intermediate stages.

3.1.2. Correlation with Overall Team Performance

Figure 3 illustrates Spearman's Rho correlation results between designers' self-confidence at various points of human-AI design collaboration and their overall team performance. When the participants are working with a high-performing AI, there is no significant relationship between their self-confidence and the overall team performance. However, when working with a low-performing AI, the participants' self-confidence shows a strong, positive correlation (above the blue line) with the overall team performance throughout the experiment, except before problem 5. This means that designers who achieve high final team scores tend to be highly confident in themselves throughout the human-AI collaboration, particularly after the first few problems and, likely as a result, do not rely on the AI as discussed in Section 3.1.1. Furthermore, the trend in the strength of the correlation is very interesting in the low-performing AI condition. The trend starts from an insignificant correlation between starting self-confidence and overall team performance. Soon after, during problems 6-10, the correlation becomes significant and positive, which then remains this way until the end. As a result, when collaborating with a low-performing AI, designers' self-confidence directly reflects overall team performance after the early stages of collaboration.

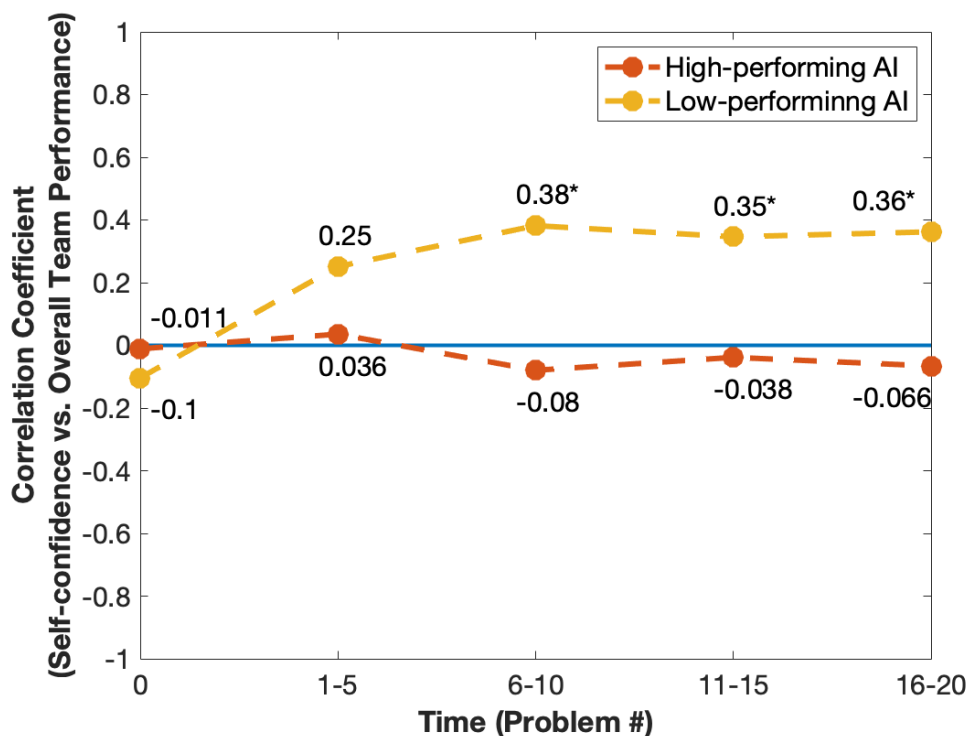


Figure 3. Spearman's Rho results between designers' self-confidence at different points of collaboration and overall team performance. * indicates significance at 95% level

3.2. Competence

Noting that the results so far are based on the designers' confidence in their truss design ability and not their actual competence, this section displays the Spearman's Rho correlation results between designers' competence and their overall collaborative performance (see Table 1). Competence is calculated by summing the 20 action scores of the participants' unassisted actions, therefore not divided in time intervals.

3.2.1. Correlation with Overall Reliance on AI

The first row in Table 1 illustrates that regardless of the AI accuracy, there is a negative but statistically insignificant correlation between the participants' competence and their overall reliance on AI. Negative correlation here means that designers who are more competent at designing trusses are

less reliant on AI throughout the collaboration. However, this tendency is not strong enough to be statistically significant in either of the conditions.

