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Social perception in Human-AI teams: Warmth and competence predict receptivity to AI teammates

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ABSTRACT

Advances in artificial intelligence (AI) promise a future where teams consist of people and intelligent machines, such as robots or virtual agents. In order for human-AI teams (HATs) to succeed, human team members will need to be receptive to their new AI counterparts. In this study, we draw on a tripartite model of human newcomer receptivity, which includes three components: reflection, knowledge utilization, and psychological acceptance. We hypothesize that two aspects of social perception—warmth and competence—are critical predictors of human receptivity to a new AI teammate. Study 1 uses a video vignette design in which participants imagine adding one of eight AI teammates to a referent team. Study 2 leverages a Wizard of Oz methodology in laboratory teams. In addition to testing the effects of perceived warmth and competence on receptivity components, Study 2 also explores the influence of receptivity components on perceived HAT viability. Though both studies find that perceived warmth and competence affect receptivity, we find competence is particularly important for knowledge utilization and psychological acceptance. Further, results of Study 2 show that psychological acceptance is positively related to perceived HAT viability. Implications for future research on social perception of AI teammates are discussed.

1. Introduction

Artificially intelligent (AI) technologies will soon join teams as fully autonomous, interdependent *teammates* in a wide range of organizational contexts. New AI teammates offer extraordinary potential for financial, productivity, safety, and security benefits in a variety of industries, from hospital systems to airlines (Hosny et al., 2018; Semuels, 2021). These technologies represent the beginnings of a future wherein new technologies are *teammates*, rather than *tools* (O'Neill et al., 2020). AI teammates might include robots, virtual personal assistants, decision-making AI, online avatars, and other forms that we have not yet imagined. Importantly, AI teammates are autonomous technologies that go beyond mere support roles. AI teammates on human-AI teams (HATs) can make decisions and execute tasks autonomously from humans while also working interdependently with humans to accomplish overarching team goals more efficiently or effectively than human-only teams (Marble et al., 2004).

Although the benefits of HATs are pronounced, the addition of a new kind of teammate presents unique challenges that impact the overall success of the HAT. When teams bring on a new teammate, they typically encounter changes to team roles and responsibilities and are required to redevelop norms and processes to accommodate the new teammate (Levine & Moreland, 1994). The introduction of an AI teammate presents additional challenges because it is a particularly novel and disruptive team membership change event (Trainer et al., 2020). Team members may also encounter general anxiety toward the AI related to job security, surveillance, etc. (Anderson et al., 2018; Talamadupula et al., 2014; Yam et al., 2022).

Given the challenges inherent to introducing new AI teammates, it is imperative that researchers and practitioners develop strategies for facilitating human team members' receptivity to their new AI counterparts. Indeed, O'Neill et al. (2020) identify designing AI to facilitate

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HAT effectiveness as a critical area of future research. In the current paper, we argue that the universal dimensions of social *person-*-perception—warmth and competence (Fiske et al., 2007)—offer a particularly useful framework for understanding *AI teammate*-perception and predicting receptivity to AI teammates. As defined by Fiske and colleagues, competence encompasses "traits that are related to perceived ability, including intelligence, skill, creativity, and efficacy" while warmth encompasses "traits that are related to perceived intent, including friendliness, helpfulness, sincerity, trustworthiness, and morality" (2007, p. 77). We draw on a tripartite model of receptivity to human newcomers (Rink et al., 2013) to posit that warmth and competence perceptions are important predictors of the three distinct components of an individual's receptivity to an AI teammate: reflection, knowledge utilization, and psychological acceptance. In turn, because successful integration of newcomers can facilitate team processes and outcomes (Guimerà et al., 2005; McGrath et al., 2000; Rink et al., 2013), we argue that these receptivity components impact perceptions of HAT viability, an indicator of long-term team success. That is, to ensure receptivity to synthetic teammates and the perceived viability of HATs, we argue that future AI teammates "will need to be both smart *and* good teammates" (Grosz, 2019, para. 4).

The current study makes several contributions to this emerging area of research. First, we answer the call from other scholars to identify design characteristics that help enable effective HATs (e.g., O'Neill et al., 2020). Although prior work has identified warmth and competence as meaningful dimensions of how humans perceive AI agents (Carpinella et al., 2017; Collange & Guegan, 2020; Frischknecht, 2021; Liu et al., 2022; Mieczkowski et al., 2019; Piçarra & Giger, 2018; Reeves et al., 2020), to our knowledge, no extant work investigates the influence of warmth and competence perceptions on receptivity to an AI teammate in an interdependent team context. Moreover, we are the first to extend the full tripartite model of *human* newcomer receptivity to AI teammates. Our results provide important, initial insight into how social perceptions of autonomous AI teammates affect human teammates' receptivity to their new AI counterparts. Additionally, we explore and find support for the downstream benefits of receptivity to AI teammates, specifically psychological acceptance, and perceived HAT viability, an important indicator of long-term team success. With the extensive resources that organizations are putting into the development and implementation of new intelligent technologies, the long-term success of HATs is critical for realizing the benefits of new AI teammate integration. Thus, the theoretical framework and results of the current study help to advance research on how AI characteristics can increase human team member receptivity and, in turn, overall HAT success.

1.1. AI teammates as newcomers

AI technologies are embedded within countless systems and tools used in our day-to-day lives and exist in many forms for a variety of functions. AI is a *technology* that can perform tasks that normally require human intelligence, such as decision-making or visual or auditory perception and recognition (Von Krogh, 2018). AI *agents* are technologies equipped with AI such that they can self-direct their own behaviors, adapt to changing environments, and take on a unique role or set of tasks. Some AI agents also serve as AI *teammates* that work interdependently with team members to achieve shared objectives (O'Neill et al., 2020). Importantly, AI agents and AI teammates are not defined by their physical presence but rather their capabilities and functionality. Chatbots, virtual personal assistants, or robots all may be AI agents if they are sufficiently autonomous and, further, may be AI teammates if they also work interdependently with human counterparts toward a shared goal. In the current study, we focus broadly on AI teammates that are autonomous from humans yet interdependent with their fellow teammates.

Although the study of AI teammate integration is relatively nascent, the examination of human newcomer integration has been studied for decades. Work on newcomer integration considers the needs and demands of integrating a new person onto a team (Moreland & Levine, 1982). This research area considers the integration of a new teammate as a socialization process wherein the incumbent, or pre-existing, team members must adapt their teamwork to appropriately accommodate the new teammate. In a team that is integrating a new agentic, interdependent AI teammate, we can conceptualize the incoming AI teammate as akin to a human newcomer. That is, the incumbent team members must undergo a socialization process that includes the adaptation of existing team processes and states to better accommodate the new AI teammate's knowledge, skills, and abilities. At the same time, conceptualizing the addition of an AI teammate as a newcomer makes clear that this process is likely to involve many challenges. Newcomer socialization requires incumbent team members to change how they socialize and work together, which is often met with reluctance or resistance from incumbent team members (Moreland & Levine, 1982, 2006). The development of trust in newcomers can also be slow and often depends on incumbent team members' perceptions of the newcomer's competencies, social ties, reputation, or commitment to the team (Moreland & Levine, 2002).

Further, the integration of a new *AI* teammate presents a particularly strong team membership change event (Trainer et al., 2020) and challenges beyond that of a human newcomer. Prior research has shown that similarity along salient dimensions such as demographics and culture facilitates newcomer integration (Kammeyer-Mueller et al., 2011; Phillips et al., 2009). Because AI teammates are fundamentally distinct from their human counterparts and, consequently, alter work processes in unique ways, the addition of an AI teammate is a particularly novel and disruptive team membership change event. Trainer et al. (2020) call such events *strong* team membership change events and suggest that they are especially impactful for individuals, teams, and organizations. Moreover, critical team states that are already difficult to establish with human newcomers, such as trust, are likely to develop differently with technologically-enabled newcomers (Hoff & Bashir, 2015). The implementation of advanced technologies into organizations has been shown to increase job insecurity and maladaptive workplace behaviors (Yam et al., 2022). Thus, the addition of an AI teammate introduces not only those challenges commonly associated with adjustment to a newcomer, but also those of a strong team membership change event as well as challenges unique to the integration of a technologically-enabled newcomer.

The long-term success of teams is dependent on the successful integration of the new teammate (Ashforth et al., 2007; Hall, 1976). When incumbent team members resist integrating newcomers, team outcomes, such as innovation, tend to suffer (Guimera et al., 2005; McGrath et al., 2000). In contrast, successful integration of a new team member can help teams increase their collective knowledge, innovate, improve team processes, and perform at a higher level than before (Feldman, 1994; Kane et al., 2005; Levine & Moreland, 1985; Sutton & Louis, 1987). The addition of an autonomous interdependent AI teammate presents further opportunities for team process and performance improvement. As such, a critical factor in the success of future human-AI collaboration is ensuring that the incumbent human team members are receptive to the incoming AI teammate newcomer.

1.2. Conceptualizing receptivity to AI teammates

In particular, AI teammate integration depends on human team members' *receptivity* to their new teammate. Rink et al. (2013) define receptivity as the general response of team members to a new teammate. They assert that a theoretically complete definition distinguishes between three components: reflection, knowledge utilization (of unique newcomer knowledge), and psychological acceptance of the newcomer. According to Rink and colleagues, this tripartite model, "helps clarify the conditions under which teams are most likely to be completely receptive to newcomers (i.e., when they are open to the newcomer in all three ways)" (p. 251). Extending Rink et al.'s tripartite model from human-only teams to HATs, we would expect receptivity to a new AI teammate to likewise involve these three components of receptivity. In HATs, *reflection* involves adapting team processes and routines due to the addition of an AI teammate; *knowledge utilization* is the recognition and adoption of the AI newcomer's unique expertise and skills; and *psychological acceptance* reflects social attitudes toward and recognition of the AI newcomer as a valuable team member.

It is useful to think of these three components of receptivity as related to affective states, behavioral processes, and cognitive states (Ilgen et al., 2005). Reflection concerns the adaptation of behavioral processes. Knowledge utilization concerns the adaptation of cognitive states such as integrating newcomer expertise into existing team knowledge structures. Lastly, psychological acceptance concerns affective states, which include general social attitudes, liking, and trust. When framed this way, we see that the human-computer interaction (HCI) and human-robot interaction (HRI) literatures include constructs that overlap with the three receptivity components. For example, the HCI literature has considered affective states such as trust and emotional responses (Glikson & Woolley, 2020), behavioral processes such as technology adoption (Davis, 1989; Venkatesh et al., 2003), and cognitive states such as the incorporation of robot abilities into mental models (Nikolaidis et al., 2015). However, no existing research of which we are aware has explicitly considered any of the three receptivity components in HATs, let alone together.

