Investigating the relationship between AI and trust in human-AI collaboration

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Abstract

With the increasing development of information technology, the implementation of artificial intelligence (AI) has been widespread and has empowered virtual team collaboration by increasing collaboration efficiency and achieving superior collaboration results in recent years. Trust in the process of human-AI interaction has been identified as a challenge for team collaboration in this context. However, little research has investigated the relationship between human-AI interaction and trust. This study proposes a theoretical model of the relationship between human-AI interaction and team members' trust during collaboration processes. We conclude that team members' cognitive and emotional perceptions during the interaction process are associated with their trust towards AI. Moreover, the relationship could also be moderated by the specific AI implementation traits. Our model provides a holistic view of human-AI interaction and its association with team members' trust in the context of team collaboration.

1. Introduction

The increasing use of advanced information and communication technology (ICT), such as Artificial Intelligence (AI) and big data, has empowered online team collaboration in business. For example, companies such as IBM, e-Bay, and Microsoft organize their many meetings and seminars online, instead of holding traditional face-to-face meetings [1]. In such meetings, according to Bader et al. [2], knowledge-based systems can take on the role of assistant, critic, second opinion, expert consultant, tutor, and automated decision-maker [2]. In the context of team collaboration, the role of AI can also transform from tool to partner [3]: For example, instead of facilitating the collaboration process, AI can also participate in decision making and interact with humans during the collaboration process. This new trend has attracted lots of attention and controversy [4]. On the one hand, AI can provide deeper insights during collaboration process and increase team members' trust and reliance [3]. On the other hand, the trust relationship between human and AI is volatile. For example, in a survey of US consumers' perception of AI services (e.g., investment advice, medical diagnosis, home services), 41.5% of participants said they did not trust the services provided by AI, while only 9% of the participants said they trusted the financial services provided by AI, and only 4% trusted the employee hiring based on AI [5]. In addition to the role of AI, other AI implementation traits such as the task-AI fit can also impact team collaboration and trust [6]. AI should fit individuals' preference or collaboration task in the team. As a result, there is a need for a deeper understanding of the antecedents of trust during the human-AI interaction and deriving guidelines for the development and deployment of AI in such a way to facilitate the development of trust.

Existing studies have dealt with several antecedents of trust in traditional research settings, including in the social commerce, team collaboration, and e-government [5][6][7][8]. In addition, trust has also been investigated with respect to several objects of trust, such as trust towards technology [11], team [12], and team leader [13]. Although trust has been shown to be an important issue in the human-AI interaction context, the systematic understanding of trust during human-AI interaction, especially in the team collaboration context, is still limited. In addition, unlike the trust relationship in the traditional team collaboration context, trust in the human-AI interaction context is a broader phenomenon: it involves not only interpersonal trust but also trust in the AI technology. We refer to a person's trust in AI technology as "AI trust". Therefore, we tend to provide a holistic view and a deeper understanding of team members' trust in human-AI collaboration. To this end, we pursue the following research questions in this study:

Research question 1 (RQ1): What are the antecedents of team members' AI trust in the context of human-AI collaboration?

Research question 2 (RQ2): How does specific AI implementation traits associate with the relationship between user perception and AI trust?

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To answer the above research questions, we first report on a systematic literature review of trust and human-AI interaction research, especially in the team collaboration context. Then we develop a theoretical model of trust in a human-AI collaboration context, where humans communicate or collaborate with a machine teammate.

The remainder of this paper is structured as follows. First, we introduce the research background and literature review on trust, human-AI interaction, and impact of IT adoption. Next, we present the research model and hypotheses. Finally, we conclude with a summary of this research and describe future research.

2. Literature review

Trust has been shown to be an important element in the building rapport among people [14]. However, relatively little is known about trust issues related to the adoption of AI in team collaboration. Therefore, we present relevant literature on IT adoption in team collaboration, trust, and human-AI interaction in this section.

