The Task Matters: The Effect of Perceived Similarity to AI on Intention to Use in Different Task Types

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Abstract

With the development of AI technologies, especially generative AI (GAI) like ChatGPT, GAI is increasingly assisting people in various tasks. However, people may have different requirements for GAI when using it for different kinds of tasks. For instance, when brainstorming new ideas, people may want GAI to propose different ideas that supplement theirs with different problem-solving perspectives, but for decision-making tasks, they may prefer GAI adopt a similar problem-solving process with people to make a similar or even the same decision as they would. We conducted an online experiment examining how perceived similarities between GAI and human task-solving influence people's intention to use GAI, mediated by trust, for four task types (creativity, planning, intellective, and decision-making tasks). We demonstrate that the effect of similarity on trust (and so intent to use AI) depends on the type of task. This paper contributes to understanding the impact of task types on the relationship between perceived similarity and GAI adoption, with implications for future use of GAI in various task contexts.

Keywords: AI, generative AI, perceived similarity, task types, trust, AI adoption

1. Introduction

Generative AI (more specifically, large language models) has gradually been introduced into people's daily lives with its ability to assist with different types of tasks. Take ChatGPT (the most widely used generative AI) as an example. It can help people reply to emails, perform text analysis and translation, code modification, and many other tasks. In the form of "hybrid intelligence" (Dellermann et al., 2019, p. 640), humans and AI collaborate as a team, combining their complementary capabilities to achieve "superior results to those each of them could have accomplished separately" (Dellermann et al., 2019, p. 640). Thus, human and AI teaming is regarded as an important format for the future of work (Seeber, 2020). However, people will ultimately decide whether they will work with AI teammates (use AI techniques) and how they arrange their AI teammates to assist with tasks in different business scenarios. Therefore, we argue that the relationship between people and AI in human-AI teaming resembles the relationship between managers and subordinates in human-human teams.

To analyze the relationship between people and AI in human-AI teaming, we draw on research on the relationship between managers and subordinates in human-human teams, because in human-AI teams, people can delegate work to the AI, which is akin to a supervisor delegating work to a subordinate. In supervisor-subordinate dyads within human-human teams, supervisors' perceived similarity of their subordinates has been demonstrated to affect their interaction, such as evaluations of subordinate performance (Senger, 1971), and higher frequency of communication (Hatfield & Huseman, 1982). Perceived similarity has also been shown to influences people's attitudes toward interacting with their AI subordinates (Bernier & Scassellati, 2010). For instance, a similar work style and personality will let people have a more positive attitude toward working with robots (You and Robert, 2018). Andrist et al. (2015) found that matching a user's and a robot's personality led to people giving higher subjective ratings to the robot's performance. These findings provide important implications for the design of AI's behaviors in assistive human-AI interaction, that is, how to design AI to enhance people's perceptions of similarity of themselves with AI (Andrist et al., 2015).

However, people may not want a GAI subordinate who is exactly like them in all cases. This is because people may have different requirements for GAI's answers when they use it to solve different types of tasks. For example, when brainstorming new ideas, people may want different answers from GAI to supplement their own responses. However, when handling decision-making tasks, people may prefer that GAI aligns with their perspectives or values, making decisions that resonate with them. Consequently, it is reasonable to assume that the different task types might

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influence the effect of perceived similarity on the intention to use GAI. Yet, existing research exploring the impact of human–AI similarity on GAI adoption has not incorporated the impacts of task types. Thus, in this research, we proposed the following research question to address:

RQ: How do different task types relate to the impact of perceived similarity on individuals' intentions to use GAI?

To answer our research question, we conducted an experimental study. 236 participants were randomly assigned to one of the four task types (creativity task, intellective task, planning task, and decision-making task) in a between-subjects experimental design. Participants first finish the task by themselves and then compare ChatGPT's (one popular GAI application) answers and problem-solving process for the same task. After the task with GAI, the participants were asked a series of questions regarding their attitudes toward the ChatGPT for the specific task type and their intention to use it. The paper is structured as follows. We introduce the research background in the next section. In section 3, we introduce our research model and propose our research hypothesis. Then, in section 4, we describe our research methods in detail. We then show the results in section 5. In section 6, we describe the key findings of our study. Then, we discuss the theoretical and practical implications in section 7. In section 8, we discuss our research limitations and future research. Finally, we conclude our research.