Nonetheless, Rink and colleagues emphasize that a "theoretically exhaustive" framework for newcomer receptivity requires reflection, knowledge utilization, and psychological acceptance (2013, p. 249). Therefore, predicting the successful integration of AI teammates requires understanding how AI teammate design affects all three components. In the current study, we propose that two AI teammate characteristics are likely to be particularly important for a tripartite model of team member receptivity to an AI teammate: perceived warmth and competence.

1.3. Universal dimensions of agent perception

Within the social cognition and psychological science literature, there is increasing convergence on warmth and competence as the "Big Two" dimensions that govern person-perception (Abele & Wojciszke, 2019; Fiske et al., 2007). Decades of research have consistently shown that people use these two dimensions to quickly categorize others as either friendly or threatening (Fiske et al., 2007). *Warmth* broadly pertains to perceptions of others' intentions, whereas *competence* describes perceptions of others' capabilities. Moreover, researchers have shown that the Big Two framework can categorize a wide range of other highly studied dimensions, such as motivations, values, and personality traits (Abele & Wojciszke, 2019). A substantial body of research has demonstrated the importance of the Big Two in interpersonal dynamics, including in organizational settings (Cuddy et al., 2011) and teams specifically (Thomas et al., 2020).

Scholars assert that the dimensions of warmth and competence have emerged in part because such perceptions are evolutionarily adaptive by allowing humans to make quick judgements about the intent, trustworthiness, and threat of others (Fiske et al., 2007). Consequently, warmth and competence perceptions are likely to be particularly relevant for making quick judgements about newcomers to a team, including AI newcomers. As noted above, Fiske and colleagues categorize warmth as "perceived intent" and competence as "perceived ability." Thus, within the context of AI teammates, warmth concerns perceptions of the AI teammate as either good- or ill-intentioned toward its human counterparts, and competence concerns whether the AI teammate has the skills and abilities to fulfill its responsibilities as teammate.

In fact, what have long been termed the "universal dimensions of person perception" are also emerging as universal dimensions of AI agent perception. Humans ascribe many of the same human attributes to nonhuman social actors, such as computers, robots, and virtual assistants (Nass et al., 1994, 1996), and warmth and competence specifically have already been extensively used to conceptualize perceptions of technology in the HCI and HRI literatures. Some researchers have drawn directly from the literature on human social perception by applying measures originally written for humans to AI agents (e.g., Collange & Guegan, 2020; Frischknecht, 2021; Liu et al., 2022; Mieczkowski et al., 2019; Piçarra & Giger, 2018; Reeves et al., 2020). Additionally, researchers have developed measures of social attributes specific to robots that incorporate warmth- and competence-related constructs. For example, the popular Godspeed measure of robot social attributes (Bartneck et al., 2009) includes measures of likability and perceived intelligence. Moreover, the Robotic Social Attributes Scale (RoSAS) was developed by drawing parallels between the Godspeed measure and the social perception literature and explicitly includes warmth and competence dimensions (Carpinella et al., 2017). A number of studies have also utilized and shown support for human personality constructs related to warmth and competence, such as extraversion and perceived intelligence, respectively (see Robert et al., 2020 for a review of personality in social robots). Finally, a growing body of research has shown the applicability of warmth and competence perceptions to not only physically embodied robots but also disembodied AI, such as avatars in virtual environments (Collange & Guegan, 2020), intelligent personal assistants (Hu et al., 2021), and chatbots (Huang et al., 2021; Kull et al., 2021).

Still, although the relevance of warmth and competence to AI agents seems well established, very little research has considered their application in HAT contexts specifically. Studying HAT contexts specifically is important because HATs imply a greater level of interdependence between humans and AI *teammates* than do interactions between humans and most other AI *agents*. This greater level of interdependence may affect the ways in which warmth and competence perceptions influence reactions to AI teammates relative to AI agents. Notably, research suggests that humans are more likely to ascribe human-like characteristics to nonhumans when there is greater attachment and anticipated interaction (Epley et al., 2007). Thus, warmth and competence seem even more likely to be ascribed—and to matter—for AI teammates in HATs relative to the contexts of focus in much of the HCI and HRI literatures broadly. Moreover, as described above, in order to fully understand how warmth and competence perceptions influence human responses to AI teammates, we must consider criteria that fully capture the type of newcomer receptivity described in the newcomer socialization literature. Next, we do just that by integrating research on warmth and competence in the HCI, HRI, and human social perception literatures with Rink et al. (2013)'s tripartite model of newcomer receptivity.

1.3.1. Reflection

As described above, reflection describes the behavioral adaptation of work processes and routines in response to the addition of a newcomer. Within the HCI literature, the construct that is perhaps most closely related to this behavioral adaptation is technology adoption as defined by the Technology Acceptance Model (TAM; Brown et al., 2010; Davis, 1989; Venkatesh et al., 2003). In TAM, adoption is generally defined as intent to use a technology. Because one of the key antecedents of technology adoption is perceived usefulness (Davis et al., 1989), this model generally emphasizes competence-related constructs. That is, TAM suggests that humans are more likely to use a technology they perceive to be useful (e.g., Miltgen et al., 2013; Sun et al., 2014). Extended to HATs, TAM would suggest that team members are more likely to adapt their processes and routines to the AI teammate if they believe that the AI is competent such that it has the ability to benefit key team tasks.

Within the human teaming and relationships literatures, a related construct is willingness and intent to work with other humans. This intent to work with others suggests that individuals have reflected on and are willing to adapt their processes in response to the other. In contrast to technology adoption, intent and willingness to work with other humans has long shown a primacy of warmth such that humans place greater value on warmth relative to competence (Cuddy et al., 2011). When choosing who to work with, humans likewise prioritize affiliative-relationships to instrumental-relationships; that is, humans prefer “lovable fools” over “competent jerks” (Casciaro & Lobo, 2005; 2008, 2015). Similarly, Newton et al. found that when self-assembling into teams, “team members appear to value advocates who build affiliative bridges at work more so than those with instrumental skill who could yield very capable teams” (2022, p. 2276). These findings suggest that when making decisions about how they are going to structure their work and who to incorporate into work processes, humans place greater emphasis on warmth-related constructs (e.g., friendship, affiliation, trust).

This preference for warmth may be even more salient in team contexts. Thomas et al. (2020) found that the role of warmth and competence was dependent on task interdependence such that when task interdependence was high, a dyadic partner’s *likability* was more strongly related to willingness to work together. However, when task interdependence was low, *competence* was more strongly related to willingness to work together. Still, it is important to keep in mind that although research on warmth and competence suggests humans place a *greater* emphasis on warmth, competence still matters such that the ideal human partner is both “lovable” and “competent” (Casciaro & Lobo, 2005; 2008).

Because AI teammates reflect both a technology that humans must be willing to use and a highly interdependent teammate akin to human newcomers, we expect both warmth and competence perceptions to facilitate reflection. That is, if human teammates do not *like* an AI teammate, they may be unwilling to expend the effort needed to change team processes, regardless of the AI teammate’s potential usefulness and value-add. Indeed, both warmth and competence have been shown to have a positive influence on intentions to work with robots and intelligent personal assistants (Hu et al., 2021; Piçarra & Giger, 2018), although Hu et al. (2021) found that competence had a stronger influence on intentions to use a personal assistant than did warmth. Thus, overall, we expect both perceived warmth and competence to be positively related to reflection.

Hypothesis 1a. Perceived warmth is positively related to team member reflection regarding the AI teammate.

Hypothesis 1b. Perceived competence is positively related to team member reflection regarding the AI teammate.

1.3.2. Knowledge utilization

Knowledge utilization concerns the adoption of a newcomer’s “unique knowledge, skills, and aptitudes” (Rink et al., 2013, p. 249). Whereas reflection concerns the behavioral adaptation of routines and work processes, Rink and colleagues assert that “knowledge utilization measures clearly differ from the more general measures of team reflection” due to their focus on “newcomer input” specifically (2013, p. 261). Thus, with regards to HATs, knowledge utilization refers to both the perception and integration of an AI teammate’s knowledge.

Intuitively, because knowledge utilization concerns perceptions of the newcomer’s expertise and abilities, we would expect competence (i.e., perceived skills and abilities) to be positively related to knowledge utilization. That is, we would expect team members to more readily recognize potential unique task contributions of AI agents when those AI agents are perceived to be high in competence. Likewise, we would expect team members to be more willing to integrate that knowledge when the AI agent is perceived as highly competent. Indeed, this is supported by the literature on voice, which is an individual’s expression of task relevant ideas and opinions (Van Dyne & LePine, 1998) and akin to expressions of competence. Prior research has shown that voice can help teams better utilize member expertise (Bunderson & Barton, 2010; Sherf et al., 2018). Similarly, we expect that expressions of competence by AI teammates will help teams to better recognize and utilize their expertise. Moreover, knowledge utilization may be thought of as a form of cognitive trust, which is often operationalized as “whether users are willing to take factual information or advice and act on it, as well as whether they see the technology as helpful, competent, or useful” (Glikson & Woolley, 2020, p. 631). In their review of trust in AI, Glikson and Woolley highlight that reliability (i.e., consistent behavior and performance) is an important predictor of cognitive trust in AI.

However, we also expect recognition and adoption of an AI teammate’s potential contributions to be dependent on perceived warmth. Team performance depends on both taskwork and teamwork factors (Driskell et al., 2018). According to Driskell and colleagues, taskwork concerns “task-specific behaviors related to performing the task at hand” whereas teamwork concerns “the set of behaviors that facilitate the coordinated functioning of the team itself” (2018, p. 338). Some of these teamwork processes involve promoting and maintaining interpersonal relationships, which are particularly likely to be influenced by warmth-related characteristics. For example, Bell et al. (2018) note that sociable traits such as extraversion and agreeableness help facilitate the development of key cognitive and affective team states. The importance of warmth in these sociable roles has also been supported in the HCI literature. For example, researchers have found that when robots are used in applications that emphasize sociability (e.g., service and companionship), humans expect them to be increasingly social (Dou et al., 2020). Finally, in their review, Glikson and Woolley (2020) note that prosocial behaviors are likely to be important antecedents of cognitive trust in AI.