Table 1. Spearman's Rho results between designers' competence and their overall collaborative performance (reliance on AI and team performance)

| | High-performing AI | Low-performing AI |
|--|--------------------|-------------------|
| Competence vs. Overall Reliance on AI | -0.028 (0.85) | -0.042 (0.77) |
| Competence vs. Overall Team Performance | 0.11 (0.44) | 0.33* (0.018) |

P-values are in parentheses.

* indicates significance at 95% level.

3.2.2. Correlation with Overall Team Performance

The second row in Table 1 displays the correlation coefficients between the participants' competence and overall team performance during human-AI design collaboration. In both conditions, there is a positive correlation: more competent designers correspond to higher team scores. However, the strength of this relationship is only significant when the AI teammate is performing poorly. This means that designers' task competence reflects human-AI joint performance better when working with a low-performing AI teammate than when working with a high-performing AI.

3.3. Self-Confidence vs. Competence

The results thus far have shown how the participants' self-confidence at various points of human-AI collaboration and competence are each associated (or not associated) with their overall collaborative performance. In this work, self-confidence is measured by asking the participants to report their perceived competence (How good are you at designing trusses?), assuming a considerable relationship between self-confidence and competence. Therefore, this section studies the correlation between designers' self-confidence (perceived competence) and their actual competence.

Figure 4 is the Spearman's Rho correlation results between the participants' self-confidence at different points of the experiment and their overall competence. In the high-performing AI condition, there is a consistent, positive correlation (above the blue line) throughout the experiment. As expected, more competent designers tend to be more confident in their abilities. In the low-performing AI condition, however, this relationship between self-confidence and competence is mostly insignificant. This result is surprising as this means that designers' self-confidence and competence do not reflect one another when working with a poorly performing AI.

In order to gain further insight into the results, it is important to recognize the trends in the correlation between self-confidence and competence over the course of collaboration. The two conditions show notably different results. When collaborating with a high-performing AI, the results indicate a symmetrical trend in the strength of the positive correlation, decreasing (approaching the blue line) until midway through the experiment and increasing (moving away from the blue line) thereafter. This means that with a high-performing AI, designers' self-confidence closer to the start or the end of the collaboration reflects their competence better than their self-confidence during the intermediate stages. Contrastingly, when collaborating with a low-performing AI, the correlation starts negative and slowly moves towards the positive direction.

Table 2 includes the mean self-confidence of the participants at each point in time, as well as the mean competence of the participants. The results in Table 2 demonstrate no stark differences between the two conditions. However, the results may be indicating that in both conditions, mean self-confidence is always higher than mean competence over the course of the collaboration. As introduced earlier in the paper, self-confidence ranges between 0 and 1, and competence ranges between -100 and 100. For visual comparison, competence values are scaled to the range of self-confidence, shown in parentheses in Table 2. In the Discussion, these results are used to gain a better understanding of the correlation results.

