

# Overconfident and Unconfident AI Hinder Human-AI Collaboration

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## Abstract

AI transparency is a central pillar of responsible AI deployment and effective human-AI collaboration. A critical approach is communicating uncertainty, such as displaying AI's confidence level, or its correctness likelihood (CL), to users. However, these confidence levels are often uncalibrated, either overestimating or underestimating actual CL, posing risks and harms to human-AI collaboration. This study examines the effects of uncalibrated AI confidence on users' trust in AI, AI advice adoption, and collaboration outcomes. We further examined the impact of increased transparency, achieved through trust calibration support, on these outcomes. Our results reveal that uncalibrated AI confidence leads to both the misuse of overconfident AI and disuse of unconfident AI, thereby hindering outcomes of human-AI collaboration. Deficiency of trust calibration support exacerbates this issue by making it harder to detect uncalibrated confidence, promoting misuse and disuse of AI. Conversely, trust calibration support aids in recognizing uncalibration and reducing misuse, but it also fosters distrust and causes disuse of AI. Our findings highlight the importance of AI confidence calibration for enhancing human-AI collaboration and suggest directions for AI design and regulation.

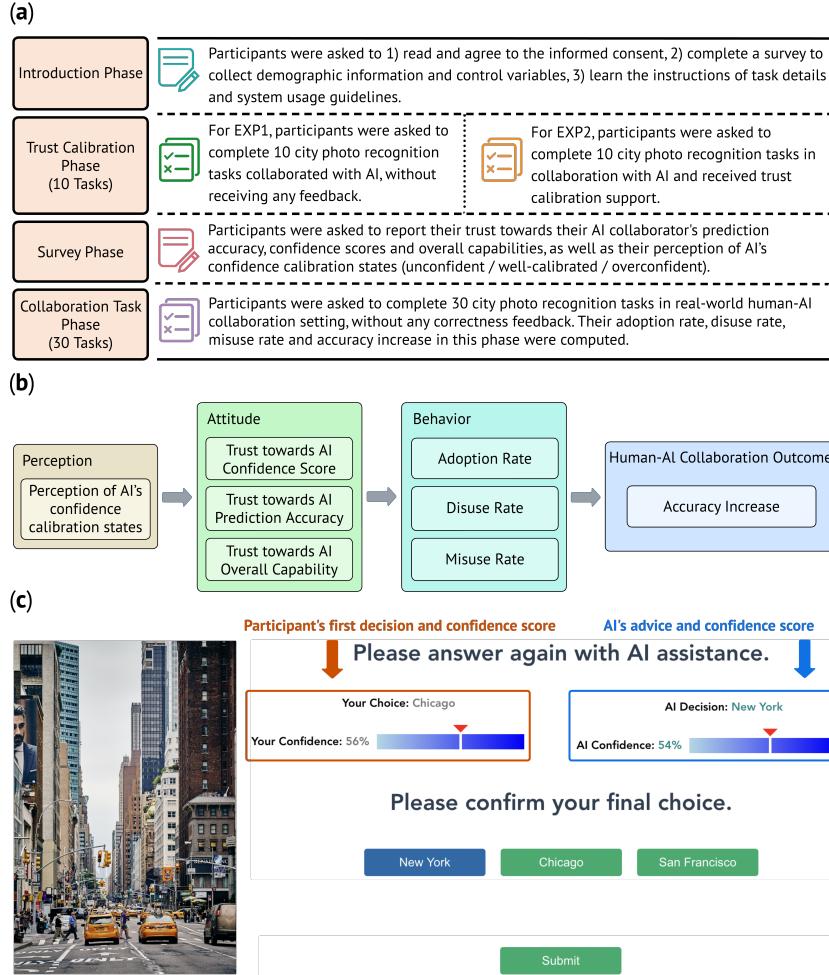
**Keywords:** Human-AI Collaboration, AI Confidence Calibration, Trust Calibration

## 1 Introduction

Artificial intelligence (AI) has become a significant force in various domains, demonstrating its capacity to extract valuable insights from data and opening new avenues for human-AI collaboration. From everyday decisions, such as deciding daily outfits [1, 2], to high-risk sectors such as healthcare [3, 4, 5, 6] and investment [7, 8], AI can aid humans in accomplishing a myriad of tasks. However, recent studies found that the effectiveness of human-AI teams often does not surpass that of AI operating alone, primarily because humans might follow AI's incorrect advice, despite having the capability to make superior judgments independently [9, 10, 11, 12, 13]. In fact, the efficacy of human-AI collaboration is conditioned on many factors, one of which is the human ability to accurately assess when AI's guidance is dependable and when it might falter, thus *calibrating their trust* accordingly [14, 15, 16, 17]. *Trust calibration* in human-AI collaboration refers to the process by which a person adjusts their trust to match the actual reliability and trustworthiness of the AI system [16, 14]. Adequate support for trust calibration enables humans to utilize AI judiciously—leveraging it when it is reliable and refraining from using it when it is not. Conversely, excessive trust in AI, or *overtrust*, can lead to its *misuse* by relying on it in unreliable scenarios. Similarly, insufficient trust, or *distrust*, results in the *disuse* of AI, even in instances where AI could offer more reliable advice than human judgment [15, 16].

Recent studies show that improving AI transparency by disclosing its uncertainty levels can help humans calibrate trust towards AI and improve human decision-making about AI use, fostering more effective human-AI collaboration [18, 19, 20, 21, 13]. An effective approach to conveying AI uncertainty is expression of *confidence*, which estimate the probability of AI making correct decision, i.e., correctness likelihood [19]. Classification models, for instance, can yield a percentage output as its confidence score to denote uncertainty [21]. Large language models (LLMs), when prompted appropriately, can articulate their confidence using words or sentences [22]. Unlike *accuracy*, which evaluates AI's *overall* performance and reliability, confidence levels quantify the uncertainty of each *individual* task [23, 24]. Thus, AI's confidence may serve as a more powerful indicator of task-level uncertainty that influence human trust and use of AI. Higher AI confidence facilitates trust in AI and its usage, whereas lower confidence may lead to preference for human judgment [17, 25]. Accurately calibrated AI confidence can enhance not only trust calibration but also the efficiency and effectiveness of human-AI collaboration [23, 19, 26].

While existing research often regards well-calibrated AI confidence as a foundational premise [25, 18, 19, 27], it overlooks a critical reality: achieving well-calibrated AI confidence is more challenging and less common than assumed. Despite numerous efforts to calibrate AI confidence [28, 23], many AI systems still exhibit misaligned confidence levels, failing to accurately reflect their actual CL [23, 29, 30, 31]. This discrepancy is evident in AI systems that exhibit overconfidence (i.e., their expressed confidence exceeds their actual CL), notably in some LLMs providing highly confident yet incorrect answers [21, 22]. Conversely, there are instances of unconfidence, where AI's confidence falls short of their actual capability [31]. This misalignment highlights the complexity and necessity of accurate confidence calibration in AI systems. Furthermore, the influences and risks of uncalibrated AI confidence are not sufficiently



**Fig. 1** (a) A flowchart illustrating the study procedure. Participants were required to sequentially complete these four phases. (b) Conceptual map of variables: attitude is informed by perception and influences behavior. Human-AI collaboration outcome is the result of behavior. (c) City photo recognition task interface. Participants were tasked with identifying the origins of city photos from three choices. In each task, participants made an initial decision, followed by the AI providing a suggestion along with a percentage confidence score, after which participants made their final decision.

understood. Encouraging AI to express uncertainty without recognizing its potential downsides, especially in high-stake scenarios, could lead to negative outcomes. Thus, it is imperative to elucidate the impacts and risks of uncalibrated AI on humans' trust calibration and human-AI collaboration and to identify strategies for mitigating these issues.

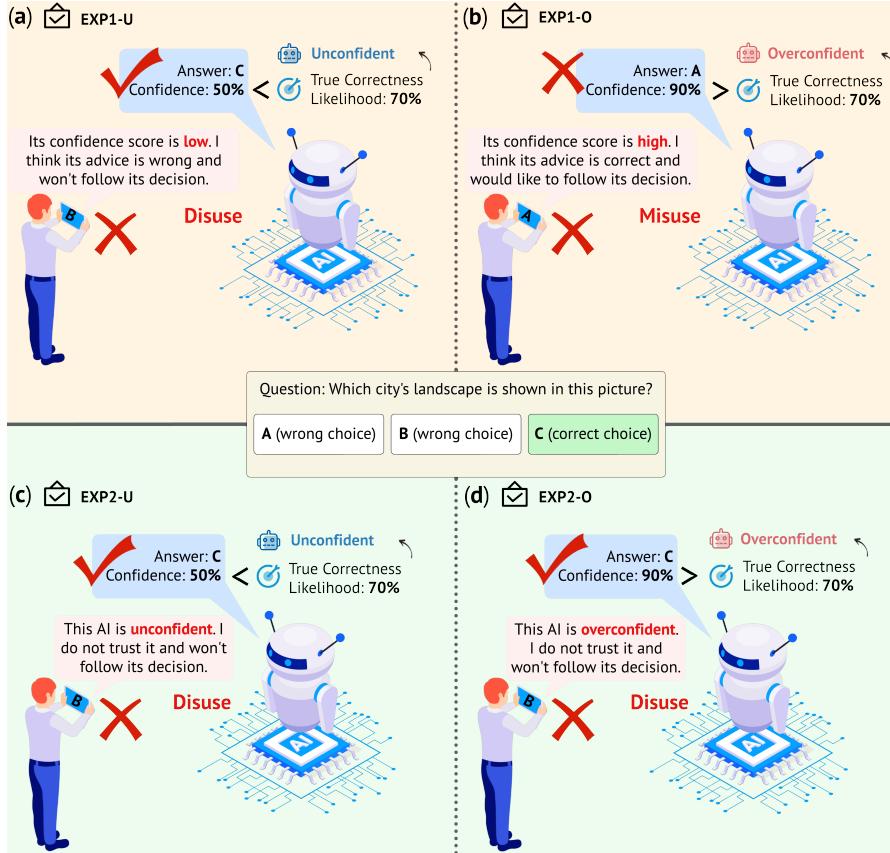
Therefore, this study examines the effects of uncalibrated AI confidence on trust towards AI, adoption of AI's advice, and the outcomes of human-AI collaboration. We

also examine to extent to which individuals are able to perceive uncalibrated AI confidence. We also explore the extent to which individuals can perceive uncalibrated AI confidence. Prior research suggests that individual attitudes, shaped by perceptions and beliefs, influence behavior and actions [16, 32, 33]. Thus, we assume that perception of an AI’s confidence calibration underpins trust calibration, which in turn affects the adoption of AI advice and the success of human-AI collaboration (as shown in Fig. 1 (b)). Exploring the effects of uncalibrated AI on trust calibration can provide deeper insights into its negative impacts on human-AI collaboration, rather than just focusing on collaboration outcomes.

