Behaviour & Information Technology

ISSN: 0144-929X (Print) 1362-3001 (Online) Journal homepage: www.tandfonline.com/journals/tbit20

Modeling perceived information needs in human-AI teams: improving AI teammate utility and driving team cognition

Beau G. Schelble, Christopher Flathmann, Jacob P. Macdonald, Bart Knijnenburg, Camden Brady & Nathan J. McNeese

To cite this article: Beau G. Schelble, Christopher Flathmann, Jacob P. Macdonald, Bart Knijnenburg, Camden Brady & Nathan J. McNeese (2025) Modeling perceived information needs in human-AI teams: improving AI teammate utility and driving team cognition, Behaviour & Information Technology, 44:9, 2069-2092, DOI: 10.1080/0144929X.2024.2396476

To link to this article: https://doi.org/10.1080/0144929X.2024.2396476

Published online: 27 Aug 2024.

BEHAVIOUR & INFORMATION TECHNOLOGY
2025, VOL. 44, NO. 9, 2069–2092
https://doi.org/10.1080/0144929X.2024.2396476

Modeling perceived information needs in human-AI teams: improving AI teammate utility and driving team cognition

Beau G. Schelble[a], Christopher Flathmann[b], Jacob P. Macdonald[b], Bart Knijnenburg[b], Camden Brady[b] and Nathan J. McNeese[b]

[a]Industrial & Systems Engineering, The University of Tennessee-Knoxville, Knoxville, Tennessee, USA; [b]School of Computing, Clemson University, Clemson, South Carolina, USA

ABSTRACT

As AI technologies advance, teams are beginning to see AI transition from a tool to a full-fledged teammate. Introducing an AI teammate brings several challenges, ranging from how human teammates perceive their new AI teammates from an affective standpoint to how AI should engage in the various teaming behaviors that make up effective teamwork. The current study used a mixed factorial survey and structural equation modeling to assess how participants in hypothetical human-AI teams respond to various forms of AI information-sharing, including information related to explainability, back-up behavior, situational awareness, and augmenting team memory. The study's results found that AI design features related to situational awareness and augmenting the teams' memory had the strongest effect on participants' attitudes and perceived team cognition with their teammates. However, much of this effect was mediated by participants' affective attitudes towards the AI as a teammate, with higher ratings leading directly to higher levels of perceived team cognition constructs. These results highlight the importance of fostering positive attitudes towards AI teammates, such as trust and cohesion in human-AI teams, to support the development of effective team cognition and the ability of AI information-sharing to bring about such positive impacts.

ARTICLE HISTORY
Received 25 November 2023
Accepted 12 August 2024

KEYWORDS
Team cognition; artificial intelligence; human-machine systems; human-AI interaction; situational awareness

1. Introduction

Teams are an essential construct of society frequently utilized to accomplish difficult work in various environments and tasks (Salas, Cooke, and Rosen 2008). To continually address such challenges, teams have consistently leveraged the latest technologies to extend and enhance their operational capabilities. One of the newest technologies being brought into the fold of teaming is artificial intelligence (AI), which has seen several rapid technological advances over the past decade, enhancing its ability to engage in complex and human-facing tasks (Choi et al. 2023; Schelble et al. 2020; Schelble, Flathmann, and McNeese 2020). However, several critical questions regarding the dynamics of teamwork within human-AI teams remain unanswered as AI begins taking center stage (National Academies of Sciences Engineering and Medicine 2022; McNeese et al. 2018), causing research on human-AI teaming to be published at an ever-increasing rate (O'Neill et al. 2020). This research has highlighted that successfully joining humans and AI together in teams is not entirely dependent on AI's technical ability but also on numerous human factors that impact humans' and AI's ability to collaborate within human-AI teams (O'Neill et al. 2020; Shneiderman 2020). For instance, merely perceiving that a teammate is artificial has been linked to several adverse effects on team processes and outcomes (Musick, O'Neill, et al. 2021; Walliser, Mead, and Shaw 2017), such as performance (Demir, McNeese, and Cooke 2018; Schelble, Flathmann, McNeese, O'Neill, et al. 2022). Consequentially, human-AI teaming literature has found that human-AI teams struggle more when engaging in complex interdependent tasks that require high levels of shared knowledge compared to human-only teams (Fan and Yen 2010; Wright and Kaber 2005). This difficulty stems from the increased coordination and communication inherent to completing complex tasks, which humans and AI currently struggle to engage in effectively (Demir, McNeese, and Cooke 2017). This shortcoming of AI teammates holds them back from widespread adoption, and a failure to rectify it will further propagate the negative perception that AI teammates are inadequate.

CONTACT Beau G. Schelble bschelbl@utk.edu Industrial & Systems Engineering, The University of Tennessee-Knoxville, 851 Neyland Drive, 515 John Tickle Building, Knoxville, Tennessee 37996, USA

Current AI teammates can engage in taskwork that contributes to positive team outcomes. However, unlocking the true potential of human-AI teams will require AI capabilities and design, focussing on the innately human elements of teaming. Specifically, AI must begin to integrate itself within the highly social and complex role of a teammate, as the responsibilities of a teammate exceed those of a tool. AI teammates must consider how to properly handle communication, coordination, and training with human teammates as they are essential to developing team-specific constructs such as team cognition. Team cognition involves any cognitive activity regarding the team's shared knowledge of the team and task (Cannon-Bowers, Salas, and Converse 1993; Cooke et al. 2013), which is critical to outcomes such as satisfaction, performance, and efficiency (Mathieu et al. 2000; Mohammed, Ferzandi, and Hamilton 2010; Niler et al. 2021). This construct represents the importance of shared knowledge to teaming outcomes, specifically, shared knowledge in the form of shared mental models (SMM)s and team situational awareness (SA) (Cooke et al. 2007), which are both critical to human-AI team performance (Demir, McNeese, and Cooke 2017; Endsley 2023; Schelble, Flathmann, McNeese, Freeman, et al. 2022). SA, specifically, serves a critical function in teams as it involves the perception of elements within the environment, understanding their relevance, and using that information to project their statuses in the future (Endsley 1988b). SMMs, on the other hand, represent structured knowledge shared amongst team members on topics related to the task and team (Cannon-Bowers, Salas, and Converse 1993). These SMMs help drive improved team SA development (Endsley 2021; Stout, Cannon-Bowers, and Salas 2017), leading to improved overall team cognition and performance (Mathieu et al. 2000). However, developing effective team cognition relies upon team members sharing the relevant information at the correct times (McNeese et al. 2021; Salas et al. 1995), which human-AI teams, in particular, struggle to do effectively (Demir, McNeese, and Cooke 2017). As such, SA is a ripe area for AI teammates to significantly contribute to team cognition and improve the shortcomings noted in its development and maintenance within human-AI teams (Demir, McNeese, and Cooke 2017, 2018; Musick, O'Neill, et al. 2021). However, for human teammates to accept these contributions to team cognition from an AI teammate, adequate trust and cohesion must be developed with the AI first (Vaes et al. 2003).

Strengthening AI's contributions to team cognition directly emphasizes improving the coordination struggles human-AI teams experience and subsequently, their overall performance. One way to confront these concerns centres on information-sharing, because information lies at the heart of team cognition development and support (Cannon-Bowers, Salas, and Converse 1993; Cooke et al. 2013). As such, AI teammates can begin to engage in proper teaming behaviors through design meant to build on team cognition throughout the team by utilising effective information-sharing tactics, which can benefit a host of constructs representative of team cognition, including team SA (Endsley 2023), SMMs (Schelble, Flathmann, McNeese, Freeman, et al. 2022), and transactive memory systems (Brandon and Hollingshead 2004). These information-sharing tactics involve any information communicated by a teammate that contributes to taskwork or teamwork (Bunderson and Sutcliffe 2002; Mesmer-Magnus and DeChurch 2009). Information-sharing from AI can take advantage of their inherent technical advantages such as improved memory and bandwidth by providing instantaneous information as it happens (Mughal 2018), recalling data for teammates, and even analysing a situation based on information not readily available to teammates to provide enhanced suggestions for direction (Cuevas et al. 2007). Augmenting team cognition through effective information-sharing and direction based on that information also presents a unique advantage to SA as it is predicated on accurate and timely information, which can uniquely enhance coordination and outcomes within human-AI teams. Providing direction based on that information is then regarded as information processing, which is a form of information-sharing that can improve performance when team members can communicate their intent and understanding based on shared information (Mesmer-Magnus and DeChurch 2009).

Information communication develops and empowers team cognition, directly enabling effective coordination toward team-relevant goals. One of the critical challenges in human-AI teaming is how to design AI teammates that can share information with human teammates to foster positive attitudes and lead directly to more effective team cognition and outcomes. The current study confronts this critical challenge and gap in the research by addressing the following research questions:

RQ1: *How do the information-sharing attributes of AI influence their human teammates' affective attitudes towards them?*

RQ2: *Do information-sharing tendencies by an AI teammate affect human teammates' perceived team cognition?*

The current study utilises a factorial survey with scenarios of human-AI teams working in a team-based video game context to examine how various types of information-sharing attributes by an AI teammate influence affective attitudes and perceptions of constructs representative of team cognition. As such, this research provides a detailed picture of how information-sharing by an AI teammate influences various affective perceptions such as teammate rating and how such attitudes subsequently affect perceptions of team cognition and mediate the effect of information-sharing. The specific contributions of the research include: (1) detailing the relationship between information-sharing behaviour by an AI teammate and human teammates' affective attitudes towards that AI teammate; (2) identifying the relationship between perceptions of the AI teammate and perceptions between human teammates; and (3) the prominent influence that AI teammates can have on their human teammates' perception of SA. These insights help focus team cognition research in human-AI teaming and provide direct information to designers and developers of AI teammates to help improve information-sharing strategies for AI teammates.

2. Background

The following section reviews current literature to define the role of team cognition in teaming and its relevance to information-sharing attributes within human-AI teams.

2.1. The role of shared knowledge in teaming

Team cognition is a fundamental construct within teaming research as it holds significant sway over the success and execution of various team processes and outcomes. The construct is an umbrella term for all team member cognition concentrated on team interaction and task execution knowledge. In practice, teams are able to create a shared cognition that governs the processes of shared knowledge, such as storing, understanding, and retrieving information relevant to individual tasks and team goals based on the environment (Cooke et al. 2013; Fiore and Salas 2004). Thus, team cognition is classified as a cognitive emergent state of teaming, which are themselves defined as the collective experiences of team members. By their very nature emergent team states are highly dynamic, changing as a consequence of the team's context, inputs, processes, and outcomes (Marks, Mathieu, and Zaccaro 2001). As such, the construct *depends* on that knowledge among the team existing within all team members, focussing on team roles and tasks applicable to personal and team objectives (Fiore and Salas 2004). Moreover, the empirical evidence of team cognition being a predominant driving factor in team performance makes it clear that team cognition necessitates additional research attention in human-AI teams (DeChurch and Mesmer-Magnus 2010; Mesmer-Magnus et al. 2017) and prompts investigation into the individual constructs making up the concept, such as team SA and SMMs. These two examples are not exhaustive but are meant to demonstrate the breadth of cognitive activity for team cognition occurring at the team level, defining it as an umbrella term encompassing similar but distinct, team-level cognitive emergent states (Cooke et al. 2013; Cooke, Gorman, and Winner 2007; Coultas et al. 2014).

SMMs were one of the first operationalizations of team cognition in research settings (Cannon-Bowers, Salas, and Converse 1990, 1993; Klimoski and Mohammed 1994; Kozlowski and Ilgen 2006). Specifically, mental models represent organised knowledge structures that individuals hold to embody, understand, and interact with aspects of their environment (Mathieu et al. 2000; Wilson and Rutherford 1989). In team settings, teams draw upon SMMs to efficiently and effectively respond to dynamic teaming environments, using them to make decisions on actions that maintain consistency and coordination with their teammates (Cannon-Bowers, Salas, and Converse 1993). Other aspects of team cognition exist in the form of constructs such as team SA, which represents the overlapping elements of SA within all team members, and the elements from individual team member SA applicable to respective team roles (Endsley 1989, 1995a; McNeese, Salas, and Endsley and Jones 2001; Thompson 2004). This last item concerned with individual SA is 'the degree to which every team member possesses the situational awareness required for his or her responsibilities' (Endsley 1995a, 39). Specifically, individual SA is an individual's general cognizance, or 'knowing what is going on' (Endsley 1987, 1988b). Endsley argues SA to be 'the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future', (Endsley 1988a, 97). From this scope, three levels of SA may be derived, beginning with Level 1, which details an elementary perception of the environment, their basic details (Endsley 1995b, 2021). Level 2 SA advances this, abstracting the elements discovered in Level 1 into an understanding of their meaning within the environment. Lastly, Level 3 couples the knowledge of Level 2 with the information of Level 1 to predict possible future environmental states. Moreover, SA is constantly evolving as the current state of SA is replaced by a new state, brought on by the flow of new self-derived information or information shared between peers (Adams, Tenney, and Pew 1995). Within a teaming context, this information-sharing is intrinsically vital to team cognition, being a platform available for updating and improving SA among teammates (Salmon et al. 2008).

Information-sharing itself yields SMMs, which then drives the rapid development of shared SA (Bolstad and Endsley 1999; Endsley 2023). Shared SA, a subset of team SA, is 'the degree to which team members possess the same SA on shared SA requirements' (Endsley and Jones 2001, 48; Endsley 2023). Shared SA functions upon various components related to information-sharing, such as shared SA mechanisms and shared SA requirements (Bolstad and Endsley 1999). Shared SA mechanisms address modalities that support similarity of information understanding and accurate projection of team member actions, indicative of strong SMMs, which 'greatly facilitate communication and coordination in team settings' (Bolstad and Endsley 1999, 213).

AI teammates can be designed to support shared SA in various capacities, primarily and conventionally via information sharing, but also with vigilant supervision of human processes (Endsley 2023). Traditionally, with information sharing, AI teammates attend to shared SA requirements, its constituents being task work SA, agent SA, and teamwork SA (Bolstad and Endsley 1999; Endsley and Jones 1997; Endsley 2023). These elements respectively regard information relevant to task performance, AI projection and meta-awareness, and then also team goals, functions, and planning (Endsley 2023). Further, these requirements are satisfied by including explainable AI processes, which afford consistency between human and AI SA (Endsley 2023). But, AI may too be modelled with an attempt to address effective human-human team processes: to detect and remedy shortcomings in counterpart human team member SA, draw human attention to critical information, and team-wide encouragement of contingency planning (Endsley 2023). However, these approaches may easily impede team processes if not carefully implemented; to be successful, their implementations require vigilant attention (Endsley 2023). Due to the stark difficulty and unproved feasibility of implementing AI to effectively mimic human-human team processes, information-sharing presents itself as the favoured approach to support shared SA (Calhoun 2022; Endsley 2023; Kaber et al. 2001).

