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User Reliance on AI Support for Collaborative Partner Selection

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Abstract

Whether choosing teammates for a project or partners for everyday life tasks, people constantly decide with whom to work. However, in these decisions, they often overemphasize characteristics that are not directly relevant to task performance. For example, prioritizing a partner’s trustworthiness for a task where competence is more important for good task performance. Artificial intelligence (AI) systems have the potential to mitigate these judgment errors by guiding decision-makers toward placing greater weight on traits that are more predictive of success for the specific task at hand. Although the potential usefulness of such systems is evident, previous work leaves unclear under what conditions and for what type of AI support people are willing to rely on and trust AI systems for such relational decisions (i.e., selecting a collaboration partner). To bridge this gap, our study examined how different forms of AI support shape users’ perceptions of the AI’s intellectual and social capabilities, their sense of autonomy, and their willingness to rely on and trust in AI when selecting a partner for a collaborative task. To do this, a total of 397 participants designed ideal partners for two collaborative tasks while receiving one of three forms of AI support: (1) RECOMMENDATION, (2) EXPLANATION, or (3) KNOWLEDGE NUDGES. This was tested in two different tasks: a competency-based task and a trustworthiness-based task. We found that richer AI support (through explanations or nudges) enhances perceived AI’s social and intellectual capabilities, but not autonomy. Perceptions of intellectual capabilities, rather than social capabilities, predict greater reliance. Both perceptions of AI capabilities mediate the effect of the type of AI support on reliance. Overall, the study advances understanding of human–AI collaboration by revealing how AI design features shape user perceptions and reliance when users need to evaluate and select their collaborators.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

AI support, Partner Selection, Explainable AI, Human-AI Decision Making

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1 Introduction

In everyday life, people constantly make decisions on whom to work with [4]. These partner selection choices are central to both personal and organizational outcomes, but are susceptible to judgment errors [14]. One such error involves overvaluing a partner’s trustworthiness (i.e., benevolent intentions) and underestimating the importance of competence (i.e., partner’s ability), even when competence is the more relevant factor for task success [8, 18, 39]. As a result, individuals may make suboptimal partner choices, leading to real costs related to task success, such as reduced productivity, weaker team cohesion, or financial losses [37, 39].

As artificial intelligence (AI) systems become increasingly integrated into human decision-making [1, 21], they provide a means to support individuals in selecting suitable partners for specific tasks. By providing advice about relevant partner traits, AI tools can help individuals move beyond intuitive judgments and make more balanced decisions [38]. For example, an AI system could guide users to prioritize competence over trustworthiness when selecting collaborators for highly technical or skill-intensive tasks. Conversely, when task outcomes depend more strongly on trustworthiness, the system could advise users to place greater emphasis on trustworthiness rather than competence. Although the potential usefulness of such systems is evident, it remains unclear under what conditions people are willing to rely on and trust AI systems for these *relational decisions*, such as providing recommendations

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on whom to select as a collaborator, as opposed to purely analytical or factual judgments.

Empirical evidence on this topic remains limited and presents mixed findings [10, 31, 36]. Some psychology studies find that people distrust and have no reliance on AI in social or relational domains compared to a human, when taking advice on music or dating partners [10]. This reluctance is attributed to perceptions that AI systems lack an understanding of human social cognition and possess limited social and intellectual capabilities [10]. However, others show opposite results, finding a phenomenon known as "algorithmic appreciation" where users value algorithmic support over human support [36]. Except for perceptions of an AI system's intellectual and social capabilities, additional studies also indicated that a perceived loss of autonomy can further reduce users' willingness to rely on AI support and decide to trust AI systems. This was found especially when people needed to report on their willingness to rely on AI systems when hiring other people [31, 33]. People were willing to rely and trust the AI recommendation of whom to select if they felt AI provided them control over the final decision. Taken together, these initial findings suggest that reliance on and trust in AI systems might be shaped by two key psychological factors in relational decision-making: perceived AI capability (both intellectual and social) and perceived user autonomy.

However, three key gaps remain in the current literature regarding the mechanisms of AI reliance and trust in relational decision-making and in system development. First, much of the existing evidence on AI reliance and trust for relational decisions is predominantly qualitative or theoretical, leaving a lack of systematic empirical research on how perceptions of AI's social and intellectual capabilities or users' sense of autonomy affect reliance on AI in relational contexts. Second, little is known about the broader dynamics through which AI system design choices, such as the use of different types of AI support, influence users' perceptions of AI capabilities, their sense of autonomy, and their subsequent reliance on that support when making relational decisions and trust in the AI system. Following prior literature on explainable AI [25, 42, 43], the type of AI support constitutes an important design consideration in this case, as it might meaningfully affect users' perceptions and sense of autonomy when deciding, and consequently affect reliance on and trust in AI systems. As such, it might be a good candidate to moderate people's perceptions of AI capabilities and their own autonomy, and in turn affect their overall reliance and trust in AI systems. Third, while a substantial body of work has examined the effect of explanations on users' trust, reliance, and perceptions of transparency [25, 34, 42], there is still a lack of literature comparing it to alternative forms of AI support, such as nudges. Nudges – subtle suggestions designed to encourage desired actions [62] – have also been shown to help individuals make better choices while preserving their sense of autonomy [2, 65], but how do they compare to explanations or providing mere recommendations when it comes to supporting users' autonomy or their perceptions on how capable they perceive AI to be? If nudges are more effective than explanations in supporting people's decisions, AI systems should be designed to prioritize well-crafted nudges over purely explanatory approaches. Producing empirical evidence that addresses these research questions is important, especially if we want to move towards the next steps of designing AI systems that effectively support human decision-making in settings that include relational decision-making, such as selecting a partner for future collaborations [39]).

Thus, to address these gaps, we conducted an experiment in which participants completed a partner-selection task, choosing a collaborator for a task where the partner's trustworthiness (Joint Trust Task) or competence (Joint Competence Task) was important. Participants received one of three types of AI support: (1) RECOMMENDATION, (2) EXPLANATION (recommendation followed by an explanation), or (3) KNOWLEDGE NUDGE emphasizing task-relevant criteria. Using this experimental design, this paper investigated: 1) Whether and how the type of AI support influences: (a) users' perceptions of AI's intellectual and social capabilities, (b) users' sense of autonomy, (c) trust in, and (d) reliance on the AI support; 2) Whether and how users' perceptions of AI's (a) intellectual and social capabilities, (b) users' sense of autonomy, relate to people's (a) trust in and (b) reliance on AI support. Finally, to explore a more complex relationship between design choices of type of AI support, perceptions and users' trust and reliance on AI we investigated: 3) Whether and how perceptions of AI's intellectual and social capabilities or users' sense of autonomy mediate the relationship between the type of AI support and (a) trust in the AI system, and (b) reliance on the AI system.

We found that the type of AI support influenced users' perceptions of AI capabilities in both tasks, but not their sense of autonomy. The type of AI support only had a direct effect on reliance in the Joint Competence Task, but not the Joint Trust Task. Perceived AI capabilities also had an effect on reliance. Finally, perceptions of AI's intellectual capabilities mediated the relationship between AI support type and reliance across both tasks, whereas perceptions of AI's social capabilities mediated this relationship only in the Joint Trust Task.

This paper goes towards advancing the literature on human-AI relational decision-making by systematically examining how different types of AI support, RECOMMENDATIONS, EXPLANATIONS, and KNOWLEDGE NUDGES, influence users' trust, reliance, and perceptions in relational decision-making contexts. To our knowledge, it is the first study to systematically compare these three support types and assess their differential effects on users' perceptions of AI capabilities, sense of autonomy, trust in AI, and reliance when people are making relational decisions. Additionally, beyond behavioral outcomes, we examine the mechanisms underlying these effects, showing how design choices shape users' perceptions of autonomy and the AI's social and intellectual capabilities, which in turn influence trust and reliance. By integrating these behavioral and psychological factors, this paper goes further and provides a deeper understanding of the cognitive and social dynamics of human-AI collaboration in relational contexts, and provides actionable guidance for designing AI systems that are both effective and autonomy-preserving.

2 Background and Related Work

This paper investigates people's reliance on AI support and trust in AI when selecting partners for collaborative tasks, with a focus on differences in the type of AI support, users' sense of autonomy, and perceptions of AI intelligence. Thus, we situate our work at the intersection of research on human–AI decision-making, explainable AI, and behavior change support technologies.

2.1 Trust and Reliance in AI Support in Human-AI Relational Decision-Making

Human–AI decision-making research examines how individuals integrate algorithmic input into their judgments to design decision aids that enhance rather than replace human capabilities [30, 60]. In such settings, trust and reliance are not automatic because users can accept, modify, or reject AI input. A central challenge, therefore, is understanding when people defer to AI, when they resist it, and when they trust and rely on it [59, 60].