Furthermore, previous research has indicated that appropriately increasing transparency can aid individuals in better perceiving and understanding the boundaries of AI capabilities, facilitating complementary collaboration [34, 35]. This study also examines whether increase transparency, i.e., trust calibration support, can improve participants’ perception of uncalibrated confidence, can enable a better understanding of AI’s strengths and weaknesses. Such improvement may facilitate rational complementary collaboration, thereby mitigating the adverse effects of uncalibrated AI on human-AI collaboration. Explicitly addressing these questions is crucial for researchers and developers keen on mitigating the risks of disclosing AI uncertainty, building effective and harmonious human-AI collaborative relationships.

We ran two behavioural experiments to answer these questions. In **Experiment 1** (EXP1,  $N = 126$ ), participants were randomly assigned to collaborate with AI with different confidence calibration states: well-calibrated (EXP1-W,  $N=42$ ), unconfident (EXP1-U,  $N=42$ ), and overconfident (EXP1-O,  $N=42$ ), to complete a city photo recognition task (experimental procedure as shown in Fig. 1 (a), task interface in Fig. 1 (c), with more details in Sec. 4). Participants were expected to calibrate their trust in AI through tasks in Trust Calibration Phase and reported their perceptions of AI confidence calibration and trust in AI during the Survey Phase. In Collaboration Task Phase, through formal collaborative tasks, we captured participants’ behaviors regarding AI use and assessed the outcomes of collaboration. Across all groups, the AI’s accuracy remained constant at 70%, which we used as an approximation  $\hat{p}$  for the AI’s average true correctness likelihood. Based on the relationship between the AI’s average confidence score  $\bar{c}$  and  $\hat{p}$ , the confidence calibration states of AI were defined as: unconfident ( $\bar{c} = 60\% < \hat{p}$ ), confident ( $\bar{c} = 70\% = \hat{p}$ ), and overconfident ( $\bar{c} = 80\% > \hat{p}$ ). EXP1 investigated the effects of uncalibrated AI confidence without additional support.

Subsequently, we conducted **Experiment 2** (EXP2,  $N = 126$ ) with two objectives: firstly, to examine the effects of trust calibration support taking EXP1’s results as baselines, and secondly, to explore the effects of uncalibrated AI confidence when trust calibration support is provided. Again, participants were randomly assigned to collaborate with well-calibrated (EXP2-W,  $N=42$ ), unconfident (EXP2-U,  $N=42$ ), or overconfident (EXP2-O,  $N=42$ ) AI. All participants received trust calibration support during the Trust Calibration Phase, including disclosing AI’s confidence calibration status (e.g., overconfidence, unconfidence), providing immediate feedback on each task’s correctness and presenting AI’s overall performance feedback after all tasks (more details in Sec. 4). Trust calibration support helped participants by increasing

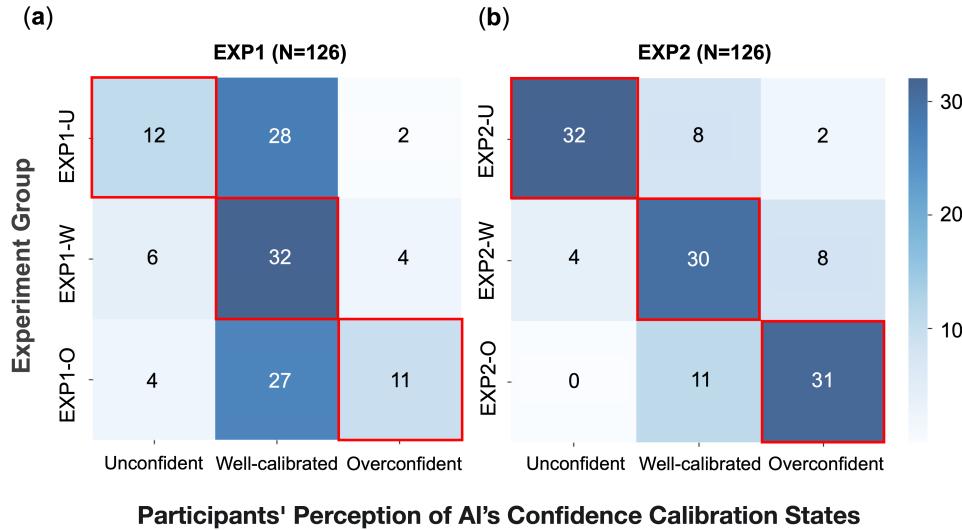


**Fig. 2** A diagram demonstrates how uncalibrated AI influences individuals and hinders human-AI collaboration. **(a)** EXP1-U: individuals are unable to detect AI's unconfidence and overtrust AI's confidence scores. They mistakenly reject its correct advice, i.e. disuse it, and get poor collaboration outcomes. **(b)** EXP1-O: individuals are unable to detect AI's overconfidence and overtrust AI's confidence scores. They mistakenly adopt its wrong advice, i.e. misuse it, and get poor collaboration outcomes. **(c)** EXP2-U: with trust calibration support, individuals are able to detect AI's unconfidence. However, they distrust AI's prediction accuracy, resulting in disuse. Finally they get poor collaboration outcomes. **(d)** EXP2-O: with trust calibration support, individuals are able to detect AI's overconfidence. However, they distrust AI's prediction accuracy, resulting in misuse. Finally they get poor collaboration outcomes.

transparency during their trust calibration phase. The rest of the settings in EXP2 remained the same as in EXP1.

## 2 Results

In both experiments, uncalibrated AI consistently hindered human-AI collaboration, and participants were unable to effectively calibrate their trust towards uncalibrated AI. Increased transparency, i.e., trust calibration support, can enhance the perception of AI's uncalibrated state by participants and reduce misuse caused by overconfident

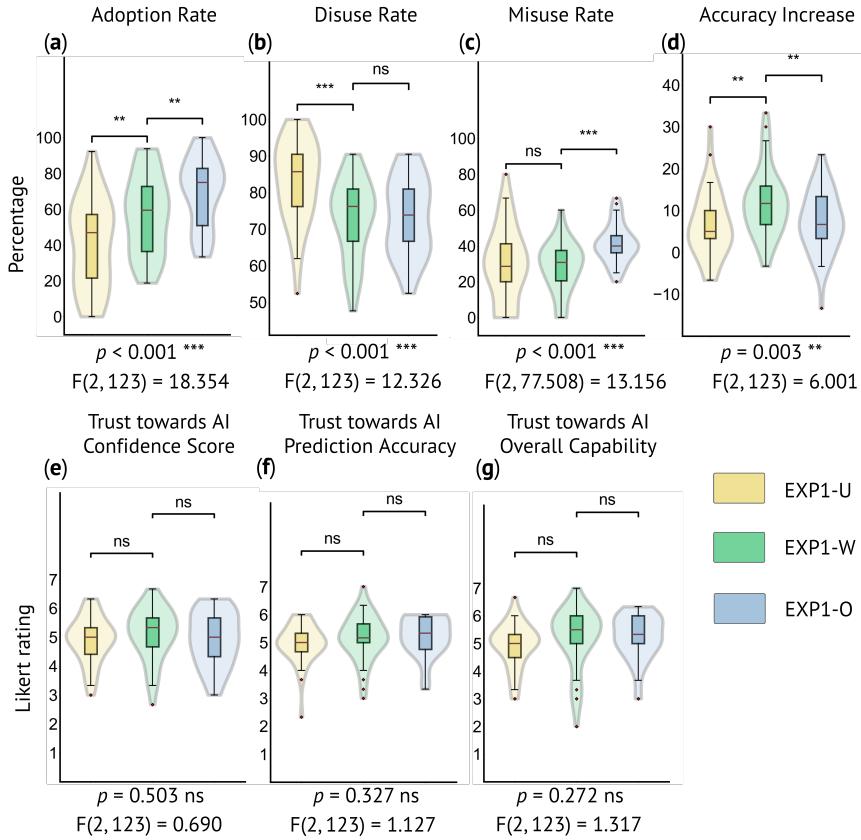


**Fig. 3** Heat maps illustrating participants' perception of AI's confidence calibration state. Each row in a given map corresponds to different groups from EXP1 and EXP2, categorized by the confidence calibration states of the AI they collaborated with. Each column represents the AI's confidence calibration states perceived by participants within that group, which could be unconfident, well-calibrated, or overconfident. The red boxes highlight instances where the perceived AI's confidence calibration state matched the AI's confidence calibration state in that group, indicating participants who correctly perceived the AI's confidence calibration state. The numbers in each cell represent the count of participants in the experimental group who perceived the corresponding AI's confidence calibration state for each column. Darker colors correspond to a greater number of participants. (a) is the result of EXP1. (b) is the result of EXP2.

AI; however, it introduces a distrust towards AI's prediction accuracy as well as an increase of disuse, thereby not significantly improving the outcome of human-AI collaboration. All statistical test result details, descriptive data, additional figures, tests related to control variables, and demographic data are provided in the supplementary material.

## 2.1 Overconfident and Unconfident AI Hinder Human-AI Collaboration

The results from EXP1 demonstrate that participants collaborating with uncalibrated AI struggled to perceive the uncalibration of AI confidence. Operating on this incorrect informational basis, their trust in AI did not significantly differ from those collaborating with well-calibrated AI. Behaviorally, overconfident and unconfident AI led to misuse and disuse, respectively, through which uncalibrated AI confidence correspondingly increased or decreased participants' adoption behaviors and resulted in poorer collaboration outcomes (Fig. 2 (a) and (b)).



**Fig. 4** One-way ANOVA results of EXP1 are depicted in violin and box plots, about the effects of AI's confidence calibration states on the dependent variables: participants' Adoption Rate, Disuse Rate, Misuse Rate, Accuracy Increase, Trust towards AI's Confidence Score, Trust towards AI's Prediction Accuracy, and Trust towards AI's Overall Capability. The center line represents the median. The box limits represent upper and lower quartiles. The whiskers represent the 1.5x interquartile range. The points represent the outliers. The width of each violin corresponds to the frequency of observations at any given number on the y axis. The cut of kernel density estimation is set to 0. The  $p$ -values of the AI confidence calibration states' main effects from the one-way ANOVA are indicated below each figure, and the significance levels from post-hoc analyses are denoted within the figures (ns:  $p > 0.05$ , \*:  $p < 0.05$ , \*\*:  $p < 0.01$ , \*\*\*:  $p < 0.001$ ). F-values with degrees of freedom are also reported below the figure. Differences between groups from post-hoc analyses, excluding comparisons between EXP1-U and EXP1-O, are marked in the figure. Further information, such as the verification of homogeneity assumptions, analytical methods, and effect sizes, can be found in the supplementary materials.