2.1. Human-AI interaction

AI has become a key target of technological innovation in business practice [2][13]. AI can be generally defined as "intelligent systems with the ability to think and learn" [16]. In recent years, AI has been implemented widely into various domains and industries, such as mental health care [17], elementary school education [18], workplace [19], and service marketing [20]. The rise of digital innovation has led scholars to increasingly investigate issues regarding human-AI interaction. Studies on human-AI interaction primarily focused on addressing the following basic questions:

- How does the nature of the machine associate with the process of human-AI interaction?
- How does the nature of the human associate with the process of human-AI interaction?

Regarding the above research questions, scholars have conducted studies on human-AI interaction from several facets. From the perspective of the nature of the machine characteristics in human-AI interaction, existing studies investigated the role of humanoid robots' lateral head tilt [21] and gaze turn-taking cues [20] on user perception. Findings indicate that the magnitude of robots' heads tilted and gaze-turn taking cues have significant effects on humans' perception during the interaction. Moreover, existing studies have also adopted the uncanny valley theory [22] to investigate the impact of machine-human similarity on their perception of human-AI interaction. The uncanny valley theory refers to the phenomenon that robots with extremely high human-like looks may lead to users' negative perception during the interaction, even with the feeling of eeriness [21]. Specifically, enriched animated elements of the robots will enhance the negative effect and uncanny valley effect of users [23].

From the perspective of human nature, scholars have investigated the effect of personality traits on human-AI interaction [28][29]. For example, age, gender, personality, cultural background, experience with technology, self-efficacy, subjective norm, and user anxiety have been investigated as important antecedents of user perception [16][26][30]. To be more specific, the perception of people in the interaction process can relate to the interaction comfort [28], discomfort [29], perceived enjoyment [18], perceived trust [14], social presence [27], usefulness and ease of use [18]. For example, studies have indicated that humanoid robots cause greater consumer discomfort, which in turn promotes their compensatory consumption behavior (i.e. consumption to reduce perceived self-threat, for example threats to one's social standing resulting in increased willingness to spend on status-signaling products) [28]. Also, a high level of interaction comfort was shown to be associated with higher users' trust [20]. Table 1 presents a summary of the human-AI interaction literature in recent years.

Table 1. Summary of the human-AI interaction literature

References	Research context	User perception	Interaction outcomes	Findings
[26]	Automated decision making based on AI	Privacy concerns, self-efficacy, age, gender, decision-making type, AI role, knowledge level	Perceived justice, perceived usefulness, perceived risk	Knowledge level of AI users has a significant positive effect on their perceived AI usefulness. Self-efficacy positively affects perceived fairness, perceived usefulness and negatively affects perceived risk. Age has a negative impact on users'

				perceived fairness and usefulness. Females see the AI as less useful that males.
[29]	Algorithmic recommendation decision	Task objectivity, trust, algorithm’s affective human likeness, discomfort, effectiveness	Reliance on algorithm	Trust in algorithm is negatively related to the subjectivity of the task. The negative effect will be eliminated when the level of algorithms' affective human-likeness is high. Effectiveness of the algorithm plays a more important role than perceived discomfort in determining users’ reliance on algorithm.
[23]	Human-chatbot interaction	Electromyography, respirometer, electrocardiograph, and electrodermal activity	Attitude towards collaborate with chatbot	Comparing with a more complex chatbot, humans experience fewer fear effects and fewer negative effects when interacting with a simpler text bot. Simple chatbots elicit relatively few psychophysiological responses.
[17]	Human-robot interactions in mental health care	Interact with robot	Affective states, physiological arousal, cognitive performances and workload	There is no difference in humans’ emotional processes between human-human interaction and human-robot interaction. From the perspective of non-verbal behavior, users spent more time eye-contacting with the robot than human examiner.
[18]	Humanoid robot in preschool and elementary school	Anxiety, attitude, perceived sociability, enjoyment, adaptability	Intention to use	Anxiety and perceived adaptability positively impact users’ perceived usefulness, and thus, increase users’ intention to use the humanoid robot.
[27]	Acceptance of assistive social agents by the elderly user	Perceived adaptability, anxiety, social presence, perceived sociability, ease of use, usefulness, enjoyment, trust	Intention to use	Perceived anxiety and adaptability will increase perceived usefulness. Perceived sociability increases users’ perceived enjoyment. Users’ attitude toward the technology and perceived usefulness will increase their intention to use the technology.
[30]	Human-automation interaction	Age, personality traits, gender, culture, previous experience	Trust towards automation	Provides a systematical lens of human-automation trust (learned trust, dispositional trust and situational trust).
[19]	Human-AI symbiosis in decision making	Uncertainty, complexity, and equivocality of the task	Intelligence augmentation	AI has stronger computational information processing capacity and analytical methods, which can extend human cognition when dealing with complex problems, while humans can still provide more comprehensive and intuitive methods when dealing