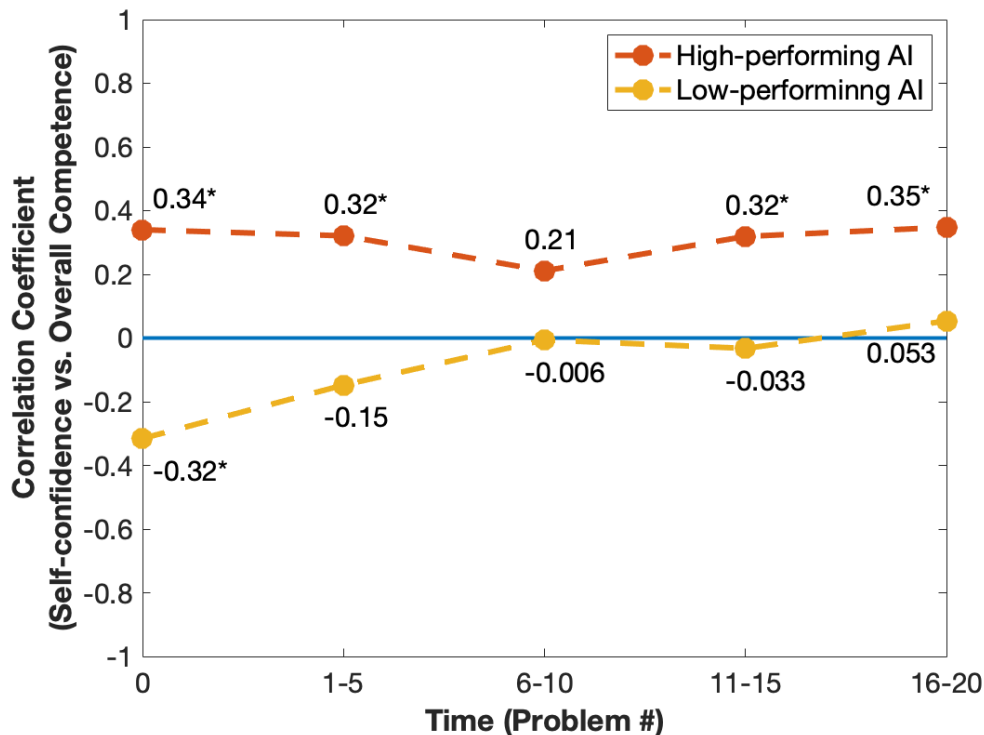


Figure 4. Spearman's Rho results between designers' self-confidence at various points of collaboration and their overall competence. * indicates significance at 95% level

Table 2. Participants' mean self-confidence in each time interval and their mean competence

| | | Time (Problem #) | | | | |
|-----------------|--------------------|------------------|------|------|-------|-------|
| | | 0 | 1-5 | 6-10 | 11-15 | 16-20 |
| Self-confidence | High-performing AI | 0.49 | 0.45 | 0.49 | 0.41 | 0.43 |
| | Low-performing AI | 0.47 | 0.43 | 0.43 | 0.39 | 0.39 |
| Competence | High-performing AI | -36 (0.18) | | | | |
| | Low-performing AI | -34 (0.17) | | | | |

Scaled competence values are in parentheses.

4. Discussion

This research investigates how designers' self-confidence at five different time intervals and their competence are associated with their overall collaborative performance with an AI teammate. Two measures of collaborative performance, reliance on AI and team performance, are considered in the analysis. Also, the analysis is conducted in two different human-AI design collaboration scenarios, one with a high-performing AI (80% accuracy) and another with a low-performing AI (20% accuracy). Interestingly, there are remarkable differences in the results between the two conditions.

In the first condition with a high-performing AI, the participants' self-confidence at various points of collaboration does not correlate with their collaborative performance: how reliant they are on the AI and how well the team performs. This is an unexpected result considering the prior works that propose human self-confidence as an important factor of AI acceptance and use. For example, [Lee and Moray \(1994\)](#) empirically demonstrated that the difference in human trust in an AI teammate and self-confidence has a strong relationship with reliance on the AI. Even [Chong et al. \(2022\)](#) who used the same data as the current work showed that designers' self-confidence at the time of decision-making correlates with their decision to accept AI input and consequently the team performance. However, it is important to recognize that these prior works studied designers' individual decisions to accept AI input based on their immediately preceding self-confidence, while the current work looks at how self-confidence at various points of collaboration is related to overall reliance on the AI and the resulting

team score. In view of what this work is investigating, in its high-performing AI condition, the participants' self-confidence at different times does not reflect how reliant they are on the AI or how well they perform together with the AI. This result may be because the impressive performance by the high-performing AI in this condition makes designers' self-confidence a trivial factor to consider for their reliance on the AI and the resulting team performance.

With a high-performing AI, designers' competence also does not correlate with their reliance on AI and the final team score. This result is surprising because it seems intuitive that when designers are competent at a given task, they would know how much and when to rely on the AI input, leading the team to good performance. One possible explanation for this finding is that when the AI teammate is highly proficient, designers' competence may not be a big factor in whether they rely on the AI or not. Rather, the AI's performance may be a greater factor. Additionally, based on the strong, positive correlation results between the participants' self-confidence and competence in this condition, it is rational that their competence does not reflect their collaborative performance in the same way their self-confidence does not.

The second condition with a low-performing AI illustrates contrasting results: designers' self-confidence displaying some strong correlations with their collaborative performance. First, designers' self-confidence at various points of collaboration consistently shows a negative correlation with their reliance on AI. This means that when working with a poorly performing AI, designers' low confidence in their own task ability at a certain point indicates that they are highly reliant on the AI throughout the collaboration and vice versa. This result is unique to this condition likely because learning that the AI teammate is often inaccurate, designers are resorting to AI suggestions only when they are not confident in themselves. Such behaviour agrees with the prior finding by [Vialle et al. \(2011\)](#) that people tend to show free-riding behaviours in teams when they are not confident in themselves. The trend in the strength of the negative correlation is also very interesting. The initially strong, negative relationship becomes insignificant midway into the experiment, then strengthens back. This means that designers' self-confidence near the start and end of collaboration hints at their overall reliance on AI more than their self-confidence during the intermediate stages does. Secondly, when working with a low-performing AI, designers' self-confidence after the early stages of collaboration steadily shows a positive correlation with the overall team performance. This result indicates that designers who eventually achieve a high performance with the AI tend to be highly confident in themselves particularly during the intermediate to late stages of collaboration.