2. Research background

2.1 Task types and generative AI's capability

The term generative AI refers to "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data." (Feuerriegel et al., 2024, p.111) Currently, ChatGPT, Copilot, and Dall-E are all very popular GAI products that are changing people's way of handling different businesses.

We adopted McGrath's (1984) group task classification framework for this study to identify the task types that GAI can assist people to solve. McGrath's framework is one of the most frequently cited classifications of group task types, which aligns with the human collaboration context. This framework posits that group tasks can be categorized into four types: generate (creativity tasks and planning tasks), choose (intellective tasks and decision-making tasks), negotiate (cognitive conflict tasks and mixed-motive tasks), and execute (performances/psycho-motor tasks and contests/battles/competitive tasks). For this study, we excluded the execute tasks because of the online setting of our experiment. We also excluded negotiation tasks, since these involve multiple parties, and we were planning an individual experiment. We, therefore, study generating and choosing tasks, which can be supported with GAI.

2.2 Perceived similarity in human-AI collaboration

Similarity can be divided into surface-level and deep-level characteristics (see Harrison et al., 2002). Regarding surface-level similarity, the main focus has been on demographic characteristics, including age, gender, and race; while deep-level similarity focuses on values, attitudes, and personality (Harrison et al., 1998). In supervisor-subordinate dyads, similarity was shown to be a critical factor affecting organizational outcomes, like attitudes, relationships, and behavioral outcomes (Tepper et al., 2011). For example, the perceived similarity among teams is associated with job satisfaction (Turban & Joned, 1988) and relationships among group members (Liden et al., 1993). The similarity and attraction theory (SAT) helps explain the significant role of similarity in teams, as people tend to attract or be attracted to other people who they see as similar to them in ways they consider important (see Montoya & Horton, 2013).

Prior research has also found that people tend to prefer computers that exhibit characteristics similar to their own, such as similarity in action and thought, because the similarity makes the behavior of the computer more predictable, which in turn increases people's comfort (Berger & Calabrese 1974; Epley et al. 2007). In human-AI teams, similarity (including surface or deep-level) between humans and AI also has been shown to play a key role in influencing people's attitudes toward interacting with AI. For example, You and Robert (2018) found that surface-level similarity (male or female voice) does not increase trust in robots, but deep-level similarity (workstyle) can. Andrist et al. (2015) found that matching a user's and a robot's personality (introverted and extroverted) led to people's more positive evaluation of the robot. Alawi et al. (2023) found that similarity (gender and ethnicity) with AI agents (chatbots) influences individuals' IT identity and intention to continue working with it.

In our research, we examine GAI in a chatbot format. Additionally, we only focus on deep-level perceived similarity. Bakar and McCann, (2017) found that deep-level perceived similarity, especially at the functional/task level, facilitates leader-member communication agreement and performance evaluation in human-human teams. In this study, we let people and the GAI complete the same task separately and measure perceived deep-level similarity after comparing the answers and the problem-solving process (i.e., function/task level) between themselves and the GAI.

3. Research model and hypotheses development

To examine the impacts of deep-level perceived similarity on people's intention to use GAI under different task types (specifically: creativity tasks, planning tasks, intellective tasks, and decision-making tasks), we proposed our research model as seen in Figure 1 and the following hypotheses.

Prior research suggests that perceived similarity positively affects people's intention to use AI in terms of subjective willingness (e.g., Alawi et al., 2023; Andrist et al., 2015; You & Robert, 2018, You & Robert, 2024). However, the impact of task types on the effect of perceived similarity on the intention to adopt AI has not yet been explored. We hypothesized that the relationship between similarity and intention to use is mediated by trust. We develop this relationship in the following sections.

3.1 Perceived trust predicts intention to use

According to Mayer et al.'s (1995) description, trust refers to an individual's readiness to expose themselves to the actions of another party in a risky situation. Rousseau et al. (1998) pointed out that trust is commonly defined as an individual's confidence in the expected behavior of another individual, which involves elements of risk and vulnerability.