				with uncertain and ambiguous decisions.
[28]	Humanoid robots in service experiences	Consumer discomfort	Compensatory purchase behavior	Humanoid robots cause greater consumer discomfort, which in turn promotes their compensatory consumption behavior.
[21]	Human responses to android and humanoid robots	Lateral head tilt	Perceived warmth, eeriness, attractiveness, and dominance	Robots with tilted heads scored higher on users' perceived similarity, likability, and excitement than those with upright heads.
[31]	Interaction with social robots in the workplace	Negative and positive anticipated emotions, perceived behavioral control, subjective norm, competence	Intention to work with social robots	Perceived warmth of robots will increase users' attitude, positive emotions, perceived behavior control, subjective norm and decrease users' negative emotions. Moreover, subjective norm, positive and negative emotions will significantly impact the behavior desire and intention to work with the robot.
[14]	Interaction with collaborative Robot in the workplace	Perception of interaction	Rapport building hindering bahavior	Individuals have a positive attitude toward building close relationships with their robot teammates, such as thanking and praising the robot.
[32]	Interaction with service-providing humanoid robots	Automated social presence, perceptions of psychological ownership	Service and customer outcomes	Social cognition and psychological contract act as mediators of the relationship between human social presence and service and cutomer outcomes.
[20]	Humanoid robots in services marketing	Consumers' perceived anthropomorphism, comfort	Trust, enjoyment, intention to use	Perceived interaction comfort moderates the relationship between gaze-turn taking cues and anthropomorphism, and thus, leads to higher level of trust, enjoyment and intention to use.
[33]	Interaction with service robots	Perceived ease of use, usefulness, suejective social norm, interactivity, social presence, trust, rapport	Acceptancce and actual use of service robots	This paper provides the definition of a service robot, describes its key attributes, and compares it with the services of front-line employees. It concludes that robots and humans are suitable for leading tasks respectively. Secondly, it investigates consumers' cognitive beliefs and behaviors towards service robots, and proposes a service robot acceptance model.

2.2. IT implementation traits in team collaboration

In human-AI interaction, both humans' perception and AI implementation characteristics play an important role in the interaction results. Previous studies have investigated the impact of IT implementation on team performance or team collaboration. Existing studies have investigated several factors that affect team members' perceptions of IT artifacts. For example, perceived interaction comfort with a robot was found to moderate the relationship between robots' gaze turn-taking cues and humans' perceived anthropomorphism [20]. Computer playfulness can predict users' acceptance of technology [34]. Perceived flexibility of the IT infrastructure was found to have an indirect effect on performance in the context of mergers and acquisitions [35]. Additionally, task-technology fit has also been shown to be an important trait of IT implementation. Liu et al. [36] argued that the IT elements should fit the individuals, tasks and even desired user-system interactions [36]. In this study, we mainly focus on two types of AI implementation characteristics in the team collaboration context: task-AI fit and the role of AI.

As mentioned earlier, knowledge-based systems can act as the role of assistant, critic, second opinion, expert consultant, tutor, and automated decision-maker [2]. Therefore, the role that AI plays in team collaboration can also impact users' perception of the human-AI interaction process [26]. And in the AI-facilitated team collaboration context, the role of AI can also be an important element in determining the team members' perceptions. For example, team members' perceptions will differ when AI acts as a facilitator, team leader, or team member in the collaboration [3]. In our research, we mainly focus on the following two roles of AI in the team collaboration: facilitator and team member.