Because knowledge utilization incorporates the perception of knowledge useful to the team, both warmth and competence perceptions are likely to affect knowledge utilization in HATs. Thus, we expect both perceived warmth and competence to be positively related to knowledge utilization of AI teammates.

Hypothesis 2a. Perceived warmth is positively related to team member knowledge utilization of the AI teammate.

Hypothesis 2b. Perceived competence is positively related to team member knowledge utilization of the AI teammate.

1.3.3. Psychological acceptance

Psychological acceptance is the most frequently researched component of receptivity in the human newcomer socialization literature (Rink et al., 2013). Broadly, psychological acceptance represents the extent to which teams are willing to accept a newcomer as a teammate (Rink et al., 2013). In HATs, psychological acceptance reflects the extent to which human members see their AI counterpart as a full and valuable team member.

Within the human newcomer literature, research suggests that both warmth and competence are likely to influence acceptance of the newcomer. Kammeyer-Mueller and Wanberg (2003) found that newcomers are more likely to be accepted by their teammates when they exhibit more openness and agreeableness, traits often associated with warmth. Research findings also suggest that newcomer empowerment, which includes newcomer’s impressions of their own competence, is positively related to positive evaluations by other team members (Chen & Klimoski, 2003).

In contrast, we are not aware of any research that directly investigates the influence of warmth and competence on psychological acceptance specifically in the HCI/HRI literature. However, several related streams of research suggest that both warmth and competence perceptions are likely to be positively related to psychological acceptance. According to Rink et al. (2013), psychological acceptance includes a variety of general social attitudes. For example, psychological acceptance could represent the extent to which team members and the newcomer have a shared identity, the belief that the newcomer is an important member of the team, or the extent to which the team members trust the newcomer. We next review some of these related constructs (e.g., trust and emotional responses) and the corresponding influence of warmth and competence.

Within the HCI and HRI literature, research on several criteria closely related to psychological acceptance also suggests the importance of both warmth and competence. For example, in their seminal review of trust in AI, Glikson and Woolley (2020) draw directly on the social perception literature and state, "Trust in AI is likely to depend on both AI's likability and perceived intelligence." Indeed, both warmth and competence have been shown to be positively related to trust in AI agents. Kulms and Kopp (2018) found a positive effect of both warmth and competence perceptions on behavioral trust in computers, and Christoforakos et al. (2021) found that warmth and competence both had a positive effect on trust in human-robot interactions. This is consistent with broader research on trustworthiness perceptions among humans. Prior research suggests trust is dependent on perceptions of both ability, which is closely related to competence, and benevolence, which describes perceived intent to do good and is therefore closely related to the concept of warmth (Fiske et al., 2002; Mayer et al., 1995).

Similarly, empirical findings support the influence of both warmth and competence on emotional responses to robots. Mieczkowski et al. (2019) found that both warmth and competence perceptions of a robot influenced emotional responses (i.e., admiration, contempt, pity, envy). Moreover, in one of the only studies to our knowledge to evaluate the role of warmth and competence in HATs specifically, Oliveira et al. (2019) again found that both warmth and competence influence emotional responses to an AI teammate. Finally, in a study of how observing robot-robot interaction affects overall human evaluations of the robots (e.g., like vs. dislike), Söderlund (2021) found that warmth was positively related to overall evaluations of "liking" the robot.

Thus, although no research has directly evaluated the influence of perceived warmth and competence of an AI teammate on psychological acceptance of that teammate, ample research from both the newcomer socialization literature and the HCI/HRI literature suggest that warmth and competence are both important for closely related constructs. Consequently, we expect both perceived warmth and competence to be positively related to AI teammate psychological acceptance.

Hypothesis 3a. Perceived warmth is positively related to team member psychological acceptance of the AI teammate.

Hypothesis 3b. Perceived competence is positively related to team member psychological acceptance of the AI teammate.

1.3.4. HAT viability perceptions

Taken together, reflection, knowledge utilization, and psychological acceptance "determine a team's ability to yield long-term benefits from the introduction of the newcomer" (Rink et al., 2013, p. 251). That is, receptivity to an AI teammate is in part critical because it is expected to predict other important outcome variables. Because, to our knowledge, we are the first to explore all three components of newcomer receptivity in either human-only teams or HATs, we also consider whether these three components show the expected relationships with a key outcome variable: perceived viability of the HAT. Although there are a wide variety of definitions and operationalizations of viability, at the broadest level, it has been defined as a team's overall willingness and ability to continue working together (Sundstrom et al., 1990). Thus, viability perceptions are a particularly useful indicator of the potential for sustained HAT performance. Whereas receptivity concerns team member responses to the AI teammate, *viability* perceptions concern team members' desire to continue working together. Within an HAT, perceived viability concerns team members' willingness to continue working with both the AI teammate and other human teammates as an interdependent HAT.

Further, viability is one of the most commonly studied team effectiveness outcomes (Mathieu et al., 2017) and is likely to be particularly relevant for HATs (O'Neill et al., 2020). Bell and Marentette (2011) note that viability is most relevant for ongoing and long-term teams with multiple performance episodes such as organizational work teams, as well as teams that need to withstand membership change. Because the introduction of an AI teammate reflects a substantial membership change event, understanding how an AI teammate impacts overall team member's perceptions of viability is particularly important for ensuring continued HAT success.

We expect each of the three components of receptivity to be positively related to perceived HAT viability. First, team members must believe that the team has the potential to be successful long-term. This capability perception may be influenced by both reflection and knowledge utilization. Team members that perceive their team to have successfully adapted to the integration of an AI teammate (i.e., reflection) are also likely to believe that the team has the potential to successfully adapt to other challenges in the future. Relatedly, prior research has also suggested that team self-managing behaviors, which includes monitoring and adapting work processes, are positively related to viability (Rousseau & Aube, 2010). Similarly, we would also expect knowledge utilization to impact team members' beliefs that the team has the ability to successfully work together. In their review of the viability construct, Bell and Marentette state:

> … In order for the team to have the capacity for continued existence and growth, the team must be managed in such a way that ensures that it will have the requisite knowledge and skills to meet the demands of future performance episodes. This requires both the continued availability of needed knowledge and skills that can evolve as the demands from external influences change" (2011, pp. 280–281).

Thus, if team members perceive the AI teammate to have unique skills and abilities that contribute meaningfully to the team, we would also expect the team members' perceptions of HAT viability to be higher.

Finally, we also expect psychological acceptance to be positively related to perceived HAT viability. As described above, psychological acceptance is an affective state that reflects general social attitudes toward newcomers. Relatedly, both team social cohesion and satisfaction are positively related to viability (Bell & Marentette, 2011; Chang & Bordia, 2001). Moreover, within the HRI literature, You and Robert (2017a, b) found that emotional attachment to a robot affects overall team viability. Thus, we hypothesize that all three components of receptivity to an AI teammate—reflection, knowledge utilizations, and psychological acceptance—are important predictors of team members' perceptions of their HAT viability.

Hypothesis 4. Team member reflection regarding the AI teammate is positively related to perceived viability of the HAT.

Hypothesis 5. Team member knowledge utilization of the AI teammate is positively related to perceived viability of the HAT.

Hypothesis 6. Team member psychological acceptance of the AI teammate is positively related to perceived viability of the HAT.

1.4. The current studies

In the current research, we test the influence of perceived warmth and competence on individuals' receptivity to AI teammates across two studies. In Study 1, we test the influence of perceived warmth and competence on the three receptivity components (i.e., reflection, knowledge utilization, and psychological acceptance, H1–H3, respectively) using a video vignette design. Participants first watched a short clip of an AI teammate and then imagined adding that teammate to a referent team. In Study 2, we replicate our tests of H1–H3 in real, 2–3 person lab teams interacting with an AI agent. Study 2 leverages a Wizard of Oz methodology (also outlined by Schecter et al., 2023) in a realistic laboratory experiment to simulate these types of HATs. Additionally, because we are the first to consider a complete tripartite model of receptivity in either humans or newcomers, Study 2 also considers whether reflection, knowledge utilization, and psychological acceptance show the expected relationships with an important indicator of team success: perceived HAT viability. Thus, in Study 2 we also test H4, H5, and H6 regarding whether the three receptivity components are positively related to perceived HAT viability. The current study therefore offers insight into how perceived warmth and competence influence receptivity to an AI teammate, as well as the implications of that receptivity for sustained team effectiveness.

2. Study 1

2.1. Method

2.1.1. Participants

Participants were recruited through the platform Amazon Mechanical Turk (MTurk) to complete an online survey via Qualtrics. To qualify for the study, participants were required to reside in the United States, possess at least a bachelor's degree, and speak English as a first language. Informed consent was obtained from all participants prior to completing the online survey. Prior to analysis, participants who showed evidence of inattentive responding were removed (e.g., via attention check items, insufficient response times, and appropriate answers to open-ended questions). The final sample for Study 1 included 536 participants.

2.1.2. Procedure

Participants were asked to think about a referent team on which they either had previously worked or were currently a member. Participants were then asked to complete a few basic questions about their referent teams, including whether they had previously worked or were currently working on the team, the size of the referent team, and the referent team type (Hollenbeck et al., 2012). Overall, about half of participants were currently on their referent team and about half reported a referent team of which they were no longer a member (47.0% vs. 53.0%, respectively). Median reported size of the referent team was 5 people. The most commonly reported type of referent team was a project/development team (48.3%), followed by a service team (22.6%), production team (8.6%), action/negotiation team (6.5%), and advice/involvement team (5.6%); 8.4% of participants reported a referent team type of "other." After a short survey about their referent team, participants watched a brief video clip of an AI teammate with this referent team in mind. Participants were asked to imagine that the AI teammate would be joining their team and answer the remaining survey questions accordingly.

Each participant was randomly assigned to one of eight possible AI teammate videos.[1] Six of the videos showed either real AI agents or AI agents from movies. These videos were selected to represent a range of AI features, including realism (i.e., whether the technologies were currently available or fictionalized), anthropomorphization (i.e., whether appearance more or less closely resembled a human), embodiment (i.e., the extent to which the AI teammate had a physical presence or not), relative intelligence (i.e., the extent to which the AI teammate seemed more or less competent in intelligence-based tasks), and sociability (i.e., the extent to which the AI teammate might make humans feel more or less comfortable engaging in social interactions with the AI teammate). AI teammate videos included Pepper (realistic commercially available social robot created by SoftBank Robotics), IBM Watson (realistic disembodied AI with high intelligence), Sophia (realistic, human-like robot designed to interact with the public by Hanson Robotics), TARS and CASE (fictional, intelligent, embodied robots from the movie *Interstellar*), and K–2SO (fictional, intelligent, social robot from the *Star Wars* movie franchise). In order to expose participants to a range of AI types and abilities, we also included two videos of AI teammates that exhibited either "good" (Vero) or "bad" (Rove) teamwork skills. For example in their respective videos, Vero (the good teammate) says, "When I make this motion, it means I am idle and simply listening" whereas Rove (the bad teammate) says, "When I make this motion, it means I am idle and simply think your conversation is not worth my computing power." These videos were developed for the current data collection effort. Both Vero and Rove are presented as realistic disembodied virtual agents with similar visual animations. In sum, there were eight AI teammates included in the current study: Pepper, IBM Watson, Sophia, TARS, CASE, K–2SO, Vero, and Rove. Sample sizes for participants assigned to each of the eight AI teammates are shown in Table 1.