Within the domain of human-AI collaboration, trust is delineated as the confidence in the reliability and dependability of the services and reported outcomes delivered by an AI-enabled agent (Shin, 2021). Trust is widely regarded as a significant predictor of the adoption of new technologies (Sollner et al., 2016) and the perceived trust in AI is recognized as a significant predictor of the adoption of AI (Choung et al., 2023). Thus, we propose the following hypothesis:

H1: *Trust in the GAI positively predicts intention to use the GAI.*

3.2 Perceived similarity predicts trust, depending on task type

How to build trust in AI agents is an important research topic today (Nordheim et al., 2019). People who are perceived as being similar are frequently regarded as more trustworthy, whereas people who are not similar are regarded as less trustworthy (see Lauren et al., 2009). The impact of similarity can be found in the relationships between humans and technology agents. For instance, You and Robert (2018) found that human-robot similarity in work style promoted trust in a robot. They also found that gender dissimilarity had a stronger negative impact on swift trust in a robot co-worker (You & Robert, 2024). Research conducted by Emily et al. (2010) demonstrates that personality similarity fosters trust in robots. Therefore, individuals' perception of similarity with the AI agent will positively influence people's trust in the AI agent.

Furthermore, we argue that people will decide whether and the degree to trust AI based on the nature of the tasks performed, as tasks may have different requirements. In general, the nature of the task plays a significant role in a group's interaction process and performance (Poole et al., 1985). Consequently, we expect that people have varying requirements (i.e., expectations for AI) when utilizing AI to assist them with different types of tasks.

Specifically, creativity tasks require people to generate many different and related ideas (McGrath, 1984). Since the quantity of ideas is a vital evaluation criterion for creativity tasks, people may seek AI assistance to augment their solutions with a broader

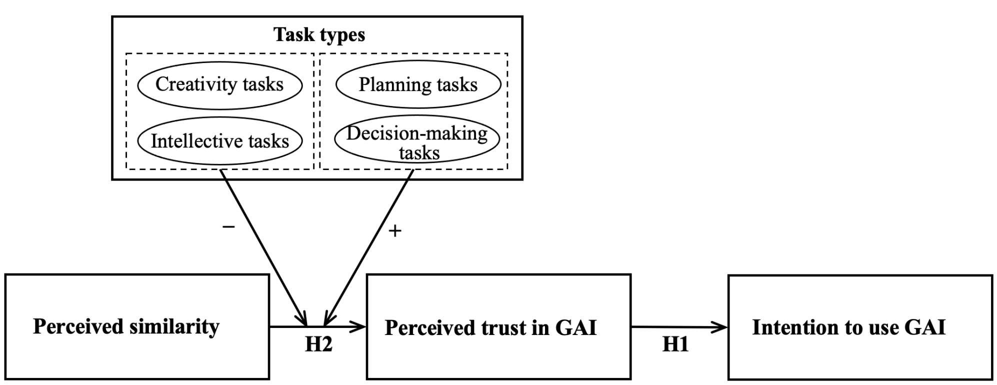


Figure 1. Proposed Research Model

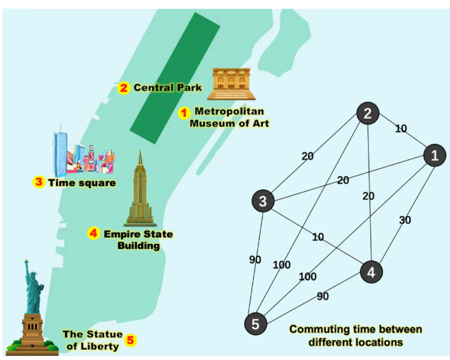
range of diverse answers. Consequently, we believe that dissimilarity between humans and AI, characterized by varied perspectives to solve problems, becomes an advantage when individuals consider utilizing AI for creativity tasks.

Regarding intellective tasks, people more pay attention to the final correct answer (McGrath, 1984). If individuals possess an incorrect answer, they are unlikely to be inclined towards AI providing a similarly incorrect answer, but rather, they seek the correct answer. Conversely, if individuals already possess the correct answer, they aim to verify its accuracy through AI rather than comparing it with AI's responses to determine similarities or differences. Consequently, we argue that people do not consider questions related to similarity when handling intellective tasks.

In contrast, when dealing with decision-making tasks, personal subjective preferences hold greater influence since there is no right or wrong decision (McGrath, 1984). For example, the differences in decision-making styles among decision-makers will influence their different decision-making behavior (Henderson & Nutt, 1980). To ensure that AI agents' behavior aligns with users' subjective preferences, people would prefer an AI agent that is more similar to them in terms of cognitive abilities, attitudes, and values to assist them in handling decision-making tasks. Thus, we argue that decision-making tasks significantly influence the effect of perceived similarity on people's intention to use AI. Similarly, for planning tasks, there is no correct or single answer, but rather multiple possibilities. Therefore, we posit that individuals will prioritize whether AI agents resemble themselves, as this similarity can ensure that the AI agents generate answers aligned with their preferences, i.e., they hold the same perceptions of the importance of the things (see Montoya & Horton, 2013). Accordingly, we propose the following hypothesis:

***H2:** Perceived similarity predicts trust for decision-making and planning tasks but not for creativity and intellective tasks*

Planning Task Scenario



Task: Now, please make a plan for a 1-day trip in New York City, you need to visit all of these five places. Please be specific about the timeline and what you will do within the determined time frame.