### 2.1.1 Perceiving AI's Overconfidence and Unconfidence is Challenging

The results of the groups EXP1-U and EXP1-O, as depicted on Fig. 3 (a), indicate that, it is difficult for the majority of participants to perceive if the provided AI's confidence level aligns with its actual correctness likelihood. In EXP1-U, 28.571% of participants correctly perceived the AI's unconfidence. In EXP1-O, only 26.190%

of participants correctly perceived the overconfidence. The majority of participants deemed the AI's confidence calibration state appropriate when the AI was either overconfident or unconfident, suggesting an overtrust in AI's confidence.

Additionally, as shown in Fig. 4 (e)-(g), there were no significant differences between participants' trust towards AI's confidence, predictions, and overall capability within EXP1.

### 2.1.2 Overconfident AI Leads to Misuse

As the main effects of AI confidence calibration states in one-way ANOVA are significant, according to post-hoc analysis, as shown in Fig. 4 (c), participants in EXP1-O exhibited a significantly higher misuse rate ( $M = 41.257\%$ ,  $s.d. = 10.835\%$ ,  $p < 0.001$ ) compared to those in EXP1-W ( $M = 28.207\%$ ,  $s.d. = 14.002\%$ ). Moreover, the adoption rate (see Fig. 4 (a)) for participants in EXP1-O ( $M = 69.587\%$ ,  $s.d. = 19.246\%$ ,  $p = 0.027$ ) was significantly higher than for participants in EXP1-W ( $M = 56.975\%$ ,  $s.d. = 21.868\%$ ). In terms of human-AI collaboration outcomes shown in Fig. 4 (d), the increase of accuracy in EXP1-O ( $M = 7.221\%$ ,  $s.d. = 7.433\%$ ,  $p = 0.018$ ) was significantly lower than the increase observed in EXP1-W ( $M = 11.905\%$ ,  $s.d. = 7.967\%$ ).

### 2.1.3 Unconfident AI Leads to Disuse

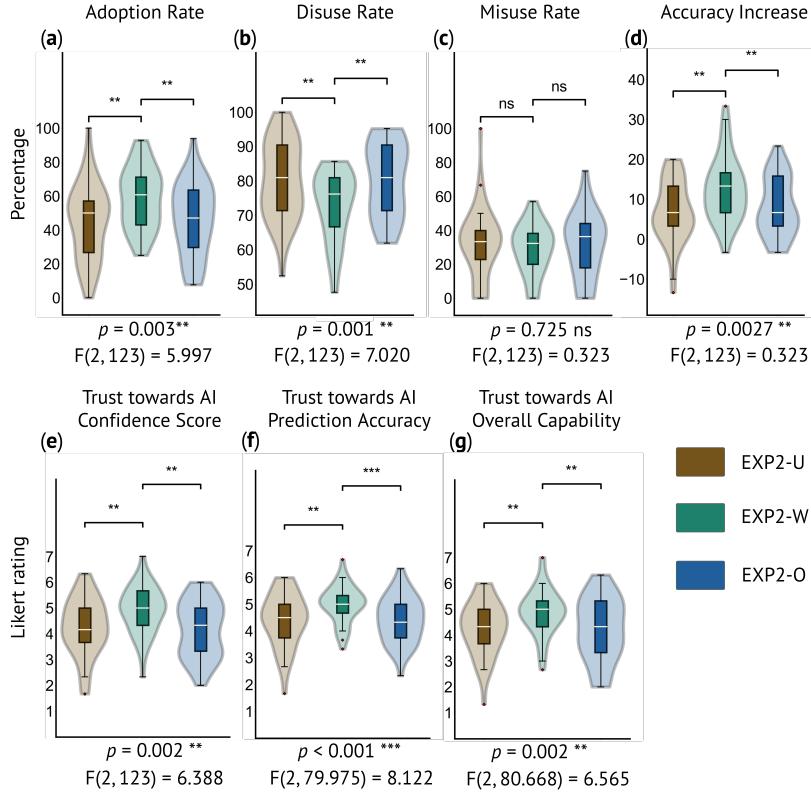
On the other hand, participants in EXP1-U showed a significantly higher disuse rate ( $M = 83.333\%$ ,  $s.d. = 11.242\%$ ,  $p < 0.001$ ) compared to those in EXP1-W ( $M = 73.016\%$ ,  $s.d. = 10.657\%$ ) as shown in Fig. 4 (b). Additionally, the adoption rate for participants in EXP1-U ( $M = 40.492\%$ ,  $s.d. = 24.752\%$ ,  $p = 0.002$ ) was significantly lower than that for participants in EXP1-W. From the perspective of Human-AI collaboration outcomes, the increase of accuracy in EXP1-U ( $M = 6.508\%$ ,  $s.d. = 7.859\%$ ,  $p = 0.018$ ) was significantly lower than the increase observed in EXP1-W.

### 2.1.4 Misuse and Disuse Further Impair Human-AI Collaboration Outcomes

The results of the mediation analysis in Fig. 6 (a) and (b) further revealed the effects of uncalibrated AI confidence on accuracy increase, mediated by adoption rate and misuse. Utilizing data from EXP1-W and EXP1-O, we found that the misuse rate ( $\beta_i$  (indirect effect) =  $-6.228$ ,  $p < 0.001$ ) and adoption rate ( $\beta_i = 2.854$ ,  $p = 0.007$ ) fully mediated the influence of AI's overconfidence on accuracy increase ( $\beta_d$  (direct effect) =  $-1.309$ ,  $p = 0.231$ ). With data from EXP1-U and EXP1-W, it was discovered that the disuse rate ( $\beta_i = -9.081$ ,  $p < 0.001$ ) and adoption rate ( $\beta_i = 3.196$ ,  $p = 0.003$ ) fully mediated the effect of AI's unconfidence on accuracy increase ( $\beta_d = 0.487$ ,  $p = 0.612$ ).

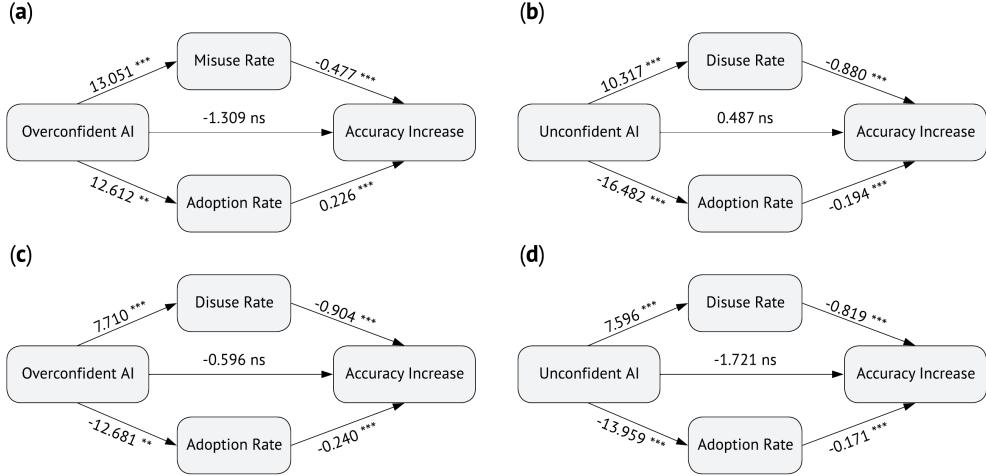
## 2.2 Trust Calibration Support Is A Double-Edged Sword

Combining EXP1 and EXP2, our results indicate that trust calibration support can aid participants in perceiving AI's uncalibrated confidence and reduce misuse when



**Fig. 5** One-way ANOVA results of EXP2 are depicted in violin and box plots, about the effects of AI's confidence calibration states on the dependent variables: participants' Adoption Rate, Disuse Rate, Misuse Rate, Accuracy Increase, Trust towards AI's Confidence Score, Trust towards AI's Prediction Accuracy, and Trust towards AI's Overall Capability. The center line represents the median. The box limits represent upper and lower quartiles. The whiskers represent the 1.5x interquartile range. The points represent the outliers. The width of each violin corresponds to the frequency of observations at any given number on the y axis. The cut of kernel density estimation is set to 0. The  $p$ -values of the AI confidence calibration states' main effects from the one-way ANOVA are indicated below each figure, and the significance levels from post-hoc analyses are denoted within the figures (ns:  $p > 0.05$ , \*:  $p < 0.05$ , \*\*:  $p < 0.01$ , \*\*\*:  $p < 0.001$ ). F-values with degrees of freedom are also reported below the figure. Differences between groups from post-hoc analyses, excluding comparisons between EXP2-U and EXP2-O, are marked in the figure. Further information, such as the verification of homogeneity assumptions, analytical methods, and effect sizes, can be found in the supplementary materials.

the AI is overconfident. While it improves participants' trust calibration by reducing their trust towards AI confidence and overall capability, it concurrently lowers their trust towards AI's prediction accuracy. It not only fails to address the issue of disuse when the AI is unconfident, but also facilitates disuse in cases of AI overconfidence. Ultimately, it failed to enhance the outcomes of human-AI collaboration.



**Fig. 6** The diagrams above illustrates the results of mediation analysis (ns:  $p > 0.05$ , \*:  $p < 0.05$ , \*\*:  $p < 0.01$ , \*\*\*:  $p < 0.001$ ). Arrows indicate the paths of effect, while numbers represent the coefficients on each path. See more details in supplementary materials. (a) Mediation analysis on EXP1-W and EXP1-O about the effects of overconfident AI confidence on accuracy increase, mediated by adoption rate and misuse. (b) Mediation analysis on EXP1-U and EXP1-W about the effects of unconfident AI confidence on accuracy increase, mediated by adoption rate and disuse. (c) Mediation analysis on EXP2-W and EXP2-O about the effects of overconfident AI confidence on accuracy increase, mediated by adoption rate and disuse. (d) Mediation analysis on EXP2-U and EXP2-W about the effects of unconfident AI confidence on accuracy increase, mediated by adoption rate and disuse.

### 2.2.1 Trust Calibration Helps Human Perceive AI's Uncalibrated Confidence

According to the findings in Fig. 3 (b), our results in EXP2-U and EXP2-O reveals that most participants were able to perceive AI's overconfidence or unconfidence when provided with trust calibration support. In EXP2-U, 76.190% of participants correctly recognized the AI's unconfidence, which, according to the results of the  $\chi^2$  test, was significantly higher than in EXP1-U ( $\chi^2 = 20.202, p < 0.001$ ). In EXP2-O, 73.810% of participants correctly identified the overconfidence, significantly higher than in EXP1-O ( $\chi^2 = 20.261, p < 0.001$ ). In EXP2-W, the distribution of participants' perceptions of the AI's confidence calibration state showed no significant difference from EXP1-W ( $\chi^2 = 1,798, p = 0.407$ ).