From the perspective of task-AI fit, we synthesized previous studies on systems design in team collaboration and technology fit into a task-AI fit framework in this research context [42][43]. Existing studies provide an extension of system design in the team collaboration context. In the traditional team collaboration context, scholars have been developing and applying the approach to assist group collaboration [39]. For example, the collaboration engineering (CE) approach has been used to package technology and usage documentation to design a collaborative process [40]. In the human-AI team collaboration context, additional requirements have to be taken into consideration when using the CE approach to design effective team collaboration. For example, the selected AI to serve as a facilitator should fit the collaboration tasks while the AI acting as a team member should be fit the humans' individual preferences [3].

2.3. Trust in human-AI interaction

Among the various antecedents of effective human-AI interaction, the trust relationship between human and machine has been found to be an important issue and received much attention. According to technology transition model (TTM), the team chooses to embrace or abandon collaboration technology due to their perceived frequency of the net value, magnitude of net value and perceived value of technology transition [41][42][43]. As such, trust can be regarded as an important instantiation of the magnitude of value in the TTM. A low level of trust will reduce users' perceived magnitude of value, as thus, leading the possibility to technology abandonment. Therefore, trust in the human-AI interaction is also essential in this research context.

Trust has also been investigated in many other research contexts. In the context of service marketing, trust has been identified as an important antecedent of consumers' use behavior [33]. In the context of assistive social agent technology, Heerink et al. [27] investigated the relationship between older adults' trust and their acceptance of assistant technology [27]. Results indicate that a high level of trust will lead to users' acceptance intention and behavior. In the team collaboration context, team trust can, for example, increase team effectiveness [44], emergent use intention [45]. The influence of trust/distrust has also been evaluated from a longitudinal perspective [8]. Findings indicate that trust varies from the initial collaboration stage to the final stage. Seeber et al. [3] has also considered trust and argued that the objects of trust in this context can include machine teammates, intelligence algorithms and their recommendations [3]. In this research, we mainly focus on humans' trust with AI as different roles.

Regarding the antecedents of trust, existing research on the antecedents of trust can be divided into two perspectives: cognitive perspective and emotional perspective [51] [52]. Specifically, cognition-based antecedents mainly refer to computational or rational characteristics, including factors related to the trustworthiness of individuals' perception of others/organizations. Emotion-based antecedents are mainly based on the interaction between individuals and mutual social relationships [12]. In order to have a deeper understanding of the trust antecedents between human-AI interaction, we will also focus on humans' perception from the above two perspectives.

3. Research model and hypotheses

According to the literature review of trust, human-AI interaction and IT implementation traits, we propose the theoretical model in Figure 1. Specifically, the research model provides a holistic view of the effects of team members' perception of the human-AI interaction on their trust. According to McAllister (1995), we investigate the team members' perception in the team member-AI interaction from two perspectives: cognitive perspective and emotional perspective [46]. Previous research on TAM (Technology Acceptance Model) [48], TTM (Technology Transition Model) [41], and Roger's stage model of innovation [49] also summarized several cognitive and emotional dimensions that affect the effectiveness and adoption intention of IT [42]. Antecedents in this research model were derived from the existing studies on IT adoption, trust, and human-AI interaction. The moderating role of AI implementation traits is also considered in this research model.

From the cognitive perspective, computational or rational characteristics will affect individuals' cognitive-based trust. In the context of human-AI collaboration, interaction complexity and coordination costs are included in our theoretical model as cognitive foundations of trust in AI. Interaction complexity in this research refers to the degree to which the AI facilitator or team member is perceived to be difficult to interact with. Perceived high level of interaction complexity of the team members will lead to their doubt on the effectiveness of AI. On the other hand, no matter whether the AI acts as a facilitator or as a team member, coordination between team members and AI is inevitable. For instance, teams coordinate to process the timing of workflow [44]. As a result, the high level of interaction coordination cost will also decrease individuals' trust level. Thus, we propose the following hypotheses:

H1a: *Interaction complexity has a negative relationship with team members' trust towards AI.*

H1b: *Interaction coordination cost has a negative relationship with team members' trust towards AI.*