Question 1: In what order do you plan to visit the eight places across the one-day trip? When will you arrive at each and how long will you spend? Be sure to include travel and meal breaks in the plan.

Question 2: What steps did you take in performing this task? (i.e., your problem-solving process)

Decision-making Task Scenario

Task: Your boat is sinking! There is a desert island nearby. You can swim to there, but you can only take four items with you. There are 20 items in total, including lamp, sunscreen, toilet paper, pot, first aid kit, hiking boots, axe, flare gun, inflatable raft, lighter, insect repellent, hammock, compass, mirror, knife, water filter, fishing rod, rope, rifle, and tent. Now, name the four items and explain why you chose each one.

Question 1: Write the four items you choose and your reasons for choosing them here:

Question 2: What steps did you take in performing this task? (i.e., your problem-solving process)

Creativity Task Scenario

Task: Now, please list five unconventional and creative uses for a paperclip.

Instructions: Your answers should go beyond the traditional purpose of holding papers together. Consider how the shape, material, and properties of a paperclip can be utilized in unexpected and innovative ways. Be creative exploring the alternative uses of a paperclip!

Question 1: Please write down your five uses here:

Question 2: What steps did you take in performing this task? (i.e., your problem-solving process)

Intellective Task Scenario

2	3	1	4	0	5	X

Task: You need to handle a number series task. The order of the numbers is 2,3,1,4,0,5, X. Do you know what the X position number is?

Question 1: Please write down your answer here:

Question 2: What steps did you take in performing this task? (i.e., your problem-solving process)

Figure 2. Four experimental task scenarios

4. Research design

To test our hypotheses, we conducted a 4-way (four types of tasks: creativity task, intellective task, planning task, and decision-making task) between-subjects experimental study. Specifically, we collected data through an online survey, where participants were randomly assigned to one of four task scenarios and completed a questionnaire. Following the completion of a task and after being exposed to ChatGPT's responses for the same task, participants answered several open-ended questions related to the specific task scenarios they just finished.

As for the treatment of tasks, in line with the classification and definition of tasks (McGrath, 1984), as shown in Figure 2, we created four task scenarios, including (1) Number Series Task (intellective task), (2) Alternate uses task (Creativity Task), (3) City Itinerary Planning Task (Planning Task), (4) The Island Survival Problem (Decision-making Task). Based on the preliminary tests conducted by the authors, ChatGPT has demonstrated excellent performance in completing these tasks.

4.1 Participants

Participants are recruited in three phases and comprise convenience samples aged 18 years and older. In the first phase, we solicited participants using a large social network (i.e., WeChat); those participants were entered into a drawing for $20. In the second phase, we recruited undergraduate and graduate students from a U.S. university research pool; those participants received course credit for participation. In the third phase, we used Prolific and Amazon Mechanical Turk to recruit more people to answer the questionnaire; each participant was paid $1. For each scenario, invitations to participate were shared on relevant boards, we posted invitations on relevant forums, allowing individuals with direct access to the survey link directly and complete the questionnaire online. After collecting the questionnaire data, we eliminated duplicate submissions and ones with too many missing or vacant items. Finally, N = 236 cases analyzed (Planning = 61, creativity = 62, intellective = 55, decision-making = 58). The sample comprised 106 women, and 130 men; the mean age was 27.28 years (SD = 9.12, range 18 - 70).