The importance of understanding team cognition in all its forms cannot be overstated, with multiple notable examples of catastrophic failures being directly related to a breakdown of team cognition in either SMMs or team SA. For example, the USS Vincennes accidental shoot-down of an Iranian passenger aircraft (Iran Air Flight 655) (Collyer and Malecki 1998), the actions and decisions of NASA and its related contractors leading up to the Challenger shuttle disaster (Vaughan 1996), and the inappropriate and delayed disaster response to Hurricane Katrina (Leonard and Howitt 2006). Empirical research on team cognition has linked it to team performance outcomes for several decades as it significantly enhances critical aspects of teaming: (1) team behavioural processes in the transition and action phases (DeChurch and Mesmer-Magnus 2010; LePine et al. 2008; Mathieu et al. 2000; Stout et al. 1999); (2) motivational states like trust, conflict, and satisfaction (Cannon-Bowers and Salas 2001; DeChurch and Mesmer-Magnus 2010; Park 2008; Rau 2005); and (3) team performance (Mathieu et al. 2000; Rapert, Velliquette, and Garretson 2002). These benefits can also be continually refined to be more effective over time, enhancing various team outcomes like objective performance, communication, coordination, and strategy (Cooke 2015; Kilduff, Angelmar, and Mehra 2000). As such, team cognition constructs enhance the ability of teams to understand their shared environment effectively, correctly interpret current team needs and anticipate future ones using appropriate communication strategies, and competently adapt to and address dynamic environments in tandem with other team members. However, team cognition constructs do not exist alone within teaming; they must co-exist and interact with other essential factors like trust and cohesion (Salas, Cooke, and Rosen 2008), which are affective (relating to moods, attitudes, and feelings) emergent states (Marks, Mathieu, and Zaccaro 2001) that are critical to supporting and developing team cognition (Fiore, Salas, and Cannon-Bowers 2001; Kelly and Barsade 2001). AI teammates can be efficiently designed to vigilantly monitor environmental/context-related changes, with relentlessness unachievable by any person, a testament showcased by the advent of AI collision avoidance systems (Lyons et al. 2016; Schulman et al. 2017). However, regardless of efficacy, AI teammates are useless if they cannot effectively share information with teammates and contribute to their team cognition. Moreover, within human-AI teaming literature, neither design nor recommendations exist for information-sharing attributes meant to support team cognition specifically, a subject paramount and necessary to tactfully realising human-AI teams.

2.2. Contributing to team cognition within human-AI teams

Human-AI teaming is the current evolutionary phase of teaming, allowing teams the unique ability to step past typical teaming conventions traditionally bound by human limitations. As the name suggests, human-AI teams couple humans and highly autonomous systems utilising AI technologies for interdependent cooperation towards a common goal (O'Neill et al. 2020; Schelble, Flathmann, and McNeese 2020). Further, the different abilities of humans and AI cater to the breadth of specialisation within human-AI teams, a feature that should complement team cognition (National Academies of Sciences Engineering and Medicine 2022). However, benefits within human-AI teaming have yet to be fully realised as human-AI teams have proven to struggle with intra-communicative team ability (Demir et al. 2018), poor affective emergent state development such as trust and cohesion with AI teammates (Schelble, Flathmann, McNeese, Freeman, et al. 2022). These problems harm team cognition and, consequently, team performance (Kelly and Barsade 2001; Lewicki, McAllister, and Bies 1998; Musick, O'Neill, et al. 2021; Scheutz, DeLoach, and Adams 2017). Discovering human-AI team design principles that capitalise on specialisation while fostering team cognition is essential to remedy this ineffectiveness within human-AI teaming. To correct current shortcomings, the design of AI teammates must heed practices of team cognition building by fostering more positive relationships with their human counterparts, thereby establishing healthy affective emergent states, which then support the development of the cognitive emergent states such as team cognition (Fiore, Salas, and Cannon-Bowers 2001; Kelly and Barsade 2001).

Human team members' affective emergent states directly influence the ability of teams to engage in behaviours that develop and support team cognition, and, as a result, attitudes affect team processes and outcomes. Firstly, attitudes are 'knowledge structures containing the specific thoughts and feelings people have about other people', p.532 but also, attitudes define and structure interaction (Jones and George 1998). Various attitudes are antecedent to developing effective team cognition, governing essential teaming aspects such as coordination, communication, and member perceptions (Beal et al. 2003; Fiore, Salas, and Cannon-Bowers 2001; Kelly and Barsade 2001). Within human-AI teaming, designs supporting team attitudes must focus on team-level performance rather than individual AI performance or ability (Zhang et al. 2021). AI should be perceived 'as an individual subject and teammate in human-AI teaming design' (Zhang et al. 2021, 21) rather than a mere employable tool. This simplification would suffocate team success within high complexity collaborative tasks (Zhang et al. 2021), which human-AI teams currently struggle to complete effectively (Demir, McNeese, and Cooke 2018). In this shift from a tool to a teammate, AI teammates must be highly productive in taskwork, but their design must heed and apply principles that are acutely aware of human attitudes and teaming behaviours that drive team cognition, such as effective information-sharing (Li, Huang, et al. 2022; Zhang et al. 2021). For example, AI teammates that intelligibly explain their black-box processes effectively bolster team trust – 'the attitude that an agent will help achieve an individual's goals in a situation characterised by uncertainty and vulnerability' (Lee and See 2004, 54). Further, AI teammates fail when un-calibrated for appropriate levels of trust; a disproportionate scale of trust and AI ability yields sub-optimal team performance, assured by either human over-trust or disinterest in cooperation (Jones and George 1998; Lee et al. 2021; Lee and See 2004). Endsley's HASO model illustrates that human over-trust in AI teammates hinders SA when accompanied by a sub-optimal automation interface, an information-sharing vehicle (Endsley 2017). Hence, for AI teammates to engage in teaming behaviours that benefit the team as a whole, investigating information-sharing techniques serves as a prime candidate for a teaming behaviour that AI teammates can excel at to contribute to team cognition; however, as collaboration and interdependency between humans and AI teammates continues to garner popularity, the question of what information should be shared by AI and how it should share that information begs exploration. Information-sharing is a critical aspect of effective teaming and team cognition development stands to benefit from the introduction of AI teammates if properly designed. Information-sharing processes are an excellent aspect of design for this goal, as they elicit numerous effects on teaming, such as the maintenance and development of SMMs for individual or team SA (Cuevas et al. 2007; Endsley 2023; Lee et al. 2004). AI teammates contribute to team cognition through information-sharing abilities by enriching team processes related to 'information gathering, transformation, analysis', and implication inference (Cuevas et al. 2007, 67). Further, AI teammates who aptly share information benefit overall team attitudes; humans develop bettered trust when intelligibly informed of tasks and processes of counterpart AI teammates (Zhang et al. 2021).

AI is also a prime candidate to take advantage of the benefits of information-sharing as individuals' information needs are not static and change according to the environment and past experiences (Hauptman, Schelble, and McNeese 2022). Further, humans expect AI to adapt its interaction behaviours to keep them knowledgeable of critical information (Liao, Gruen, and Miller 2020). Recent advances in Natural Language Processing (NLP) technologies have fostered new robust forms of communication within human-AI teaming; natural language is now available as an effective medium between human and AI teammates (Liang et al. 2023; Macdonald et al. 2024; Rana et al. 2023). Robust information sharing between humans and AI is no longer a far-fetched Jetsons-esque future, but rather the promising reality of today. Large-language-model-enabled autonomous systems designed for human interaction, and information sharing has focussed on AI explainability, having systems offer human-understandable insight into their decision-making process, an exploration that has demonstrated benefits to team cognition through more effective trust repair (Krantz, Balkenius, and Johansson 2023; Macdonald et al. 2024). With this, our study explores aspects of AI information-sharing with applications to human-AI teams. The full breadth of human-AI teaming cannot be capitalised if AI design principles remain disconnected from information-sharing, as logically, information systems such as AI present meager utility if they are disjointed from such a critical teaming behaviour as information-sharing. Ultimately, this dearth concerning human-AI information-sharing warrants correction, a plea echoed within the continued multi-disciplinary adoption of human-AI teaming (Fan et al. 2005; Iftikhar et al. 2020).

3. Methodology

The current study used a factorial survey methodology, which implements experimental manipulations through descriptive scenarios that participants read and consider when answering subsequent survey questions. The advantages of factorial surveys are numerous as they are frequently utilised to assess the impact of various manipulations on participant's beliefs, judgments, and potential decision-making (Auspurg and Hinz 2014), especially within human-AI interaction to understand human perceptions regarding different AI attributes and actions (Li, Vorvoreanu, et al. 2022). The advantages of factorial surveys lie in their ability to study human perceptions and possible responses to complex scenarios. These surveys can provide higher levels of involvement and realism when compared to traditional surveys, allowing for more accurate measures of perceptions and providing highly standardised stimuli to all participants, which results in greater levels of instrument reliability and internal validity (Wason, Polonsky, and Hyman 2002).

3.1. Experimental task and design

The experimental task involved a text-based scenario that described a paintball video game, which tasked the team in the scenario with capturing the opposing team's flag with one AI and one human teammate. Certain aspects of the scenario were manipulated to include a between-subjects manipulation with two levels (AI direction) and a within-subjects manipulation of six levels (AI Information-Sharing Attribute), making for a 2×6 mixed factorial design. The following section describes the text-based scenario in detail, followed by a description of the experimental manipulations. Lastly, because the study utilised a factorial survey with text-based scenarios, the participants did not directly interact with the teammates or the actual scenario itself. Participants only read the text-based scenarios, and all measures of their perceptions for that instance were based on that single scenario observation.

3.1.1. Experimental task

The factorial survey utilised the same text-based scenario for all conditions, with the only change across conditions being the communication by the AI teammate. The experimental task was a human-AI teaming scenario presented as an eSports version of paintball where the objective was to capture the opposing team's flag. The context of eSports was chosen as it is an excellent example of current human-AI teams and is frequently used in similar human-AI teaming research (Musick, Zhang, et al. 2021; Zhang et al. 2021), and the target population (those with video game experience) would be readily familiar with this or a similar experience. The teaming aspects of the scenario were based on prior research studies involving human-AI teams (McNeese et al. 2018; Zhang et al. 2024), and the information-sharing attributes themselves were also based on prior research (Cuevas et al. 2007). The scenarios were developed with three authors and reviewed by the remaining authors. Finally, any disagreements were discussed and settled unanimously. Once the draft scenarios had been finalised, two unrelated experts in human-AI teaming reviewed the scenarios, and their critiques were implemented until a final agreement had been reached among all parties. These fully developed scenarios were tested using a first-round piloting session for clarity before a final pilot was run with twenty unrelated participants to confirm the scenarios were adequately developed. At this point, the scenarios were used for the final data collection process. This scenario was written as follows:

> For the rest of this survey, you will be shown multiple scenarios and asked questions about each scenario. In the following scenarios, you will be a member of a *human-AI team* playing an online paintball capture the flag video game, and you will be asked about how *six different AI teammates* and their *information-sharing* affect your perceptions of your team and the situation described.
>
> Specifically, capture the flag is where two teams each have a flag located in their home base, and the objective is to steal the other team's flag and bring it safely back to your base. Players can be knocked out of the game if they are tagged with a paintball fired by the opposing team. You and your two teammates must go up against three other players, successfully get past their defenses, steal the opposing team's flag, and then return it to your team's base without being eliminated by enemy paintballs.

As described in this scenario the two teammates are described similarly except for the AI teammate's information-sharing and suggested direction. The human teammate is not given any additional information-sharing attributes or suggested directions and is simply presented as a member of the team and has the same level of interaction with the team as the participant. This control was necessary as the current study seeks to examine how information-sharing by an AI teammate influences potential perceptions a human teammate could have about them and their possible human teammates.

3.1.2. AI information-sharing attribute (within-subjects)

The within-subjects manipulation consisted of the following AI information-sharing attributes: (1) situational awareness of team members; (2) situational awareness of intra/extra team information changes; (3) back-up behaviour; (4) augmenting team memory; (5) explainability; and (6) control (see Table 1). It is important to note that the first and second AI information-sharing attributes share some overlap in the relevant task information they would cover (i.e. teammate statuses). However, the two are distinguished from one another as the first only covers teammate status, while the second includes information on the nature of the change and also addresses changes occurring outside the team. These types of information-sharing attributes are modelled based on previous conceptual models augmenting team cognition (SA) (Cuevas et al. 2007), and fundamentally they focus on the task relevant data integral to effective team SA at all levels (Endsley and Jones 2001).

Each within-subjects level was presented randomly, with the names of the AI teammate and human teammate changed across all six conditions, and the names of both teammates were explicitly chosen to control for any potential gender biases by the participants. For example, AI teammates were always named after a letter from the Greek alphabet (i.e. Sigma, Iota), while human teammates' names were unisex (i.e. Harper, Logan). These traits were selected based on the existing literature that emphasizes the ability of autonomous systems to contribute to shared knowledge in these areas (Cuevas et al. 2007), and that these traits represent common information-sharing tendencies and needs based on their ability to contribute to the effective execution of team processes such as monitoring (Marks, Mathieu, and Zaccaro 2001). These traits were also chosen as they are realistic for AI teammates to

Table 1. Information provided by the AI teammate in each within-subjects condition.