2.1.3. Measures

Warmth and Competence Perceptions. Participants completed 6-item measures of warmth (*friendly, well-intentioned, trustworthy, warm, good-natured, and sincere*) and competence (*competent, confident, capable, efficient, intelligent, and skillful*) perceptions of the AI teammate (Fiske et al., 2002) on a scale of 1 = "not at all" to 5 = "extremely." Internal consistency was sufficient for both measures (Cronbach's α = 0.91 for warmth; Cronbach's α = 0.91 for competence).

Receptivity to the AI Teammate. Consistent with the three components of newcomer receptivity described above (Rink et al., 2013), we utilized measures of team members' perceptions of reflection, knowledge utilization, and psychological acceptance in HATs. Table 1 includes item content for all measures written for Study 1. Reflection was assessed using a 7-item measure of dynamic restructuration (Larson, 2021) written to capture the extent to which teams reflect on and adapt their cognitive structures and interaction processes to integrate the AI teammate (Cronbach's α = 0.87). Knowledge utilization was assessed using 6 items from an overall AI expectancies measure (Larson, 2021). Items were written to reflect participants' ratings of the AI knowledge and expertise relevant to team tasks (Cronbach's α = 0.91). Finally,

Table 1
Item content written for study 1.

Item Content
Reflection
Instructions: Please indicate the extent to which you agree or disagree with the following statements. Having an AI teammate would _________.
1. Prompt myself and others to change our roles on the team.
2. Prompt myself and others to change our expertise.
3. Prompt some members to refocus their efforts.
4. Not change how we work together in any way.
5. Prompt me and others to play to different strengths.
6. Prompt me to work with my teammates differently.
Knowledge Utilization
Instructions: Please indicate the extent to which you agree or disagree with the following statements.
1. I anticipate an AI teammate would have expertise that my team members would not have.
2. I anticipate an AI teammate would be an expert at all aspects of the task.
2. An AI teammate would be more knowledgeable than myself and my teammates about the task(s) at hand.
3. An AI teammate would surely be an expert in our team tasks.
4. Adding an AI teammate would improve the overall expertise of our team.
5. Our collective expertise would improve with the addition of an AI teammate.
6. Instructions: Please indicate the extent to which you agree or disagree with the following statements.
Psychological Acceptance
Instructions: Please rate the extent to which you agree with the following statements regarding the AI teammate in the video you just watched.
1. This AI teammate would be a good teammate.
2. This AI teammate would be a bad teammate.
3. I would enjoy working with this AI teammate.
4. I would dislike working with this AI teammate.

[1] We conducted chi-square tests to evaluate whether reported characteristics of referent teams (e.g., size, type, and whether the participants were currently or previously on the team) varied across AI teammates. In no case were there meaningful differences in referent teams across AI teammates.

psychological acceptance was assessed using a 4-item measure of participants' overall impressions of the AI teammate as a team member (Cronbach's α = 0.92). For all measures, participants indicated the extent to which they agreed or disagreed with statements on a scale of 1 = "strongly disagree" to 5 = "strongly agree."

2.1.4. Data analysis

All measures were collected at the individual level. We first conducted a one-way ANOVA to evaluate whether there were significant differences in the warmth and competence perceptions of AI teammates. Then, to test H1–H3 regarding the relationship of perceived warmth and competence with reflection, knowledge utilization, and psychological acceptance, we tested three separate multiple regressions models in which each receptivity variable was regressed on warmth and competence perceptions. Consistent with best practices in hypothesis testing, p-values for our hypothesis tests are one-tailed (Cho & Abe, 2013). All variables were z-scored prior to analysis.

2.2. Results

2.2.1. Warmth and competence perceptions

We first conducted a one-way ANOVA to evaluate whether there were significant differences in the mean perceived warmth and competence ratings of the AI teammates in Study 1 (see Table 2). Results revealed significant differences in both the perceived warmth and competence ratings of the AI teammates (competence: $F(7) = 26.55$, $p < .001$; warmth: $F(7) = 4.66$, $p < .001$). With regard to perceived competence, Tukey post-hoc comparisons revealed that Pepper was significantly lower in perceived competence than all other AI teammates. Sophia was also significantly lower in perceived competence than all other AI teammates but was significantly higher in competence than Pepper. Finally, Rove was significantly lower in perceived competence than CASE and IBM Watson but significantly higher in perceived competence than Pepper and Sophia. With regards to perceived warmth, Tukey post-hoc comparisons revealed that both Rove and IBM Watson were significantly lower in perceived warmth than K–2SO, Pepper, and Vero. Thus, results suggest that there was meaningful variance in the perceived warmth and competence of the AI teammates.

2.2.2. Receptivity

Table 3 displays descriptive statistics for all variables in Study 1. To test H1–H3, we conducted multiple regression analyses in which reflection (H1), knowledge utilization (H2), and psychological acceptance (H3) were regressed on perceptions of AI teammate warmth and competence. There was a significant effect of both perceived warmth and competence on reflection (warmth: $b = 0.15$, $p = .001$; competence: $b = 0.17$, $p < .001$), knowledge utilization (warmth: $b = 0.24$, $p < .001$; competence: $b = 0.58$, $p < .001$), and psychological acceptance (warmth: $b = 0.35$, $p < .001$; competence: $b = 0.45$, $p < .001$). Thus, results of Study 1 support all three hypotheses such that both warmth and competence perceptions of the AI teammate positively influence all components of receptivity to the AI teammate. Results are shown in Table 4.

Table 2
Mean and standard deviations of warmth and competence for all AI teammates in study 1.

AI Teammate		Competence		Warmth	
	N	Mean	*SD*	Mean	*SD*
CASE	79	4.34	0.63	3.54	0.96
IBM Watson	89	4.38	0.54	3.11	1.09
K–2SO	91	4.11	0.75	3.67	0.90
Pepper	59	3.05	0.89	3.64	0.95
Rove	60	3.95	0.73	3.04	1.00
Sophia	58	3.47	0.93	3.39	1.10
TARS	58	4.21	0.63	3.49	0.84
Vero	56	4.07	0.64	3.68	0.75

Table 3
Descriptive statistics and correlations for variables in study 1.

Variable	M	SD	1	2	3	4	5
1. Warmth	3.44	0.98	.91				
2. Competence	3.99	0.83	.46***	.91			
3. Reflection	3.25	0.87	.23***	.24***	.87		
4. Knowledge Utilization	3.54	0.97	.50***	.68***	.40***	.91	
5. Psychological Acceptance	3.81	1.02	.55***	.61***	.22***	.68***	.92

Note. Coefficient alphas are on diagonal. p-values are two-tailed. ***$p < .001$.

2.3. Discussion of study 1

Overall, results of Study 1 support H1–H3 such that both warmth and competence perceptions showed significant, positive relationships with all components of receptivity to the AI teammate. Notably, perceived competence showed a substantially stronger effect on knowledge utilization than did perceived warmth. These results suggest that perceived competence of the AI teammate is particularly salient for team members' assessments of the AI teammate's expertise and subsequent knowledge utilization. In contrast, perceived warmth and competence showed somewhat similar effect sizes for reflection and psychological acceptance.

A notable limitation of Study 1 is that the integration of the AI teammates was purely hypothetical. Participants were asked to reflect on adding an AI teammate to a referent team on which they had participated in the past. In Study 2, we aimed to increase the fidelity of the methodology by utilizing lab-based teams. Additionally, in Study 2, the use of real lab teams allowed us to evaluate the influence of the three receptivity components on team member's perceptions of HAT viability.

3. Study 2

In Study 2, we aimed to replicate the results of Study 1 for H1–H3 while increasing fidelity by using real lab-based teams and a Wizard of Oz methodology. As in Study 1, we utilized measures of all three receptivity constructs. Additionally, in Study 2 we collected data on team member's viability perceptions in order to evaluate H4–H6 regarding how reflection, knowledge utilization, and psychological acceptance impacted team member perception of HAT viability.

3.1. Method

3.1.1. Participants

Participants were students from a midwestern university as well as local community members. Informed consent was obtained from all participants prior to participating in the study. Prior to analysis, participants who showed evidence of inattentive responding were removed from analyses (e.g., via attention check items and appropriate answers to open-ended questions). Additionally, participants who reported believing that the AI teammate was human (as described in the procedure below) were removed from analyses. The original sample included 225 participants. After removing participants as described, the final sample included 185 participants (76% female; 45% white, non-Hispanic; $Age_{median} = 25$; $Age_{mean} = 30$, $Age_{SD} = 14$). Of the final participants, 71 were on a two-person team and 114 were on a three-person team.

3.1.2. Procedure

Participants completed a 3-h virtual session via Zoom in which they engaged in several rounds of problem-solving and creativity tasks. First, participants were randomly assigned to 2- or 3- person teams and completed one problem-solving task and one creativity task as a human-

Table 4
Regression results predicting receptivity variables from AI teammate warmth and competence in study 1.

	Reflection			Knowledge Utilization			Psychological Acceptance		
	b	SE	*p*	*b*	SE	*p*	*b*	SE	*p*
Warmth	0.15**	.05	.001	0.24***	.03	<.001	0.35***	.04	<.001
Competence	0.17***	.05	<.001	0.58***	.03	<.001	0.45***	.04	<.001

***$p < .001$.**$p < .01$.

only team. Next, participants watched a brief video introducing them to a new AI teammate, Vero. Participants then completed 2 more rounds of the same kind of tasks (i.e., problem-solving and creativity) in their HATs with Vero. All teams completed the same tasks in the same order, and human team membership was consistent across the study. In the current study, all measures were collected after the final round of interacting with Vero via the online survey platform Qualtrics.