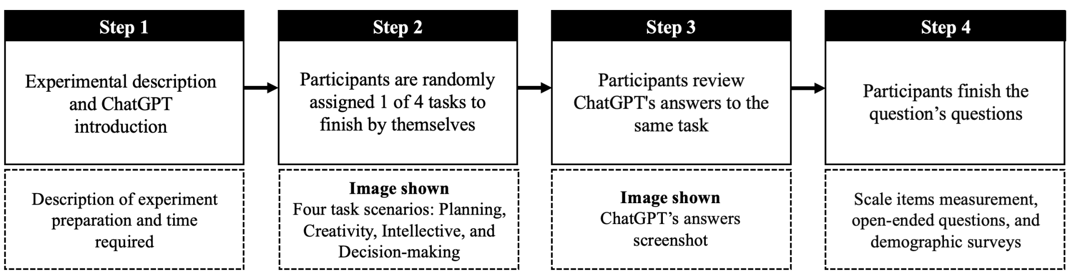


Figure 3. Proposed Research Model

Table 1. Measurement Items

Variables	Measure items	Reference
Perceived Similarity	1. ChatGPT and I are similar in terms of our outlook, perspective, and value. 2. ChatGPT and I see things in much the same way. 3. ChatGPT and I handle this task in a similar way. 4. ChatGPT and I analyze problems in a similar way. 5. ChatGPT and I think alike in terms of coming up with a similar solution. 6. ChatGPT and I hold similar attitudes concerning task-related issues. 7. ChatGPT and I have similar views on how this task should be performed.	Liden et al. (1993); Bakar and McCann (2018)
Perceived trust in GAI	1. ChatGPT has the features necessary to complete the task. 2. ChatGPT is competent in handling the task of expertise. 3. ChatGPT is reliable when it provides solutions of handling the task. 4. ChatGPT is dependable when it handles with the task. 5. I am confident that ChatGPT can work well on this task.	Jian et al. (2000) and Choung et al. (2023)
Intention to use GAI	1. How likely are you to continue using ChatGPT in the future for handling similar type of tasks? 2. If I were faced with a similar type of task in the future, I would use ChatGPT again. 3. If a similar type of task handle need arises in the future, I would feel confidence in Chat GPT's ability to handle it. 4. I would recommend others to use ChatGPT, especially those who might face similar type of task as mine.	Nicolaou and McKnight (2006)

4.2 Procedure

The procedure for the online experiment is depicted in Figure 3. In step 1, participants read the introduction to the experiment to understand the details about the tasks to be accomplished, such as the preparation for the experiment (including pen and paper for potential calculations) and the approximate time required. Participants complete an informed consent agreement to officially begin the experiment. Second, participants are randomly assigned one of four tasks and asked to finish it by themselves. As shown in Figure 2, we prepared two questions in this stage for each type of task, including a first question to collect participants' answers for the tasks. Since the tasks are different, the question descriptions vary. The second question is the same for all four groups: What steps did you take in performing this task? (i.e., your problem-solving process). In step 2, participants in the same group will receive the same responses from ChatGPT in a screenshot format. Since different users might phrase their questions differently, this could introduce variability and uncertainties. By providing standardized screenshots, we aimed to control for these differences and focus on assessing participants' perceptions to a consistent set of AI outputs. Additionally, using screenshots makes the experiment process shorter and better suited to a survey format.

In Step 3, we presented screenshots of ChatGPT's answers and its problem-solving process for the same task as the participants and asked three open-ended questions: (1) Describe the similarities or/and differences between you and ChatGPT in handling this type of task; (2) How important are these similarities or/and differences between you and ChatGPT when addressing this type of task? Please explain why; (3) Do these similarities or/and differences influence your decision to continue using or stop relying on ChatGPT to perform this type of task? Please explain why. The open and closed-ended questions were designed to explore the underlying mechanisms behind the relationship between perceived similarity and trust, due to the lack of existing research on how task types influence this relationship. Finally, the questionnaire collected demographic information: age, gender, education, and profession.

4.4 Variables and Measurements

All constructs in the research model were measured using scales adapted from previous studies, with slight modifications made to suit our research context. Specifically, deep-level perceived similarity was measured with items adapted from Liden et al., (1993) and Bakar and McCann (2018). Perceived trust was measured with items adapted from Jian et al. (2000) and Choung et al. (2023). Intention to use AI was measured with items adapted from Nicolaou and McKnight (2006). All items were rated on a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). To prevent participants from changing their answers when they realized the purpose of the experiment, they were not permitted to revise their responses on previous questionnaire pages. The specific measurement items are shown in Table 1.