Yet, how trust and reliance are measured can vary across different research studies. On the one hand, trust can be conceptualized as a belief, defined as an individual's willingness to be vulnerable to another's actions based on the expectation that the other will act in their best interest [40]. Trust can also be assessed as behavior, reflected in the extent to which individuals rely on a system's advice or recommendations [25]. Prior research has shown that although these two forms of trust are correlated, they may lead to different outcomes, as individuals may report trusting an AI system yet choose not to rely on it [25, 55]. This distinction between trust and reliance aligns with the classical psychological Theory of Reasoned Action [19], which presents a common gap between beliefs or attitudes and actual behaviors. Therefore, in our study, we assess trust and reliance as separate constructs to capture both dimensions of this relationship.

To date, most existing research on human-AI decision-making have examined human reliance on AI support and trust in AI for tasks requiring analytic and objective decisions, across domains such as law (e.g., prediction of recidivism [30, 64] or sentencing outcomes [25]), medicine (e.g., medical image search [9], stroke rehabilitation assessment [32]), finance (e.g., credit prediction [51]), or even artificial prediction tasks (e.g., symbol prediction [34]). However, the role of AI in relational decision-making, which depends on subjective and interpersonal judgments (e.g., evaluating or selecting people), has received much less attention [10, 36]. Investigating users' reliance on AI support in tasks involving relational decision-making is important because these types of decisions tend to differ from analytical ones.

For example, while analytical decisions are based on objective non-social reasoning, relational choices are based on subjective judgment and interpersonal sensitivity [6, 63]. This distinction may help explain why individuals vary in their willingness to rely on AI systems when making analytical versus relational decisions, which has been found in prior literature [10, 36]. For instance, Castelo et al. [10] suggest that doubts about AI's social capabilities, such as demonstrating empathy or social understanding, may play a role in leading users to dismiss or rely on AI support when making relational decisions. Perception of AI's social capabilities might be less important in analytical tasks, when the user's need is to detect an (objectively) correct solution [10]. After all, an application trying to predict whether a person will recover from a stroke does not require strong social capabilities to be relied upon.

Similarly to perceptions, the impact of the sense of autonomy, a key element of human decision-making and one of the basic psychological needs [16], on reliance and trust can vary depending on the type of decision a user is making. It may be especially relevant in situations where people are evaluating or judging others, as these tasks often rely on subjective judgment rather than objective reasoning. Indeed, one user study on AI-assisted hiring suggests that people are more receptive to AI recommendations when these are accompanied by explanations, as explanations help preserve their sense of decision autonomy, which hiring managers reported to be especially important when deciding when evaluating and selecting future employees [31].

Together, this literature indicates that there might be different dynamics taking place when people are making relational decisions. As such, more research is needed to understand the dynamics and underlying mechanisms of why people decide to rely on AI systems when making relational decisions, such as selecting a partner for collaboration.

2.2 The Effects of Different Types of AI Support

The design and model behavior of AI systems can have important consequences on people's willingness to trust AI systems and rely on their support [11, 46, 49]. The most researched aspect of such behavior is the type of AI support that should be exhibited during human-AI decision-making.

How AI support is presented can have important consequences on people's willingness to rely on AI's support. Explanations are the most studied approach [12, 25, 32, 54]. Here, most of the literature shows that explanations can have positive effects on user trust in the system or their behavioral reliance [32, 54], and decrease overreliance (i.e., situations where people rely on AI even when it is wrong) [66]. These effects have also been reported in the context of AI support in recruitment, where recruiters indicated that they would be more willing to rely on AI recommendations when these recommendations are followed by an explanation of the recommendation [31]. Yet, this relationship can also have negative consequences as explanations can also lead to overreliance [27], and increased decision bias [67]. In this paper, we follow a general assumption underlying the literature on explainable AI, which is that providing explanations of AI recommendations will equip users with more information to understand the rationale of the AI advice and therefore rely on and trust it more [22, 41, 42].

Beyond providing explanations, another design strategy is to use nudges [35, 71]. Nudges are contextual information that guide choices without prescribing outcomes or recommendations [35, 62]. These interventions can vary in subtlety, ranging from structural adjustments, such as implementing opt-out decision architectures to increase organ donor registration [62], to knowledge-based approaches that inform individuals about their behavior [71]. For instance, sharing comparative energy consumption data (e.g., how much energy a household used compared to the previous week, and the potential savings from reducing usage) can effectively encourage more energy-efficient behavior. Prior research in behavioral economics and psychology has shown that nudges can increase adherence to desirable behaviors [62, 65], compared to not using them. Rather than providing direct recommendations that users are expected to follow, nudges function as subtle mechanisms that inform and empower decision-making while gently steering users toward desirable outcomes.

Overall, the literature suggests that different forms of AI support may differentially shape both users' trust and reliance. However, existing findings remain fragmented and sometimes contradictory, warranting direct empirical testing in relational domains such as collaborator selection. Thus, here we test the following hypotheses:

> ***H1:*** *The type of AI support will have a direct effect on reliance, such that providing only* Recommendations *will result in the lowest,* Explanations *in a moderate, and* Knowledge Nudges *in the highest level of reliance.*
>
> ***H2:*** *The type of AI support will have a direct effect on users' trust in AI support, such that providing only* Recommendations *will result in the lowest,* Explanations *in a moderate, and* Knowledge Nudges *in the highest level of trust in specific AI.*

Beyond their direct effects on trust and reliance, different forms of AI support may also shape how people perceive the AI itself and their own role in the decision process. Prior work in recruitment shows that providing explanations increases perceived transparency and strengthens users' sense of autonomy [31]. In psychology literature, providing explanations has also been related to higher perceptions of source reliability [61]. On the other hand, nudges were deemed an autonomy-preserving communication strategy both in human-human interactions [65] and human-computer interactions [35, 71]. Indeed, prior research in behavioral economics and psychology has shown that nudges can increase adherence to desirable behaviors while being better at preserving users' sense of autonomy [62, 65]. This property may be especially relevant in relational tasks, where individuals might be more skeptical of AI's social capabilities to make a good recommendation [10]. Nudges may therefore allow AI systems to influence users' decisions in ways that feel less intrusive to their sense of autonomy.

Similarly, using different types of AI support can also play a role in highlighting the AI's "reasoning", which in turn can affect perceptions of the AI's intelligence and even social capabilities [61]. For example, explanations make the reasoning behind a recommendation explicit, giving users additional information to evaluate the advice and make informed decisions. By providing explanations, AI systems may be attributed with intellectual and social capabilities that users would not otherwise assume, thereby influencing whether the system is considered suitable for relational decision-making. Knowledge nudges can have an even stronger effect by addressing the social context and clarifying why selecting a particular partner is important [71].

Taken together, this literature suggests that AI support strategies can shape not only reliance and trust but also people's perceptions of AI. Thus, we hypothesize that:

> ***H3:*** *The type of AI support will affect users' perceived level of autonomy, such that providing only* Recommendations *will result in the lowest,* Explanations *in a moderate, and* Knowledge Nudges *in the highest level of perceived autonomy.*
>
> ***H4:*** *The type of AI support will affect users' perceptions of (a) AI's social and (b) intellectual capabilities, such that providing only* Recommendations *will result in the lowest,* Explanations *in a moderate, and* Knowledge Nudges *in the highest level of perceived AI's social and intellectual capabilities.*

2.3 The Role of User Perceptions on AI reliance

Previous research on human-AI decision making has emphasized the importance of user perceptions in shaping AI adoption. For instance, following the Theory of Reasoned Action [19] and the Technology Acceptance Model [15], perceptions are thought to inform people's attitudes towards AI systems, which can then lead to behavioral intentions, ultimately resulting in reliance on or indicated trust in AI systems.

Although the Technology Acceptance Model [15] mainly emphasized user perceptions of usefulness and ease of use, recent research in human-AI decision-making suggests that perceptions of AI's competencies, intentions, and other characteristics also significantly influence user reliance on AI [12, 17, 26, 29, 50, 57]. Thus, perceptions can also shape the reliance of individuals on AI. For example, users' reluctance to rely on and trust AI for relational decision-making might be explained by the belief that AI lacks the social or intellectual capabilities necessary to perform such tasks effectively, as discussed in prior literature [10]. Therefore, perceptions of AI's social and intellectual capabilities can also play a role in determining whether individuals choose to rely on AI in these contexts [57]. Selecting a partner is inherently a subjective and socially nuanced decision. If individuals believe that an AI system lacks the necessary social understanding to make such judgments, they may be less inclined to accept its recommendations.