### 2.2.2 Trust Calibration Reduces Humans' Trust towards Uncalibrated AI

Considering trust calibration support as a factor, the results of one-way ANOVA between EXP1-U and EXP2-U, as well as EXP1-O and EXP2-O, indicate that trust calibration support reduced participants' trust towards AI when AI expresses uncalibrated confidence. In EXP2-O, participants' trust towards the AI's confidence score ( $M_{EXP2-O} = 4.182, s.d._{EXP2-O} = 1.086, M_{EXP1-O} = 4.921, s.d._{EXP1-O} = 0.933, p = 0.001$ ), trust in the AI's predictions ( $M_{EXP2-O} = 4.420, s.d._{EXP2-O} = 0.857,$

$M_{EXP1-O} = 5.215$ ,  $s.d._{EXP1-O} = 0.721$ ,  $p < 0.001$ ), and trust towards the AI's overall capability ( $M_{EXP2-O} = 4.205$ ,  $s.d._{EXP2-O} = 1.218$ ,  $M_{EXP1-O} = 5.222$ ,  $s.d._{EXP1-O} = 0.816$ ,  $p < 0.001$ ) were all significantly lower than those of participants in EXP1-O. In EXP2-U, participants' trust towards the AI's confidence score ( $M_{EXP2-U} = 4.262$ ,  $s.d._{EXP2-U} = 1.110$ ,  $M_{EXP1-U} = 4.912$ ,  $s.d._{EXP1-U} = 0.800$ ,  $p = 0.003$ ), trust in the AI's predictions ( $M_{EXP2-U} = 4.421$ ,  $s.d._{EXP2-U} = 0.996$ ,  $M_{EXP1-U} = 4.985$ ,  $s.d._{EXP1-U} = 0.691$ ,  $p = 0.004$ ), and trust towards the AI's overall capability ( $M_{EXP2-U} = 4.278$ ,  $s.d._{EXP2-U} = 1.043$ ,  $M_{EXP1-U} = 4.928$ ,  $s.d._{EXP1-U} = 0.802$ ,  $p = 0.002$ ) were all significantly lower than those of participants in EXP1-U.

Additionally, in EXP2-W, participants' trust towards the AI's confidence score ( $M_{EXP2-W} = 4.920$ ,  $s.d._{EXP2-W} = 0.911$ ,  $M_{EXP1-W} = 5.111$ ,  $s.d._{EXP1-W} = 0.895$ ,  $p = 0.336$ ), trust towards the AI's predictions ( $M_{EXP2-W} = 5.008$ ,  $s.d._{EXP2-W} = 0.681$ ,  $M_{EXP1-W} = 5.166$ ,  $s.d._{EXP1-W} = 0.804$ ,  $p = 0.334$ ), and trust towards the AI's overall capability ( $M_{EXP2-W} = 4.913$ ,  $s.d._{EXP2-W} = 0.887$ ,  $M_{EXP1-W} = 5.190$ ,  $s.d._{EXP1-W} = 1.087$ ,  $p = 0.203$ ) showed no significant difference from those of participants in EXP1-W.

### 2.2.3 Trust Calibration Support Does Not Improve Human-AI Collaboration Outcomes

Our results indicate that trust calibration support does not enhance the outcomes of human-AI collaboration. According to the results from one-way ANOVA, in EXP2-O, the misuse rate ( $M = 31.560\%$ ,  $s.d. = 19.112\%$ ,  $p = 0.006$ ) and adoption rate ( $M = 46.137\%$ ,  $s.d. = 21.185\%$ ,  $p < 0.001$ ) significantly decreased compared to EXP1-O, yet the disuse rate in EXP2-O ( $M_{EXP2-O} = 80.385\%$ ,  $s.d._{EXP2-O} = 10.787\%$ ,  $M_{EXP1-O} = 73.243\%$ ,  $s.d._{EXP1-O} = 10.723\%$ ,  $p = 0.003$ ) was significantly higher than in EXP1-O. The accuracy increase in EXP2-O ( $M = 8.015\%$ ,  $s.d. = 7.326\%$ ,  $p = 0.623$ ) showed no significant difference from EXP1-O. In EXP2-U, the misuse rate ( $M_{EXP2-U} = 32.067\%$ ,  $s.d._{EXP2-U} = 20.598\%$ ,  $M_{EXP1-U} = 29.632\%$ ,  $s.d._{EXP1-U} = 20.953\%$ ,  $p = 0.593$ ), disuse rate ( $M = 80.272\%$ ,  $s.d. = 11.355\%$ ,  $p = 0.218$ ), adoption rate ( $M = 44.859\%$ ,  $s.d. = 21.896\%$ ,  $p = 0.394$ ), and accuracy increase ( $M = 6.984\%$ ,  $s.d. = 7.715\%$ ,  $p = 0.780$ ) all showed no significant differences from EXP1-U. For EXP2-W, the misuse rate ( $M = 29.064\%$ ,  $s.d. = 14.806\%$ ,  $p = 0.786$ ), disuse rate ( $M = 72.676\%$ ,  $s.d. = 10.254\%$ ,  $p = 0.882$ ), adoption rate ( $M = 58.818\%$ ,  $s.d. = 17.967\%$ ,  $p = 0.674$ ), and accuracy increase ( $M = 12.540\%$ ,  $s.d. = 7.990\%$ ,  $p = 0.716$ ) all showed no significant differences from EXP1-W.

## 2.3 Overconfident and Unconfident AI Still Hinder Human-AI Collaboration with Trust Calibration Support

Quantitative results in EXP2 indicate that, while AI's overconfidence and unconfidence could be perceived by the majority of participants with the help of trust calibration support, they still struggled to adequately calibrate their trust towards AI. Uncalibrated AI confidence increased participants' distrust towards AI prediction accuracy.

Moreover, uncalibrated AI caused significant higher disuse, through which it hinder human-AI collaboration outcomes.

### 2.3.1 With Trust Calibration Support, Uncalibrated AI Lead to Distrust

Regarding trust towards AI, as depicted in Fig. 5 (e)-(g), our findings indicate that participants in EXP2-U and EXP2-O decreased their trust towards the AI's confidence scores and overall capabilities when the AI exhibited either overconfidence or unconfidence. As the main effects of AI confidence calibration states in one-way ANOVA of EXP2 are significant, according to post-hoc analysis results, participants in EXP2-O had significantly lower trust towards AI's confidence score ( $p = 0.004$ ) compared to those in EXP2-W. Similarly, participants in EXP2-U also showed significantly lower trust towards AI's confidence score ( $p = 0.012$ ) than those in EXP2-W. Additionally, trust towards the overall capability of AI for participants in EXP2-O ( $p = 0.009$ ) was significantly lower compared to those in EXP2-W, and the same trend was observed in EXP2-U ( $p = 0.010$ ) compared to EXP2-W. These results were expected since the AI in EXP2-U and EXP2-O presented uncalibrated confidence scores.

However, as trust in AI's confidence waned, trust towards AI's predictions accuracy also declined. Notably, the accuracy of AI's predictions remained unchanged, yet participants developed distrust in AI's ability to make accurate forecasts. Trust towards AI's predictions of participants in EXP2-O ( $p = 0.002$ ) and EXP2-U ( $p = 0.007$ ) were both significantly lower than those in EXP2-W. The results of the linear regression analysis (details in supplementary material) revealed a positive linear correlation between participants' trust towards AI's predictions and their trust towards AI's confidence ( $R = 0.649$ ,  $p < 0.001$ ).

### 2.3.2 With Trust Calibration Support, Uncalibrated AI Lead to Disuse

Regardless of collaborating with overconfident or unconfident AI, with trust calibration support, participants exhibited a significant increase in disuse rate, and a significant decrease in both adoption rate and final accuracy increase. As Fig.5 (a)-(d) show, participants in EXP2-O exhibited a significantly higher disuse rate ( $p = 0.004$ ) as did those in EXP2-U ( $p = 0.005$ ), compared to those in EXP2-W. The adoption rate for participants in EXP2-O ( $p = 0.014$ ) and EXP2-U ( $p = 0.006$ ) was significantly lower than for those in EXP2-W. In terms of Human-AI collaboration outcomes, the increase in accuracy in EXP2-O ( $p = 0.021$ ) and EXP2-U ( $p = 0.003$ ) was significantly lower than EXP2-W's. There was no significant difference in misuse rate among the three treatments.

Linear regression results (details in supplementary material) revealed a connection between participants' distrust towards AI's predictions and their disuse behaviors: the disuse rate increased as trust towards AI's predictions decreased ( $R = 0.345$ ,  $p < 0.001$ ). Although the  $R$  values for these linear regressions are low due to variation in the data, the probability of rejecting the null hypothesis is below 0.05, indicating a significant trend.

### 2.3.3 Disuse Further Worsen Human-AI Collaboration Outcomes

The results of the mediation analysis in EXP2 were shown in Fig. 6 (c) and (d) : Using data from EXP2-W and EXP2-O, we found that disuse rate ( $\beta_i = -6.969, p < 0.001$ ) and adoption rate ( $\beta_i = 3.041, p = 0.005$ ) fully mediated the effect of AI overconfidence on accuracy increase ( $\beta_d = -0.596, p = 0.459$ ). With data from EXP2-U and EXP2-W, disuse rate ( $\beta_i = -6.218, p = 0.002$ ) and adoption rate ( $\beta_i = 2.383, p = 0.008$ ) fully mediated the effect of AI unconfidence on accuracy increase ( $\beta_d = -1.721, p = 0.082$ ).

## 3 Discussion

This study unveils the detrimental impacts of uncalibrated AI confidence on human-AI collaboration and the mixed effect of AI transparency. Our findings indicate that under conditions of insufficient transparency, individuals struggle to accurately identify AI overconfidence and unconfidence, assuming AI possesses accurate confidence. In this case, they were unable to calibrate their trust towards AI, exhibiting an overtrust on the AI's confidence scores. Uncalibrated AI confidence then misleads individuals and impairs their ability to make informed decisions when heeding AI advice. Overconfident AI misleads individuals into accepting AI advice when AI is wrong, significantly increasing misuse and thus diminishing collaboration outcomes. Conversely, unconfident AI, by displaying confidence levels lower than its actual correctness likelihood, may lead individuals to disregard AI advice when AI is correct, significantly increasing disuse and ultimately worsen collaboration outcomes. Unlike previous studies that solely focused on the effects of different AI confidence levels [24], this research delves deeper into the influence of the calibration states of AI's confidence scores on trust calibration and human-AI collaboration. Prior research has indicated that high AI confidence scores can enhance individuals' belief in the correctness of AI suggestions [24]. This study corroborates similar findings and further elucidates the negative impacts of uncalibrated AI confidence scores on human behavior and collaborative outcomes.