5. Data analysis and results

5.1 Construct Reliability and Validity

We used Mplus 8.9 and SPSS 27 software to test and validate the proposed research model and hypothesis. All constructs were found to be reliable and valid. Specifically, perceived similarity ($\alpha = 0.93$), perceived trust ($\alpha = 0.88$), and intention to use ($\alpha = 0.90$) were reliable. We also tested the correlations among constructs to ensure discriminant and convergent validity. The correlations were below the square root of the average variance extracted (AVEs), indicating discriminant validity. Additionally, all constructs' AVEs were above 0.50, supporting convergent validity (Fornell & Larcker, 1981). In addition, multicollinearity diagnostics showed that the VIF values for the predictors were well below the threshold of 3. All items loaded onto their respective constructs without significant cross-loading, with factor loadings ranging from 0.768 to 0.937, indicating strong convergent validity for the constructs of intention to use, trust, and perceived similarity. Table 2 shows the specific data analysis results.

5.2 Multiple-group analysis (MGA)

The regression analyses from the whole sample ($N = 236$) indicated that perceived similarity significantly predicts perceived trust ($R^2 = 0.110$, $\beta = 0.331$, $p < 0.05$), and perceived trust significantly predicts intention to use ($R^2 = 0.424$, $\beta = 0.651$, $p < 0.05$). The adjusted R^2 values (0.106 and 0.422) suggest that the models are robust and account for a substantial portion of the variance in the dependent variables. Overall, these diagnostic tests and model fit indices suggest that the proposed chain model is well-fitted and appropriate for the data.

Given the categorical nature of the four task types including (1) intellective task, (2) creativity task, (3) planning task, and (4) decision-making task, respectively, we conducted an MGA analysis to test the hypothesis related to the differentiating effect of task type on the relationship between perceived similarity and intention to use. Figure 4 shows the analysis results.

The path analysis indicates that Hypothesis 1 was supported. That is, in all four tasks, trust in the GAI positively predicts the intention to use GAI. The strength of this prediction varies across tasks. Specifically, for the planning task, β = 0.792, 95% CI [0.665, 0.909]; for the decision-making task, β = 0.683, 95% CI [0.410, 0.942]; for the creativity task, β = 0.498, 95% CI [0.259, 0.752]; for the Intellectual task, β = 0.484, 95% CI [0.228, 0.686].

The reported level of trust was quite similar across the four groups: Planning (M = 5.09, SD = 1.15), Creativity (M = 5.19, SD = 0.99), Intellective (M = 5.28, SD = 0.94), and Decision-making (M = 5.40, SD = 1.11). However, the predictive relationship between perceived similarity and trust varied across the groups.

H2 is partially supported. We found that perceived similarity positively predicts trust in planning tasks (β = 0.324, 95% CI [0.025, 0.608]), decision-making tasks scenarios (β = 0.494, 95% CI [0.303, 0.768]), and creativity tasks (β = 0.357, 95% CI [0.072, 0.641]). The perceived similarity does not predict trust in intellective tasks (β = 0.213, 95% CI [-0.048, 0.368]), as expected.

6. Discussion

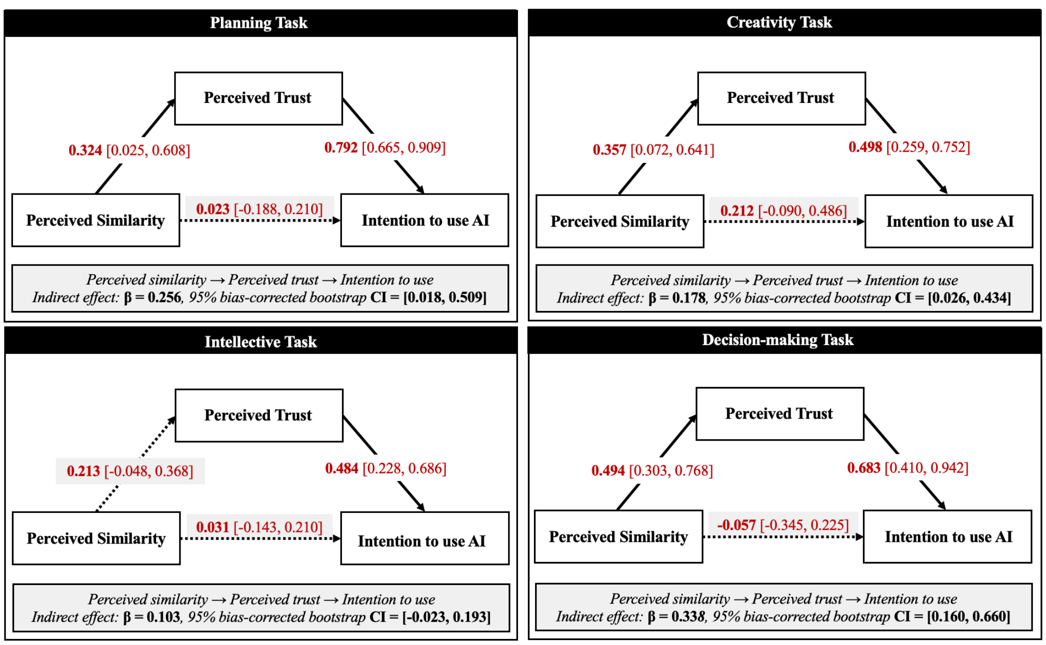
6.1 The role of trust in predicting intention to use GAI