Although participants were led to believe they were interacting with a fully autonomous AI teammate, we used a Wizard of Oz methodology in which a confederate acted as the virtual AI teammate Vero using predetermined verbalizations and visual animations. Confederates were assigned to one of four conditions that dictated the specific verbalization script that they could use. The first three conditions were: (1) a script with task-relevant information only, (2) a script with teamwork-relevant information only, and (3) the combined scripts from the first two conditions (i.e., both taskwork- and teamwork-relevant information). Confederates in conditions 1–3 were encouraged to communicate as many of the pre-written phrases as possible but not to deviate from the assigned script. In condition 4, confederates utilized the combined script from condition 3 but were also allowed to deviate from the script in order to use more naturalistic expressions. The methodology used here is further detailed in Schecter et al. (2023). Notably, these data were originally collected to test separate hypotheses and research questions specific to how the manipulation and corresponding conditions affected team processes and states. In the current study, the manipulation and corresponding conditions are relevant insofar as they introduce a valuable source of variance in perceptions of AI teammate warmth and competence.

A manipulation check at the end of the session confirmed that the majority of participants believed that Vero was a technology (88%), as opposed to a human acting as an AI teammate. Any participants who indicated in this manipulation check that Vero might be human were removed prior to analysis. Of an original 198 participants who passed all other attention checks, 23 participants reported thinking Vero might be human; of these 23, the majority were in condition 4, which allowed for more naturalistic deviation from the script.

3.1.3. Measures

Warmth and Competence. Participants completed 6-item measures of warmth and competence perceptions of the AI teammate from the Robotic Social Attributes Scale (RoSAS; Carpinella et al., 2017). The RoSAS uses semantic differential scales on which participants are asked to rate on a scale of 1–5 the extent to which one of two terms applies (e.g., sad vs. happy; incapable vs. capable). Internal consistency was appropriate for the resultant 5-item warmth measure (Cronbach's $\alpha = 0.87$) and 6-item competence measure (Cronbach's $\alpha = 0.91$).[2]

Receptivity to the AI Teammate. As in Study 1, we utilized measures intended to represent team members' perceptions of reflection, knowledge utilization, and psychological acceptance (Rink et al., 2013). Reflection was assessed using the same measure as Study 1 (Cronbach's $\alpha = 0.89$). Knowledge utilization and psychological acceptance were assessed using measures that differed slightly from Study 1. Knowledge utilization was assessed using a 4-item measure; 2 items were exact matches for items in Study 1, and 2 items reflected combinations of the remaining 4 items (Cronbach's $\alpha = 0.86$). Psychological acceptance was assessed using a 3-item measure that, relative to the measure used in Study 1, more specifically captured teammate's impressions of the extent to which the AI teammate was a valuable team member (Cronbach's $\alpha = 0.91$) on a scale of 1 = "not at all" to 7 = "to a great extent." Table 5 includes additional items written or adapted for Study 2.

HAT Viability Perceptions. Individual perceptions of HAT viability were measured with 4-items (Cronbach's $\alpha = 0.79$) developed by Resick et al. (2010). Participants were asked to indicate the extent to which they agreed or disagreed with each of the statements (e.g., "I really enjoy being a member of my team") on a scale of 1 = "strongly disagree" to 7 = "strongly agree."

3.1.4. Data analysis

All variables were measured at the individual level. Whereas in Study 1 we manipulated the AI teammate video that participants watched, in Study 2, we manipulated the scripts used by the AI teammates. Warmth and competence perceptions were expected to vary as a function of the script characteristics. Because a substantial portion of the scripts overlapped between conditions, we compared perceptions of warmth and competence along the three key script characteristics: taskwork, teamwork, and scripted vs. unscripted. Specifically, we conducted t-tests to compare warmth and competence perceptions by condition: taskwork vs. no taskwork included, teamwork vs. no teamwork included, and

[2] The RoSAS is a well-known measure of warmth and competence perceptions of AI agents. The RoSAS was developed, in part, by drawing directly on literature regarding the importance of warmth and competence in person-perception as described by Fiske et al. (2007). Still, we are not aware of any research that directly compares the RoSAS with the traditional measure of warmth and competence used in humans (i.e., Fiske et al., 2002, used in Study 1). To ensure equivalence of our focal constructs across both studies, we administered both the RoSAS and the Fiske measures to a sample of 60 students at a large university in a separate pilot study. We then conducted a confirmatory factor analysis to determine whether all items adequately loaded onto warmth and competence dimensions as expected. Results of psychometric analyses suggested that one item in the RoSAS measure did not adequately load onto the warmth dimension ("non-interactive vs. interactive"; standardized loading less than 0.1). Given the results of this separate psychometric analysis, we removed the corresponding item from the warmth measure in Study 2. For both warmth and competence, mean Fiske and RoSAS scores correlated above 0.70.

Table 5
Item content written for study 2.

Item Content
Knowledge Utilization
Instructions: Please indicate the extent to which you agree or disagree with the following statements regarding your new AI teammate, Vero.
1. The AI teammate had expertise that my team members did not have.
2. The AI teammate was more knowledgeable than myself and my teammates about the task(s) at hand.
3. The AI teammate was surely an expert in all aspects of our team tasks.
4. The AI teammate improved the collective expertise on our team.
Psychological Acceptance
Instructions: Please indicate the extent to which you agree or disagree with the following statements based on your experience during the task you just completed.
1. How confident are you in each teammate's ability to effectively complete tasks?
2. To what extent do you enjoy working with each teammate?
3. To what extent is each teammate instrumental in helping your team achieve its goals?

Note. Reflection was measured using the same items as Study 1. Psychological acceptance items were completed for each teammate separately, including the AI teammate.

included unscripted phrases vs. only scripted phrases included.

Then, as in Study 1, we evaluated H1–H3 by testing models in which each of the three receptivity variables were regressed on perceived warmth and competence. However, because team members in Study 2 were nested within lab teams, we expected some variance in the individual team member ratings of receptivity (level 1) to be attributable to the team membership (level 2). To determine the degree to which variance was attributable to the team level, we utilized Hierarchical Linear Modeling (HLM). First, we evaluated intraclass correlation coefficients, including ICC [1] and ICC [2]. Results suggested that while there was meaningful variance attributable to group variance for all components of receptivity, not all components showed sufficiently high reliability to warrant aggregation to the team level (reflection: ICC [1] = 0.10, ICC [2] = 0.19; knowledge utilization: ICC [1] = 0.44, ICC [2] = 0.64; psychological acceptance: ICC [1] = 0.35, ICC [2] = 0.52; LeBreton & Senter, 2008). Low ICC values are not surprising given that conceptualization of all measures was at the individual level. Further, teams in the current study included only 2–3 human members, and reliability of group means in groups with few members is typically very low (Klein & Kozlowski, 2000). Thus, we proceeded with HLM using the R package *multilevel* (Bliese, 2022). HLM affords controlling for variance attributable to the team while still analyzing all variables at the individual level (level 1). R^2 values were calculated using the R package MuMIn (Bartoń, 2022).

Finally, we evaluated H4, H5, and H6 by testing three separate regression models in which perceived HAT viability was regressed on reflection, knowledge utilization, or psychological acceptance, respectively, while controlling for perceived warmth and competence. Intraclass correlation coefficients suggested that variance in team member's viability perceptions was attributable to the team level but not so much as to warrant aggregating to the team level (ICC [1] = 0.12; ICC [2] = 0.22). Thus, we again conducted analyses at the individual level but used HLM to control for variance attributable to the team level.

3.2. Results

3.2.1. Warmth and competence perceptions

Table 6 shows mean and standard deviation values for warmth and competence perceptions for each condition and by script characteristics. Results of the t-tests comparing along the three script characteristics (teamwork, taskwork, and scripted vs. unscripted) revealed that perceived competence was significantly higher in conditions that involved taskwork phrases relative to those that did not, t (61.86) = −3.92, p < .001. Moreover, perceived competence was significantly higher in the condition that included unscripted phrases relative to those

Table 6
Mean and standard deviations of warmth and competence by condition and script characteristics in study 2.

Condition			Competence		Warmth	
	N	*k*	Mean	*SD*	Mean	*SD*
1. Taskwork-only	52	23	4.02	0.65	2.75	0.77
2. Teamwork-only	47	20	3.50	1.04	2.89	1.01
3. Combined	41	20	4.18	0.78	2.98	0.83
4. Unscripted	45	23	4.24	0.74	3.16	0.66
Script Characteristics						
Taskwork vs. No Taskwork						
Taskwork Included	138	66	4.14	0.72	2.95	0.77
No Taskwork Included	47	20	3.50	1.04	2.89	1.01
Teamwork vs. No Teamwork						
Teamwork Included	133	63	3.96	0.93	3.01	0.85
No Teamwork Included	52	23	4.02	0.65	2.75	0.77
Unscripted vs. Scripted						
Unscripted Included	45	23	4.24	0.74	3.16	0.66
Scripted Only (i.e., no unscripted included)	140	63	3.89	0.88	2.87	0.87

Note. "Taskwork included" reflects conditions 1, 3, and 4; "no taskwork included" reflects condition 2. "Teamwork included" reflects conditions 2, 3, and 4; "no teamwork included" reflects condition 1. "Unscripted included" reflects condition 4; "scripted only" reflects conditions 1, 2, and 3.

conditions that included only scripted phrases, t (87.14) = −2.66, p < .001. Perceived competence was not significantly different in conditions that involved teamwork phrases relative to those that did not.

In contrast, perceived warmth was significantly higher in conditions that involve teamwork phrases relative to those that did not, t (102.76) = −2.03, p = .048. Perceived warmth was also significantly higher in the condition that included unscripted phrases relative to those conditions that included only scripted phrases, t (97.56) = −2.36, p = .020. Perceived warmth was not significantly different in conditions that involved taskwork phrases relative to those that did not. Thus, overall results suggest that the use of multiple script conditions introduced meaningful variance in both the warmth and competence perceptions of the AI teammates.