Providing additional trust calibration support aids individuals in accurately identifying AI's overconfidence and unconfidence, and effectively reduces misuse behaviors when collaborating with overconfident AI. However, this leads to a loss of trust in the AI's expressed confidence scores, overall capability, and accuracy of predictions. Distrust in AI's confidence is reasonable, as the AI indeed presents confidence scores that do not align with reality. The distrust in the predictions, however, is concerning, given that the accuracy of AI predictions does not vary across different treatment setups. This align with research suggesting more transparency may reduce individuals' trust [34, 36]. The finding could be explained by prior studies showing that people tend to apply the same social rules and expectations to interactions with computers as they do with humans [37, 38, 39]. According to social cognitive theory, overconfidence in collaborative settings can be perceived as arrogance, while lack of confidence may be seen as a lack of skill or motivation [40], both of which can erode trust.

Our findings further uncover a nuanced impact of trust calibration support on collaboration. Increased transparency, when AI exhibits overconfidence, successfully reduces individuals' misuse, but leads to greater disuse. In both overconfident and unconfident cases, it does not improve the collaboration outcomes, contrary to our

expectation. Overall, our results show that both overconfident and unconfident AI invariably hinder the outcomes of human-AI collaboration, with individuals' misuse and disuse fully mediating the impact of AI's uncalibrated confidence on outcomes.

We believe that the fundamental and effective solution to the aforementioned issues is to provide calibrated confidence scores that can accurately estimate the correctness likelihood, necessitating further development in AI model calibration techniques. This continues to require persistent efforts and investments in the field of trustworthiness, especially for the calibration of currently prevalent and widely used LLMs [22]. We also advocate for actions to be taken from policy and regulatory perspectives to advance the calibration of AI.

However, we must confront the reality that, at least for the present, we continue to collaborate with numerous uncalibrated AIs in various scenarios. In such cases, we propose that, firstly, individuals need to know whether AI confidence is calibrated, recognizing the potential inaccuracies in AI confidence rather than assuming AI possesses well-calibrated confidence scores. Being explicitly aware of AI's potential shortcomings, or its error boundaries, may reduce trust but is essential for complementary human-AI collaboration. Therefore, we argue that trust calibration support, which aids users in perceiving whether AI is calibrated, is necessary. Only then can individuals calibrate their trust towards AI and estimate a true correctness likelihood based on the provided AI confidence scores instead of blindly trusting AI. Indeed, in such scenarios, not displaying AI confidence might be one approach, but this not only forfeits the benefits of presenting uncertainty [19] but also loses the potential to enhance collaboration outcomes through altering human subjective perceptions.

However, merely enhancing transparency as a form of trust calibration support is insufficient. Once individuals have a correct understanding of uncalibrated AI confidence, it is necessary to further restore trust in AI predictions. This depends on enhancing human understanding of AI confidence, clarifying the distinction and connection between AI confidence and its predictive capabilities, and minimizing the impact of distrust in AI confidence on the trust in other AI capabilities, which could be achieved through quantifying and visualization methods [24, 41]. Importantly, not only users but also researchers need to deepen their understanding of AI confidence. We advocate for future research to increasingly view confidence as an aspect of AI's self-evaluation capabilities, considering humans' trust attitudes towards it separately, rather than merely as a means to express uncertainty and increase transparency. This will contribute to a better understanding and development of more efficient human-AI collaboration.

Our research also emphasizes the urgent issue of the potential risks of uncalibrated AI confidence on human-AI collaboration. In today's era of prevalent LLMs, this raises a consideration: Should uncalibrated AI models be allowed to express their confidence unregulated, given the known potential risks? Who should bear the responsibility for the various risks that arise from this? These questions call for further deliberation among practitioners, regulators, and policymakers. Furthermore, this also raises concerns about the potential manipulation of AI confidence to influence user behavior. While such manipulation may have good intentions, such as improving the outcomes

of human-AI collaboration by adjusting AI confidence to align with human expectations [42, 43], the risks associated with this manipulation should not be ignored. For example, in situations involving high-stakes decisions or vested interests, adjusting AI confidence based on user trust could manipulate users into making choices that are detrimental to themselves. Should the manipulation of AI confidence be prohibited, with strict alignment between confidence and accuracy? Or should well-intentioned manipulation of AI confidence be allowed, encouraging developers to calibrate AI confidence in order to optimize human-AI collaboration outcomes [43]? This paper calls for extensive discussion on this matter and the establishment of a standardized industry norm. Regardless of the future answer to this question, our study’s findings indicate that malicious manipulation of AI confidence could lead to significant risks and harm.

### 3.1 Limitations

There are several limitations of our work. Beyond the most basic probabilistic expression of AI confidence, there are other forms of representing AI confidence, such as categorizing AI confidence from high to low in discrete classes, and the verbalization methods commonly used in LLM research [22]. It would be valuable to explore whether the impact of AI uncalibrated confidence and individuals’ perception of AI confidence quality differ under these various representations compared to the probabilistic form. Additionally, the generalizability of this study is limited to the category of generic AI-assisted decision-making scenarios represented by city recognition. In high-risk scenarios such as in healthcare and military applications, people’s decision-making may lean towards conservatism based on Loss Aversion and Prospect Theory [44, 45]. In such contexts, individuals may exhibit behaviors different from those observed in our experiments. AI uncalibrated confidence might pose greater risks, and its specific impacts warrant further investigation.

## 4 Method

To understand the potential impact of overconfident and unconfident AI on individuals’ trust calibration and human-AI collaboration, we designed and conducted an online randomized behavioral experiment, EXP1. To investigate the effect of trust calibration support in mitigating the harms brought by overconfident and unconfident AI, we further carried out another online randomized behavioral experiment, EXP2. The design and procedure of EXP1 and EXP2 are fundamentally the same, with differences only in Trust Calibration Phase, which will be detailed subsequently. Participants were recruited from Prolific for both experiments.

### 4.1 Task Description

For both EXP1 and EXP2, the human-AI collaborative task was city photo recognition task. This task entailed classifying images from three U.S. cities: New York, Chicago, and San Francisco, which captured the architectural, cultural, or geographical features of each city. All images were derived from publicly available datasets [46] and online resources, and underwent preprocessing to ensure consistency in quality and format.

On the image dataset of this experiment, the average accuracy of participants without AI assistance was 65.1%. For each task, participants initially assessed the city photos independently, forming a preliminary decision about their origin. The AI collaborator then provided its decision along with their confidence about the decision. The AI's confidence was visually represented by a percentage figure, supplemented by a color gradient bar with a pointer. The position of the pointer on the gradient conveyed the confidence, with positions further to the right denoting higher confidence. After receiving this information, participants made their final decision on the origin of the image.

## 4.2 Human-AI Collaboration System Implication

To support the experiment, an online experimental system was implemented using the *JavaScript* framework *Vue.js*, with the web interface shown in Fig. 1 (b). The system embedded pre-programmed rules to assist users in the city photo recognition tasks, with decisions and confidence scores for each task predefined. Participants were announced that they would collaborate with an AI assistant during the tasks. For each task, the system displayed the evaluated image and the associated choices to the participants, and after a preliminary decision was made by the participants, it further presented the AI's recommended decision and confidence score. The system was capable of capturing participants' preliminary and final decisions, with backend storage managed using *MySQL*.

## 4.3 Experiment Procedure

As shown in Fig. 1 (a), the experiment procedure was organized into four sequential phases: Introduction Phase, Trust Calibration Phase, Survey Phase, and Collaboration Task Phase. For both EXP1 and EXP2, the procedures were similar and the only difference was in Trust Calibration Phase.

### 4.3.1 Introduction Phase

Participants were initially presented with the terms of the informed consent document. After agreeing to the study terms, participants entered a pre-task survey designed to gather demographic information and control variables. Additionally, at this stage, participants were instructed to review the introduction to task details and guidance on system usage.

### 4.3.2 Trust Calibration Phase

Following the Introduction Phase, all participants underwent Trust Calibration Phase, which acted as a trust calibration stage. This phase involved 10 city recognition tasks. For participants in EXP1, they completed the 10 tasks in the sequence outlined in 4.1 with the assistance of AI, without receiving any feedback. At this point, participants calibrated their trust in AI based on the consistency between AI and their own decisions. For participants in EXP2, they received trust calibration support in this phase, including statement about the AI's confidence calibration state (i.e., whether the AI

was unconfident, well-calibrated or overconfident), correctness feedback for each task and overall accuracy feedback after completing all tasks. Participants could use such additional information to further calibrate their trust.

#### 4.3.3 Survey Phase

After the Trust Calibration Phase, participants were required to complete a survey aimed at capturing their trust in the AI collaborator and their perception of AI's confidence calibration states. Participants were to report their perception of the AI collaborator's confidence calibration state, that is, whether they perceived their AI collaborator as unconfident, well-calibrated, or overconfident. Additionally, they were also asked to report their trust towards the AI's prediction accuracy, their trust towards the AI's expressed confidence scores, and their trust towards the AI's overall capabilities.

#### 4.3.4 Collaboration Task Phase

The last phase was designed to observe the participants' behavior and the outcomes of human-AI collaboration. Participants were tasked with completing 30 city photo recognition tasks. This phase did not provide any correctness feedback for both EXP1 and EXP2, as it aimed to simulate real-world human-AI collaborative recognition tasks where immediate feedback from ground truth is not available. The adoption rates, misuse rates, disuse rates, and accuracy increase of the participants were computed after this phase.

### 4.4 AI Confidence Calibration States

In both EXP1 and EXP2, there are three different AI's confidence calibration states: unconfident (EXP1-U and EXP2-U), well-calibrated (EXP1-W and EXP2-W), and overconfident (EXP1-O and EXP2-O). The definitions of different AI's confidence calibration states depend on the relationship between the AI's confidence level and its true correctness likelihood: an AI is considered *unconfident* when its average confidence score is lower than its average true correctness likelihood; it is considered *well-calibrated* when its average confidence score equals the average true correctness likelihood; and it is considered *overconfident* when its average confidence score exceeds the average true correctness likelihood.

Given that this experiment utilized pre-programmed tasks, where each task was unequivocally right or wrong with predetermined correctness, and not probabilistically correct, the experiment adopted AI's accuracy as an approximation of the AI's average true correctness likelihood. The accuracy of AI across all groups in EXP1 and EXP2 was maintained at 70% during both the Trust Calibration Phase and Collaboration Task Phase. In both phases, the average confidence score of the unconfident AI is 60%, 10% below the approximation of average true correctness likelihood for both phases; the well-calibrated AI's average confidence score is 70%, aligning with the approximation of average true correctness likelihood; and the overconfident AI's average confidence score is 80%, 10% above the approximation of average true correctness likelihood. For each specific task, the confidence score is set to fluctuate within  $\pm 15\%$

of the AI's average score, and our setup guarantees that the AI's average confidence score across all tasks in each phase equals the predetermined average.