Figure 4 shows that trust in the GAI significantly predicts the intention to use it across all task types, with the strength of this prediction varying by task but remaining consistently robust. A path coefficient greater than 0.50 indicates a strong predictive ability, underscoring the importance of trust in fostering the intention to use GAI, even though coefficients such as 0.484 and 0.498 are slightly below 0.50. This indicates that regardless of the task type, fostering trust in GAI is crucial for increasing users' intention to use it.

Table 2. Descriptive statistics, reliabilities, and correlations

Construct	Mean	SD	AVE	CR	(1)	(2)	(3)
(1) Perceived Similarity	4.709	1.291	0.708	0.944	**0.841**		
(2) Perceived Trust	5.237	1.053	0.680	0.914	0.331	**0.824**	
(3) Intention to Use	5.264	1.262	0.762	0.928	0.258	0.651	**0.873**

Note. Boldfaced diagonal elements are the square roots of AVE



Note. a) Standardized path estimates [95% confidence intervals] are presented. a) Solid lines indicate significance and dashed lines indicate non-significant paths.

Figure 4. Results of path analyses in four task scenarios

6.2 The influence of perceived similarity on trust

We found that perceived similarity can predict trust in GAI, however, the impact of perceived similarity is influenced by task type. The analysis shows that perceived similarity significantly predicts trust in decision-making and planning tasks. For intellective tasks, the relationship between perceived similarity and trust is not significant. This partially validates our hypothesis, confirming that in intellectual tasks, people do not focus on perceived similarity. This suggests that other factors may be more influential in building trust in GAI for intellectual tasks, and different strategies may be needed to foster trust in these contexts.

However, contrary to our initial hypothesis, perceived similarity also predicts trust in creativity tasks. To identify possible underlying causes, we analyzed participants' answers to open-ended questions. Some participants stated: "*[...] these similarities show that ChatGPT's answers are the same as what humans would say, making them accurate and trustable.*" Someone mentioned that "*my goal is to get the most human-like advice/output as possible from the model,*" "*Because we have a similar thinking framework [...]*", and "*[...] it does not take away from personal experience.*" Meanwhile, some participants mentioned from different perspectives, for instance: "*If ChatGPT doesn't have any similar answer as I listed above, I would probably think it does not fit with me and cannot support me.*"

We argue two potential reasons can explain why perceived similarity can predict trust also in creativity tasks based on analyzing participants' explanations in this study. The first reason is that people hope ChatGPT can "stay on the same page" with themselves, i.e., GAI has a similar human-thinking framework, and the ideas match people's thinking logic. For example, the ideas developed by people and ChatGPT are all related to people's real lives, and people can quickly understand AI's ideas. The second reason is that perceived similarity with themselves can let people feel they are on the right track, which offers people a sense of support that comes from GAI to let people more trust in GAI. In sum, people do not want GAI to act completely differently from themselves.

6.3 Mediating role of trust between perceived similarity and intention to use

The path analysis shows that perceived trust mediates the relationship between perceived similarity and intention to use GAI in planning, creativity, and decision-making tasks. However, this mediation effect is not significant for intellectual tasks. This suggests that in tasks involving strategic planning, creativity, and decision-making, enhancing perceived similarity can increase users' intention to use GAI through the mediating effect of trust. In contrast, for intellectual tasks, perceived similarity does not significantly impact the intention to use GAI through trust, suggesting that different strategies may be needed to promote GAI adoption in these contexts.

7 Research implications

7.1 Implications for research

First, this study contributes to the literature on GAI acceptance. We empirically investigate how deep-level perceived similarity influences the intentions to use GAI. Perceived similarity is a key factor affecting collaboration performance and satisfaction in human-human teams (Turban & Jones, 1988). Today, human-AI teaming is a new format of work, so this study draws on the concept of manager-subordinate similarity in human-human teams to explore how perceived similarity between a human manager and GAI subordinates when handling different tasks influences the adoption of ChatGPT. Currently, research on the impact of perceived similarity on AI (and robot) adoption remains very limited (e.g., Alawi et al., 2023; You & Robert, 2024; You & Robert, 2018). This study further supplements the understanding of the effects of deep-level perceived similarity on GAI adoption.