3.2.2. Receptivity

Table 7 displays descriptive statistics for all variables in Study 2. As described above, we regressed each of the three receptivity components on perceived warmth and competence using HLM to control for nesting due to team membership.[3] Results are shown in Table 8. Regarding H1, there was a significant effect of both perceived warmth and competence on reflection (warmth: b = 0.23, p = .003; competence: b = 0.24, p = .003). In contrast, regarding H2, there was a significant effect of perceived competence but not perceived warmth on knowledge utilization (warmth: b = 0.02, p = .353; competence: b = 0.62, p < .001). Finally, regarding H3, there was a significant effect of both perceived warmth and competence on psychological acceptance (warmth: b = 0.17, p = .006; competence: b = 0.58, p < .001). Thus, results of Study 2 support H1 and H3 such that both warmth and competence perceptions of the AI teammate positively influenced receptivity to the AI teammate for reflection and psychological acceptance. However, results only

[3] An anonymous reviewer suggested that hypotheses should be tested by considering the effect of perceived warmth and competence separately. For Study 1, independent effects are equivalent to the correlations shown in Table 3. For Study 2, the direct effect requires controlling for non-independence due to team membership. Consequently, we present HLM results for the independent effects of perceived warmth and competence on all receptivity variables here. The effect of perceived warmth on reflection was b = 0.36, p < .001, knowledge utilization was b = 0.35, p < .001, and psychological acceptance was b = 0.48, p < .001. The effect of competence on reflection was b = 0.37, p < .001, knowledge utilization was b = 0.63, p < .01, and psychological acceptance was b = 0.71, p < .001.

Table 7
Descriptive statistics and correlations for variables in study 2.

Variable	M	SD	1	2	3	4	5	6
1. Warmth	2.94	0.83	.87					
2. Competence	3.98	0.86	.57***	.91				
3. Reflection	3.05	0.90	.38***	.70***	.89			
4. Knowledge Utilization	3.37	0.99	.36***	.37***	.50**	.86		
5. Psychological Acceptance	5.01	1.77	.48***	.70***	.75***	.37***	.91	
6. Viability	6.02	1.10	.11	.17*	.11	−.01	.23**	.79

Note. Coefficient alphas are on diagonal. p-values are two-tailed.
***$p < .001$. **$p < .01$. *$p < .05$.

Table 8
Hierarchical linear model results predicting receptivity variables from AI teammate warmth and competence in study 2.

	Reflection			Knowledge Utilization			Psychological Acceptance		
Variable	*b*	SE	*p*	*b*	SE	*p*	*b*	SE	*p*
Warmth	0.23**	.08	.003	0.02	.06	.353	0.16**	.06	.007
Competence	0.24**	.08	.003	0.62***	.06	<.001	0.61***	.07	<.001
R^2 (fixed)	0.17			0.44			0.48		
R^2 (fixed + random)	0.25			0.59			0.61		

Note. R^2 (fixed) = proportion of total variance explained by fixed effects. R^2 (fixed + random) = proportion of total variance explained by fixed and random intercept variation.
***$p < .001$. **$p < .01$.

partially supported H2 such that competence but not warmth perceptions were positively related to knowledge utilization.[4]

3.2.3. HAT viability perceptions

H4, H5, and H6 stated that reflection, knowledge utilization, and psychological acceptance would be positively related to individual perceptions of HAT viability, respectively. We tested three separate models in which perceived HAT viability was regressed on each of the teammate receptivity components using HLM while controlling for warmth and competence perceptions. Results of these analyses are shown in Tables 9–11 respectively. There was a significant positive effect of psychological acceptance on perceived HAT viability ($b = 0.25$, $p = .010$), but not reflection or knowledge utilization. Thus, in Study 2 results support only H6 regarding a positive relationship between psychological acceptance and perceived HAT viability.

Given the positive relationship of psychological acceptance with perceived HAT viability, as well as the positive relationship of perceived warmth and competence with psychological acceptance, it is possible that there is an effect of perceived warmth and competence on perceived HAT viability via psychological acceptance. Indeed, this influence of interactive processes on team outcomes is consistent with the input-process-output (IPO) framework (Ilgen et al., 2005) from the extant human teams literature such that individual and team characteristics (e.g., warmth and competence) predict processes, and processes in turn predict outcomes. To test this possibility, we also tested a multilevel mediation model using the R package *lavaan* (Rosseel, 2012). There was a significant indirect effect of both perceived warmth and competence on perceived HAT viability (warmth: $b = 0.02$, $p = .014$, 95% CI [0.002, 0.029]; competence: $b = 0.05$, $p = .011$, 95% CI [0.007, 0.094]), as well as a significant direct effect of competence on perceived HAT viability (*b*

Table 9
Hierarchical linear model results predicting viability from reflection in study 2.

Variable	*b*	SE	*p*
Reflection	−0.08	.08	.172
Warmth	0.01	.09	.441
Competence	0.20***	.09	.014
R^2 (fixed)	.04		.163
R^2 (fixed + random)	.15		

Note. R^2 (fixed) = proportion of total variance explained by fixed effects. R^2 (fixed + random) = proportion of total variance explained by fixed and random intercept variation.
***$p < .001$. **$p < .01$.

Table 10
Hierarchical linear model results predicting viability from knowledge utilization in study 2.

Variable	*b*	SE	*p*
Knowledge Utilization	0.00	.10	.489
Warmth	−0.01	.09	.471
Competence	0.19	.11	.052
R^2 (fixed)	.03		
R^2 (fixed + random)	.16		

Note. R^2 (fixed) = proportion of total variance explained by fixed effects. R^2 (fixed + random) = proportion of total variance explained by fixed and random intercept variation.
***$p < .001$. **$p < .01$.

Table 11
Hierarchical linear model results predicting viability from psychological acceptance in study 2.

Variable	*b*	SE	*p*
Psychological Acceptance	0.25**	.11	.010
Warmth	−0.02	.09	.397
Competence	0.01	.12	.463
R^2 (fixed)	.06		
R^2 (fixed + random)	.21		

Note. R^2 (fixed) = proportion of total variance explained by fixed effects. R^2 (fixed + random) = proportion of total variance explained by fixed and random intercept variation.
***$p < .001$. **$p < .01$.

[4] In Study 2, participants also completed measures of Technology Readiness (Parasuraman & Colby, 2015) and the Negative Attitudes toward Robots (Nomura et al., 2008) measures. We ran all analyses including these variables, as well as age and gender, as controls. In no case did inclusion of these controls meaningfully change results (i.e., coefficients remained similar in magnitude and no changes in significance).

= 0.07, $p = .031$). All paths in the mediation model are shown in Fig. 2. Thus, results are consistent with an indirect effect of perceived warmth and competence on perceived HAT viability. However, results also show direct effects of both perceived warmth and competence on perceived HAT viability even when controlling for psychological acceptance.

3.3. Discussion of study 2

Results of Study 2 support H1 and H3 such that both perceived warmth and competence showed significant, positive relationships with reflection and psychological acceptance, respectively. However, results only partially supported H2 regarding knowledge utilization such that there was a positive effect of perceived competence but not perceived warmth. Additionally, whereas results showed a similar effect magnitude of perceived warmth and competence on reflection, the effect of competence was stronger than that of perceived warmth for psychological acceptance. Overall results of Study 2 suggest that although perceived warmth is positively related to some components of receptivity to AI teammates (i.e., reflection and psychological acceptance), perceived competence is positively related to *all* components of receptivity and, moreover, shows a stronger relationship with psychological acceptance than does perceived warmth.

Additionally, we also tested the effect of reflection, knowledge utilization, and psychological acceptance on overall perceived viability of the HAT (H4, H5, and H6, respectively). However, of all receptivity variables, only psychological acceptance showed a relationship with overall perceptions of HAT viability. Thus, only H5 was supported. To test whether there may be an effect of perceived warmth and competence on perceived HAT viability via psychological acceptance, we also conducted a mediation analysis. Results supported an indirect effect of perceived warmth and competence on perceived HAT viability via psychological acceptance. We elaborate on these results in the context of Study 1 results in our general discussion below.

4. General discussion

One of the most important design considerations for successful human-AI teamwork is how AI teammate characteristics influence human receptivity to new AI teammates. In the current study, we assert that fully understanding and predicting the successful integration of AI teammates into HATs requires synthesizing research on HCI and HRI with models of human newcomer socialization. Moreover, the universal dimensions of person-perception offer a particularly useful framework for understanding the social perception of AI teammates. Cutting across two studies, we found support for our hypotheses such that both perceived warmth and competence are positively related to the three components of receptivity to the AI teammate, albeit with some important nuances and differences between the two studies.

Further, because the current study is the first to test the complete tripartite model of receptivity to newcomers (Rink et al., 2013) in any kind of team, including human-only or human-AI teams, we also tested the relationship between the three components of receptivity and perceived HAT viability, a key indicator of team effectiveness (Bell & Marentette, 2011). Results were partially supported such that there was a positive relationship between psychological acceptance and perceived HAT viability, but not reflection or knowledge utilization. We summarize results across both studies for receptivity and perceived HAT viability respectively, as well as their implications for the future research and design of AI teammates.

4.1. Implications for receptivity to an AI teammate

H1, H2, and H3 concerned the influence of perceived warmth and competence on the three components of receptivity: reflection, knowledge utilization, and psychological acceptance, respectively. Across both Study 1 and Study 2, results for reflection were relatively consistent such that perceived warmth and competence showed similar, positive relationships with reflection. Indeed, of the three receptivity components, results for reflection were most consistent with the hypothesis such that perceived warmth and competence showed positive effects of similar magnitudes. These results suggest that without perceiving both warmth and competence, team members may not be willing to adapt their work processes to integrate an AI teammate.

In contrast, for knowledge utilization, there was a positive, significant influence of both perceived warmth and competence in Study 1, although the effect magnitude was larger for competence. In Study 2, only competence showed a significant relationship with knowledge utilization. Taken together, results suggest a much stronger influence of perceived competence than perceived warmth on knowledge utilization. Thus, AI teammates should be designed such that their skills and abilities are clearly apparent and can be integrated to maximize knowledge utilization.