AI Information-Sharing Attribute	Information Shared by the AI Teammate
SA of Team Members	'You (Teammate A) are currently taking cover in front of the center of the opposing team's base, and you are nearly full of paintball ammo. Alex (Teammate B) is currently taking cover on the left side of the opposing team's base and is low on paintballs. I (Teammate C) am currently also taking cover on the left side of the opposing team's base, and I am nearly full of paintball ammo'.
SA of Intra/Extra Team Information	'Harper (Teammate B) has used 70% of their paintballs, providing the team with cover while getting to the other team's base. The opposing team has shifted their positions since we began advancing on them, and they are now concentrated on defending the right side of their base'.
Back-Up Behavior	'Logan (Teammate B) crossed through several open areas without waiting for Teammate A and myself (Teammate C) to provide cover and support. The chances of having a teammate eliminated will be decreased if this is corrected'.
Augmenting Team Memory	'This is a reminder that Chandler (Teammate B) excels at the close-quarters movements required to enter the enemy base successfully. I am reminding the team that we have five minutes left to successfully capture the other team's flag. When we move forward, I will share the map of the enemy base with everyone since I have it saved'.
Explainability	'I believe that the team should help provide cover to Taylor (Teammate B) while they move forward for the flag because Taylor does not have enough paintballs to provide covering support for Teammate A or myself (Teammate C-Lambda) and the enemy team is largely focussed on the right side of their base, which Taylor can avoid'.
Control	The AI teammate was present in this condition but did not share any information. (*Note. If in the AI Direction between-subjects condition the AI teammate would provide the standard suggested direction. If not in the AI Direction condition, then the AI teammate would provide no information and no suggested direction, which served as the baseline control condition of the experiment.*)

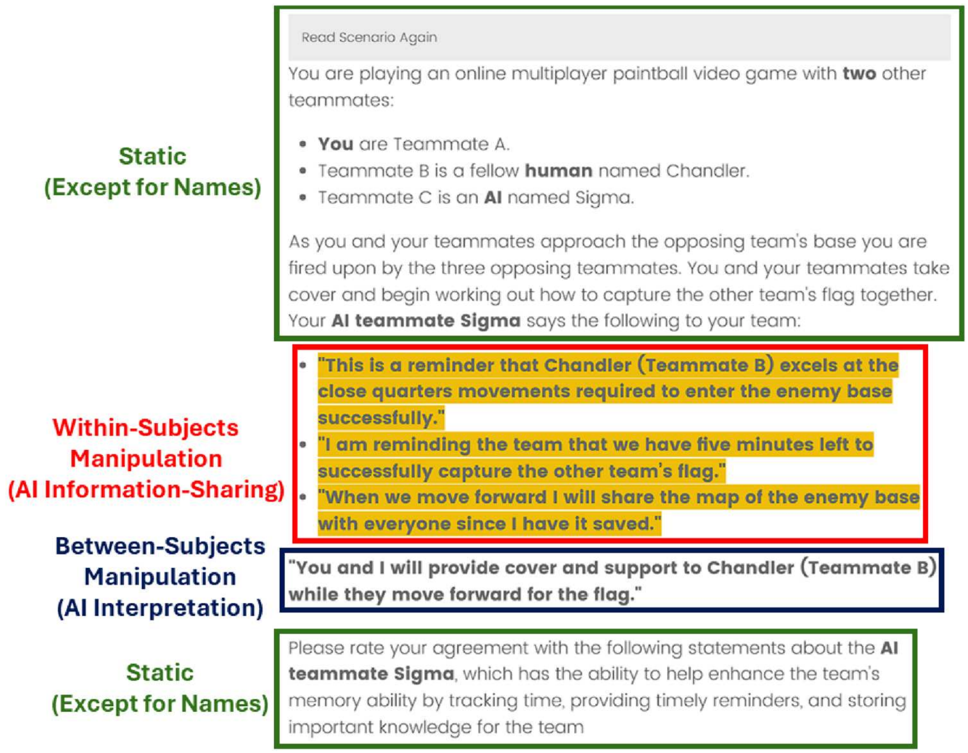


Figure 1. Example of vignette participants read and responded to based on their perceptions and experience. The within-subjects manipulation of AI information-sharing attribute shown above is identified as the text within the black square. The between-subjects manipulation of AI direction is identified as the text within the blue square. Lastly, the static text is identified as all text within the green squares.

implement using current technology and lend themselves well to the computational strengths presented by AI teammates, such as speed, accuracy, and processing power.

3.1.3. AI direction (between-subjects)

The between-subjects AI direction manipulation changed whether or not the AI provided direction to the team. The specific direction given by the AI teammate was always the same as each AI information-sharing attribute concerned the same scenario. As such, the AI direction manipulation can be seen as the AI teammate providing additional information on what it perceives as the best course of action in the given scenario. That information was included towards the bottom of the vignette, as seen in Figure 1 surrounded by the blue square. This manipulation was conducted between-subjects and thus applied to all levels of the within-subjects manipulation. Finally, the AI direction manipulation is also applied to the control level of the within-subjects manipulation.

3.2. Vignette scenarios

At this point, the participants were randomly assigned to one of the two between-subjects conditions and were given the task description (detailed above). Participants were then shown the first of the six within-subjects conditions counterbalanced to control for potential spill-over effects. The task description was also available as a drop-down option throughout the survey for participants to reference if needed, as seen in Figure 1. The six scenarios represented the six information-sharing attributes: there was one scenario for SA1, one for SA2, one for Back-up, one for ATM, one for Explainability, and one for control. Each scenario was the same (see Figure 1) except for the highlighted part, which was manipulated according to Table 1. Each vignette also included a short briefing, seen in Figure 1 surrounded by green, which had common language regarding the scenario but with different names for all six within-subjects conditions. This static text was followed up by bolded and highlighted text, seen in Figure 1 surrounded by red, that was specific to the within-subject condition the participant was reading at the time. Under the text for the within-subjects manipulation was the text for the between-subjects manipulation, seen in Figure 1 surrounded by blue. If participants were assessing the control condition of the within-subjects manipulation (AI information-sharing attribute), then no text would be visible within the

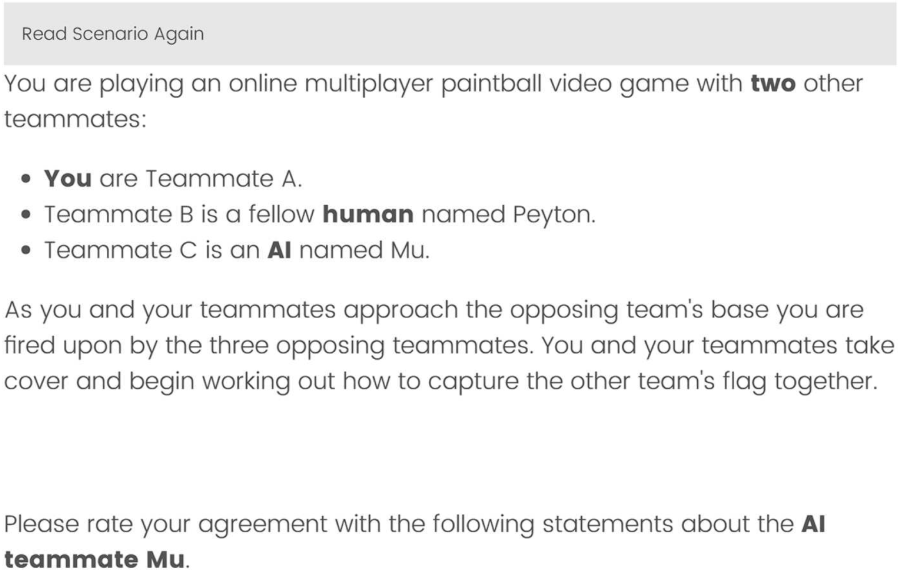


Figure 2. Example of vignette of the control level of the within-subjects manipulation for AI information-sharing attribute.

red square seen in Figure 1. However, the control level did not affect the between-subjects manipulation, as participants with AI that gave directions still saw the direction in the control level (see Table 2). In the double-control (no AI information-sharing and no AI direction) the AI teammate was present but did not provide any additional information to the scenario. Once participants completed the questions about one AI information-sharing attribute scenario, they moved on to the next vignette.

3.3. Participants

The current study received all necessary approvals from the university's institutional review board, with the approval code IRB2022-0183. An a priori power analysis determined that to reach adequate power ($\beta = .85$) for the design of the current study given a medium effect size of $\eta^2 = .10$, at *least* 139 total participants would be needed to complete the online survey. This effect size was selected based on prior literature involving factorial survey studies on human-AI teaming (Flathmann, Schelble, McNeese, et al. 2023; Zhang et al. 2024), and the external piloting session conducted before full data collection commenced. As such, 173 participants were recruited to participate in the survey, with 22 returning the survey as incomplete (participants chose not to finish for one reason or another) and one participant failing the survey attention checks. This left unequal cell sizes between-subjects, and additional participants were recruited until the groups were balanced, making for 156 participants used in data analysis (see Table 3). These participants had an average age of 32.28 (*SD* = 9.06), with 121 participants identifying as male, 29 as female, five as non-binary or third gender, and one choosing not to disclose. The participants were recruited using the Prolific online platform, which allows individuals to sign up for and complete research studies online for monetary incentives. Prolific allows researchers to select specific attributes that participants must have to participate in a research study. The current study required participants to be at least 18 years old and have experience playing video games at least

Table 2. Suggested direction provided by the AI teammate within the scenario.

AI Direction Level	Information Shared
Yes	'You and I will provide cover and support to Harper (Teammate B) while they move forward for the flag'.
No	The AI teammate was present but did not provide any suggested direction.

Table 3. Participant numbers for the AI direction manipulation (between-subjects) and the AI information-sharing attribute manipulation (within-subjects).

AI Direction (Between-Subjects): 78					
SA of Team Members: 78	SA of Intra/Extra Team Information: 78	Back-Up Behavior: 78	Augmenting Team Memory: 78	Explainability: 78	Control: 78
No AI Direction (Within-Subjects): 78					
SA of Team Members: 78	SA of Intra/Extra Team Information: 78	Back-Up Behavior: 78	Augmenting Team Memory: 78	Explainability: 78	Control: 78

between 0-3 hours per week (could not be 0 hours). Participant data were removed before analysis if they answered at least two of the four attention check questions incorrectly. These questions ensured the reliability of the answers provided by the respondents, with those failing two of the four being removed from the subsequent data analysis (one participant failed two or more attention checks).

3.4. Procedure

Once the participants had chosen to participate in the study from the list of available studies on Prolific, they were directed to a Qualtrics survey link, which they clicked on to begin the study. The first thing presented to participants in the survey was the informed consent document, which participants were instructed to read before moving forward with their participation in the study. If participants chose to provide informed consent and complete the study, they moved on to the next question. If they did not, they closed the tab with the survey. Participants who chose to move on in the survey by providing informed consent answered a series of demographic questions like race and gender. Before participants viewed each vignette, they were shown a description of the forthcoming AI teammate's information-sharing ability. These descriptions helped participants understand the information-sharing attribute they were about to evaluate, ensured all participants had a similar understanding of each attribute, and helped to re-orient them to a new AI teammate, as this factor was manipulated within-subjects.

Participants read six vignettes in total; an example of how vignettes were displayed can also be seen in Figure 1. Each vignette included survey measures that participants completed before moving on to the following scenario. These measures included perceived situational awareness, perceived trust in each teammate, perceived AI transparency, and perceived SMM with each teammate. Once participants read all six AI information-sharing attribute conditions and responded to their respective follow-up questions, they finished the study. They were compensated $8.00 for their time (an average survey time of 20 minutes).

3.5. Measures

Each of the following measures was given to participants after each of the six scenarios, providing an assessment for each of the six AI information-sharing conditions. Several measures utilised a single-item measure given the constraints of survey fatigue, meaning the post-scenario surveys had to be concise. However, this is a common practice in human-AI teaming research, and several examples of single-item measures are used to assess emergent states in human-AI teaming like trust and perceived ethicality (Tenhundfeld et al. 2020; Textor et al. 2022).

3.5.1. Perceived shared mental model

Participants perceived SMM was measured using a modified version of the five-factor perceived SMM scale developed by van Rensburg and colleagues (Van Rensburg et al. 2021). The version of the scale used in the current study included three items rated on a seven-point Likert scale ranging from 'Strongly Disagree' to 'Strongly Agree'. The specific items from this scale can be found in the CFA table (see Table 4). The items selected came from the execution factor (one item) and the interaction factor (two items). These factors were selected as they best represented the team and task SMMs that are most common to SMM research for shared knowledge, in general, (Schelble, Flathmann, and McNeese 2020; Schelble, Flathmann, McNeese, O'Neill, et al. 2022). Lastly, participants' perceived SMM metric was taken for both their human and their AI teammate, resulting in a distinct score for each teammate.

3.5.2. Perceived influence over the team compared to AI teammate

Participants' perceived influence over the human-AI team compared to the AI teammate was measured using the power sub-scale from the Human-Machine-Interaction-Interdependence questionnaire (HMII), developed and validated by Woide and colleagues in 2021 (Woide et al. 2021). The power sub-scale included four items that participants responded to using a five-point Likert scale that ranged from 'Definitely the AI Teammate' to 'Definitely Myself'. The specific items from this scale can be found in the CFA table (see Table 4).

3.5.3. Perceived AI transparency

Perceived AI transparency was measured using a scale of information certainty developed by Woide and colleagues (Woide et al. 2021). Participants' level of perceived AI transparency was measured using a modified version of the information certainty sub-scale from the HMII scale developed by Woide and colleagues (Woide et al. 2021). This sub-scale focussed on questions associated with perceived certainty of AI behaviour at the moment, which is a critical facet of AI transparency (National Academies of Sciences Engineering and Medicine 2022). The modifications included utilising four items from the original ten and referencing the name of the AI teammate in bold instead

Table 4. Survey items organized by measure with each item's factor loading.

Measurement	Items	Factor Loading
Perceived SMM with AI	I believe *AI NAME*, and I have a similar understanding about specific strategies for completing the task in the scenario.	0.933
	I believe *AI NAME*, and I have a similar understanding about how to communicate with each other in the scenario.	0.942
	I believe *AI NAME*, and I have a similar understanding about sharing information with the team in the scenario.	0.937
Perceived SMM with Human	I believe *HUMAN NAME*, and I have a similar understanding about specific strategies for completing the task in the scenario.	0.954
	I believe *HUMAN NAME*, and I have a similar understanding about how to communicate with each other in the scenario.	0.974
	I believe *HUMAN NAME*, and I have a similar understanding about sharing information with the team in the scenario.	0.967
Perceived Influence Over the Team	Who did you feel had the most influence on what happened in this situation?	0.925
	Who did you feel had the most influence on the action that was taken?	0.925
	Who did you feel had the least influence on what happened in the situation?	0.851
	Who did you feel had the least influence on the action carried out?	0.881
Perceived AI Transparency	I believe I understand how my action would affect *AI NAME*.	0.815
	I believe I know what *AI NAME* is planning in this situation.	0.951
	I believe I am informed about *AI NAME* planned action in this situation.	0.955
	I believe I know why *AI NAME* prefers a certain action.	0.908
AI Teammate Rating	I believe **NAME** (Teammate B/C) would be a good teammate.	NA
Perceived Contribution of the AI to SA	**NAME** improves the team's understanding of the current situation.	NA

of the term 'system'. The four items from the measure were rated by participants using a seven-point Likert scale ranging from 'Strongly Disagree' to 'Strongly Agree'. The specific items from this scale can be found in the CFA table (see Table 4).