When collaborating with a low-performing AI, designers' competence is not correlated with their reliance on AI but is positively correlated with the final team score. This positive correlation indicates that competent designers tend to perform well together with the AI and vice versa. This result can be explained by the preceding results. With a poorly performing AI, designers are reliant on AI suggestions only when they are not confident in themselves. However, they seem to be over-confident (i.e., self-confidence > competence) throughout the human-AI collaboration (see Table 2), confirming prior works that proposed that people tend to over-estimate their ability ([Fischhoff et al., 1977](#); [Larwood and Whittaker, 1977](#); [Myers and Twenge, 2018](#); [Svenson, 1981](#)). Therefore, this over-confidence leads designers to be reliant not on the AI but alternatively on themselves, making sense of the positive correlation between designers' competence and the final team score. Finally, this positive correlation explains why designers' self-confidence (after the early stages of collaboration) also shows a positive correlation with the final team score in the low-performing AI condition. In this condition, designers' self-confidence and their competence directly reflect one another quickly after the early stages of collaboration. Therefore, they demonstrate a similar relationship to team performance.

This findings in this work provide insights into the relationship between designers' self-confidence (at various points of collaboration), competence, and their performance as a teammate during human-AI joint design decision-making. When collaborating with a high-performing AI, designers' self-confidence and competence are directly correlated with one another. Furthermore, they both do not imply any information about designers' collaborative performance: reliance on the AI and overall team performance. These results suggest useful insight that in design, more competent and/or more confident designers are not necessarily better collaborators when they are working with a high-performing AI. Additionally, any efforts to alter designers' self-confidence or competence (e.g.,

training, positive feedback, etc.) would not be effective for improving the outcome of collaboration. In contrast, when collaborating with a low-performing AI, designers' self-confidence and competence are not correlated with one another. Therefore, they each have a unique relationship to designers' collaborative performance: more confident designers are less reliant on AI and achieve higher team scores, and more competent designers achieve higher team scores. These insights indicate that with a poorly performing AI, more confident and/or more competent designers are preferable for an effective human-AI design collaboration. Overall, the results in this work inspire ways to appropriately exploit designers' self-confidence and competence based on the accuracy of the AI teammate to enhance the outcome of human-AI collaboration in design.

There are few limitations in this work that offer opportunities for future research. The first limitation is that the correlation analysis in this work studies the independent relationships between each pair of variables because of the discrete nature of the variables. However, it is more than likely that there are some combined and interaction effects between these variables, such as reliance behaviour and overall team performance. Therefore, it would be beneficial to collect continuous data for these variables and conduct multiple regression analyses. Another shortcoming of this work is that self-confidence data are self-reported, which may not be the most accurate measure. It has also been shown that explicit repeated reporting influences people's subsequent judgements (Kvam et al., 2015). Therefore, although the analysis in this work takes the data's reported nature into consideration, it would be helpful to use more inconspicuous approaches to measure self-confidence.

5. Conclusion

In summary, this work examines how designers' confidence in their own task ability throughout the process of human-AI collaboration and their competence are correlated with their performance as a teammate. The major findings reveal that there are notably different correlation results depending on the accuracy of the AI teammate. When the AI is highly proficient, neither designers' self-confidence nor competence is associated with their reliance on AI or final team score. This lack of association may be due to the attractive suggestions from the high-performing AI, potentially making self-confidence and competence less important in designers' decision-making process. In contrast, with a poorly performing AI, significant correlations are observed. With suggestions that are not as attractive, designers follow a more distinct pattern of relying on the AI only when they are not confident in themselves. Overall, the results from this work offer valuable insight into the relationship between designers' self-confidence, competence, and their collaborative performance, opening doors to improving the effectiveness of human-AI collaboration in design.

Acknowledgement

This work was supported by the Air Force Office of Scientific Research under grant No. FA9550-18-1-0088. Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the sponsors.

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