From the emotional perspective, emotional and psychological elements during the human-AI interaction process also play an essential role in determining humans' trust. In this research context, we focus on interaction comfort and interaction enjoyment of individuals as they relate to their trust in AI. Specifically, interaction comfort refers to an emotional state. When feeling discomfort during the interaction with AI, humans are expected to take uncertainty reduction strategies to increase AI's predictability [20]. We propose that perceived high comfort during the interaction process will decrease the uncertainty and increase team members' trust in AI. Yet, the implementation of AI in the team collaboration context can be regarded as a technology innovation. As is discussed by Hess et al [50], technology playfulness will affect users' social presence, as thus, increasing their trust in the recommendation agents. As a result, team members' perceived interaction enjoyment can also impact their trust in the AI. Therefore, the following hypotheses are proposed:

H2a: *Interaction comfort has a positive relationship with team members' trust towards AI.*

H2b: *Interaction enjoyment has a positive relationship with team members' trust towards AI.*

Specific traits of AI implementation are also thought to be important in the interaction process. Accordingly, we include two IT-specific traits in our theoretical model.

In the traditional team collaboration context, the team's task has been shown to account for large variation in the interaction [6]. Moreover, task-technology fit is also a principle for the effective technology implementation in collaboration settings [6]. Specifically, task-technology fit can be defined as the ideal alignment of tasks and technology. In the team collaboration context, team members are assigned in a group to address a task together with AI acting as a facilitator or team member. A high level of task-AI fit will enhance or release the effects of individuals' perception of their trust towards AI. For example, when experiencing high task/AI fit, individuals will be more tolerant of the interaction complexity, as thus, decreasing the negative correlations between the interaction complexity and trust. Thus, the following hypotheses are proposed:

H3a: *Task-AI fit negatively moderates the relationship between interaction complexity and trust towards AI.*

H3b: *Task-AI fit negatively moderates the relationship between interaction coordination cost and trust towards AI.*

H3c: *Task-AI fit positively moderates the relationship between interaction comfort and trust towards AI.*

H3d: *Task-AI fit positively moderates the relationship between interaction enjoyment and trust towards AI.*

In addition to task-AI fit, the role that AI plays in the team collaboration process is also expected to correlates with the relationship between team members' perception and trust. According to existing studies [2][3], we focus on the role of AI as a facilitator and team member in this research. For example, in the traditional team collaboration context, the facilitators were usually professional and hired internally or externally [42]. These professional facilitators are normally expected to be efficient and effective in the facilitation support. Therefore, when AI acts as a facilitator in the team collaboration, team members will put more emphasis on the effectiveness and coordination ability of the facilitator. As a result, we propose that team members' cognitive perception has a significant positive relationship with the role of the AI. Therefore, the effects of interaction complexity and coordination cost on trust will be different regarding the different roles of AI. Likewise, when the AI acts as a team member, the interaction between human and the AI "teammate" will be more frequent in the discussion or decision-making process. Therefore, team members will emphasize their emotional perception during the interaction process. Consequently, the effects of interaction comfort and enjoyment on trust will be associated with the different roles of AI. Therefore, the following hypotheses are proposed:

H4a: *The role of AI as a facilitator negatively moderates the relationship between interaction complexity and trust towards AI.*

H4b: *The role of AI as a facilitator negatively moderates the relationship between interaction coordination cost and trust towards AI.*

H4c: *The role of AI as a facilitator negatively moderates the relationship between interaction comfort and trust towards AI.*

H4d: *The role of AI as a facilitator negatively moderates the relationship between interaction enjoyment and trust towards AI.*