3.5.4. Perceived contribution of the AI to situational awareness

Participants' perceived contribution of the AI to situational awareness was rated on a single item which read: '*Alpha* improves the team's understanding of the current situation', and this item was rated on a seven-point Likert scale ranging from 'Strongly Disagree' to 'Strongly Agree'. The AI teammate's name (bolded) was changed for each vignette.

3.5.5. Teammate rating

Teammate rating was measured using a single item for each teammate, which was presented as follows for the human teammate: 'I believe *Alex* (Teammate B) would be a good teammate' and as 'I believe *Alpha* (Teammate C) would be a good teammate' for the AI teammate. These items were rated on a seven-point Likert scale ranging from 'Strongly Disagree' to 'Strongly Agree'. Teammate names (bolded) changed for each of the six vignettes.

3.6. Measure validation

A multi-level confirmatory factor analysis (CFA) was conducted on the multi-item constructs measured in the current study. These constructs included: (1) perceived SMM with the AI teammate; (2) perceived SMM with the human teammate; (3) perceived influence over the team; and (4) perceived AI transparency. Each factor was measured once for each level of the within-subjects variable (AI information-sharing attribute) six times per participant. No items were found with a loading lower than 0.70. As such, no items were removed from the constructs measured. The factor solution had adequate fit ($\chi^2(71) = 512.928$, CFI = .991, TLI = .988, RMSEA: 0.082, 90% CI: [0.075, 0.088]), and the factor loadings are presented in Table 4.

The correlations among the factors measured are listed in Table 5, with the factors revealing good convergent validity as the average variance extracted (AVE) exceeded .80. Additionally, each factor displayed good discriminant validity, given the correlation between each factor was less than the square root of each factor's AVE.

Table 5. A summary of correlations between each factor measured. The italicised diagonal values represent the square root of this factor's AVE.

	AVE	AI Transparency	Influence	SMM AI	SMM Human
AI Transparency	.827	*.909*	–	–	–
Influence	.803	−.138	*.896*	–	–
SMM AI	.879	−.192	−.064	*.937*	–
SMM Human	.932	.102	−.138	−.010	*.965*

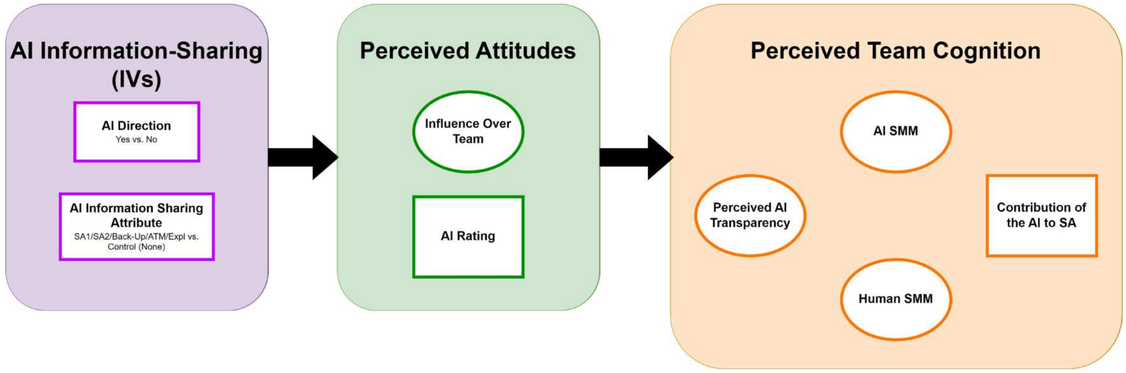


Figure 3. The hypothesized model.

3.7. Hypotheses

Just as the research questions proposed in the introduction highlight the concepts and research gaps motivating the current study, a set of hypotheses helps drive clear testable predictions. Further, the following hypotheses help delineate the two research questions from one another, while also providing structure to the forthcoming results and their discussion. Specifically, the hypotheses centre on how information-sharing related to SA is critical to perceptions of the team and AI *and* to perceptions of team cognition constructs. While the latter two hypotheses address the role of AI direction on perceived attitudes and how those perceived attitudes mediate the effect of AI information-sharing attributes on perceptions of team cognition. The hypotheses read as follows:

H1: *AI information-sharing attributes contributing to aspects of situational awareness will significantly improve perceived attitudes and perceptions of shared knowledge.*
H2: *Direction provided by AI teammates will improve perceived attitudes.*
H3: *Perceived attitudes towards the AI teammate will mediate the effect of AI information-sharing attributes on measures of shared knowledge.*

4. Results

The results of the factorial survey were first run through a measurement validation process using CFA and then fitted to a multi-level SEM describing the ad-hoc *and* causal hypothesised relationships between the manipulations of the experiment and subjective measures elicited from participants. SEM is defined by a series of linear regressions among observed (SA, AI Rating) and latent (AI SMM, AI transparency) variables. The SEM model described here highlights the effect of AI information-sharing on participants' perceived attitude towards the AI, team, and the constructs that make-up team cognition. Specifically, the manipulations of AI-provided information were structurally related to the subjective variables measured and validated in the CFA based on the hypothesised model seen in Figure 3. Following the technique set forth by Knijnenburg and Willemsen (2015), a fully saturated model was created and subsequently trimmed of non-significant effects in an iterative nature. This model answers RQ1 and RQ2 regarding how the information-sharing tendencies of AI influence their human teammates' perceived attitudes towards their AI teammate(s) and their levels of perceived team cognition. Lastly, the SEM addresses H1, H2, and H3 by providing information on the role of AI direction and information-sharing on perceived attitudes and perceptions of team cognition constructs. To improve the readability of the full SEM it has been broken down into three parts, with each part highlighting two constructs and the direct effects influencing those constructs. See the full figure for a comprehensive depiction of the full and mediated effects indicative of SEM.

4.1. Structural model of affective attitudes and team cognition

The final structural model is shown in Figure 4 and highlights the full and mediated effects of all latent and observed variables. However, to improve readability of the model, it has been broken down into three parts seen in Figures 5, 6, and 7. The model has a good overall fit ($\chi^2(237) = 732.032$, CFI = .984, TLI = .980, RMSEA: 0.047, 90% CI: [0.043–0.051]). These fit statistics display a good model fit according to the cut-off values proposed by Hu and Bentler, which several HCI researchers have adopted (Knijnenburg, Reijmer,

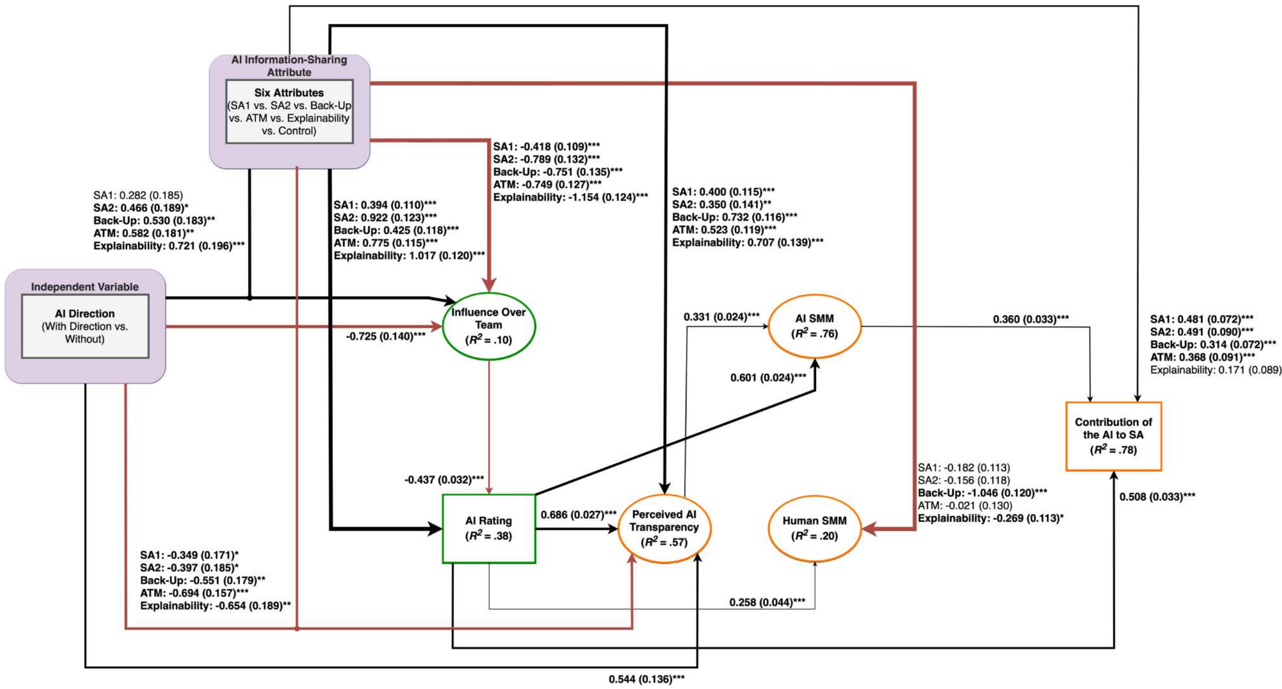


Figure 4. Full structural model of AI information-sharing, perceived attitudes, and perception of team cognition constructs with significant results (* $p < .05$, ** $p < .01$, *** $p < .001$). The numbers represent the β coefficients signifying the standardised decrease or increase in one construct given a corresponding decrease or increase in the other. However, because AI Direction and Information-Sharing represent independent variables, their β coefficients represent the standardised difference between the experimental conditions, effectively making them Cohen's d measures of effect size. The number in parentheses next to the β coefficients represent standard error.

and Willemsen 2011; Knijnenburg and Willemsen 2015): CFI > 0.96, TLI > 0.95, RMSEA < 0.05, and the upper bound of the RMSEA CI being <.10 (Hu and Bentler 1999). The SEM shown in Figure 4 utilises standardised path coefficients, which increases simplicity and readability. For example, a path between A and B includes a β coefficient indicating the standardised increase or decrease in construct B, given a single standard deviation increase or decrease in construct A. However, this does not apply to the AI information-sharing boxes as they are independent variables, and the β coefficients are the standardised difference between the experimental conditions (control in the case of attributes), effectively making them Cohen's d effect sizes. The numbers next to the β coefficients and in parentheses are standard errors. Line segments

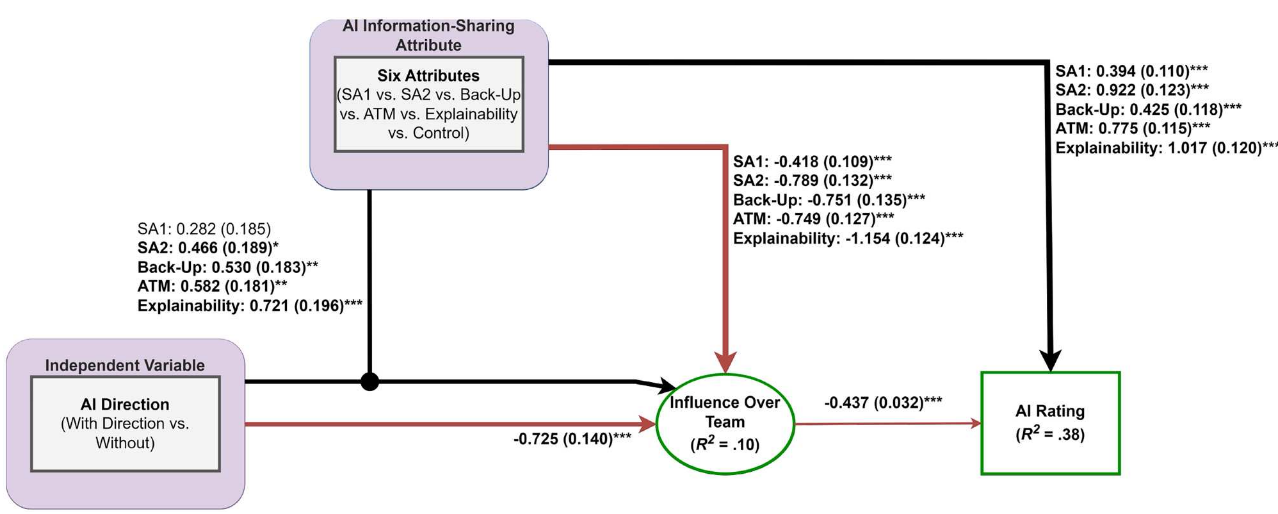


Figure 5. Part 1 of the full SEM, showcasing participants perceived influence over the team and rating of the AI as a teammate.

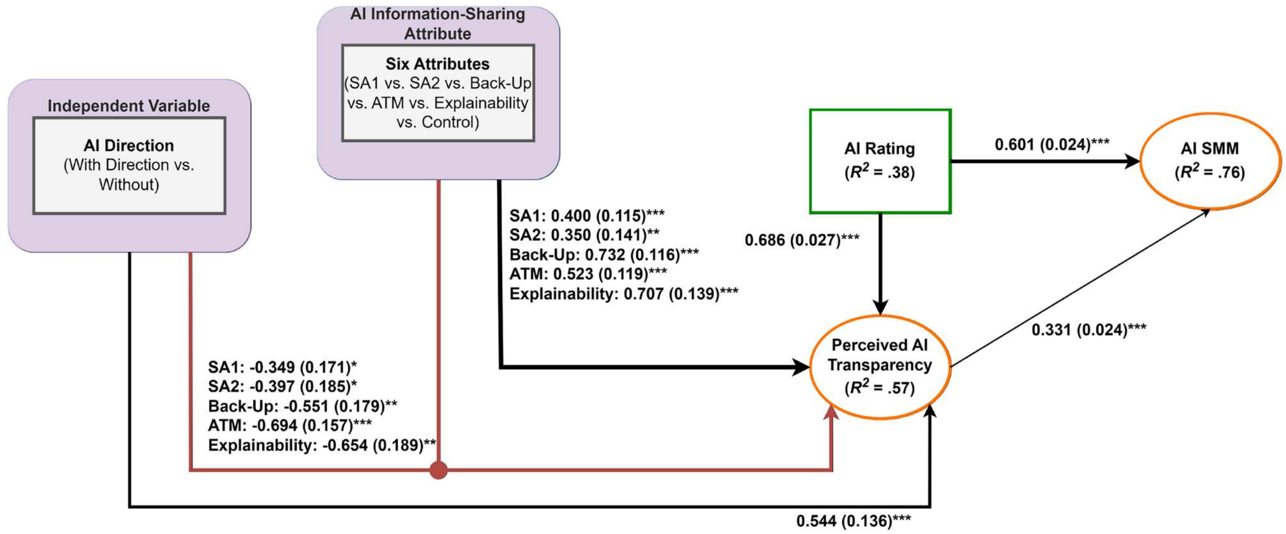


Figure 6. Part 2 of the full SEM, showcasing how transparent they perceived their AI teammate and their perception of a SMM with the AI teammate, with direct effects shown from their perception of the AI as a teammate.

connecting to arrows represent an interaction effect between the two on the variable at the end of the arrow. Six AI information-sharing attributes are shown: situational awareness of teammates *SA1*, situational awareness of intra and extra-team information changes *SA2*, back-up behaviour information *Back-Up*, augmenting team memory information *ATM*, AI explainability information *Explainability*, which are all compared to the baseline control condition. As such, the experimental conditions are encoded into the purple squares on the left, and the arrows from these purple boxes to the subsequent constructs represent the differences in these constructs between the experimental conditions.