#### 4.5 Trust Calibration Support

In EXP2, to investigate whether the enhancement of transparency mitigates uncalibrated AI confidence's influences, experiments were conducted in conditions with trust calibration support. Participants in EXP2 were provided with statements about the AI's confidence calibration state during the Trust Calibration Phase, along with AI's overall accuracy feedback and task-specific correctness feedback. These interventions aimed to aid participants in calibrating their trust in the AI collaborator and their perception of its confidence calibration state.

Specifically, for participants in the trust calibration support treatments, they were presented with statements regarding the AI's confidence calibration state prior to initiating the tasks in the Trust Calibration Phase:

- For participants collaborating with an unconfident AI, they received the information: *"The AI you will collaborate with is unconfident. When the AI's confidence level is lower than the accuracy of its predictions, we term it 'unconfident.' For instance, the AI might assert a 70% confidence in its predictions, yet in reality, it achieves accuracy 90% of the time."*
- For participants working with a well-calibrated AI, they were informed: *"The AI you will collaborate with is well-calibrated. When the AI's confidence level aligns closely with the accuracy of its predictions, we describe it as 'well-calibrated.' For example, the AI might show an 80% confidence in its predictions, and it indeed reflects an 80% accuracy rate."*
- For those engaging with an overconfident AI, the message was: *"The AI you will collaborate with is overconfident. When the AI's confidence level exceeds the accuracy of its predictions, we label this 'overconfident.' This implies that the AI frequently exhibits high certainty in its outputs, yet these are not as dependable or accurate as the AI's confidence might suggest. For instance, the AI could claim a 90% confidence in its predictions, but in reality, it is correct merely 70% of the time."*

To ensure that participants absorbed and comprehended the statement, they were obliged to spend a minimum of 10 seconds on this information page and affirm their understanding by ticking a checkbox. Then, after each task, participants immediately received feedback on the correction of their final decision for that task. After completing all the tasks in the Trust Calibration Phase, they also received feedback on the accuracy of AI and their final decisions.

#### 4.6 Measurements

EXP1 and EXP2 assessed control variables that could influence human-AI collaboration tasks and participant behaviors using scales, and evaluated the dependent variables of interest through both scales and behavioral measures, as specified below:

#### 4.6.1 Control Variables

Control variables comprise participants' familiarity with the cities in the photo localization tasks, their general attitudes towards AI, and their self-assessed level of confidence, which could influence their willingness to adopt AI suggestions and the task accuracy [47, 48].

- *City Familiarity* was gauged using three Likert-scale questions, with a range from 1 (completely unfamiliar) to 5 (very familiar), to evaluate participants' familiarity with the cities of New York, Chicago, and San Francisco, respectively.
- *General Attitudes towards AI* was measured through a 5-point Likert scale, derived from General Attitudes towards Artificial Intelligence Scale [48].
- *General Self-confidence* was assessed through a 5-point Likert scale, derived from prior studies [49], which reflects the overall self-confidence level of the participants.

#### 4.6.2 Dependent Variables Measured by Survey

In human-AI collaboration process, human *trust* is defined as *the attitude that an AI will help humans complete the task appropriately in collaboration*, which directly influences whether people depend on AI [16]. This study assessed participants' perception of AI confidence calibration states and their trust towards AI's prediction accuracy, AI's confidence score, and AI's overall capability, utilizing scales in Survey Phase.

- *Perception of AI Confidence Calibration States* collected participants' self-reported perception about the confidence calibration state of the AI they collaborated with, measured by a one-choice question with choices including *unconfident*, *well-calibrated*, and *overconfident*.
- *Trust towards AI Prediction Accuracy* captured the extent of participants' trust in the correctness of AI's predictions during the collaboration, measured on a 7-point Likert scale derived from previous studies [50, 51, 52].
- *Trust towards AI Confidence Score* focused on the degree to which participants are willing to trust the confidence scores provided by AI during the collaboration, measured through a 7-point Likert scale derived from previous studies [50, 51, 52].
- *Trust towards AI Overall Capability* evaluated the level of trust participants have in the overall performance of AI during the collaboration, using a 7-point Likert scale derived from previous studies [53].

#### 4.6.3 Dependent Variables from Behavioral Measurements

In addition to the previous measurements of perception and trust, the Collaboration Task Phase introduced behavioral measurements to assess the influences of AI's overconfidence and unconfidence on individuals' adoption behaviors and collaboration outcomes.

- *Adoption Rate* is defined as the percentage of tasks when a participant switched its final decision to AI decision in Collaboration Task Phase [19]. It represents a behavioral manifestation of the participant's trust in the AI.

- *Misuse Rate* is defined as the percentage of tasks when a participant switched its final decision to AI incorrect decision in Collaboration Task Phase. It represents the extent to which the participants are misusing AI.
- *Disuse Rate* is defined as the percentage of tasks when a participant did not switch its final decision to AI's correct prediction in Collaboration Task Phase. It represents the level of disuse of AI by the participants.
- *Accuracy Increase* is the difference between the accuracy of the participants' final decision after combining the AI recommendations and the accuracy of the participants' decision before seeing the AI recommendations in Collaboration Task Phase. It represents the outcome improvements brought about by human-AI collaboration.

## 4.7 Participants

Participants were recruited from the Prolific platform to partake in our experiments anticipated to last 25 minutes, for which they would receive financial compensation. We ensured a balance between male and female participants and pre-screened them to confirm their proficiency in English as their first language. To ensure the validity of the results, participants who erred on multiple attention check questions were excluded. Following exclusions, we had a total of 252 participants, with 126 in each experiment. The sample size was predetermined prior to the experiment. Demographic information on gender, age, and education level is available in the supplementary materials.

## 4.8 Approvals

This research was reviewed and approved by the NUS School of Computing Departmental Ethics Review Committee, protocol number SOC-23-27.

## 4.9 Analysis

In statistical analysis strategy, statistical tests, including ANOVA for scale measurements and  $\chi^2$  test for categorical measurements, were employed to capture the difference between treatments. For ANOVA's assumption check, given that each group in our study consisted of 42 participants, our sample size was sufficiently large ( $> 30$ ) for the normality assumption [54]. To examine the homogeneity of the variances, we used Levene's test in different confidence calibration state groups for each dependent variable [55]. When the assumption of equal variances was satisfied ( $p\text{-value} > 0.05$ ), we proceeded with a standard ANOVA [56] followed by Tukey's Honest Significant Difference (HSD) test [57] for post hoc comparisons. If the homogeneity assumption was not met, Welch's ANOVA was used [58], coupled with the Games-Howell [59] post hoc test.

Our analysis strategy also includes linear regression (LR), which models the relationship between a dependent variable and independent variables. It calculates regression coefficients to understand the direction and magnitude of these relationships. The significance of these coefficients, assessed through  $p$ -values, determines the reliability of the observed relationships. The  $p$ -values are calculated based on the t-statistic, which emerges from the regression coefficient divided by the standard error

of this coefficient. Furthermore, we employed mediation analysis to uncover potential mediating effects. Mediation analysis, conducted using the principles of Structural Equation Modeling (SEM) [60], allows for the assessment of not only the direct effects of an independent variable on a dependent variable but also the indirect effects that operate through one or more mediators.

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## Appendix A Supplementary Information

### A.1 Survey Items

#### A.1.1 City Familiarity

Participants were asked their familiarity with the cities of New York, Chicago, and San Francisco. The following items were on a Likert scale from 1 (Not familiar at all) to 5 (Extremely familiar).

1. *Please indicate your familiarity with New York.*
2. *Please indicate your familiarity with Chicago.*
3. *Please indicate your familiarity with San Francisco.*

#### A.1.2 General Attitudes towards AI

The survey probed participants' general attitudes towards AI. Questions were derived from the General Attitudes towards Artificial Intelligence Scale (GAAIS), as developed by Schepman and Rodway [48]. The following items were on a Likert scale from 1 (Strongly disagree) to 5 (strongly agree).

1. I am interested in using AI systems in my daily life.
2. AI systems can perform better than humans.
3. AI systems can help me make a better decision.
4. AI systems can be basically honest.
5. AI systems can be trustworthy.

#### A.1.3 General Self-confidence

Participants' general self-confidence was measured by a 5-point Likert scale including the following items, ranging from 1 (Strongly disagree) to 5 (strongly agree). The questions were partly derived from the General Self-Efficacy Scale, as established by Schwarzer and Jerusalem [49].

1. *If I am in trouble, I can usually think of a solution.*
2. *I can usually handle whatever comes my way.*
3. *I can solve most problems if I invest the necessary effort.*
4. *Thanks to my resourcefulness, I know how to handle unforeseen situations.*
5. *It is easy for me to stick to my aims and accomplish my goals.*

#### A.1.4 Perception of AI Confidence Calibration State

Participants were asked to report their perception of the AI's confidence calibration state in previous tasks, choosing between *Unconfident*, *Well-calibrated*, or *Overconfident*. When answering questions, participants first received descriptions of three AI confidence types:

- *When the AI's confidence level is lower than the accuracy of its predictions, we term it 'unconfident.' For instance, the AI might assert a 70% confidence in its predictions, yet in reality, it achieves accuracy 90% of the time.*

- When the AI's confidence level aligns closely with the accuracy of its predictions, we describe it as 'well-calibrated.' For example, the AI might profess an 80% confidence in its predictions, and it indeed reflects an 80% accuracy rate.
- When the AI's confidence level exceeds the accuracy of its predictions, we label this 'overconfident.' This implies that the AI frequently exhibits high certainty in its outputs, yet these are not as dependable or accurate as the AI's confidence might suggest. For instance, the AI could claim a 90% confidence in its predictions, but in reality, it is correct merely 70% of the time.

Then, they were asked to assess the AI's confidence calibration state:

- Please assess the AI's confidence calibration state in the previous tasks.

#### A.1.5 Trust towards AI's Prediction Accuracy

Participants' trust towards AI's prediction accuracy was measured by a 7-point Likert scale ranging from 1 (Strongly disagree) to 7 (strongly agree). The scale questions are derived from previous studies [50, 51, 52]. Here are the questions:

1. I trust the AI's predictions.
2. I am comfortable adopting the AI's predictions.
3. I believe the AI uses appropriate methods to reach predictions.

#### A.1.6 Trust towards AI's Confidence Scores

Participants' trust towards AI's confidence scores was measured by a 7-point Likert scale ranging from 1 (Strongly disagree) to 7 (strongly agree). The scale questions are derived from previous studies [50, 51, 52]. Here are the questions:

1. I trust the AI's confidence scores in its predictions.
2. I am comfortable referring to the AI's confidence scores.
3. I believe the AI uses reasonable methods to evaluate confidence scores.