On the other hand, users' perception of their personal autonomy can also be very important during joint decision-making. For instance, if individuals feel that AI systems limit their autonomy or override their preferences, they may resist collaboration, even if the system provides accurate or efficient outcomes. Research suggests that preserving a sense of personal autonomy in users is important, as it represents a basic human need [16]. This helps users maintain ownership over the final decision, reduces the risk of feeling dependent, and can ultimately lead to greater reliance on AI support. Based on this reasoning, we hypothesize that:

> ***H5:*** *Perceptions of AI's (a) social and (b) intellectual capabilities will be positively related to users' reliance and trust in specific AI.*
>
> ***H6:*** *Perceptions of users' sense of autonomy will be positively related to (a) users' reliance on AI support and (b) trust in AI.*

Following previous literature supporting the above direct relationships, we also hypothesize that the direct effect of the type of AI support on reliance and trust in AI can be explained by the mediating effect of users' perceptions of AI capabilities and users' sense of autonomy.

> ***H7:*** *The perception of (a) AI social and (b) intellectual capabilities and users' (c) sense of autonomy will mediate the link between the type of AI support and reliance on and trust in AI.*

3 Research Model

Given the complexity of the hypotheses and the combination of tests for both direct and indirect effects, we present and evaluate them collectively in an integrated model (see Fig. 1).

As prior literature found that the type of task might also play a role in determining people's perceptions of AI systems [10], we also tested our model across two distinct task types. In one task, selecting a competent partner was more important, while in the

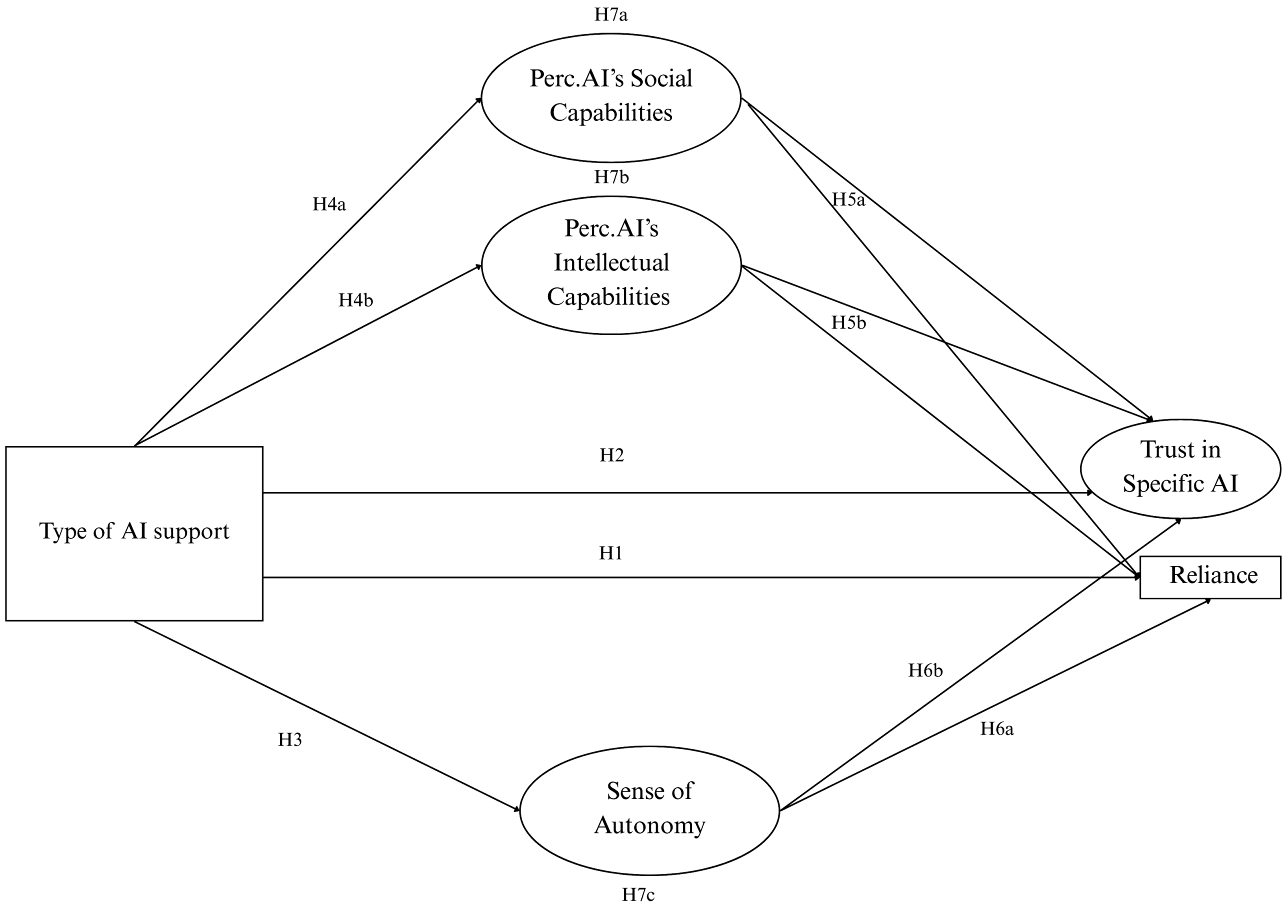


Figure 1: The figure represents the visualization of the theoretical SEM with all the hypotheses discussed in Related Work. The oblong shapes present latent variables, and rectangular shapes represent observed variables.

other, selecting a trustworthy partner was more important (see *Section 4* for details). These two tasks were chosen because they reflect contexts that differ in the relative importance of social versus intellectual attributes. Specifically, tasks emphasizing trustworthiness highlight social qualities, whereas tasks emphasizing competence and skill highlight intellectual abilities. Such differences may affect the relationships between perceptions of an AI's social and intellectual capabilities and users' willingness to rely on its support. For example, suppose users perceive that an AI lacks social awareness or interpersonal sensitivity. In that case, they may be less inclined to rely on it when selecting a partner for a cooperative task that requires a partner's trustworthiness. Conversely, when the task emphasizes competence, users may be more willing to rely on the AI's recommendations if they believe the AI demonstrates strong analytical or problem-solving capabilities.

In addition to building on prior literature, our research model also draws on a well-established conceptual framework commonly applied in the context of recommender systems. This framework, developed by Knijnenburg and colleagues (2012) [28], provides a systematic approach to understanding how users form perceptions and attitudes toward intelligent systems. Specifically, it delineates the pathways through which objective characteristics of system design, in our case type of AI support, affect subjective system evaluations, such as perceived AI's social and intellectual capabilities or sense of autonomy. These subjective evaluations, in turn, shape users' behavioral responses, such as reliance on the system's outputs. By emphasizing the dynamics between technological features, user perceptions, and behavioral outcomes, this framework offers a useful environment for examining human–AI interactions. Therefore, it serves as an appropriate framework for our proposed research model, which seeks to explain how variations in AI design influence user judgments and decision-making behaviors in our specific context.

4 Method

4.1 Participants

A total of 452 UK participants participated in the study. Of these, 51 participants did not consent or complete the survey. Following our preregistered criteria, we also excluded participants who correctly answered fewer than approximately four (60%) attention checks, resulting in a final sample of 397 participants (M_{age} = 41.58, SD_{age} = 11.20, Age range = 19–65). Within this sample, 203 participants identified as female, 191 as male, two preferred not to disclose their gender, and one identified as nonbinary. Participants were assigned to one of three experimental conditions: 133 in the recommendation condition, 135 in the recommendation with the explanation condition, and 129 in the knowledge nudge condition.

4.2 Procedure

All participants first read an informed consent letter and agreed to participate in the study, including the sharing of anonymized data. After providing consent, participants were introduced to the study procedure and informed that they would read a task description and create a profile for a partner with whom they would complete that task. They then reported demographic information and completed surveys assessing general attitudes toward AI and personal traits, including advice-taking dispositions (see *Fig. 2* for the experimental design). Following this introduction and the demographic questions, participants were randomly assigned to first receive either a Joint Trust Task or a Joint Competence Task. This was done to counterbalance potential ordering effects of the tasks.

The Joint Trust Task was a modified two-player version of the Trust Game [7], assessing trust and reciprocity. Each player received 10 monetary units (MU) and decided how much to send to their partner, with the amount increasing by 20% during the transaction. Cooperation allowed both players to maximize earnings, but success depended on mutual trust. MUs were later converted into real money (1 MU = £0.50) and paid as a bonus. On the other hand, *The Joint Competence Task* focused on competence (i.e., intelligence). In this task, participants had aligned interests but could only achieve mutual benefits by solving intelligence-based problems from a validated non-verbal intelligence test. Success depended on problem-solving ability rather than trust. Both tasks were already used in previous literature [39]. In the Joint Competence Task session, after the task descriptions, participants additionally took part in a non-verbal abstract problem-solving task (UCMRT) [48]. This task was added because UCMRT performance was important for the Joint Competence Task.

After it was clear that the participants were familiar with the task, they were asked to build a profile for a human partner they would want to do the task with by assigning weights (from 0 to 100) to four traits: sociability, attractiveness, trustworthiness, and competence (see Fig. 3). After participants gave their initial partner profile, they were then randomly assigned to one of the three AI support conditions, which differed in the type of AI support provided: 1) RECOMMENDATION: AI recommendation without explanation; 2) EXPLANATION: AI recommendation with explanation; or 3) KNOWLEDGE NUDGE: provision of additional information about available options to nudge users into a specific decision (see Fig. 3 for examples). The task of building a partner profile of four traits was used to measure reliance on AI support. Specifically, the vectors of weights were compared between initial and final decisions, as well as the support given by the AI.