4.1.1. Perception of affective attitudes influence over perceived team cognition constructs

The model displays that aside from AI information-sharing (see Figure 9(d)), the effects on participants' perceived contributions of the AI teammate to SA were mediated by the participants' perception of a SMM with their AI teammate and by their rating of the AI as a teammate (AI Information-Sharing, AI SMM, AI Rating → SA). The higher the participants perceived SMM with their AI teammate, the more they saw the AI as contributing to SA. The same was true for their rating of the AI as a teammate; as it increased, so did their perception of the AI's contribution to their SA. Notably absent from affecting the

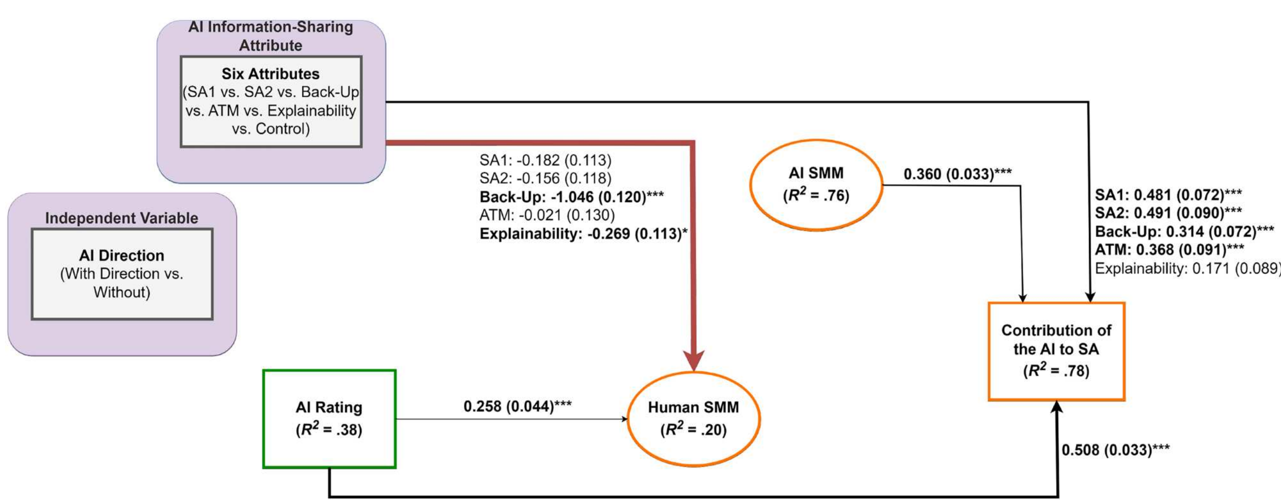
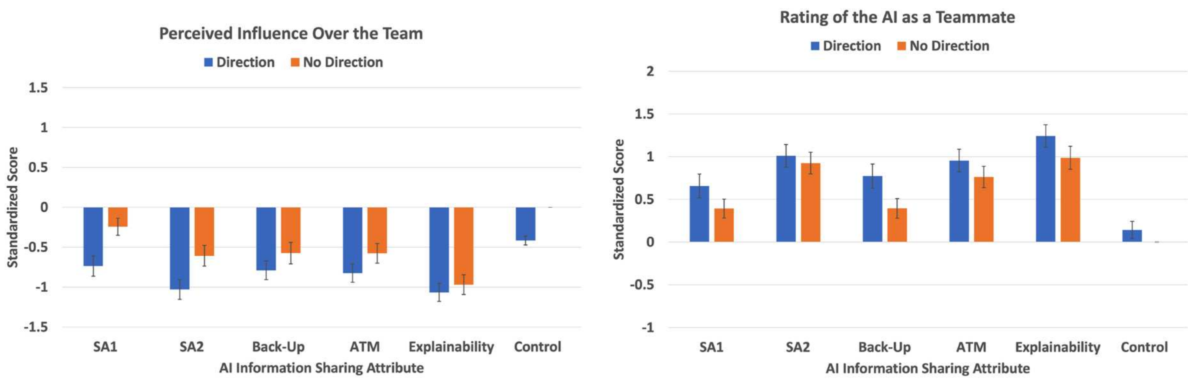


Figure 7. Part 3 of the full SEM, showcasing participants perception of a SMM with the human teammate and their perception of the AI teammates contribution to SA, with direct effects shown from their perception of a SMM with the AI teammate.



(a) (b)

Figure 8. Marginal effects of AI information-sharing and AI direction on participants' perceived attitudes towards the team and the AI teammate. The effect of the 'control' condition at the 'no direction' level is set to zero. Error bars represent the standard error of the differences between each condition and the condition set to zero (control+no direction). (a) Marginal effects of AI information-sharing attribute and AI direction on influence over the team. (b) Marginal effects of AI information-sharing attribute and AI direction on AI teammate rating.

AI teammate's perceived contribution to SA was the perception of a SMM with their human teammate. When it came to SMMs, the perceptions of the human and AI were related as AI SMM *and* human SMM were higher for participants who saw the AI as a good teammate, though the effect of AI rating on AI SMM was stronger than on human SMM (AI Rating → AI SMM, Human SMM). Ratings of perceived SMM with the AI teammate were also higher for those with greater perceived AI transparency (AI Transparency → AI SMM). However, the effect of AI information-sharing on AI SMM was fully mediated by AI rating and AI transparency, though their impact was not fully mediated when it came to human SMM (AI Information-Sharing Attribute → Human SMM; see Figure 9(b)). From these results it is clear that there is support for both H1 and H3 in the SEM. Specifically, for H1 the information-sharing attributes related to aspects of SA had the strongest effect on several of the variables related to perceptions of team cognition. Alternatively, H3 was only partially supported as perceived SMM with the AI teammate was the only variable where the effect of the information-sharing attributes were fully mediated by the preceding variables.

Perceived AI transparency increased the more positively participants rated the AI as a teammate. However, AI information-sharing also affected perceived AI transparency, as seen in Figure 9(a) (AI Information-Sharing Attributes, AI Direction, AI Rating → AI Transparency). The two AI information-sharing manipulations both had positive effects on perceived AI transparency with the AI teammate; however, the interaction effect between the two factors on perceived AI transparency was negative (AI Information-Sharing Attributes × AI Direction → AI Transparency). This type of interaction in SEM indicates that the two manipulations increase perceived AI transparency individually, but their interaction effect does not significantly increase it compared to the control. The simple main effects of this interaction will be examined in the following section. The participants' rating of the AI as a teammate was higher for those perceiving less control over the team. AI information-sharing attributes and direction also increased the AI's teammate rating, seen in Figure 8(b) (AI Information-Sharing Attributes, AI Direction, Influence Over Team → AI Rating). In other words, the less control the participants perceived over the team due to the AI teammate taking on a more prominent role by handling aspects of information-sharing typical to teaming behaviours, the better the AI was perceived as a teammate. This result leads to a cascade of benefits to perceived AI transparency, human SMM, AI SMM, and SA. The model backs up this assertion by showcasing that the participants' perceived influence over the team was reduced whenever the AI teammate had any information-sharing attribute or interpreted the information, as shown in Figure 8(a) (AI Information-Sharing Attribute, AI Direction → Influence Over Team). Conversely, the interaction effect of the two factors on influence was positive (AI Information-Sharing Attribute × AI Direction → Influence Over Team). Showcasing another sub-additive effect for both variables where their individual effects are positive but do not come together to increase their effect significantly over the control. This time on perceived influence over the team, with the simple main effects of the interaction covered in the following section. These results further show partial support for H2 as AI direction did

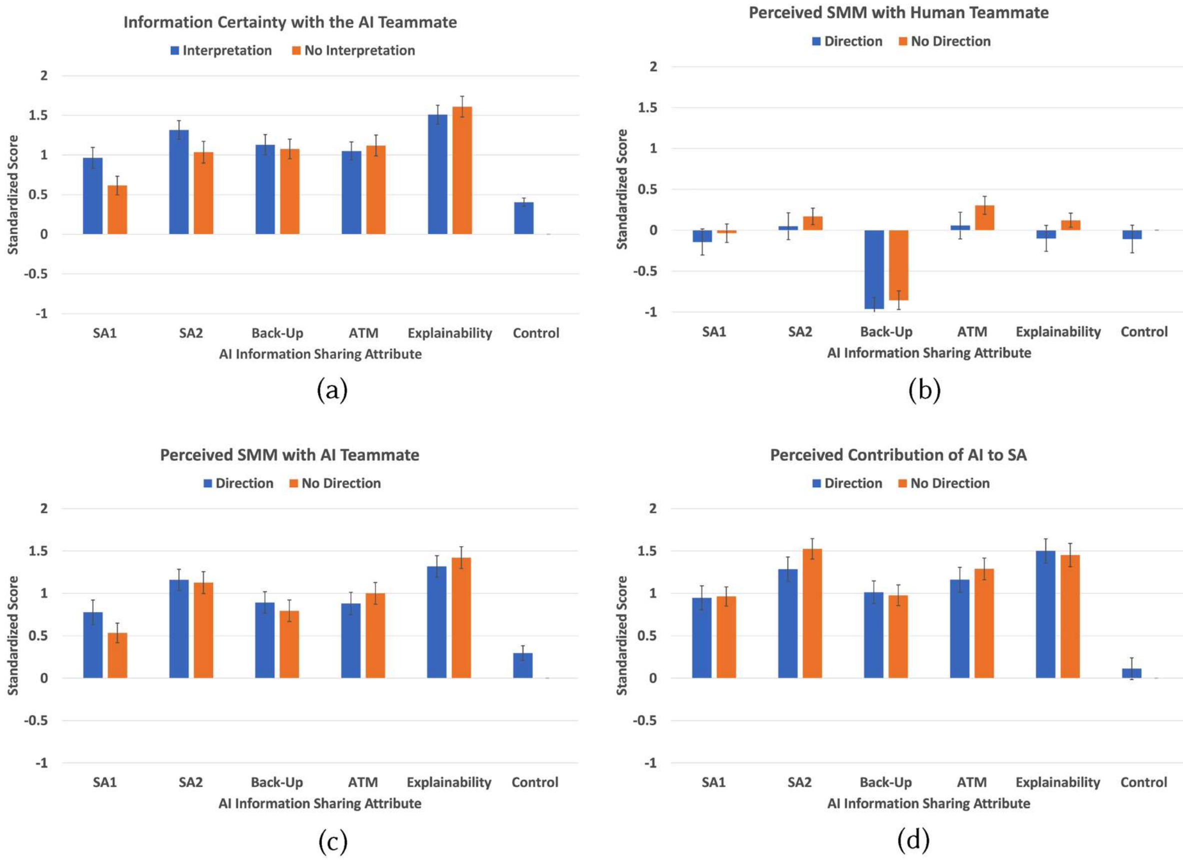


Figure 9. Marginal effects of AI information-sharing attribute and AI direction on participants' perception of elements of team cognition. The effect of the 'control' condition at the 'no direction' level is set to zero. Error bars represent the standard error of the differences between each condition and the condition set to zero (control+no direction). (a) Marginal effects of AI information-sharing attribute and AI direction on perceived transparency of the AI teammate. (b) Marginal effects of AI information-sharing attribute and AI direction on perceived SMM with the human teammate. (c) Marginal effects of AI information-sharing attribute and AI direction on perceived SMM with the AI teammate. (d) Marginal effects of AI information-sharing attribute and AI direction on the contribution of the AI teammate to SA.

influence more than the variables for perceived attitudes, going on to influence perceived AI transparency as well. H1 also continues to receive support as the SA related information-sharing attributes had the greatest influence on the perceived attitudes towards influence and the AI as a teammate. Lastly, H3 is given substantial support as it is shown to play a significant mediating role on several of the perceived team cognition variables.

4.1.2. The mediated effect of AI information-sharing on perceptions within human-AI teams

The AI information-sharing factors also had several significant effects on aspects of the model, as described briefly above and shown in Figures 8 and 9. Specifically, the AI information-sharing attributes significantly impacted participants' influence over the team, AI rating, perceived AI transparency, human SMM, and SA (AI Information-Sharing Attribute → Influence Over Team, AI Rating, AI Transparency, Human SMM, SA). All information-sharing attributes reduced influence over the team, increased perceived AI transparency, and all but explainability increased perceived contribution of the AI teammate to SA (see Figures 8(a), 9(a), 9(d) respectively). As for human SMM, the back-up behaviour and explainability attributes resulted in lower perceptions of a SMM with human teammates (see Figure 9(b)). This result is likely due to the back-up behaviour condition represented by an AI teammate correcting the other human teammate. However, this finding is still pertinent as it shows AI teammates can say or do things to influence human teammates' perceptions of one another and their level of team cognition. Alternatively, AI direction reduces influence over the team by .725 (see Figure 8(a)) and increases perceived AI transparency by .544 (see Figure 9(a)). While nearly all information-sharing attributes always had a significant effect when an effect existed, such as augmenting team memory on team influence (−0.751) and SA1 on perceived AI transparency (0.400), explainability had the most considerable effect on many of the participants' measured perceptions. Specifically, explainability information from the AI had the most substantial impact on perceived influence over the team (−1.154), their rating of the AI as a teammate (1.017), and the second largest on perceived AI transparency (0.707), behind back-up behaviour (0.732). However, when it came to participants' perceived contribution of the AI teammate to SA, the two SA information-sharing attributes had the most considerable effect on participants' perceived contribution of the AI teammate to their SA, with SA2 (0.491) edging out SA1 (0.481), shown in Figure 9(d). Notably, the main effects of the two AI information-sharing factors are qualified by a significant interaction effect on perceived influence over the team and perceived AI transparency. Both interaction effects were sub-additive of their main effects, with their effect on influence being positive for all conditions except for SA1 (see Figure 8(a)). The sub-additive interaction effect on perceived AI transparency was negative, with all conditions being significant (see Figure 9(a)). The simple main effects of the interaction effect on influence found that AI direction caused a significant difference in participants' perceived influence for SA1, SA2, and the control conditions only (see Figure 8(a)). As for perceived AI transparency with the AI teammate, the simple main effects found that AI direction made a significant difference in the SA1 and control conditions only (see Figure 9(a)). These results align with the previous statements made on the three hypotheses, as H1 and H3 are fully supported and H2 is only partially supported.