#### A.1.7 Trust towards AI's Overall Capability

Participants' trust towards AI overall capability was measured by a 7-point Likert scale ranging from 1 (Strongly disagree) to 7 (strongly agree). The scale questions are derived from a previous study [53]. Here are the questions:

1. I can trust the Al's overall capability.
2. I believe the Al is dependable.
3. I believe the Al is reliable.

## A.2 Statistical Results

	EXP1			EXP2		
	EXP1-U	EXP1-W	EXP1-O	EXP2-U	EXP2-W	EXP2-O
Gender						
Male	0.405	0.476	0.524	0.405	0.524	0.524
Female	0.595	0.524	0.476	0.595	0.476	0.476
Age						
21-24	0.262	0.238	0.238	0.262	0.214	0.167
25-34	0.429	0.476	0.357	0.357	0.452	0.405
35-44	0.214	0.262	0.167	0.167	0.310	0.286
45-54	0.095	0.024	0.167	0.119	0.024	0.095
55+	0	0	0.071	0.095	0	0.048
Education						
Less than high school	0	0.024	0	0.024	0	0
High school graduate	0.214	0.333	0.262	0.333	0.310	0.119
Bachelors Degree	0.619	0.452	0.571	0.405	0.571	0.476
Masters Degree	0.167	0.190	0.119	0.167	0.119	0.357
Doctorate	0	0	0.048	0.071	0	0.048

**Fig. A1** Demographics of the participants in different groups from EXP1 and EXP2. Values are proportions.

Experiment #	Control Variable	Statistical Test	Main Effect of AI Confidence Calibration States			Experiment Group	Mean	S.D.
			Effect Size ( $\eta^2$ )	F	p			
EXP1	City Familiarity	Basic One-Way ANOVA	0.004	0.227	0.797	EXP1-U	2.302	0.948
		Welch's ANOVA	0.005	0.227	0.797	EXP1-W	2.278	0.916
		Basic One-Way ANOVA	0.005	0.281	0.756	EXP1-O	2.175	0.887
	General Self-confidence	Basic One-Way ANOVA	1.687×10 <sup>-4</sup>	0.010	0.990	EXP1-U	4.062	0.533
		Basic One-Way ANOVA	0.016	0.984	0.377	EXP1-W	3.967	0.740
		Basic One-Way ANOVA	0.016	1.023	0.363	EXP1-O	4.029	0.418
	General Attitudes towards AI	Basic One-Way ANOVA				EXP1-U	3.510	0.614
		Basic One-Way ANOVA				EXP1-W	3.614	0.669
		Basic One-Way ANOVA				EXP1-O	3.557	0.641
EXP2	City Familiarity	Basic One-Way ANOVA				EXP2-U	2.206	0.747
		Basic One-Way ANOVA				EXP2-W	2.183	0.787
		Basic One-Way ANOVA				EXP2-O	2.198	0.779
	General Self-confidence	Basic One-Way ANOVA				EXP2-U	3.895	0.498
		Basic One-Way ANOVA				EXP2-W	3.981	0.528
		Basic One-Way ANOVA				EXP2-O	4.048	0.469
	General Attitudes towards AI	Basic One-Way ANOVA				EXP2-U	3.324	0.716
		Basic One-Way ANOVA				EXP2-W	3.505	0.637
		Basic One-Way ANOVA				EXP2-O	3.314	0.707

**Fig. A2** One-way ANOVA results for control variables in EXP1 and EXP2. The symbols used to denote significance levels are as follows: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), and \*\*\* ( $p < 0.001$ ).

Dependent Variable	Statistical Test	Main Effect of AI Confidence Calibration States					Experiment Group	Mean	S.D.			
		Effect Size ( $\eta^2$ )	df		F	p						
			Group	Residuals								
Trust towards AI Prediction Accuracy	Basic One-Way ANOVA	0.018	2	123	1.127	0.327	EXP1-U	4.985	0.691			
							EXP1-W	5.166	0.804			
							EXP1-O	5.215	0.721			
							EXP1-U	4.912	0.800			
Trust towards AI Confidence Score	Basic One-Way ANOVA	0.011	2	123	0.690	0.503	EXP1-W	5.111	0.895			
							EXP1-O	4.921	0.933			
Trust towards AI Overall Capability	Basic One-Way ANOVA	0.021	2	123	1.317	0.272	EXP1-U	4.928	0.802			
							EXP1-W	5.190	1.087			
							EXP1-O	5.222	0.816			
Adoption Rate	Basic One-Way ANOVA	0.230	2	123	18.354	<.001 ***	EXP1-U	40.492	24.752			
							EXP1-W	56.975	21.868			
							EXP1-O	69.587	19.246			
Misuse Rate	Welch's ANOVA	0.122	2	77.508	8.581	<.001 ***	EXP1-U	29.632	20.953			
							EXP1-W	28.207	14.002			
							EXP1-O	41.257	10.835			
Disuse Rate	Basic One-Way ANOVA	0.167	2	123	12.326	<.001 ***	EXP1-U	83.333	11.242			
							EXP1-W	73.016	10.657			
							EXP1-O	73.243	10.723			
Accuracy Increase	Basic One-Way ANOVA	0.089	2	123	6.001	0.003 **	EXP1-U	6.508	7.859			
							EXP1-W	11.905	7.967			
							EXP1-O	7.221	7.433			

**Fig. A3** One-way ANOVA results of EXP1 in Fig. 4 about the effects of AI confidence calibration states. The symbols used to denote significance levels are as follows: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), and \*\*\* ( $p < 0.001$ ).

Dependent Variable	Statistical Test	Main Effect of AI Confidence Calibration States						Experiment Group	Mean	S.D.
		Effect Size ( $\eta^2$ )		df		F	p			
		Group	Residuals							
Trust towards AI Prediction Accuracy	Welch's ANOVA	0.097	2	79.975	8.122	< .001 ***		EXP2-U	4.421	0.996
								EXP2-W	5.008	0.681
								EXP2-O	4.420	0.857
Trust towards AI Confidence Score	Basic One-Way ANOVA	0.094	2	123	6.388	0.002 **		EXP2-U	4.262	1.110
								EXP2-W	4.920	0.911
								EXP2-O	4.182	1.086
Trust towards AI Overall Capability	Welch's ANOVA	0.085	2	80.668	5.680	0.004 **		EXP2-U	4.278	1.043
								EXP2-W	4.913	0.887
								EXP2-O	4.205	1.218
Adoption Rate	Basic One-Way ANOVA	0.089	2	123	5.997	0.003 **		EXP2-U	44.859	21.896
								EXP2-W	58.818	17.967
								EXP2-O	46.137	21.185
Misuse Rate	Basic One-Way ANOVA	0.005	2	123	0.323	0.725		EXP2-U	32.067	20.598
								EXP2-W	29.064	14.806
								EXP2-O	31.560	19.112
Disuse Rate	Basic One-Way ANOVA	0.102	2	123	7.020	0.001 **		EXP2-U	80.272	11.355
								EXP2-W	72.676	10.254
								EXP2-O	80.385	10.787
Accuracy Increase	Basic One-Way ANOVA	0.092	2	123	6.217	0.003 **		EXP2-U	6.984	7.715
								EXP2-W	12.540	7.990
								EXP2-O	8.015	7.326

**Fig. A4** One-way ANOVA results of EXP2 in Fig. 5 about the effects of AI confidence calibration states. The symbols used to denote significance levels are as follows: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), and \*\*\* ( $p < 0.001$ ).

Dependent Variable	AI Confidence Calibration State	Statistical Test	Main Effect of Trust Calibration Support						Experiment Group	Mean	S.D.	
			Effect Size ( $\eta^2$ )		df		F	p				
				Group	Residuals							
Trust towards AI Prediction Accuracy	Unconfident	Welch's ANOVA	0.100	1	73.027	9.090	0.004 **		EXP1-U	4.985	0.691	
	Well-calibrated	Basic One-Way ANOVA	0.011	1	82	0.946	0.334		EXP2-U	4.421	0.996	
	Overconfident	Basic One-Way ANOVA	0.205	1	82	21.160	<.001 ***		EXP1-W	5.166	0.804	
Trust towards AI Confidence Score	Unconfident	Welch's ANOVA	0.104	1	74.521	9.479	0.003 **		EXP2-W	5.008	0.681	
	Well-calibrated	Basic One-Way ANOVA	0.011	1	82	0.937	0.336		EXP1-O	5.215	0.721	
	Overconfident	Basic One-Way ANOVA	0.120	1	82	11.192	0.001 **		EXP2-O	4.420	0.857	
Trust towards AI Overall Capability	Unconfident	Basic One-Way ANOVA	0.111	1	82	10.266	0.002 **		EXP1-U	4.912	0.800	
	Well-calibrated	Basic One-Way ANOVA	0.020	1	82	1.647	0.203		EXP2-U	4.262	1.110	
	Overconfident	Welch's ANOVA	0.198	1	71.605	20.189	<.001 ***		EXP1-W	5.111	0.895	
Adoption Rate	Unconfident	Basic One-Way ANOVA	0.009	1	82	0.733	0.394		EXP2-W	4.920	0.911	
	Well-calibrated	Basic One-Way ANOVA	0.002	1	82	0.178	0.674		EXP1-O	4.921	0.933	
	Overconfident	Basic One-Way ANOVA	0.256	1	82	28.192	<.001 ***		EXP2-O	4.182	1.086	
Misuse Rate	Unconfident	Basic One-Way ANOVA	0.004	1	82	0.288	0.593		EXP1-U	40.492	24.752	
	Well-calibrated	Basic One-Way ANOVA	9.055×10 <sup>-4</sup>	1	82	0.074	0.786		EXP2-U	44.859	21.896	
	Overconfident	Welch's ANOVA	0.091	1	64.890	8.182	0.006 *		EXP1-W	56.975	21.868	
Disuse Rate	Unconfident	Basic One-Way ANOVA	0.018	1	82	1.542	0.218		EXP2-W	58.818	17.967	
	Well-calibrated	Basic One-Way ANOVA	2.709×10 <sup>-4</sup>	1	82	0.022	0.882		EXP1-O	69.587	19.246	
	Overconfident	Basic One-Way ANOVA	0.101	1	82	9.262	0.003 **		EXP2-O	46.137	21.185	
Accuracy Increase	Unconfident	Basic One-Way ANOVA	9.557×10 <sup>-4</sup>	1	82	0.078	0.780		EXP1-U	29.632	20.953	
	Well-calibrated	Basic One-Way ANOVA	0.002	1	82	0.133	0.716		EXP2-U	32.067	20.598	
	Overconfident	Basic One-Way ANOVA	0.003	1	82	0.243	0.623		EXP1-W	28.207	14.002	
									EXP2-W	29.064	14.806	
									EXP1-O	41.257	10.835	
									EXP2-O	31.560	19.112	
									EXP1-U	83.333	11.242	
									EXP2-U	80.272	11.355	
									EXP1-W	73.016	10.657	
									EXP2-W	72.676	10.254	
									EXP1-O	73.243	10.723	
									EXP2-O	80.385	10.787	
									EXP1-U	6.508	7.859	
									EXP2-U	6.984	7.715	
									EXP1-W	11.905	7.967	
									EXP2-W	12.540	7.990	
									EXP1-O	7.221	7.433	
									EXP2-O	8.015	7.326	

**Fig. A5** One-way ANOVA results between EXP1 and EXP2 in Sec. 2.2.2 and Sec. 2.2.3 about the effects of trust calibration support. The symbols used to denote significance levels are as follows: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), and \*\*\* ( $p < 0.001$ ).