Subsequently, they were asked to rate their perceptions of the social and intellectual competencies and their trust in the specific AI system. After reviewing AI support and reporting their perceptions, participants were instructed to make a final decision on their partner profiles. Participants then completed a zero-shot version of either the Joint Competence Task or the Joint Trust Task with a specific partner that corresponded to their preferred profile. The partner was shortly described to them along with important traits, such as trustworthiness and competence. To increase the internal validity of the experiment, the partner descriptions, as well as partner responses in the Joint Tasks, were based on actual participants' reports on scales and tasks measuring their agreeableness, trustworthiness, and intelligence competencies, and their behavior in the two Joint Tasks from another dataset [23]. After completing the first task, participants repeated the entire procedure with the other task (i.e., if they started with the Joint Competence Task, they next completed the Joint Trust Task, and vice versa). The study was approved by the Ethical Board of Eindhoven University of Technology (Reference Number: ERB2025JADS13).

4.3 Target Variables

The primary target variables of interest were reliance, trust in the specific AI system, perceptions of the AI's competencies, and the type of AI support.

Reliance was measured as an observable behavior following the methodology adopted in prior research [25]. The experimental design employed a sequential decision-making process, where participants first made an initial decision, then received AI advice, and finally submitted a revised (final) decision. This setup allowed us to capture dynamic changes in the participants' decision-making process, as we could explore whether they adjusted, overrode, or adopted the AI's input in their decisions. To quantify this process, we adopted a logic similar to the Weight of Advice (WoA) metric [56], which measures the extent to which individuals adjust their judgments toward external advice. However, WoA assumes that decisions are represented as a single scalar value, making it less suitable for our study, where decisions involved assigning values to four partner traits. In this context, each decision was represented as a vector of four values, necessitating a vector-based approach.

To address this, we combined the logic of WoA with a cosine similarity measure, commonly used in machine learning to assess the similarity between multi-dimensional vectors [24]. Cosine similarity captures the degree of alignment between two vectors, ranging from 0 (no similarity) to 1 (identical vectors). We calculated cosine similarity for decision vectors from all pairs of decision stages: (initial, advice), (advice, final), and (initial, final). This approach allowed us to evaluate how closely participants' final decisions aligned with the AI's advice, while also accounting for the multidimensional nature of the task.

After calculating the cosine similarity for all pairs of decisions, we followed the logic of computing WoA to distinguish between clear instances where "no reliance" or "no learning" occurred [56]. Specifically, cases where the initial and AI-advised profiles were identical (cosine similarity = 1) were labeled as "no learning", as there was no new information to incorporate; cases where the initial and final decisions were identical, but the initial profile was not identical to AI advice, were labeled as "no reliance". In the remaining cases, where there was room for change, we calculated

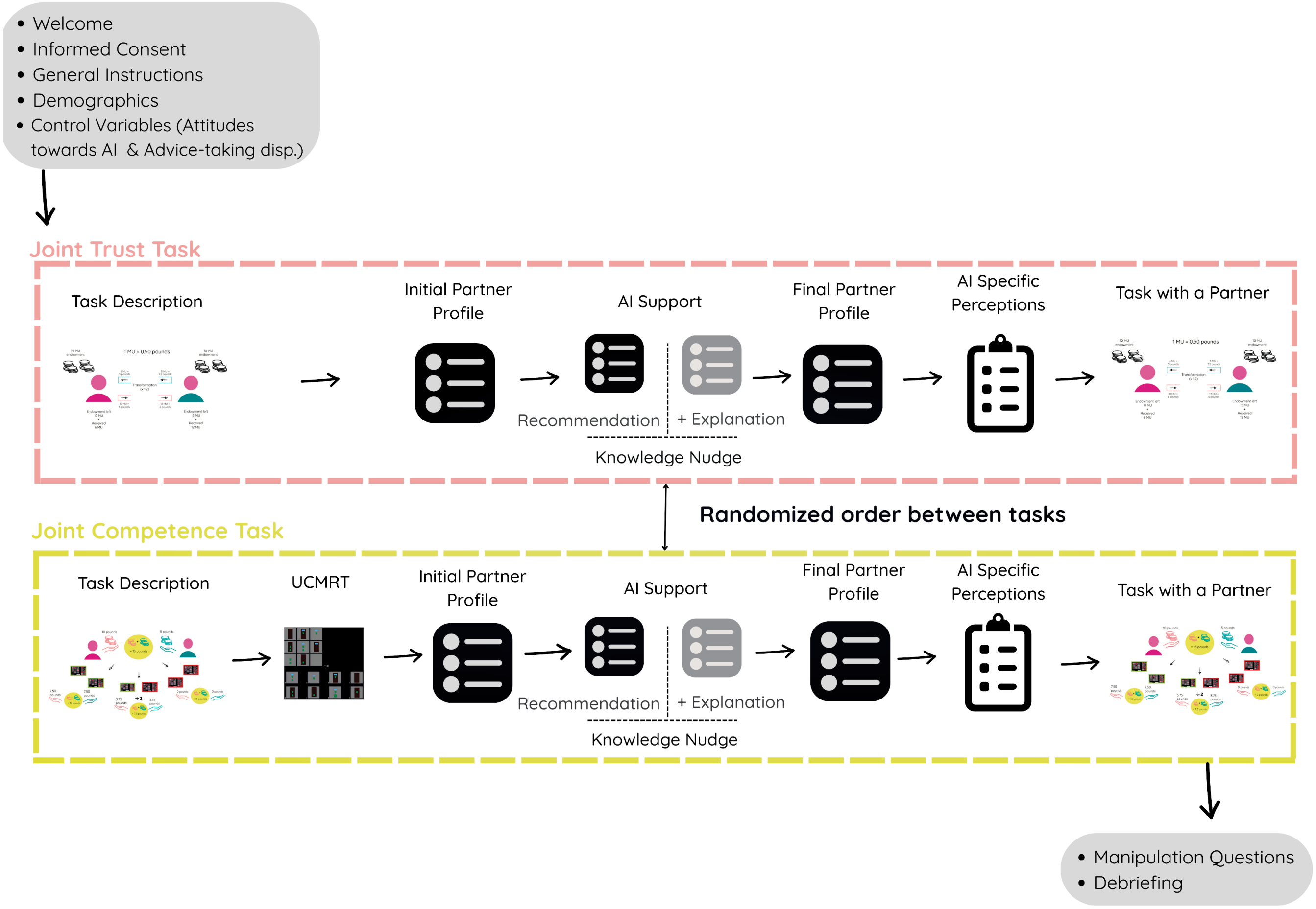


Figure 2: Study procedure: After the introduction (informed consent, general introduction), participants were introduced to the task for which they needed to create a partner profile, and for which they received one out of three possible types of AI support. Participants finish the study by going through a set of post-trial questions and a debrief about the study. Find more details about the setup in Procedure.

the cosine similarity between the AI advice and the final decision. If the final profile fully matched the AI advice (cosine similarity = 1), the case was labeled as "full reliance". To identify "partial reliance", we determined a data-driven threshold for meaningful similarity. Thus, we needed a high similarity in the context of the profiles, which differed from full reliance. Based on our dataset, a cosine similarity of 0.97828 served as the cutoff point where cases with a similarity above 0.978 were labeled as partial reliance, while those below were labeled as no reliance. The value 0.978 was determined using a weighting procedure designed to satisfy two constraints. First, the dominant trait was selected based on task requirements. For tasks emphasizing a trustworthy partner, trustworthiness needed to be assigned the highest weight; for tasks emphasizing problem-solving ability, competence needed to be assigned the highest weight. Second, weights for the remaining dimensions were assigned according to a fixed ordinal hierarchy of importance: the primary dimension (Trustworthiness or Competence) > the secondary dimension (Competence or Trustworthiness) > Sociability or Attractiveness. For illustration, under the Joint Trust Task, this threshold captured scenarios in which Trustworthiness received the highest number of points, followed by Competence. In contrast, Attractiveness and Sociability received an equal number of points. For reproducibility, the data is available on OSF Project Files under the following link: https://osf.io/6apf9/overview?view_only=4081b6a194d342ac855a0463c2e87013. We emphasize that this threshold was empirically derived from our data and should not be used as a data-agnostic threshold. This approach was used for the Recommendation and Explanation conditions, where the AI advice was provided as numerical values (see Fig. 3).