The model's results highlight the importance of human teammates' attitudes in designing and developing AI teammates to contribute through teaming behaviours such as information-sharing. This notion is especially critical as AI information-sharing was found to have significant effects on the perception of team cognition constructs, though attitudes such perceived influence and rating of the AI as a teammate heavily mediated their impact. The interaction effects between the two manipulations on perceived influence and perceived AI transparency were both sub-additive, which can be seen as an indicator of a possible point of diminishing return as their combined influence did not exceed their individual influence. This interaction effect also showcases that including direction based on the information shared is valuable but does not typically increase the perceived value of the information when added to other information, such as back-up behaviour or augmenting team memory, though SA was a notable exception. Given this commentary, it is important to understand the effect of antecedent constructs on the model. Specifically, the marginal effects described in the various figures of bar charts (Figures 8 and 9) describe the effects of the antecedents in isolation. Furthermore, the SEM as a whole describes their combined effects on downstream variables (Figure 4).

5. Discussion

The SEM analysis provided by the current study showcases an exciting glimpse into the formation of situational awareness and, in turn, team cognition within human-autonomy teams. Most notably, the findings of this work demonstrate that team cognition formation is often the result of affective attitudes within human-AI teams, and the information shared by AI teammates can impact these attitudes. This finding provides a direct answer to RQ1, which asked how the information-sharing tendencies of AI influenced human teammates' affective attitudes towards them. Additionally, RQ2 sought to determine how those same information-sharing tendencies affected human teammates' perceived levels of team cognition. This question was also addressed by the SEM, which showed how information-sharing by AI teammates can have a significant impact on specific aspects of team cognition at the perceived level and that perceived attitudes primarily mediate its effect.

Addressing the hypotheses, H1 was fully supported as the SA information-sharing attributes had the strongest effect on both perceived attitudes and perceptions of team cognition constructs. H2 was only partially supported as AI direction influenced perceived attitudes but also went on to influence perceptions of team cognition. Lastly, H3 was fully supported as the SEM showed perceived attitudes towards the AI acting as a mediating variable for several subsequent perceived team cognition variables. The following discussion thus further elaborates on the future role of affective attitudes within human-AI teams and then details how the results of this study should be used best to design the information-sharing capabilities of AI teammates to benefit these attitudes and subsequent team cognition constructs.

5.1. Leveraging perceived affective attitudes to build more effective team cognition in human-AI teams

One of the most interesting findings from this study is the strong and pervasive relationship that perceived affective attitudes, particularly AI-focussed attitudes, can have on perceived constructs of team cognition. In particular, the results of this work denote that the rating participants gave their AI teammates strongly influenced the level of expected team cognition based on their interpretation of the scenario. These findings align with prior work in human-human teams, showing how affective attitudes help form team cognition through repeated interaction (Fiore, Salas, and Cannon-Bowers 2001; Kelly and Barsade 2001). However, this study posits a unique contribution as it takes the first approach to exploring the linkage between these states within a context that considers both human and AI affective and cognitive states through the use of survey-based vignettes. In doing so, this work provides an excellent first step into studying this linkage as the perceived attitudes towards these two different types of teammates are shown to have different influences on the perceived team cognition constructs within their team.

The perception of a SMM with the human teammate was not related to the perception of a SMM with the AI teammate. This lack of a relationship is somewhat surprising given the inter-connected nature of team cognition development and the perception of interdependence within teams (Cooke et al. 2013; Niler et al. 2021). In turn, the results of this work demonstrate that AI teammates stand to play a demonstrable role in the potential formation of cognitive states within human-AI teams, especially as AI rating had a significant effect on human SMM. In particular, the design of AI teammates may impact the expected attitudes towards AI teammates and even human teammates, as demonstrated by the manipulations of this study. Given the significance of human SMMs in improving and predicting team performance (Mathieu et al. 2000), AI teammates should be designed in a way that has direct positive effects on human teammates' attitudes towards the AI and team to further improve the environment for human teammates to develop effective SMMs.

Overall, these findings are positive for the field of human-AI teamwork. Currently, fundamental work is being conducted around the cognitive states of human-AI teams, with work identifying the importance of mental models (Bansal et al. 2019), trust (Schelble, Flathmann, McNeese, Freeman, et al. 2022), and SA (Crowder and Carbone 2014). However, the overwhelming majority of work explores affective attitudes, such as perceived performance (Flathmann, McNeese, et al. 2023), trust (Lyons et al. 2019; McNeese et al. 2019; Schelble, Lopez, et al. 2022), and shared influence (Flathmann, Schelble, Rosopa, et al. 2023). This research mainly focuses on designing AI teammates to benefit these attitudes. At first glance, this would appear as a notable limitation within human-AI teaming research as it would prevent cognitive states such as SA from being well-researched. However, the results of this work demonstrate that this is, in fact, not the case, as the attention and considerations put towards these attitudes will ultimately bolster the environment within the team for the formation of more effective cognitive states over time.

5.2. Giving AI teammates active roles in benefiting cognitive states in human-AI teams

The connection between AI rating and AI SMM (0.601), identified in *Section 5.1*, resemble a distinct connection between perceived attitudes and perceived team cognition constructs. Accordingly, AI teammates should actively play a role in forming both of these within human-AI teams. To usher in these roles, the following discussion section elaborates on AI teammates' potential information-sharing responsibilities to best benefit their teams' perceptions and outcomes. Critically, these responsibilities should exist in addition to their assigned roles, as AI teammates' information gathering and processing speed will make it feasible to simultaneously leverage this information for itself while sharing it with their team. In particular, the results of this study can speak to designing the content and methodology of information-sharing responsibilities for AI teammates.

Given this study didn't measure team SA, the results indicate AI teammates will benefit teams with shared SA, individual SA, and by providing explanations alongside their behaviours (Figure 4). Shared SA accounts for environmental or task related factors of mutual interest to more than one team member contributing to the development of team coordination (Endsley and Jones 1997; Kaber and Endsley 1998). Related literature has also shown mutual agreement and understanding as necessary in building SMMs between human teammates further mediating team effectiveness and performance (Baker 1995, 1999; Van den Bossche et al. 2011). Critically, while these types of information were examined individually, they provide a holistic benefit when combined. Likewise, AI transparency and explainability are essential for maintaining shared SA about the environment and moving beyond the black-box nature of these systems to further link its behaviours with its actions and drive the formation of perceived attitudes and team cognition constructs (Endsley 2023). Moreover, in addition to benefiting these shared perceptual states, this combined information-sharing also can benefit the individual SA humans form Chen et al. (2018). AI teammates and roles that leverage this type of information-sharing will act as a catalyst for affective and cognitive state development, improving individual and team performance levels, in turn, (Marks, Mathieu, and Zaccaro 2001; Mathieu et al. 2008).

Second, it's crucial to understand how AI teammates should share this information. Based on the results of this study's second manipulation the AI teammate should provide recommendations for action sparingly in human-AI teams. This is not to say that AI teammates should never make recommendations, as recent research has shown the likelihood for humans to follow AI directives when they have greater levels of trust (Caldwell and O'Reilly 2003; Chong et al. 2022). Instead, AI teammates should predominately act as an information conduit through which information can be repeatedly gathered and disseminated, which human teammates can interpret. In turn, the effects of including AI direction did not significantly affect perceived influence or perceived AI transparency when interacting with the six information-sharing attributes. Based on participant perspectives when reading through the six information-sharing attributes, including AI direction did not significantly affect perceived influence or perceived AI transparency; however, the SA information-sharing attributes were an exception to this regarding the sub-additive interaction effects. Moreover, while this study explored the perceptions of singular human teammates, this methodology would also allow for information to be more generally applicable to multiple human teammates simultaneously, as directions may need to be tailored to specific human teammates.

In closing, while this study can recommend information-sharing content and methods, research still needs to make several contributions to ensure AI teammate roles are designed to benefit these emergent states. This is especially true as the current study only utilised a factorial survey and not a true simulated exercise. First, research should identify the modalities through which information can be shared. While this study showed promise with natural language-based information-sharing, recent research has noted the importance of continuous visual and graphical transparency to support awareness (Endsley 2023). In particular, research must identify how AI teammates should share information when uncertain about the information and its accuracy (Tomsett et al. 2020). Lastly, research needs to explore design considerations in addition to information-sharing that might bolster affective attitudes. In sum, AI teammates can and should be designed to drive the formation of emergent states such as attitudes and team cognition constructs in teams. Future research should build on the results of this study to ensure these roles are holistically designed and empirically validated.

5.3. Limitations and future work

In addition to the research pathways outlined above, four distinct limitations also impact this study and should be resolved by future research. First, this study was conducted on an online platform where team interaction was limited. While this methodology is excellent for exploring various potential information-sharing methods, the highly beneficial processes identified in this study should be validated using in-person experimentation because the current study measured expectations of cognitive states and not actual states as it was conducted online.Future work should extend this study of subjective measures through survey-based vignettes to objectively measure cognitive states associated with real-life interaction. Second, as the experimental design was a 2x6 factorial design, it was not feasible to fully counterbalance the study, thus requiring partial counterbalancing. Since not all orders could be tested, participant perceptions towards within-subjects conditions could be influenced by the previous within-subjects condition they experienced. Third, this study was predominately comprised of male participants. While the sample distribution of this study was representative of the targeted population, video game players, this distribution is not fully representative of the broader population in which human-AI teams will be implemented. As such, future work should also explore the various cultural and individual differences that are known to impact technology design and potential AI teammate design. Finally, this study was shorter than common team tasks, which resulted in prioritising short-term perceptions and not long-term team cognition formation. Once again, while this limitation was necessary for the design and goals of this study, the eventual implementation of human-AI teams will require a greater understanding of long-term effects. As such, this work should be extended via longitudinal studies that explore how repeated information might accelerate or diminish the formation of team cognition in human-AI teams. Critically, these three limitations cannot be resolved without considering the presented findings. As such, future research that addresses these limitations will extend the relevance of this work and further contextualize it in the field of human-AI teamwork.

5.4. Conclusion

As human-AI teams are shaping future teamwork, further research must be done to understand how these teams can operate successfully. These findings provide a solid foundation on how AI teammates shape human perceptions, and we recognise the importance of the AI agent in developing shared SA between the team members. Previously, human-AI SMMs have shown vast potential for the development of SA despite additional challenges in the way AI and humans process information and, in turn, how to communicate said information (Endsley 2023; Liao, Gruen, and Miller 2020; Miller 2019). Limited to survey-based methods with no real interaction, the results in this study promote the consideration of human-AI SMMs as having the capability of providing more value to a team's SA, with further research required to understand if these results translate to real-world human-AI teams. Therefore, we hope this contribution is recognised in future research on human-AI teams.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Adams, Marilyn Jager, Yvette J. Tenney, and Richard W. Pew. 1995. "Situation Awareness and the Cognitive Management of Complex Systems." *Human Factors* 37 (1): 85–104. https://doi.org/10.1518/001872095779049462.

Auspurg, Katrin, and Thomas Hinz. 2014. *Factorial Survey Experiments*. Vol. 175. Los Angeles: Sage Publications.

Baker, Michael J. 1995. "Negotiation in Collaborative Problem-Solving Dialogues." *Nato Asi Series F Computer and Systems Sciences* 142:39–39.

Baker, Michael J. 1999. "Argumentation and Constructive Interaction." *Foundations of Argumentative Text Processing* 5:179–202.

Bansal, Gagan, Besmira Nushi, Ece Kamar, Walter S. Lasecki, Daniel S. Weld, and Eric Horvitz. 2019. "Beyond Accuracy: The Role of Mental Models in Human-AI Team Performance." In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, Vol. 7, 2–11.

Beal, Daniel J., Robin R. Cohen, Michael J. Burke, and Christy L. McLendon. 2003. "Cohesion and Performance in Groups: A Meta-Analytic Clarification of Construct Relations." *Journal of Applied Psychology* 88 (6): 989–1004. https://doi.org/10.1037/0021-9010.88.6.989.

Bolstad, Cheryl A., and Mica R. Endsley. 1999. "Shared Mental Models and Shared Displays: An Empirical Evaluation of Team Performance." In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 43, 213–217. Los Angeles, CA: SAGE Publications.

Brandon, David P., and Andrea B. Hollingshead. 2004. "Transactive Memory Systems in Organizations: Matching Tasks, Expertise, and People." *Organization Science* 15 (6): 633–644. https://doi.org/10.1287/orsc.1040.0069.

Bunderson, J. Stuart, and Kathleen M. Sutcliffe. 2002. "Comparing Alternative Conceptualizations of Functional Diversity in Management Teams: Process and Performance Effects." *Academy of Management Journal* 45 (5): 875–893. https://doi.org/10.2307/3069319.

Caldwell, David F., and Charles A. O'Reilly. 2003. "The Determinants of Team-Based Innovation in Organizations: The Role of Social Influence." *Small Group Research* 34 (4): 497–517. https://doi.org/10.1177/1046496403254395.

Calhoun, Gloria. 2022. "Adaptable (Not Adaptive) Automation: Forefront of Human–Automation Teaming." *Human Factors* 64 (2): 269–277. https://doi.org/10.1177/00187208211037457.

Cannon-Bowers, Janis A., and Eduardo Salas. 2001. "Reflections on Shared Cognition." *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior* 22 (2): 195–202. https://doi.org/10.1002/job.v22:2.

Cannon-Bowers, J. A., E. Salas, and S. A. Converse. 1990. "Cognitive Psychology and Team Training: Shared Mental Models in Complex Systems." In *5th Annual Conference ofthe Society for Industrial and Organizational Psychology*.

Cannon-Bowers, J. A., E. Salas, and Sharolyn Converse. 1993. "Shared Mental Models in Expert Team Decision Making." *Individual and Group Decision Making: Current Issues* 221:221–46.

Chen, Jessie Y. C., Shan G. Lakhmani, Kimberly Stowers, Anthony R. Selkowitz, Julia L. Wright, and Michael Barnes. 2018. "Situation Awareness-Based Agent Transparency and Human-Autonomy Teaming Effectiveness." *Theoretical Issues in Ergonomics Science* 19 (3): 259–282. https://doi.org/10.1080/1463922X.2017.1315750.