At the same time, the null relationship of warmth and knowledge utilization in Study 2 is consistent with the hypothesized relationship. Notably, knowledge utilization concerns both the recognition *and* adoption of a newcomer's unique skills and abilities. Our measure of knowledge utilization primarily assessed the recognition of these abilities. Although this focus on recognition is consistent with prior perceptual measures of knowledge utilization (e.g., newcomer task contributions and ratings; Rink et al., 2013), it may also help to explain

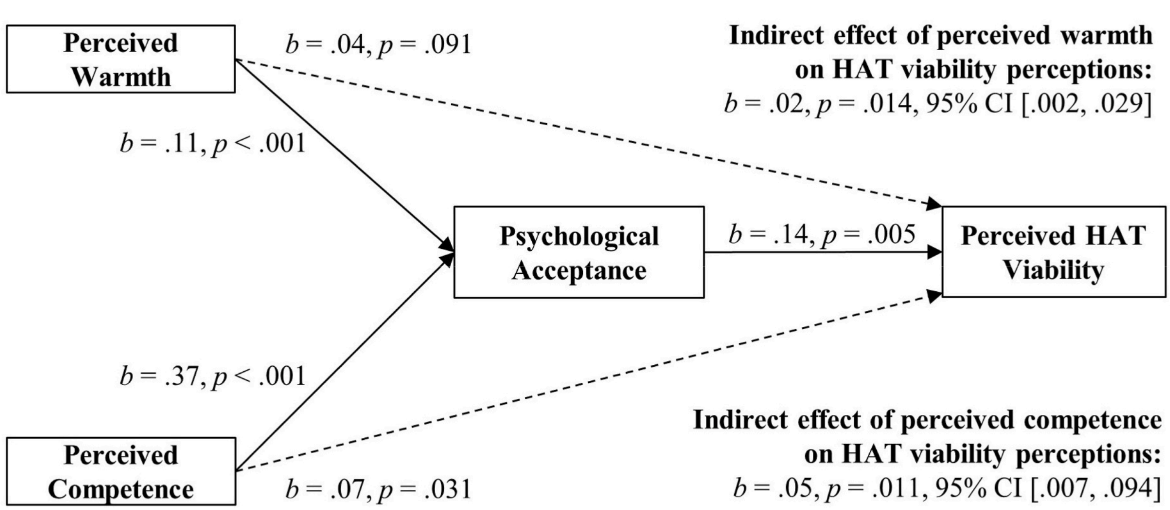

Fig. 2. *Results of Mediation Model in Study 2. Note.* p-values are one-tailed consistent with best practices in directional hypothesis testing (Cho & Abe, 2013).

why perceived warmth did not exhibit a stronger relationship with knowledge utilization in the current study. Results for reflection suggest that perceived warmth matters for willingness to change team and work processes. Had our measure included a greater emphasis on behavioral indicators of newcomer knowledge *adoption*, which are similarly likely to require some changes to a team member's current behavioral patterns, perceived warmth may have shown a stronger relationship.

Results for psychological acceptance also differed across the two studies. In Study 1, perceived competence showed a slightly larger effect magnitude for psychological acceptance than did perceived warmth. In Study 2, perceived competence showed a substantially stronger effect on psychological acceptance than did perceived warmth. Thus, results are consistent with the hypothesis such that both warmth and competence perceptions are positively related to psychological acceptance, but their relative importance remains unclear.

One possible explanation for the differences between the two studies is the nature of the tasks and team types across the two studies. Participants may have valued the warmth and competence of AI teammates differently depending on the type of task. In Study 2, teams completed an "intellective" problem-solving task and a "creativity" alternative uses task (McGrath, 1984, pp. 53–66). Competence perceptions may have been particularly salient for these types of tasks. In contrast, in Study 1, we had relatively little control over the referent teams that participants chose and the corresponding team tasks. Participants in Study 1 may have envisioned teams with more social interaction than the tasks used in Study 2. For example, some of the reported referent team types were conflict resolution or negotiation teams, which may have resulted in teams more heavily weighting perceptions of AI teammate warmth than they would have for the types of tasks in Study 2. Indeed, Dou et al. (2020) found that people's expectations for warmth and competence are in part dependent on the intended application of the robot. Had our HATs in Study 2 also participated in conflict resolution and/or negotiation tasks, participants may have reported perceptions of warmth as greater in importance than they did in the intellective and creativity tasks of Study 2. Our results are consistent with this suggestion that attributes may have differential importance dependent on task types. For example, humans may place greater emphasis on AI competence in problem-solving tasks and greater emphasis on warmth in tasks involving high levels of social interaction. Future research should continue to explore the influence of team context and task types.

Moreover, the type of AI teammate and characteristics represented in each study may also have affected findings. There is a wide variety in types of AI teammates, including social robots, virtual personal assistants, and chat bots, each ranging in their level of autonomy, capabilities, and physical attributes. Several studies have shown that a wide range of physical, interactive, verbal, and nonverbal features can affect the perceptions of warmth and competence (Frischknecht, 2021; Pan et al., 2018; Piçarra & Giger, 2018; Reeves et al., 2020; Spatola & Wudarczyk, 2021). In Study 1, we selected eight AI teammates that differed in level of physical embodiment, interpersonal skills, competency skills, etc. In Study 2, the AI teammate was disembodied, moderately interpersonal, moderately skilled, and limited in its available functions (i.e., the extent to which it completed teamwork and/or taskwork functions).

Thus, differences in results between Study 1 and Study 2 may be in part attributable to differences in agent type. For instance, warmth perceptions may be more important for physically embodied AI, which would explain the stronger influence of warmth in Study 1 relative to Study 2. This is also consistent with Glikson and Woolley (2020)'s suggestion that human-likeness (i.e., physical presence and socially responsive behaviors) may be more important for emotional trust than cognitive trust. It is possible that such behaviors are important because they influence perceptions of warmth, which in turn influences trust. Future research should continue to explore how AI agent features influence perceptions of warmth and competence.

Further, this study was the first to our knowledge to test the effect of warmth and competence perceptions on the three components of the tripartite model of receptivity. Consequently, results also have important implications for the conceptualization of receptivity to AI teammates. Although our three receptivity components were highly correlated, they did not show the same pattern of relationships with perceived warmth and competence. For example, results suggest that perceived warmth is more important for psychological acceptance than it is for knowledge utilization. These differences highlight that while perceived competence may be sufficient to spur integration of an AI's expertise, fully integrating an AI as a socially interdependent teammate depends on both competence and at least some level of perceived warmth. Looking at just one of the receptivity criteria (i.e., reflection, knowledge utilization, or psychological acceptance) would have yielded different understandings of how warmth and competence perceptions impact adjustment to an AI teammate.

These differential relationships underscore Rink and colleagues' (2013) assertion that all three components are critical to fully capturing receptivity. Much of the work on human-AI interaction focuses on broadly defined willingness to work with the AI, trust, or general emotional reaction. Because broad criteria could obscure meaningful differences in antecedents, specifying the criterion more narrowly may be important to delineating the influence of perceived warmth and competence or other characteristics. Indeed, this need for narrower criterion specification is consistent with Glikson and Woolley (2020)'s review of the differential antecedents of cognitive and affective trust in AI, which overlap with knowledge utilization and psychological acceptance, respectively.

Finally, results highlight the value of integrating research on AI agents in the HCI/HRI literature and adjustment to human newcomers in the teams literature. Most models of human reactions to AI agents do not yet capture the complex social and psychological processes of receptivity to a fully interdependent AI teammate. On the other hand, inferences about the role of warmth and competence in human-only relationships may not apply to AI teammates. In contrast to the well-established primacy of warmth in human interpersonal dynamics (Casciaro & Lobo, 2005; 2008; Cuddy et al., 2011), a "competent jerk" may be preferable to a "lovable fool" among AI teammates. Across both studies and the three receptivity components, only reflection showed similar effect sizes with perceived warmth and competence. For both knowledge utilization and psychological acceptance, results showed that perceived competence had a greater influence than did perceived warmth. The stronger influence of warmth relative to competence was not hypothesized and suggests that humans may place greater importance on the perceived competence of AI teammates than the perceived competence of human teammates. Still, it is clear that team members would prefer both human and AI newcomers who are perceived as both competent *and* lovable.

4.2. Implications for HAT viability

In H4, H5, and H6, we proposed that the three receptivity components would influence perceived HAT viability. However, only H6, looking at the psychological acceptance of the AI teammate, was supported. These results suggest that the extent to which an AI teammate is seen as a full team member may impact the perceived viability of the HAT, a critical and commonly studied indicator of long-term team effectiveness (Kozlowski & Ilgen, 2006). In contrast, reflection and knowledge utilization did not show the expected relationships with perceived HAT viability. These results call into question whether the tripartite model of receptivity used here is the best framework for understanding and predicting the effectiveness of HATs. Notably, because we are the first to test a complete tripartite model of receptivity in either human-only teams or HATs, it is not entirely clear whether these results are unique to the HAT context. Thus, our results emphasize the need for more theorizing regarding the conceptualization and operationalization of successful integration of AI teammates.

Finally, given evidence that perceived warmth and competence are positively related psychological acceptance, and that psychological acceptance is positively related to perceived HAT viability, we tested an indirect effect of perceived warmth and competence on HAT viability perceptions via mediation. Results supported an indirect effect consistent with the IPO model such that newcomer characteristics of warmth and competence may influence outcomes such as perceived HAT viability through psychological acceptance.

It is important to note that the current study used cross-sectional data. Consequently, we cannot establish causality such that perceived warmth and competence precede receptivity components, or that receptivity components precede perceived HAT viability, as would be suggested by mediation. Nonetheless, although the mechanism remains unclear, these results suggest that perceived competence—and potentially perceived warmth—may influence more distal team effectiveness constructs such as HAT viability. Given the novelty of the constructs and study design used here, we believe that our results offer important initial insights for understanding how AI teammate characteristics are related to receptivity components and, in turn, how those receptivity components are (and are not) related to perceived HAT viability. We hope that future researchers can build on these insights, as well as utilize more complex designs over longer time periods, to further establish the relationship between AI teammate characteristics, receptivity, and critical team outcomes.

4.3. Limitations and future directions

4.3.1. Study design

One of the key advantages and contributions of the present study is the use of actual lab-based HATs in Study 2 relative to the purely hypothetical, video vignette design in Study 1. However, the methodology of the current study also includes several key limitations. For example, this difference in fidelity between studies could account for the stronger effects of competence in Study 2 relative to Study 1. These results might suggest that although participants expect warmth to matter for knowledge utilization and expect warmth to matter about as much as competence for psychological acceptance, in reality competence matters more. As more HAT research is conducted in organizational psychology and organizational behavior, where vignette studies are common, there will likely be more attempts at using vignettes to understand HATs (for a more in-depth discussion of the use of experimental vignette methodology in the study of technologies, see Aguinis & Bradley, 2014). In particular, vignette designs may be appealing because they allow researchers to study the influence of AI teammates that are either not yet fully realized or cost prohibitive to implement. However, our results suggest that it may be important to use actual teams when studying HATs as opposed to merely vignette studies.