In contrast, the knowledge nudge condition did not produce numerical vectors for direct comparison (see Fig. 3). However, this knowledge-nudge type of support hinted at a ranking relevance that could be used to annotate the reliance manually. Therefore, decisions in this condition were manually annotated using a rule-based procedure. Specifically, if participants' final partner profiles matched the AI's indicated ranking on three or more traits, the decision was classified as partial reliance; otherwise, it was classified as no reliance. Similarly, the dominant trait needed to be correctly selected based on task requirements (e.g., trustworthiness for the Joint Trust Task and competence for the Joint Competence Task). Given the nature of the task, full reliance was not expected.

Trust in specific AI was measured as a self-reported measure on the User's Trust scale from the Artificial Social Agent Questionnaire [20]. The trust was measured using three items (i.e., "*The AI agent gives good advice.*"; "*The AI agent acts truthfully.*"; "*I can rely on the AI agent.*"). All items were measured on a 7-point scale (1 = Strongly Disagree to 7 = Strongly Agree). The scale had a high internal reliability across both tasks (average $\alpha = 0.91$).

Perceptions of AI's Capabilities were measured on two different scales to assess perceptions of AI's social competencies and its perceived intelligence. Perceptions of AI's social competencies were measured using the Perception of Social Competencies subscale of the Perceived Social Intelligence (PSI) Scales [3]. The scale had good internal reliability for both tasks (average $\alpha = 0.89$). The perception of intellectual competencies was measured using the subscale Perceived Intelligence from the Godspeed Questionnaire Series [5]. Both subscales were measured on a 7-point scale, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). The scale had good internal reliability for both tasks (average $\alpha = 0.92$).

Sense of Autonomy was assessed using four items designed to capture both autonomy satisfaction and frustration in the AI context: "The AI pressures me to act in a certain way.", "The AI makes me feel like I don't have a real choice.", "The AI restricts my freedom in decision-making," and "The AI allows me to make my own decisions." These items were adapted from established measures of autonomy support, including the Learning Climate Questionnaire [70] and the Basic Psychological Need Satisfaction and Frustration Scale (BPNSFS) [13]. All items were measured on a 7-point scale (1 = Strongly Disagree to 7 = Strongly Agree). The scale had good internal reliability across both tasks (average $\alpha = 0.85$).

Type of AI Support was experimentally manipulated. Participants were exposed to one of three types of feedback: (1) RECOMMENDATIONS: AI recommendations without explanation, where the system provided a decision with no additional information; (2) EXPLANATIONS: AI recommendations with explanation, where the rationale behind the AI's suggestion was provided; and (3) KNOWLEDGE NUDGES: which offered domain-relevant information intended to guide decision-making without directly recommending a specific action. The type of AI support was treated as an ordinal categorical variable, s.t. the higher the amount of information, the higher the condition is in our coding (1 = RECOMMENDATION; 2 = EXPLANATION, and 3 = KNOWLEDGE NUDGE).

In addition to the target variables, we measured two additional user aspects that could influence responses to AI feedback, including participants' advice-taking disposition and general attitudes toward AI [68]. These traits were assessed to ensure that the three AI support groups were balanced and to rule out alternative explanations for observed effects. Advice-taking disposition was measured using a four-item scale adapted from prior research on decision-making [69] on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree; $\alpha = 0.73$). Attitudes toward AI were assessed using the ATTARI-12 scale [58], a twelve-item psychometric tool designed to capture individuals' overall perceptions, feelings, and predispositions toward AI on the same 7-point scale ($\alpha = 0.95$).

4.4 Generation of AI Support

To generate different AI support conditions, we used OpenAI's *ChatGPT-5 mini* model. The model was prompted with the task descriptions and was asked to provide one type of AI support. Specifically, the prompt for Joint Competence Task for the Recommendation Condition started as: "*You need to provide a recommendation of a partner profile without explanation to a participant; This profile presents a partner profile that is suitable for the task. You will be presented with a list of traits, including sociability, attractiveness, trustworthiness (i.e., honesty), and competence (i.e., intelligence). For each trait, assign a value between 0 and 100 based on how important it is to you that your partner possesses that trait. The higher the value allocated to a characteristic, the more this characteristic will be expressed in your partner. Your total allocation across all traits must add up to exactly 100 points.* The process was repeated 10 times for each type of AI support (RECOMMENDATION, EXPLANATION, and KNOWLEDGE NUDGE), resulting in 30 AI supports. The results of all 10 times and the original prompts can be found at the OSF Project Files (https://osf.io/6apf9/overview?view_only=4081b6a194d342ac855a0463c2e87013). For each condition, we then used ChatGPT to create an average (or representative) recommendation by synthesizing the responses by feeding it all 10 AI supports and asking it to create a summary support. This was repeated for all three conditions.

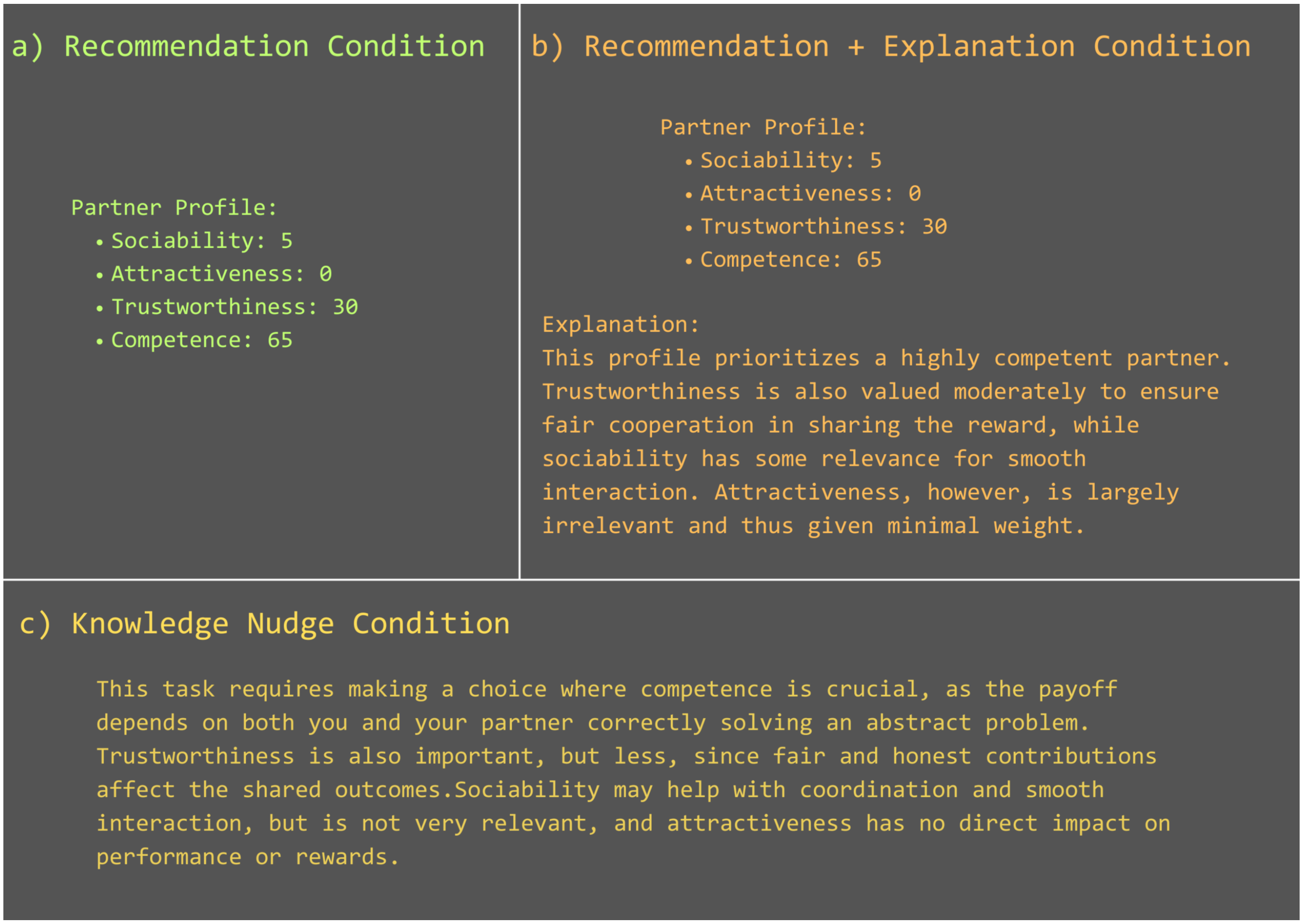
Each form of AI support was presented to participants with a five-second delay, intended to simulate the system's processing time and to signal that the AI model was generating a response. This short pause helped create a more realistic interaction experience, reflecting the brief latency users typically encounter when interacting with AI systems. After this delay, the AI's response was displayed in the form of an animated AI support in .gif version, to simulate the dynamic generation of the texts for AI support presented to users (e.g., ChatGPT-like systems). Using a dynamic presentation rather than static text helped reinforce participants' perception that the AI was actively composing its output.

5 Results

All parts of the data analysis were done in Python (version 3.9.18) and R Studio (version 4.3.2).