Dependent Variable	Statistical Test	Experiment Group	t	p	df
Trust towards AI Prediction Accuracy	Tukey Post Hoc Comparisons	EXP1-W	EXP1-U	1.124	0.501
		EXP1-O	EXP1-O	-0.301	0.951
		EXP1-O	EXP1-U	1.424	0.332
Trust towards AI Confidence Score	Tukey Post Hoc Comparisons	EXP1-W	EXP1-U	1.039	0.554
		EXP1-O	EXP1-O	0.994	0.582
		EXP1-O	EXP1-U	0.045	0.999
Trust towards AI Overall Capability	Tukey Post Hoc Comparisons	EXP1-W	EXP1-U	1.320	0.387
		EXP1-O	EXP1-O	-0.158	0.986
		EXP1-O	EXP1-U	1.478	0.305
Adoption Rate	Tukey Post Hoc Comparisons	EXP1-W	EXP1-U	3.422	0.002 **
		EXP1-O	EXP1-O	-2.619	0.027 *
		EXP1-O	EXP1-U	6.041	< .001 ***
Misuse Rate	Games-Howell Post Hoc Comparisons	EXP1-W	EXP1-U	-0.367	0.929
		EXP1-O	EXP1-O	-4.777	< .001 ***
		EXP1-O	EXP1-U	3.194	0.006 **
Disuse Rate	Tukey Post Hoc Comparisons	EXP1-W	EXP1-U	-4.347	< .001 ***
		EXP1-O	EXP1-O	-0.096	0.995
		EXP1-O	EXP1-U	-4.251	< .001 ***
Accuracy Increase	Tukey Post Hoc Comparisons	EXP1-W	EXP1-U	3.189	0.005 **
		EXP1-O	EXP1-O	2.767	0.018 *
		EXP1-O	EXP1-U	0.421	0.907

**Fig. A6** Post-hoc analysis results of EXP1 in Fig. 4 about the effects of AI confidence calibration states. The symbols used to denote significance levels are as follows: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), and \*\*\* ( $p < 0.001$ ).

Dependent Variable	Statistical Test	AI Confidence Type	t	p	df
Trust towards AI Prediction Accuracy	Games-Howell Post Hoc Comparisons	EXP2-W	EXP2-U	3.154	0.007 **
		EXP2-O	EXP2-O	3.482	0.002 **
		EXP2-O	EXP2-U	-0.004	1.000
Trust towards AI Confidence Score	Tukey Post Hoc Comparisons	EXP2-W	EXP2-U	2.903	0.012 *
		EXP2-O	EXP2-O	3.258	0.004 **
		EXP2-O	EXP2-U	-0.355	0.933
Trust towards AI Overall Capability	Games-Howell Post Hoc Comparisons	EXP2-W	EXP2-O	3.006	0.010 *
		EXP2-O	EXP2-U	3.041	0.009 **
		EXP2-O	EXP2-U	-0.292	0.954
Adoption Rate	Tukey Post Hoc Comparisons	EXP2-W	EXP2-U	3.132	0.006 **
		EXP2-O	EXP2-O	2.846	0.014 *
		EXP2-O	EXP2-U	0.287	0.956
Misuse Rate	Tukey Post Hoc Comparisons	EXP2-W	EXP2-U	-0.750	0.734
		EXP2-O	EXP2-O	-0.624	0.807
		EXP2-O	EXP2-U	-0.127	0.991
Disuse Rate	Tukey Post Hoc Comparisons	EXP2-W	EXP2-U	-3.221	0.005 **
		EXP2-O	EXP2-O	-3.269	0.004 **
		EXP2-O	EXP2-U	0.048	0.999
Accuracy Increase	Tukey Post Hoc Comparisons	EXP2-W	EXP2-U	3.315	0.003 **
		EXP2-O	EXP2-O	2.699	0.021 *
		EXP2-O	EXP2-U	0.615	0.812

**Fig. A7** Post-hoc analysis results of EXP2 in Fig. 5 about the effects of AI confidence calibration states. The symbols used to denote significance levels are as follows: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), and \*\*\* ( $p < 0.001$ ).

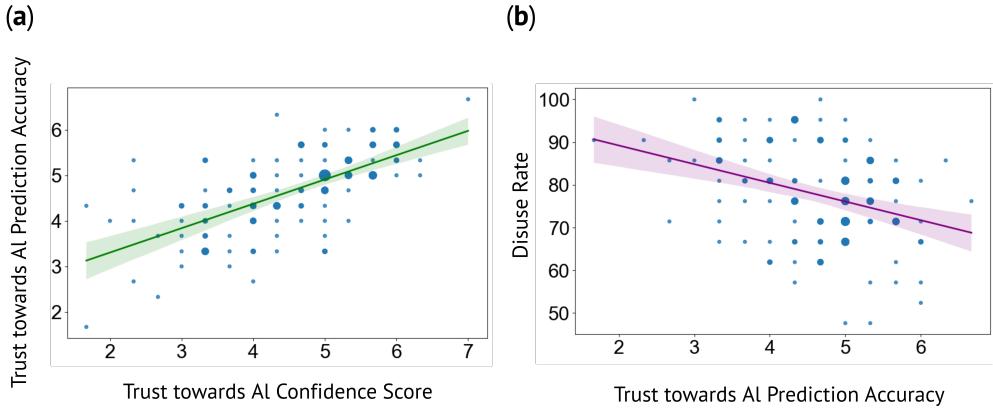
Scales	Statistical Test	Point estimate	95% CI lower bound	95% CI upper bound
General Attitudes towards AI	McDonald's $\omega$	0.778	0.735	0.821
General Self-confidence	McDonald's $\omega$	0.808	0.770	0.846
Trust towards AI Prediction Accuracy	McDonald's $\omega$	0.796	0.754	0.839
Trust towards AI Confidence Score	McDonald's $\omega$	0.862	0.833	0.892
Trust towards AI Overall Capability	McDonald's $\omega$	0.905	0.885	0.925

**Fig. A8** McDonald's  $\omega$  reliance of scales used in the study.

Experiment #	AI Confidence Calibration State	Effects Type	Path	Estimate	Std. Error	z-value	<i>p</i>	95% Confidence Interval	
								Lower	Upper
EXP1	Well-calibrated (EXP1-W) and Overconfident (EXP1-O)	Direct Effects	Overconfident AI $\rightarrow$ Accuracy Increase	-1.309	1.093	-1.197	0.231	-3.452	0.834
		Indirect Effects	Overconfident AI $\rightarrow$ Misuse $\rightarrow$ Accuracy Increase	-6.228	1.394	-4.467	<.001***	-8.961	-3.495
		Total Effects	Overconfident AI $\rightarrow$ Adoption Rate $\rightarrow$ Accuracy Increase	2.854	1.053	2.711	0.007**	0.790	4.917
	Well-calibrated (EXP1-W) and Unconfident (EXP1-U)	Direct Effects	Unconfident AI $\rightarrow$ Accuracy Increase	0.487	0.959	0.508	0.612	-1.393	2.368
		Indirect Effects	Unconfident AI $\rightarrow$ Disuse $\rightarrow$ Accuracy Increase	-9.081	2.176	-4.174	<.001***	-13.345	-4.816
		Total Effects	Unconfident AI $\rightarrow$ Adoption Rate $\rightarrow$ Accuracy Increase	3.196	1.089	2.935	0.003**	1.062	5.330
EXP2	Well-calibrated (EXP2-W) and Overconfident (EXP2-O)	Direct Effects	Overconfident AI $\rightarrow$ Accuracy Increase	-0.596	0.805	-0.741	0.459	-2.174	0.981
		Indirect Effects	Overconfident AI $\rightarrow$ Disuse $\rightarrow$ Accuracy Increase	-6.969	2.092	-3.331	<.001***	-11.070	-2.868
		Total Effects	Overconfident AI $\rightarrow$ Adoption Rate $\rightarrow$ Accuracy Increase	3.041	1.079	2.819	0.005**	0.926	5.155
	Well-calibrated (EXP2-W) and Unconfident (EXP2-U)	Direct Effects	Unconfident AI $\rightarrow$ Accuracy Increase	-4.525	1.653	-2.738	0.006**	-7.764	-1.286
		Indirect Effects	Unconfident AI $\rightarrow$ Disuse $\rightarrow$ Accuracy Increase	-1.721	0.991	-1.737	0.082	-3.664	0.221
		Total Effects	Unconfident AI $\rightarrow$ Adoption Rate $\rightarrow$ Accuracy Increase	-6.218	1.979	-3.141	0.002**	-10.098	-2.339

**Fig. A9** Mediation analysis results in Fig. 6 about the effects of uncalibrated AI confidence on accuracy increase, mediated by misuse/disuse rate and adoption rate. AI confidence type. The symbols used to denote significance levels are as follows: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), and \*\*\* ( $p < 0.001$ ).

Covariates	Dependent Variable	R	p	S.E.	Slope
Perception of AI Confidence	Trust towards AI Prediction Accuracy	0.649	< .001 ***	0.056	0.534
Trust towards AI Prediction Accuracy	Disuse Rate	0.345	< .001 ***	1.070	-4.373



**Fig. A10** Linear regression results of EXP2 in Sec. 2.3.1 and Sec. 2.3.2. The error bands represent a 95% confidence interval. The symbols used to denote significance levels are as follows: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), and \*\*\* ( $p < 0.001$ ).

AI Confidence Calibration State	X <sup>2</sup> Tests	Value	df	p
Unconfident (EXP1-U and EXP2-U)	X <sup>2</sup>	20.202	2	< .001 ***
	N	84	-	-
Well-calibrated (EXP1-W and EXP2-W)	X <sup>2</sup>	1.798	2	0.407
	N	84	-	-
Overconfident (EXP1-O and EXP2-O)	X <sup>2</sup>	20.261	2	< .001 ***
	N	84	-	-

**Fig. A11**  $\chi^2$  test results about participants' perception of AI confidence calibration state of EXP1-U&EXP2-U, EXP1-W&EXP2-W, and EXP1-O&EXP2-O in Sec. 2.2.1.