Second, perceived similarity's influence on GAI adoption across tasks is underexplored in current literature. Our research addresses this gap by considering the four distinct task types—creativity, planning, intellective, and decision-making—on the relationship between perceived similarity and AI adoption. We show task types should be considered in GAI design. Specifically, we found when people deal with intellective tasks, perceived similarity has no strong impact on GAI adoption and seems less critical for creativity tasks. However, perceived similarity significantly affects trust and GAI adoption in planning and decision-making tasks. This study contributes to the current body of knowledge by highlighting the significant role that task types play in shaping individuals' attitudes toward GAI.

7.2 Implications for practice

Our research provides practical insights for designers and developers of organizational GAI agents. In this study, we discovered that the impact of perceived similarity on trust in GAI and the adoption of GAI varies across different task scenarios. Therefore, it is crucial to customize the problem-solving processes of GAI based on the specific types of tasks users are engaged in. Specifically, our findings indicate that in decision-making and planning tasks, high perceived similarity significantly and positively influences trust in GAI and its adoption. Consequently, when introducing GAI agents in planning and decision-making task scenarios, ensuring that the GAI shares similar task-handling processes with the user should be a focal point in the design and development of GAI. However, in intellective and creativity tasks, perceived similarity may not be the key variable to focus on.

8. Limitations and future research

First, our study only focuses on deep-level perceived similarity (see Harrison et al., 2002). However, previous research has suggested that surface-level similarity also influences the effect of perceived similarity on trust and AI adoption (e.g., You & Robert, 2018, 2023). Currently, as AI technology advances, factors such as anthropomorphism, language and culture, and even physical attributes like skin color are gradually integrated with GAI. For instance, ChatGPT on smartphone applications can converse with people using voices. Therefore, the combination of these two types of similarity (surface and deep-level) could offer a more holistic understanding of their effects on human-GAI collaboration.

Second, considering the limitations of the ChatGPT application, this study only surveyed four specific task scenarios based on McGrath's (1984) task classification framework—intellective, creativity, planning, and decision-making. However, as GAI continues to evolve and take on more human tasks, future research should explore a broader range of task scenarios to understand the impact of perceived similarity on trust in GAI and GAI adoption in different task contexts. Additionally, adopting other task classifications should also be considered to provide a more comprehensive analysis.

Third, future research directions should focus on exploring additional mediating variables to verify how these variables influence GAI adoption in specific task scenarios. Our study found that perceived trust does not affect people's GAI adoption when handling intellective tasks. Therefore, future research needs to investigate the impact of other mediating variables (e.g., perceived enhancement, perceived usefulness) on GAI trust and adoption. This will help develop more targeted strategies to enhance GAI application effectiveness across various tasks.

Fourth, we just think about the final result, i.e., whether people will adopt GAI. However, we ignore the collaboration patterns between people and GAI, i.e., automation or augmentation. We argue that collaboration patterns potentially will be a crucial factor in influencing the relationship between perceived similarity and trust. We think that people may want a similar AI agent to delegate themselves and a different AI agent to augment them in the teams, and this is also potentially affected by the different task types. This phenomenon could be examined in future work.

Fifth, the AI tool we choose in this study has limitations. Because organizations who develop AI tools as a teammate may create their own AI tools related to the specific missions/goals/problems within those organizations but not employing the ChatGPT, a general AI tool. AI teammates within a private domain may be more familiar with the organizational unique situations, leading to greater similarity. Therefore, future research should continue to investigate this in real organizational contexts.

Finally, it would be valuable to understand what people expect to receive from GAI across different task types. This would help deepen our understanding of why people trust GAI to assist with (or perform) certain tasks over others.

9 Conclusion

In the future of human-AI collaboration, fostering positive attitudes towards GAI teammates is crucial for effective teamwork. This study examined the effects of perceived similarity mediated by perceived trust on GAI adoption, considering the differentiating effects of four task types. Our findings reveal that the influence of perceived similarity on trust in GAI and GAI adoption differs across various task scenarios. These insights would potentially help navigate GAI design and development strategies by considering the specific nature of the various tasks.

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