5.1 Manipulation Checks

To examine whether there were pre-existing differences between the three experimental conditions on our control variables, we conducted two separate one-way ANOVAs. Specifically, we tested whether participants differed in their attitudes towards AI and in their disposition to take advice across the three main conditions. This step is important because identifying group differences on control variables ensures that any observed effects in the main analyses can be attributed to the experimental manipulation rather than to pre-existing differences among participants. The results show that there were no significant differences between conditions in their attitudes towards AI ($F(2, 394) = 0.10$, $p = .903$. Similarly,



a) Recommendation Condition

Partner Profile:
- Sociability: 5
- Attractiveness: 0
- Trustworthiness: 30
- Competence: 65

b) Recommendation + Explanation Condition

Partner Profile:
- Sociability: 5
- Attractiveness: 0
- Trustworthiness: 30
- Competence: 65

Explanation:
This profile prioritizes a highly competent partner. Trustworthiness is also valued moderately to ensure fair cooperation in sharing the reward, while sociability has some relevance for smooth interaction. Attractiveness, however, is largely irrelevant and thus given minimal weight.

c) Knowledge Nudge Condition

This task requires making a choice where competence is crucial, as the payoff depends on both you and your partner correctly solving an abstract problem. Trustworthiness is also important, but less, since fair and honest contributions affect the shared outcomes.Sociability may help with coordination and smooth interaction, but is not very relevant, and attractiveness has no direct impact on performance or rewards.

Figure 3: The figure represents three kinds of AI support that were randomized as between-subject experimental conditions: a) recommendation of the partner profile (RECOMMENDATION); b) recommendation and explanation of the partner profile (EXPLANATION), and c) presents the knowledge nudge that individuals were presented (KNOWLEDGE NUDGE). Participants were assigned to one of three experimental conditions: 133 **in the recommendation condition,** 135 **in the recommendation with explanation condition, and** 129 **in the knowledge nudge condition.**

there was no significant difference in their disposition to take advice between conditions ($F(2, 394) = 0.66$, $p = .519$).

We also checked if participants correctly perceived which traits were most important for each of the tasks. For the Joint Trust Task, the majority of participants (78.37%) correctly reported that trustworthiness is the most important trait, while the rest of the participants said that competence is more important. Similarly, for the Joint Competence Task, the majority of participants (63.48%) correctly reported that competence is the most important trait, while the rest of the participants said that trustworthiness is the most important. These results suggest that participants generally understood and distinguished the differing emphases of the two tasks, although the distinction was somewhat clearer in the trust-focused condition than in the competence-focused one.

5.2 Proportion of Reliance on AI support

Across conditions with different types of AI support, the majority of participants did not rely on the AI support, and this pattern was consistent across both tasks (55.81%–72.93%; see Table 1). Only a small proportion of individuals fully relied on AI support, particularly in the RECOMMENDATION and EXPLANATION conditions. In the KNOWLEDGE NUDGE condition, there were no cases of full reliance, which aligns with expectations since this condition did not include numerical values, making it difficult for participants to identify the correct ones (see Table 1).

Given the low number of cases showing full reliance and the absence of any instances where no learning occurred, we decided to dichotomize the reliance variable. Specifically, we combined cases of full reliance and partial reliance into a single reliance category and excluded the no learning category, as it was not represented in our dataset. We believe this approach is justified as the threshold

	Joint Trust Task		
	Recommendation (n = 133)	Explanation (n = 135)	Knowledge Nudge (n = 129)
Full Reliance (value = 1)	7.52	12.59	0.00
Partial Reliance (cos.sim >. 978)	21.05	17.78	32.33
No Reliance	71.43	69.63	64.66
Nothing to learn	0	0.00	0.00
	Joint Competence Task		
Full Reliance (value = 1)	3.01	3.70	0.00
Partial Reliance (cos.sim >. 978)	24.06	29.63	44.19
No Reliance	72.93	66.67	55.81
Nothing to learn	0.00	0.00	0.00

Table 1: Participant reliance proportions across three different AI support conditions and two task types

was selected to still capture a substantial, but indeed partial reliance on AI advice. Thus, the following analyses rely on the measure of reliance as a dichotomized variable, where 0 indicates no reliance and 1 indicates reliance.

5.3 Confirmatory Factor Analysis

Before testing the main hypotheses, we validated the measurement model by assessing how well the observed measures (i.e., items) loaded on and measured the latent constructs, including trust, perceptions of AI's social and intellectual capabilities, and the sense of autonomy. To test this, a confirmatory factor analysis (CFA) was conducted first. The measurement model included four latent variables, which were defined by their respective items (see Appendix, Table 3).

Results indicated that all items loaded strongly on their intended latent constructs, with standardized factor loadings ranging from .72 to .92. However, three items exhibited weaker loadings (between .58 and .65) and indicated problematic cross-loadings on unintended factors (see Appendix, Table 3). Consequently, these items were excluded from subsequent analyses to enhance the reliability and discriminant validity of the measurement model. Additionally, the CFA revealed exceptionally high correlations between two latent variables, Trust in specific AI and Perceptions of AI's intelligence, with correlation coefficients of $r_{JCT} = .94$ and $r_{JTT} = .92$, respectively (see Appendix, Table 4 for remaining correlations). Such strong associations suggested poor discriminative validity between trust and perception of AI's intelligence. Therefore, to mitigate this risk and preserve the conceptual clarity of the model, Trust in specific AI was removed from further analyses. This decision was theoretically grounded, as measures of reliance were already incorporated into the model and conceptually overlapped with Trust in specific AI, capturing similar evaluative dimensions of participants' attitudes toward AI systems.

5.4 Main Results

To test our main hypotheses, following Knijnenburg and colleagues [28], we employed Structural Equation Modeling (SEM), which allowed for the simultaneous examination of multiple relationships among observed and latent variables. SEM is particularly suited for evaluating complex theoretical models and for assessing both direct and indirect effects.

5.4.1 *Direct Effect of the Type of AI Support on User Reliance.*

To examine whether the type of AI support had a direct effect on User Reliance, we ran two separate SEM models, each including only these two variables. A model was run for each task. Contrary to our first hypothesis (H1), in the Joint Trust Task, the type of AI support did not significantly influence reliance ($\beta = .06, z = 0.83, p = .404$), suggesting that variations in AI support type did not meaningfully alter users' reliance when selecting a partner for the trustworthiness-based task.

In contrast, in the Joint Competence Task, the type of AI support had a significant positive effect on reliance ($\beta = .19, z = 2.91, p = .004$), providing support for our first hypothesis (H1). This indicates that users were more likely to rely on AI systems that provided certain types of support when selecting a partner for competence-focused tasks, highlighting the contextual sensitivity of reliance in human-AI interactions.

5.4.2 *Type of AI Support, Perceptions of AI's Capabilities, Users' Sense of Autonomy, and Reliance.*

Next, to examine the effects of the type of AI support on users' perceptions of AI's capabilities and sense of autonomy, their subsequent effects on reliance, as well as the mediating effect of users' perceptions, we ran the hypothesized research model shown in Fig. 4, excluding Trust in Specific AI.

Model fit. Models for both tasks demonstrated a poor fit to the observed data (Joint Trust Task: $\chi^2(23) = 257.08$, $p < 0.001$, CFI = 0.79, TLI = 0.77, RMSEA = 0.11, SRMR = 0.12; Joint Competence Task ($\chi^2(23) = 296.44$, p < 0.000, CFI = 0.75, TLI = 0.71, RMSEA = 0.11, SRMR = 0.02) [1]. However, one reason for this was that sense of autonomy was not significantly affected by the type of AI support ($\beta_{JTT} = .06, z = 1.20, p = .229$; $\beta_{JCT} = .05, z = 0.95, p = .345$). Although not affected by the type of AI support, the sense of autonomy was positively related to reliance on AI support in the Joint Competence Task ($\beta = .19, z = 2.82, p = .005$), but not in the Joint Trust Task ($\beta = .07, z = 1.02, p = .306$). Nevertheless, to try and improve the fit of the model, we decided to remove the

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[1] All performance metrics reported are scaled and robust to deviations from model assumptions.