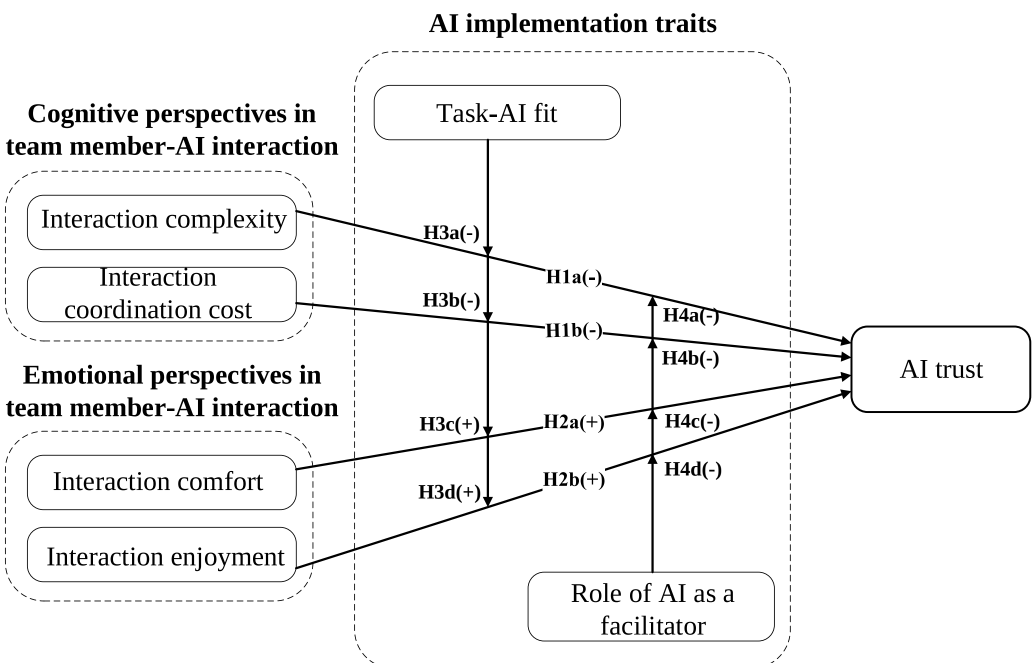

Figure 1. Research model

4. Conclusion and future research

4.1. Conclusion

Although the impact of IT implementation in different context has been investigated from several facets, the prevalence of human-AI interaction has presented new management and practical issues. The effects of AI implementation on trust has been shown to be essential in the human-AI interaction field, however, a systematic investigation into trust or collaboration performance-related issues is still limited. Inspired by studies on human-AI interaction and IT adoption, we notice the necessity and research gap in the relationship between human and AI in the collaboration context, especially considering the specific features of AI artifacts. For example, when adopting an AI program to recommend the team collaboration process automatically, cognitive and emotional perceptions of team members are expected to lead to a different evaluation of the AI artifacts, and thus, lead to diversity outcomes of collaboration performance and trust. Specifically, we conclude that the specific AI implementation traits in the team collaboration context may include the role of AI (facilitator or team member) and AI-task fit. Take the role of AI as an example, when AI plays the role as a team facilitator or team member in the collaboration, the relationship between the perceptions and AI evaluation will be different. The above discussion is also consistent with previous studies that argue that trust and the role of AI in team collaboration need to be addressed [3]. The above AI implementation traits may moderate the relationship between perceptions of human-AI interaction and team members' trust.

4.2. Future work

As this study presents a theoretical model, there are still limitations in the current version of this study. For example, the theoretical model and observed relationships between each construct are mainly based on the human-AI collaborations context in this study. New findings can be discovered in the future research under other conditions. Moreover, this research model only takes the moderating effects of AI implementation traits into consideration. In business practice and team collaboration, both team member personality traits and team traits will impact team members' perception during the human-AI interaction. By integrating insights from previous studies, more characteristics could be taken into consideration when designing AI systems to assist team collaboration in future practice and research. In future research, we will conduct a lab experiment and test the hypotheses proposed in this theoretical model empirically. Specifically, participants of the experiment will be randomly assigned to two groups, one with the AI acting as a facilitator, the other with the AI acting as a team member in the team collaboration. After completing the team collaboration process, participants will be asked to fill in a survey, involving their perceptions of the interaction with AI, trust towards AI, and trust towards the team. Results of the data analysis will provide empirical evidence of the theoretical model. Moreover, we also plan to collect interview data to supplement the results for further investigation. More antecedents and specific AI implementation traits need to be further investigated in the future research.

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