Another limitation of the current study design is that warmth and competence perceptions were indirectly manipulated. In both studies, we used experimental conditions to introduce meaningful variance in perceived warmth and competence. In Study 1, warmth and competence perceptions varied as a function of the assigned AI video. This approach is consistent with prior images (Reeves et al., 2020; Liu et al., 2021; Spatola & Wudarczyk) and short video clips (Ho & MacDorman, 2010; Piçarra & Giger, 2018) of AI agents. However, our design in Study 1 did not afford isolating the influence of specific features of the AI agents. In Study 2, warmth and competence perceptions varied as a function of the confederate scripts used (i.e., focusing on taskwork, teamwork, or a combination). This approach is consistent with other research that has manipulated warmth and competence perceptions via agents' verbal expressions (Oliveira et al., 2019) and behaviors (Kulms & Kopp, 2018; Peters et al., 2017). However, it is possible that in both Study 1 and Study 2, the manipulation may have *directly* impacted receptivity to the AI agent independent of the influence via warmth and competence perceptions. Future research should consider manipulations that more directly impact warmth and competence of the AI teammate in order to better isolate the factors that affect the three components of receptivity.

Finally, the virtual context of Study 2 provided both advantages as well as some notable limitations. Remote work became the primary work environment for many during the COVID-19 pandemic, so the virtuality of Study 2 represents an increasingly realistic modality for human-AI collaboration. Prior research suggests that newcomer assimilation in virtual teams may differ from newcomer assimilation in co-located teams (Picherit-Duthler et al., 2004, pp. 115–132). That is, virtual teams are faced with inherently greater ambiguity and artificiality because of the virtual environment, compared to co-located teams (Fiore, Salas, Cuevas, & Bowers, 2003). Moreover, within the context of HATs specifically, virtuality may impact reactions to AI teammates. Physical embodiment of a new AI teammate is likely to affect the development of critical team states, such as cognitive- and affective-based trust (Glikson & Woolley, 2020). Consequently, the extent to which human-AI collaboration occurs in person or remotely—and subsequently the physical presence and embodiment of the AI teammate—may impact both the perceptions of warmth and competence, as well as how those perceptions influence receptivity to the AI teammate. The examination of virtuality as well as the physical embodiment of the AI teammate as predictors of warmth and competence perceptions, and subsequent receptivity behaviors, present fruitful areas for future research on this topic.

4.3.2. Study timeline

The timing and sequence of our study may have affected findings. First, the unexpected null relationship between reflection and perceived HAT viability may have differed had our study been conducted over a longer period of time. It is possible that the disruption caused by high reflection (i.e., substantial changes in team processes) may actually undermine viability in the short-term. Our study was conducted in a single 3-h session whereas, typically, newcomers may be integrated into established teams over many weeks or months. Had our study continued, reflection may have shown a positive, significant relationship with long-term HAT viability. Indeed, reflection is thought to be critical to effective adaptation to team newcomers in longer time periods (e.g., over a 1 week period; Lewis et al., 2007). Additionally, the current study conceptualized all variables and conducted corresponding analyses at the individual level. Research that aims to explore the relationship between team-level processes and outcomes in HATs may need to utilize longer time periods in order to see sufficient emergence from individual level to team level processes; ICC values here did not support strong convergence among team members for all receptivity components. Thus, although short interactions are the norm for research on human-computer interaction, particularly in collaborative work contexts (O'Neill et al., 2020), real HATs in organizational contexts are likely to require long-term, ongoing collaborative work.

Additionally, some research has shown that perceptions of warmth and competence are likely to change overtime. Bergmann et al. (2012) found that impressions of AI warmth tended to decrease over time, whereas Pan et al. (2018) found that warmth ratings increased over time. In Study 1, participants rated warmth and competence after watching a short video of an AI agent. In Study 2, participants rated warmth and competence after two rounds of working with the AI teammate to complete a task. Although we believe that our study design is consistent with research broadly that supports the importance of warmth and competence in first impressions of others (Fiske et al., 2007), future research should explore how ratings of warmth and competence may change overtime and how those changes may impact overall reactions to an AI teammate.

4.3.3. Extending person-perception

Future research should continue to explore the application of person-perception to agent-perception. First, future research should directly compare the overlap between measures of warmth and competence perceptions developed for people versus AI agents. In the current research, Study 1 utilized traditional measures of warmth and competence developed for people (Fiske et al., 2002), whereas Study 2 utilized a measure of warmth and competence developed for AI agents (i.e., the RoSAS; Carpinella et al., 2017). Although both are commonly used in the HCI/HRI literatures, and the theoretical foundation of the RoSAS drew on the person-perception literature, we are not aware of any research that directly compares the two measures. Future research should consider a more extensive psychometric evaluation comparing the two measures.

Additionally, future research might also consider evaluating other critical dimensions within the Big Two framework. Here, we focused on warmth and competence, which have shown tremendous evidence for affecting human interpersonal relationships, as well as growing evidence for affecting human-computer and human-robot interaction. Although the labels "competence" and "warmth" are sometimes used interchangeably with "agency" and "communion" respectively, Abele et al. (2016) have shown that warmth and competence reflect two subdimensions of agency and communion. They argue that the Big Two are most appropriately defined as Agency and Communion, which are in turn each composed of two subdimensions: assertiveness and competence (within agency) and warmth and morality (within communion). Assertiveness and morality may reflect additional dimensions of social perception that are relevant to evaluating the value of AI teammates. In fact, several studies have examined perceptions of dominance and submissiveness in AI agents (Robert et al., 2020), which are closely related to the agentic dimension of assertiveness. Additionally, morality may have particularly important implications for AI teammates tasked with high-stakes decision–making, such as emergency response or medical treatment. Future research might consider whether the full domain of the Big Two provides a more complete theoretical framework for the social perceptions of AI teammates.

4.3.4. Human Team-HAT comparison

The current study also presents opportunities for extension and useful comparison between the human teams literature and the emerging HAT literature. In particular, this study suggests that what we know about human teams is useful for how we study and implement HATs. We applied a tripartite model of human newcomer receptivity to the entry of an AI teammate and found that perceptions of the AI teammate characteristics of warmth and competence were positively related to all three dimensions of receptivity, and in turn, the receptivity dimension of psychological acceptance is positively related to perceptions of HAT viability, a critical indicator of HAT success. Future research should extend the relationships tested here to human teammates in three ways.

First, more research is needed on the tripartite model of receptivity to newcomers in human teammates. Although the tripartite model of receptivity draws on the human newcomer socialization literature, we are not aware of any studies in human-only teams that have looked at all three components, nor that have considered the influence of warmth and competence perceptions on receptivity. Evaluating these relationships among human-only teams would afford a more direct analysis of whether newcomer receptivity and its relationships with team composition, differ in human-only teams and HATs. For example, in the current study, only psychological acceptance showed a positive relationship with perceived HAT viability. It is possible that the other two components of the tripartite model of receptivity would be more strongly related to team viability in human-only teams. More research on the tripartite model of receptivity is needed in human-only teams in order to determine if these findings are due to the HAT context or a factor specific to the study design used here.

Second, future research should extend other models and constructs from human team theory to HATs. To our knowledge, our study is one of the first to consider the influence of perceived AI teammate characteristics on indicators of long-term HAT success. Although we focused on HAT viability perceptions as a particularly useful indicator of overall HAT success, many other states and outcomes have been conceptualized as critical indicators of team success in the human teaming literature and should be explored in HATs specifically (O'Neill et al., 2020). While in the current study only psychological acceptance showed a positive relationship with perceived HAT viability, the other receptivity components may show relationships with other important processes and outcomes. In particular, viability is an affect-loaded outcome, which may explain why it was related to the most affective component of receptivity (i.e., psychological acceptance). Other cognitive states and outcomes may show stronger relationships with reflection or knowledge utilization.

Further, while the current study measures all variables at the individual level, research that explores team states and outcomes often conceptualizes these constructs at the team level. Thus, future research should consider indicators of team success beyond individual perceptions of viability, including team level measures of states and outcomes. Moreover, in existing human-only teams to which AI teammates are added, teams will already have fully formed affective, behavioral, and cognitive states, such as psychological safety or decision-making climate. These pre-existing states may themselves impact how AI teammates are received. Indeed, ample research on human teams has demonstrated a reciprocal relationship between these states; team states are themselves outcomes influenced by team processes and in turn become inputs that influence processes and outcomes (Ilgen et al., 2005). Thus, we urge future researchers to explore not only other states and outcomes salient to HATs but also how to strengthen those states in pre-existing human teams to enhance receptivity to AI teammates.

Finally, future research should directly compare the role of warmth and competence perceptions for receptivity to human and AI teammates. Among human-only studies that have considered constructs related to receptivity, findings have consistently demonstrated a primacy of warmth relative to competence in shaping human interpersonal dynamics (Fiske et al., 2007). In contrast, results of the current study suggest that although perceived warmth and competence both positively influence receptivity to AI teammates, perceived competence may matter somewhat more than perceived warmth, particularly for knowledge utilization and psychological acceptance. Although these differences may be attributable to different expectations for humans versus AI teammates, it is also possible that task type or other situational factors have also influenced findings. In order to evaluate whether perceptions of warmth and competence show truly different patterns of relationships with receptivity to new AI teammates as opposed to human newcomers, future research on HATs should investigate the influence of warmth and competence perceptions of both AI and other human newcomers within the same team using the same task types.

4.4. Conclusion

Relatively little work has explored the influence of AI teammate social attributes for facilitating human receptivity to AI teammates in HATs. To address this gap, this study investigated the influence of warmth and competence perceptions on a tripartite model of receptivity (reflection, knowledge utilization, and psychological acceptance) drawn from the human newcomer socialization literature. Results demonstrated that perceptions of AI teammate warmth and competence are positively related to receptivity, although perceived competence showed a stronger relationship than perceived warmth for both knowledge utilization and psychological acceptance. Further, results supported the influence of one receptivity component—psychological acceptance—on perceptions of HAT viability but found no support for knowledge utilization or reflection. Overall, results suggest that the same universal dimensions of warmth and competence that have been applied to understand person-perception offer a useful framework for understanding and designing social attributes of AI teammates. Differences in results across the two studies underscore the importance of using high fidelity designs to study HATs, as well as the need for additional research that applies this tripartite model of newcomer receptivity to AI teammates. Future research should continue to integrate both human- and technology-centered theory to better understand and predict effective HATs.

Credit author statement

Alexandra Harris-Watson: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Lindsay E. Larson**: Conceptualization, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing. **Nina Lauharatanahirun**: Conceptualization, Investigation, Methodology, Supervision. **Leslie A. DeChurch**: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing – original draft. **Noshir Contractor**: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision.

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Data availability

Data will be made available on request.

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