Choi, Jonathan H., Kristin E. Hickman, Amy Monahan, and Daniel Schwarcz. 2023. "ChatGPT Goes to Law School." *Available at SSRN*.

Chong, Leah, Guanglu Zhang, Kosa Goucher-Lambert, Kenneth Kotovsky, and Jonathan Cagan. 2022. "Human Confidence in Artificial Intelligence and in Themselves: The Evolution and Impact of Confidence on Adoption of AI Advice." *Computers in Human Behavior* 127:107018. https://doi.org/10.1016/j.chb.2021.107018.

Collyer, Stanley C., and Gerald S. Malecki. 1998. "Tactical decision making under stress: History and overview. In *Making decisions under stress: Implications for individual and team training*, edited by J. A. Cannon-Bowers and E. Salas, 3–15. American Psychological Association. https://doi.org/10.1037/10278-016.

Cooke, Nancy J. 2015. "Team Cognition As Interaction." *Current Directions in Psychological Science* 24 (6): 415–419. https://doi.org/10.1177/0963721415602474.

Cooke, Nancy J., Jamie C. Gorman, Jasmine L. Duran, and Amanda R. Taylor. 2007. "Team Cognition in Experienced Command-and-Control Teams." *Journal of Experimental Psychology: Applied* 13 (3): 146–157.

Cooke, Nancy J., Jamie C. Gorman, Christopher W. Myers, and Jasmine L. Duran. 2013. "Interactive Team Cognition." *Cognitive Science* 37 (2): 255–285. https://doi.org/10.1111/cogs.2013.37.issue-2.

Cooke, Nancy J., Jamie C. Gorman, and Jennifer L. Winner. 2007. "Team cognition." In *Handbook of applied cognition*. 2nd ed., edited by F. T. Durso, R. S. Nickerson, S. T. Dumais, S. Lewandowsky, and T. J. Perfect, 239–268. Hoboken, NJ: John Wiley.

Coultas, Chris W., Tripp Driskell, C. Shawn Burke, and Eduardo Salas. 2014. “A Conceptual Review of Emergent State Measurement: Current Problems, Future Solutions.” *Small Group Research* 45 (6): 671–703. https://doi.org/10.1177/1046496414552285.

Crowder, James A., and John N. Carbone. 2014. “Collaborative Shared Awareness: Human-AI Collaboration.” In *Proceedings of the International Conference on Information and Knowledge Engineering (IKE). The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp)*, Vol. 1.

Cuevas, Haydee M., Stephen M. Fiore, Barrett S. Caldwell, and Laura Strater. 2007. “Augmenting Team Cognition in Human-Automation Teams Performing in Complex Operational Environments.” *Aviation, Space, and Environmental Medicine* 78 (5): B63–B70.

DeChurch, Leslie A., and Jessica R. Mesmer-Magnus. 2010. “The Cognitive Underpinnings of Effective Teamwork: A Meta-Analysis.” *Journal of Applied Psychology* 95 (1): 32–53. https://doi.org/10.1037/a0017328.

Demir, Mustafa, Aaron D. Likens, Nancy J. Cooke, Polemnia G. Amazeen, and Nathan J. McNeese. 2018. “Team Coordination and Effectiveness in Human-Autonomy Teaming.” *IEEE Transactions on Human-Machine Systems* 49 (2): 150–159. https://doi.org/10.1109/THMS.6221037.

Demir, Mustafa, Nathan J. McNeese, and Nancy J. Cooke. 2017. “Team Situation Awareness Within the Context of Human-Autonomy Teaming.” *Cognitive Systems Research* 46:3–12. https://doi.org/10.1016/j.cogsys.2016.11.003.

Demir, Mustafa, Nathan J. McNeese, and Nancy J. Cooke. 2018. “The Impact of Perceived Autonomous Agents on Dynamic Team Behaviors.” *IEEE Transactions on Emerging Topics in Computational Intelligence* 2 (4): 258–267. https://doi.org/10.1109/TETCI.

Endsley, Mica R. 1987. *SAGAT: A Methodology for the Measurement of Situation Awareness (NOR DOC 87-83)*. Hawthorne, CA: Northrop Corporation.

Endsley, Mica R. 1988a. “Design and Evaluation for Situation Awareness Enhancement.” In *Proceedings of the Human Factors Society Annual Meeting*, Vol. 32, 97–101. Los Angeles, CA: Sage Publications.

Endsley, Mica R. 1988b. “Situation Awareness Global Assessment Technique (SAGAT).” In *Proceedings of the IEEE 1988 National Aerospace and Electronics Conference*, 789–795. IEEE.

Endsley, M. R. 1989. *Situation Awareness in an Advanced Strategic Mission (No. NOR DOC 89-32)*. Hawthorne, CA: Northrop Corporation.

Endsley, Mica R. 1995a. “Measurement of Situation Awareness in Dynamic Systems.” *Human Factors*37 (1): 65–84. https://doi.org/10.1518/001872095779049499.

Endsley, Mica R. 1995b. “Toward a theory of situation awareness in dynamic systems.” *Human factors* 37 (1): 32–64.

Endsley, Mica R. 2017. “From Here to Autonomy: Lessons Learned From Human–automation Research.” *Human Factors* 59 (1): 5–27. https://doi.org/10.1177/0018720816681350.

Endsley, Mica R and Jones, W. M. 2001. “A model of inter- and intrateam situation awareness: Implications for design, training and measurement.” In *New trends in cooperative activities: Understanding system dynamics in complex environments*, edited by M. McNeese, E. Salas, and M. End- sley, 46–67. Santa Monica, CA: Human Factors and Ergonomics Society.

Endsley, Mica R. 2021. “A Systematic Review and Meta-Analysis of Direct Objective Measures of Situation Awareness: A Comparison of SAGAT and SPAM.” *Human Factors* 63 (1): 124–150. https://doi.org/10.1177/0018720819875376.

Endsley, Mica R. 2023. “Supporting Human-AI Teams: Transparency, Explainability, and Situation Awareness.” *Computers in Human Behavior* 140:107574. https://doi.org/10.1016/j.chb.2022.107574.

Endsley, Mica, and William M. Jones. 1997. *Situation Awareness Information Dominance & Information Warfare*. Technical Report. Dayton, OH: Logicon Technical Services Inc.

Fan, Xiaocong, Shuang Sun, Michale McNeese, and John Yen. 2005. “Extending the Recognition-Primed Decision Model to Support Human-Agent Collaboration.” In *Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems*, 945–952.

Fan, Xiaocong, and John Yen. 2010. “Modeling Cognitive Loads for Evolving Shared Mental Models in Human–agent Collaboration.” *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 41 (2): 354–367.

Fiore, Stephen M., and Eduardo Salas. 2004. “Why we need team cognition.” In *Team cognition: Understanding the factors that drive process and performance*, edited by E. Salas and S. M. Fiore, 235–248. American Psychological Association. https://doi.org/10.1037/10690-011.

Fiore, Stephen M., Eduardo Salas, and Janis A. Cannon-Bowers. 2001. “Group dynamics and shared mental model development.” *How people evaluate others in organizations* 234.

Flathmann, Christopher, Nathan J. McNeese, Beau Schelble, Bart Knijnenburg, and Guo Freeman. 2023. “Understanding the Impact and Design of AI Teammate Etiquette.” *Human–Computer Interaction* 1–28. https://doi.org/10.1080/07370024.2023.2189595.

Flathmann, Christopher, Beau G. Schelble, Nathan J. McNeese, Bart Knijnenburg, Anand K. Gramopadhye, and Kapil Chalil Madathil. 2023. “The Purposeful Presentation of AI Teammates: Impacts on Human Acceptance and Perception.” *International Journal of Human–Computer Interaction* 1–18.

Flathmann, Christopher, Beau G. Schelble, Patrick J. Rosopa, Nathan J. McNeese, Rohit Mallick, and Kapil Chalil Madathil. 2023. “Examining the Impact of Varying Levels of AI Teammate Influence on Human-AI Teams.” *International Journal of Human-Computer Studies* 177:103061. https://doi.org/10.1016/j.ijhcs.2023.103061.

Hauptman, Allyson I., Beau G. Schelble, and Nathan J. McNeese. 2022. “Adaptive Autonomy as a Means for Implementing Shared Ethics in Human-AI Teams.” In *Proceedings of the AAAI Spring Symposium on AI Engineering*.

Hu, Li-Tze, and Peter M. Bentler. 1999. “Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives.” *Structural Equation Modeling: A Multidisciplinary Journal* 6 (1): 1–55. https://doi.org/10.1080/10705519909540118.

Iftikhar, Pulwasha, Marcela V. Kuijpers, Azadeh Khayyat, Aqsa Iftikhar, and Maribel DeGouvia De Sa. 2020. "Artificial Intelligence: A New Paradigm in Obstetrics and Gynecology Research and Clinical Practice." *Cureus* 12 (2): e7124.

Jones, Gareth R., and Jennifer M. George. 1998. "The Experience and Evolution of Trust: Implications for Cooperation and Teamwork." *Academy of Management Review* 23 (3): 531–546. https://doi.org/10.2307/259293.

Kaber, David B., and Mica R. Endsley. 1998. "Team Situation Awareness for Process Control Safety and Performance." *Process Safety Progress* 17 (1): 43–48. https://doi.org/10.1002/prs.v17:1.

Kaber, David B., Jennifer M. Riley, Kheng-Wooi Tan, and Mica R. Endsley. 2001. "On the Design of Adaptive Automation for Complex Systems." *International Journal of Cognitive Ergonomics* 5 (1): 37–57. https://doi.org/10.1207/S15327566IJCE0501_3.

Kelly, Janice R., and Sigal G. Barsade. 2001. "Mood and Emotions in Small Groups and Work Teams." *Organizational Behavior and Human Decision Processes* 86 (1): 99–130. https://doi.org/10.1006/obhd.2001.2974.

Kilduff, Martin, Reinhard Angelmar, and Ajay Mehra. 2000. "Top Management-Team Diversity and Firm Performance: Examining the Role of Cognitions." *Organization Science* 11 (1): 21–34. https://doi.org/10.1287/orsc.11.1.21.12569.

Klimoski, Richard, and Susan Mohammed. 1994. "Team Mental Model: Construct Or Metaphor?." *Journal of Management* 20 (2): 403–437. https://doi.org/10.1177/014920639402000206.

Knijnenburg, Bart P., Niels J. M. Reijmer, and Martijn C. Willemsen. 2011. "Each to His Own: How Different Users Call for Different Interaction Methods in Recommender Systems." In *Proceedings of the Fifth ACM Conference on Recommender Systems*, 141–148.

Knijnenburg, Bart P., and Martijn C. Willemsen. 2015. "Evaluating Recommender Systems with User Experiments." In *Recommender Systems Handbook*, 309–352.

Kozlowski, Steve W. J., and Daniel R. Ilgen. 2006. "Enhancing the Effectiveness of Work Groups and Teams." *Psychological Science in the Public Interest* 7 (3): 77–124. https://doi.org/10.1111/j.1529-1006.2006.00030.x.

Krantz, Amandus, Christian Balkenius, and Birger Johansson. 2023. "Talk to Me: Using Speech for Loss-of-Trust Mitigation in Social Robots." In *Sound and Robotics*, 61–75. Chapman and Hall/CRC.

Lee, Miyoung, Tristan Johnson, Youngmin Lee, Debra O'Connor, and Mohammed Khalil. 2004. "The Conceptual Framework of Factors Affecting Shared Mental Model." *Association for Educational Communications and Technology*

Lee, John D., Shu-Yuan Liu, Joshua Domeyer, and Azadeh DinparastDjadid. 2021. "Assessing Drivers' Trust of Automated Vehicle Driving Styles with a Two-Part Mixed Model of Intervention Tendency and Magnitude." *Human Factors* 63 (2): 197–209. https://doi.org/10.1177/0018720819880363.

Lee, John D., and Katrina A. See. 2004. "Trust in Automation: Designing for Appropriate Reliance." *Human Factors* 46 (1): 50–80. https://doi.org/10.1518/hfes.46.1.50.30392.

Leonard, Herman B., and Arnold M. Howitt. 2006. "Katrina As Prelude: Preparing for and Responding to Katrina-Class Disturbances in the United States–Testimony to US Senate Committee, March 8, 2006." *Journal of Homeland Security and Emergency Management* 3 (2): 1–22. https://doi.org/10.2202/1547-7355.1246.

LePine, Jeffery A., Ronald F. Piccolo, Christine L. Jackson, John E. Mathieu, and Jessica R. Saul. 2008. "A Meta-Analysis of Teamwork Processes: Tests of a Multidimensional Model and Relationships with Team Effectiveness Criteria." *Personnel Psychology* 61 (2): 273–307. https://doi.org/10.1111/peps.2008.61.issue-2.

Lewicki, Roy J., Daniel J. McAllister, and Robert J. Bies. 1998. "Trust and Distrust: New Relationships and Realities." *Academy of Management Review* 23 (3): 438–458. https://doi.org/10.2307/259288.

Li, Jian, Jinsong Huang, Jiaxiang Liu, and Tianqi Zheng. 2022. "Human-AI Cooperation: Modes and Their Effects on Attitudes." *Telematics and Informatics* 73:101862. https://doi.org/10.1016/j.tele.2022.101862.

Li, Tianyi, Mihaela Vorvoreanu, Derek DeBellis, and Saleema Amershi. 2022. "Assessing Human-AI Interaction Early Through Factorial Surveys: A Study on the Guidelines for Human-AI Interaction." *ACM Transactions on Computer-Human Interaction* 30 (5): 1–45. https://doi.org/10.1145/3511605.

Liang, Jacky, Wenlong Huang, Fei Xia, Peng Xu, Karol Hausman, Brian Ichter, Pete Florence, and Andy Zeng. 2023. "Code as Policies: Language Model Programs for Embodied Control." In *2023 IEEE International Conference on Robotics and Automation (ICRA)*, 9493–9500. IEEE.

Liao, Q. Vera, Daniel Gruen, and Sarah Miller. 2020. "Questioning the AI: Informing Design Practices for Explainable AI User Experiences." In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–15.

Lyons, Joseph B., Nhut T. Ho, William E. Fergueson, Garrett G. Sadler, Samantha D. Cals, Casey E. Richardson, and Mark A. Wilkins. 2016. "Trust of An Automatic Ground Collision Avoidance Technology: A Fighter Pilot Perspective." *Military Psychology* 28 (4): 271–277. https://doi.org/10.1037/mil0000124.