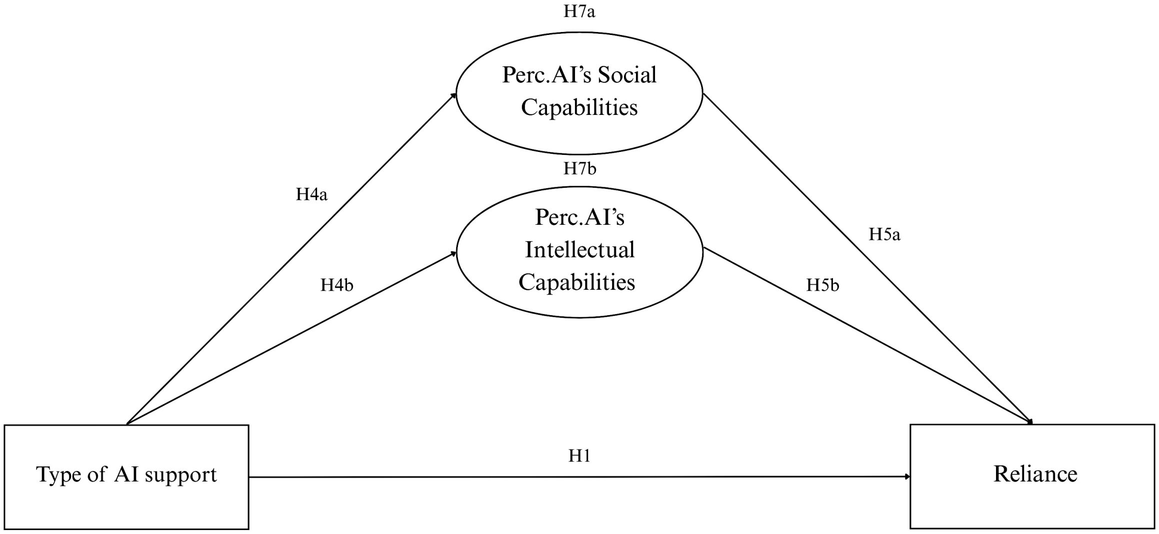

Figure 4: Represents the final model, after removing the items measuring Trust in the Specific AI and Sense of Autonomy. The final model resulted in a good fit and was used to test the remaining hypotheses.

items measuring sense of autonomy. This contributed significantly towards improving the model fit, as both models demonstrated a good fit (the Joint Trust Task ($\chi^2(23) = 49.36, p = 0.001$, CFI = 0.97, TLI = 0.97, RMSEA = 0.05, SRMR = 0.03); the Joint Competence Task ($\chi^2(23) = 38.44$, p = 0.023, CFI = 0.98, TLI = 0.97, RMSEA = 0.04, SRMR = 0.02).

Effect of Type of AI Support on Perceptions of AI's capabilities. The results of the final model (see Fig. 4) indicated that the type of AI support had a significant effect on perceptions of AI's social capabilities in both tasks ($\beta_{JTT} = .20, z = 3.93, p < .001$; $\beta_{JCT} = .22, z = 5.63, p < .001$). More specifically, higher perceptions of AI's social capabilities were reported in conditions where AI recommendation was followed by explanation ($M_{overall} = 4.92, SD_{overall} = 1.06$) and with the knowledge-nudge ($M_{overall} = 5.00, SD_{overall} = 1.22$), compared to only presenting AI recommendations ($M_{overall} = 4.38, SD_{overall} = 1.22$)(see Appendix, Table 2). Similar effects were found for perceptions of AI's intellectual capabilities ($\beta_{JTT} = .25, z = 4.94, p_{JTT} < .001$; $\beta_{JCT} = .28, z = 5.63, p < .001$). More specifically, higher perceptions of AI's intellectual capabilities were reported in conditions where AI recommendation was followed by explanation ($M_{overall} = 5.61, SD_{overall} = 1.04$) and with the knowledge-nudge ($M_{overall} = 5.84, SD_{overall} = 0.94$), compared to only presenting AI recommendations ($M_{overall} = 5.19, SD_{overall} = 1.04$). Both of these findings are in line with our hypotheses H4a and H4b.

Effect of Perceptions of AI's Capabilities on Reliance. As predicted, in both tasks, participants who perceived the AI agent as more intelligently capable were significantly more likely to rely on the AI support ($\beta_{JTT} = .25, z = 4.94, p < .001$; $\beta_{JCT} = .42, z = 4.05, p < .001$), supporting H5b. This finding confirms that users' reliance is strongly guided by perceptions of AI's intellectual capabilities. However, contrary to expectations, participants who perceived the AI agent as more socially capable were less likely to rely on the AI support ($\beta_{JTT} = -.35, z = -3.20, p < .001$; $\beta_{JCT} = -.17, z = -1.62, p = .104$), going against our hypothesis H5a. Although this negative trend appeared in both tasks, it reached statistical significance only in the Joint Trust Task. This suggests that when selecting a partner for a task, perceiving an AI as socially adept may paradoxically reduce reliance, potentially because users may interpret social competence as a signal of anthropomorphism. In contrast, in a competence-focused task, social capability seems less relevant to reliance decisions, consistent with the nonsignificant effect in the Joint Competence Task.

Mediating Effect of Perceptions of AI's capabilities. Finally, perceptions of AI's intelligent capabilities mediated the relationship between the type of AI support and reliance in both tasks. We found significant indirect effects of the AI support on reliance via perceptions of intelligent capabilities for both the Joint Trust Task (JTT) and Joint Competence Task (JCT) ($\beta_{JTT} = .11, z = 2.78, p = .005$; $\beta_{JCT} = .11, z = 3.37, p = .001$). In other words, perceiving the AI as being more intelligent helped explain why certain types of AI support increased users' reliance in both the Joint Trust Task and the Joint Competence Task, highlighting an important role of perceiving AI as intellectually capable in driving reliance. In contrast, the mediating effect of perceptions of AI's social capabilities was observed only in the Joint Trust Task ($\beta_{JTT} = -.07, z_{JTT} = -2.50, p_{JTT} = .012$), and not in the Joint Competence Task ($\beta_{JCT} = -.04, z_{JCT} = -1.53, p_{JCT} = .125$). This suggests that perceiving the AI as socially capable can actually reduce reliance on trust in trust-focused contexts. In the Joint Competence Task, however, social perceptions appear largely irrelevant to reliance. Overall, these findings indicate that in the Joint Trust Task, AI support influences reliance primarily through users' perceptions of intelligence, with the opposing effect of perceived social capability potentially offsetting any direct impact, leading to a cancellation effect of the two indirect effects. This cancellation effect also explains the lack of direct effect between the type of AI support and reliance in the Joint Trust Task. These findings go in line with the hypothesis H7b and against our hypothesis H7a.

6 Discussion

The present study investigated how different forms of AI support, which varied in the amount of information disclosed, including simple recommendations, explanations, and knowledge nudges, shape users' perceptions of AI capability, their sense of autonomy, and ultimately, their reliance on AI in a partner-selection context. This was examined across two experimental contexts: the Joint Trust Task (emphasizing trustworthiness) and the Joint Competence Task (emphasizing competence).

Overall, we found that the type of AI support directly affected how likely people were to rely on AI support in the Joint Competence task, but this was not the case in the Joint Trust Task. This is partially in line with prior literature [25, 34, 35, 62, 64, 65] demonstrating the positive effect of explanations on reliance on AI support. Additionally, the type of AI support strongly influenced perceptions of the AI's social and intellectual capabilities, but not users' sense of autonomy. Specifically, AI support that included either explanations or knowledge-nudges led participants to perceive the AI as more socially and intellectually capable than simple recommendations. This pattern held across both tasks, supporting the hypothesis that richer forms of AI support enhance perceived AI capabilities, both social and intellectual. These findings align with limited prior literature, which shows that providing explanations in human–human interactions increases the perceived reliability of the source [61], but also with literature showing that a specific type of explanations can lead users to perceive AI systems as more intelligent [25]. Contrary to expectations and previous research [31, 35, 65, 71], the type of AI support did not significantly affect participants' sense of autonomy. One possible explanation for this observation may lie in the experimental design. More specifically, descriptive statistics showed that in all conditions, on average, participants reported having a relatively moderate sense of autonomy (see Table 2 in the Appendix for values of reported sense of autonomy across conditions). This can be explained by the fact that all conditions had a sequential decision-making process and participants had the freedom to choose whether or not to rely on the AI, which may have contributed to their perception of their own autonomy in the decision and thereby reducing the between-condition differences. To address this, future research should incorporate more nuanced measures of autonomy, such as epistemic autonomy or agency, that is, individuals' capacity to independently acquire, evaluate, use, or transform knowledge [45]. Indeed, epistemic autonomy may be a more sensitive measure to capture the subtle differences of the sense of empowerment and thus autonomy that different AI support types could contribute to, given the increase of information provided to participants.

Similarly, in line with our assumptions, the perceptions of AI's intellectual capabilities had a positive effect on reliance. This effect was observed across both tasks. This indicated that individuals who perceived the AI agent to be more intelligent were more likely to rely on it. These findings are in line with prior literature, indicating that the perceptions people have of AI systems can influence their willingness and use of AI systems, including perceptions of usefulness and effort, and knowledgeability [10, 19, 57]. However, still more literature is needed to explore this relationship. This is an important endeavor, especially given the fact that people have a predominantly biased belief of AI systems as intelligent [53], which can potentially lead to overreliance if not accounted for in time.