Lyons, Joseph B., Kevin T. Wynne, Sean Mahoney, and Mark A. Roebke. 2019. "Trust and Human-Machine Teaming: A Qualitative Study." In *Artificial Intelligence for the Internet of Everything*, 101–116. Elsevier.

Macdonald, Jacob P., Rohit Mallick, Allan B. Wollaber, Jaime D. Peña, Nathan McNeese, and Ho Chit Siu. 2024. "Language, Camera, Autonomy! Prompt-Engineered Robot Control for Rapidly Evolving Deployment." In *Companion of the 2024 ACM/IEEE International Conference on Human-Robot Interaction*, 717–721.

Marks, Michelle A., John E. Mathieu, and Stephen J. Zaccaro. 2001. "A Temporally Based Framework and Taxonomy of Team Processes." *Academy of Management Review* 26 (3): 356–376. https://doi.org/10.2307/259182.

Mathieu, John E., Tonia S. Heffner, Gerald F. Goodwin, Eduardo Salas, and Janis A. Cannon-Bowers. 2000. "The Influence of Shared Mental Models on Team Process and Performance." *Journal of Applied Psychology* 85 (2): 273–283. https://doi.org/10.1037/0021-9010.85.2.273.

Mathieu, John, M. Travis Maynard, Tammy Rapp, and Lucy Gilson. 2008. "Team Effectiveness 1997-2007: A Review of Recent Advancements and a Glimpse Into the Future." *Journal of Management* 34 (3): 410–476. https://doi.org/10.1177/0149206308316061.

McNeese, Nathan, Mustafa Demir, Erin Chiou, Nancy Cooke, and Giovanni Yanikian. 2019. "Understanding the Role of Trust in Human-Autonomy Teaming." In *Proceedings of the 52nd Hawaii International Conference on System Sciences*.

McNeese, Nathan J., Mustafa Demir, Nancy J. Cooke, and Christopher Myers. 2018. "Teaming with a Synthetic Teammate: Insights Into Human-Autonomy Teaming." *Human Factors* 60 (2): 262–273. https://doi.org/10.1177/0018720817743223.

McNeese, Nathan J., Mustafa Demir, Nancy J. Cooke, and Manrong She. 2021. "Team Situation Awareness and Conflict: A Study of Human–Machine Teaming." *Journal of Cognitive Engineering and Decision Making* 15 (2–3): 83–96. https://doi.org/10.1177/15553434211017354.

McNeese, Michael, Eduardo Salas, and Mica R. Endsley. 2001. *New Trends in Cooperative Activities: Understanding System Dynamics in Complex Environments*. Human Factors & Ergonomics Society, Inc.

Mesmer-Magnus, Jessica R., and Leslie A. DeChurch. 2009. "Information Sharing and Team Performance: A Meta-Analysis." *Journal of Applied Psychology* 94 (2): 535–546. https://doi.org/10.1037/a0013773.

Mesmer-Magnus, Jessica, Ashley A. Niler, Gabriel Plummer, Lindsay E. Larson, and Leslie A. DeChurch. 2017. "The Cognitive Underpinnings of Effective Teamwork: A Continuation." *Career Development International* 22 (5): 507–519. https://doi.org/10.1108/CDI-08-2017-0140.

Miller, Tim. 2019. "Explanation in Artificial Intelligence: Insights From the Social Sciences." *Artificial Intelligence* 267:1–38. https://doi.org/10.1016/j.artint.2018.07.007.

Mohammed, Susan, Lori Ferzandi, and Katherine Hamilton. 2010. "Metaphor No More: A 15-year Review of the Team Mental Model Construct." *Journal of Management* 36 (4): 876–910. https://doi.org/10.1177/0149206309356804.

Mughal, Arif Ali. 2018. "Artificial Intelligence in Information Security: Exploring the Advantages, Challenges, and Future Directions." *Journal of Artificial Intelligence and Machine Learning in Management* 2 (1): 22–34.

Musick, Geoff, Thomas A. O'Neill, Beau G. Schelble, Nathan J. McNeese, and Jonn B. Henke. 2021. "What Happens When Humans Believe Their Teammate is An AI? An Investigation Into Humans Teaming with Autonomy." *Computers in Human Behavior* 122:106852. https://doi.org/10.1016/j.chb.2021.106852.

Musick, Geoff, Rui Zhang, Nathan J. McNeese, Guo Freeman, and Anurata Prabha Hridi. 2021. "Leveling Up Teamwork in Esports: Understanding Team Cognition in a Dynamic Virtual Environment." *Proceedings of the ACM on Human-Computer Interaction* 5 (CSCW1): 1–30. https://doi.org/10.1145/3449123.

National Academies of Sciences Engineering and Medicine. 2022. *Human-AI Teaming: State-of-the- Art and Research Needs*. Washington, DC: The National Academies Press. https://doi.org/10.17226/26355.

Niler, Ashley A., Jessica R. Mesmer-Magnus, Lindsay E. Larson, Gabriel Plummer, Leslie A. DeChurch, and Noshir S. Contractor. 2021. "Conditioning Team Cognition: A Meta-Analysis." *Organizational Psychology Review* 11 (2): 144–174. https://doi.org/10.1177/2041386620972112.

O'Neill, Thomas, Nathan McNeese, Amy Barron, and Beau G. Schelble. 2020. "Human–Autonomy Teaming: A Review and Analysis of the Empirical Literature." *Human Factors* 64 (5): 904–938. https://doi.org/10.1177/0018720820960865.

Park, Hee Sun. 2008. "The Effects of Shared Cognition on Group Satisfaction and Performance: Politeness and Efficiency in Group Interaction." *Communication Research* 35 (1): 88–108. https://doi.org/10.1177/0093650207309363.

Rana, Krishan, Jesse Haviland, Sourav Garg, Jad Abou-Chakra, Ian Reid, and Niko Suenderhauf. 2023. "Sayplan: Grounding Large Language Models using 3D Scene Graphs for Scalable Robot Task Planning." In *7th Annual Conference on Robot Learning*.

Rapert, Molly Inhofe, Anne Velliquette, and Judith A. Garretson. 2002. "The Strategic Implementation Process: Evoking Strategic Consensus Through Communication." *Journal of Business Research* 55 (4): 301–310. https://doi.org/10.1016/S0148-2963(00)00157-0.

Rau, Devaki. 2005. "The Influence of Relationship Conflict and Trust on the Transactive Memory: Performance Relation in Top Management Teams." *Small Group Research* 36 (6): 746–771. https://doi.org/10.1177/1046496405281776.

Salas, Eduardo, Nancy J. Cooke, and Michael A. Rosen. 2008. "On Teams, Teamwork, and Team Performance: Discoveries and Developments." *Human Factors* 50 (3): 540–547. https://doi.org/10.1518/001872008X288457.

Salas, Eduardo, Carolyn Prince, David P. Baker, and Lisa Shrestha. 1995. "Situation Awareness in Team Performance: Implications for Measurement and Training." *Human Factors* 37 (1): 123–136. https://doi.org/10.1518/001872095779049525.

Salmon, Paul M., Neville A. Stanton, Guy H. Walker, Chris Baber, Daniel P. Jenkins, Richard McMaster, and Mark S. Young. 2008. "What Really is Going on? Review of Situation Awareness Models for Individuals and Teams." *Theoretical Issues in Ergonomics Science* 9 (4): 297–323. https://doi.org/10.1080/14639220701561775.

Schelble, Beau, Lorenzo-Barberis Canonico, Nathan McNeese, Jack Carroll, and Casey Hird. 2020. "Designing Human-Autonomy Teaming Experiments Through Reinforcement Learning." In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 64, 1426–1430. Los Angeles, CA: SAGE Publications.

Schelble, Beau G., Christopher Flathmann, and Nathan McNeese. 2020. "Towards Meaningfully Integrating Human-Autonomy Teaming in Applied Settings." In *Proceedings of the 8th International Conference on Human-Agent Interaction*, 149–156.

Schelble, Beau G., Christopher Flathmann, Nathan J. McNeese, Guo Freeman, and Rohit Mallick. 2022. "Let's Think Together! Assessing Shared Mental Models, Performance, and Trust in Human-Agent Teams." *Proceedings of the ACM on Human-Computer Interaction* 6 (GROUP): 1–29. https://doi.org/10.1145/3492832.

Schelble, Beau G., Christopher Flathmann, Nathan J. McNeese, Thomas O'Neill, Richard Pak, and Moses

Namara. 2022. “Investigating the Effects of Perceived Teammate Artificiality on Human Performance and Cognition.” *International Journal of Human–Computer Interaction* 39 (10): 1–16.

Schelble, Beau G., Jeremy Lopez, Claire Textor, Rui Zhang, Nathan J. McNeese, Richard Pak, and Guo Freeman. 2022. “Towards Ethical AI: Empirically Investigating Dimensions of AI Ethics, Trust Repair, and Performance in Human-AI Teaming.” *Human Factors* 66 (4): 1037–1055. https://doi.org/10.1177/00187208221116952.

Scheutz, Matthias, Scott A. DeLoach, and Julie A. Adams. 2017. “A Framework for Developing and Using Shared Mental Models in Human-Agent Teams.” *Journal of Cognitive Engineering and Decision Making* 11 (3): 203–224. https://doi.org/10.1177/1555343416682891.

Schulman, John, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. 2017. “Proximal Policy Optimization Algorithms.” *arXiv preprint arXiv:1707.06347*.

Shneiderman, Ben. 2020. “Human-Centered Artificial Intelligence: Reliable, Safe & Trustworthy.” *International Journal of Human–Computer Interaction* 36 (6): 495–504. https://doi.org/10.1080/10447318.2020.1741118.

Stout, Renee J., Janis A. Cannon-Bowers, and Eduardo Salas. 2017. “The role of shared mental models in developing team situation awareness: Implications for training.” *Training Research Journal* 2: 85–116.

Stout, Renée J., Janis A. Cannon-Bowers, Eduardo Salas, and Dana M. Milanovich. 1999. “Planning, Shared Mental Models, and Coordinated Performance: An Empirical Link is Established.” *Human Factors* 41 (1): 61–71. https://doi.org/10.1518/001872099779577273.

Tenhundfeld, Nathan L., Ewart J. de Visser, Anthony J. Ries, Victor S. Finomore, and Chad C. Tossell. 2020. “Trust and Distrust of Automated Parking in a Tesla Model X.” *Human Factors* 62 (2): 194–210. https://doi.org/10.1177/0018720819865412.

Textor, Claire, Rui Zhang, Jeremy Lopez, Beau G. Schelble, Nathan J. McNeese, Guo Freeman, Richard Pak, Chad Tossell, and Ewart J. de Visser. 2022. “Exploring the Relationship Between Ethics and Trust in Human–Artificial Intelligence Teaming: A Mixed Methods Approach.” *Journal of Cognitive Engineering and Decision Making* 16 (4): 252–281. https://doi.org/10.1177/15553434221113964.

Thompson, Leigh L. 2004. *Making the team. A guide for managers*. 2nd ed. Upper Saddle River, NJ: Prentice Hall.

Tomsett, Richard, Alun Preece, Dave Braines, Federico Cerutti, Supriyo Chakraborty, Mani Srivastava, Gavin Pearson, and Lance Kaplan. 2020. “Rapid Trust Calibration Through Interpretable and Uncertainty-Aware AI.” *Patterns* 1 (4): 100049. https://doi.org/10.1016/j.patter.2020.100049.

Vaes, Jeroen, Maria Paola Paladino, Luigi Castelli, Jacques-Philippe Leyens, and Anna Giovanazzi. 2003. “On the Behavioral Consequences of Infrahumanization: The Implicit Role of Uniquely Human Emotions in Intergroup Relations.” *Journal of Personality and Social Psychology* 85 (6): 1016–1034. https://doi.org/10.1037/0022-3514.85.6.1016.

Van den Bossche, Piet, Wim Gijselaers, Mien Segers, Geert Woltjer, and Paul Kirschner. 2011. “Team Learning: Building Shared Mental Models.” *Instructional Science* 39:283–301. https://doi.org/10.1007/s11251-010-9128-3.

Van Rensburg, Jandre J., Catarina M. Santos, Simon B. de Jong, and Sjir Uitdewilligen. 2021. “The Five-Factor Perceived Shared Mental Model Scale: A Consolidation of Items Across the Contemporary Literature.” *Frontiers in Psychology* 12:784200–784200. https://doi.org/10.3389/fpsyg.2021.784200.

Vaughan, Diane. 1996. *The Challenger Launch Decision: Risky Technology, Culture, and Deviance at NASA*. University of Chicago Press.

Walliser, James C., Patrick R. Mead, and Tyler H. Shaw. 2017. “The Perception of Teamwork with an Autonomous Agent Enhances Affect and Performance Outcomes.” In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 61, 231–235. Los Angeles, CA: SAGE Publications.

Wason, Kelly D., Michael J. Polonsky, and Michael R. Hyman. 2002. “Designing Vignette Studies in Marketing.” *Australasian Marketing Journal*10 (3): 41–58. https://doi.org/10.1016/S1441-3582(02)70157-2.

Wilson, John R., and Andrew Rutherford. 1989. “Mental Models: Theory and Application in Human Factors.” *Human Factors* 31 (6): 617–634. https://doi.org/10.1177/001872088903100601.

Woide, Marcel, Dina Stiegemeier, Stefan Pfattheicher, and Martin Baumann. 2021. “Measuring Driver-Vehicle Cooperation: Development and Validation of the Human-Machine-Interaction-Interdependence Questionnaire (HMII).” *Transportation Research Part F: Traffic Psychology and Behaviour* 83:424–439. https://doi.org/10.1016/j.trf.2021.11.003.

Wright, Melanie C., and David B. Kaber. 2005. “Effects of Automation of Information-Processing Functions on Teamwork.” *Human Factors* 47 (1): 50–66. https://doi.org/10.1518/0018720053653776.

Zhang, Rui, Christopher Flathmann, Geoff Musick, Beau Schelble, Nathan J. McNeese, Bart Knijnenburg, and Wen Duan. 2024. “I Know This Looks Bad, But I Can Explain: Understanding When AI Should Explain Actions In Human-AI Teams.” *ACM Transactions on Interactive Intelligent Systems* 14 (1): 1–23.

Zhang, Rui, Nathan J. McNeese, Guo Freeman, and Geoff Musick. 2021. “‘An Ideal Human’ Expectations of AI Teammates in Human-AI Teaming.” *Proceedings of the ACM on Human-Computer Interaction*4 (CSCW3): 1–25. https://doi.org/10.1145/3432945.