Lastly, testing for the mediation effect of both perceptions of AI's social and intellectual capabilities, we found that reliance was shaped indirectly through participants' perceptions of the AI's capabilities. Specifically, perceptions of intellectual capability predicted greater reliance across both tasks. In contrast, perceiving the AI as more socially capable was associated with lower reliance, particularly in the trustworthiness-focused task. This pattern suggests that while design features like explanations and nudges successfully increased perceptions of the AI's social capabilities, these attributions did not translate into greater reliance. One possible explanation is that when AI systems are perceived as too socially capable, users may see them as similar to human judgment, thereby reducing their willingness to defer to AI advice. This interpretation aligns with recent research indicating that excessive anthropomorphism can trigger user resistance [44, 47, 52].

Furthermore, the positive mediation of AI intelligence perceptions across both tasks highlights that reliance is driven less by the social qualities of AI and more by users' perception of AI's general competence and knowledgeability. In other words, when users perceive an AI as intellectually capable, they are more likely to follow its recommendations, regardless of the type of task. Conversely, perceiving the AI as socially competent may blur the human–machine boundary, prompt skepticism, and as a result decrease people's willingness to rely on the AI's recommendation.

6.1 Theoretical and Practical Implications

This study advances the literature on AI reliance by exploring when and why people are willing to depend on AI in relational decision-making, such as selecting a collaboration partner. Prior research (e.g., [10]) suggests that people are reluctant to rely on AI for social judgments because they perceive AI as lacking social understanding. Our findings challenge this view, showing that under certain circumstances, perceiving an AI as socially competent may actually reduce reliance. In contrast, perceptions of intellectual capabilities consistently predicted greater reliance. This highlights that users' belief in the AI's intelligence and knowledge, rather than its social awareness, is the primary driver of reliance. Together, these findings extend theories of AI reliance in relational contexts and offer new insights into how perceptions of different AI capabilities interact.

From a design perspective, incorporating explanations and nudges effectively enhanced perceptions of the AI's intelligence and social capabilities. However, while perceived intellectual competence promoted reliance, perceived social capabilities had the opposite effect. This suggests that emphasizing social capability in AI design may have unintended consequences. Designers should therefore consider carefully balancing the promotion of social traits with the need to maintain user trust and deference to AI expertise. Nevertheless, more research is needed to understand these mechanisms in more detail, especially in the context of tasks where relational decisions need to be made.

6.2 Limitations and Future Research

This study is among the first to empirically compare recommendations, explanations, and knowledge nudges while examining both direct and indirect effects of AI support on perceptions of AI capabilities, users' sense of control, and reliance. Nevertheless, several limitations warrant consideration. First, the study focused on a UK-based sample, representing a predominantly Western cultural context. Future research should aim to replicate these findings in more diverse, cross-cultural samples to assess their generalizability. Second, although the study aimed to measure participants' sense of autonomy in decision-making, all participants retained significant autonomy, as they could freely accept or reject the AI's advice. This may have masked the potential effects of the AI support type. Future research could therefore incorporate alternative constructs, such as epistemic agency [45], to provide a more refined understanding of how AI systems influence users' perceived control and decision-making freedom. Thirdly, the proportion of participants who chose to rely on AI support compared to those who did not was imbalanced, as the majority preferred not to rely on it. However, this limitation is difficult to avoid, as it depends on participants' individual willingness to rely on AI. Despite these limitations, the present study provides a valuable basis for future investigations into how different forms of AI support shape perceptions, autonomy, and reliance, particularly in relational decision contexts.

7 Conclusion

Whether choosing teammates for a project or partners for everyday tasks, people constantly decide whom to work with, choices that are central to both personal and organizational outcomes but often shaped by cognitive and social biases [14]. As artificial intelligence (AI) becomes increasingly integrated into decision-making, it offers new opportunities to mitigate such biases. Yet, it remains unclear when people are willing to rely on AI when making a relational decision. To contribute to addressing this gap, the current study examined how different forms of AI support influence users' perceptions of AI's social and intellectual capabilities, sense of control, and reliance. Results show that richer AI support (through explanations or nudges) enhances perceived AI's social and intellectual capabilities, but not autonomy. Only perceptions of intellectual capability, not social capability, predict greater reliance. Overall, the study advances understanding of human–AI collaboration by revealing how AI design features shape user perceptions and reliance when users need to evaluate and select their collaborators. However, given the scarcity of literature on this topic, more research is needed to understand the complexities behind people's reliance on AI for relational decision-making.

Acknowledgments

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Usage of Generative AI Statement

The authors used Grammarly and Writefully to enhance grammar and sentence clarity. Additionally, Generative AI was employed to refine, rewrite, or perform grammatical checks on the authors' original text, as well as to assist with debugging. All uses were based on the authors' original code and text.

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Appendix

A Descriptive Statistics

	Sense of Autonomy		**Perceived AI's Social Capabilities**		**Perceived AI's Intellectual Capabilities**		**Trust in Specific AI**	
				Overall				
Conditions	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
Recommendation	5.36	1.06	4.38	1.12	5.19	1.04	4.81	1.11
Explanation	5.45	1.18	4.92	1.06	5.61	0.91	5.23	1.06
Knowledge Nudge	5.57	1.19	5.00	1.22	5.84	0.94	5.68	0.95
				Joint Trust Task				
Recommendation	5.45	1.21	4.41	1.18	5.25	1.07	4.88	1.16
Explanation	5.59	1.24	4.84	1.09	5.63	0.94	5.25	1.10
Knowledge Nudge	5.69	1.19	4.99	1.28	5.81	1.00	5.65	1.02
				Joint Competence Task				
Recommendation	5.28	1.17	4.36	1.19	5.14	1.18	4.74	1.26
Explanation	5.31	1.27	5.01	1.14	5.59	1.03	5.21	1.18
Knowledge Nudge	5.44	1.32	5.01	1.22	5.87	0.97	5.72	0.98

Table 2: Overall and task-specific descriptive statistics across three different types of AI support

B Factor loadings per Item

Joint Trust Task		
Latent Variables	Items	Factor Loading
Sense of Autonomy	I felt like the AI agent pressured me to act in a certain way. R	.83
	I felt like the AI agent made me feel like I don't have a real choice. R	.90
	I felt like the AI restricted my freedom in decision-making. R	.88
	I felt like the AI allowed me to make my own decisions.	.65
Perception of AI's Social Capabilities	The AI agent comes across as socially competent.	.92
	The AI agent comes across as socially aware.	.91
	The AI agent comes across as socially clueless. R	.58
	The AI agent seems to demonstrate good social skills.	.86
Perception of AI's Intellectual Capabilities	The AI agent comes across as competent.	.95
	The AI agent comes across as knowledgeable.	.92
	The AI agent comes across as irresponsible. R	.65
	The AI agent comes across as sensible.	.86
	The AI agent comes across as unintelligent. R	.70
Trust in Specific AI	The AI agent gave good advice.	.88
	The AI agent acted truthfully.	.84
	I could rely on the AI agent.	.91
Joint Competence Task		
Latent Variables	Items	Factor Loading
Sense of Autonomy	I felt like the AI agent pressured me to act in a certain way. R	.83
	I felt like the AI agent made me feel like I don't have a real choice. R	.87
	I felt like the AI restricted my freedom in decision-making. R	.86
	I felt like the AI allowed me to make my own decisions.	.43
Perception of AI's Social Capabilities	The AI agent comes across as socially competent.	.90
	The AI agent comes across as socially aware.	.90
	The AI agent comes across as socially clueless. R	.71
	The AI agent seems to demonstrate good social skills.	.85
Perception of AI's Intellectual Capabilities	The AI agent comes across as competent.	.94
	The AI agent comes across as knowledgeable.	.93
	The AI agent comes across as irresponsible. R	.62
	The AI agent comes across as sensible.	.91
	The AI agent comes across as unintelligent. R	.79
Trust in Specific AI	The AI agent gave good advice.	.90
	The AI agent acted truthfully.	.86
	I could rely on the AI agent.	.91

Table 3: Factors per item. The items followed with the letter R present recoded items that were recoded before running the confirmatory factor analysis.

C Correlation between Latent Variables

Joint Trust Task				
	1	2	3	4
1. Sense of Autonomy	1.00			
2. Perception of AI’s Social Capabilities	.26***	1.00		
3. Perception of AI’s Intellectual Capabilities	.37***	.77***	1.00	
4. Trust in Specific AI	.43***	.75***	.94***	1.00
5. Reliance	.04	.03	.10*	.09
Joint Competence Task				
	1	2	3	4
1. Sense of Autonomy	1.00			
2. Perception of AI’s Social Capabilities	.22***	1.00		
3. Perception of AI’s Intellectual Capabilities	.33***	.75***	1.00	
4. Trust in Specific AI	.31***	.77***	.93***	1.00
5. Reliance	.07	.14**	.13**	.12**

Note: *** $p < .001$; ** $p < .01$; * $p < .05$

Table 4: Correlation coefficients between Latent Variables and Observable Variables (i.e., Reliance)