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What you say vs what you do: Utilizing positive emotional expressions to relay AI teammate intent within human–AI teams

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ABSTRACT

With the expansive growth of AI's capabilities in recent years, researchers have been tasked with developing and improving human-centered AI collaborations, necessitating the creation of human–AI teams (HATs). However, the differences in communication styles between humans and AI often prevent human teammates from fully understanding the intent and needs of AI teammates. One core difference is that humans naturally leverage a positive emotional tone during communication to convey their confidence or lack thereof to convey doubt in their ability to complete a task. Yet, this communication strategy must be explicitly designed in order for an AI teammate to be human-centered. In this mixed-methods study, 45 participants completed a study examining how human teammates interpret the behaviors of their AI teammates when they express different positive emotions via specific words/phrases. Quantitative results show that, based on corresponding behaviors, AI teammates were able to use displays of emotion to increase trust in AI teammates and the positive mood of the human teammate. Additionally, our qualitative findings indicate that participants preferred their AI teammates to increase the intensity of their displayed emotions to help reduce the perceived risk of their AI teammate's behavior. When taken in sum, these findings describe the relevance of AI teammates expressing intensities of emotion while performing various behavioral decisions as a continued means to provide social support to the wider team and better task performance.

1. Introduction

Recent advancements in artificial intelligence (AI) technologies have significantly improved their perception in society as capable and therefore effective agents in completing a variety of tasks across numerous domains (Das et al., 2020; Seeber et al., 2020; Flathmann et al., 2023c; Van Den Bosch et al., 2018). As a result, human attitudes toward AI shift from the previous "tool" based mentality to that of a "teammate" in which AI works alongside humans (McNeese et al., 2023; O'Neill et al., 2023a). This shift in mindset enables humans to integrate AI with roles and responsibilities that best suit its strengths, thereby alleviating the workload placed on themselves when mutually completing a shared task (McNeese et al., 2018; Mallick et al., 2022). However, these advancements also propagate unease and mistrust among humans when it comes to collaborating with artificial systems that conflict with their existing mental models of appropriate teammate behavior, thereby posing significant challenges to the seamless integration of AI as team members in forming effective human–AI teams (HAT). Further expansion of HAT effectiveness requires an increased focus on enhancing AI's collaborative, human-centered nature through social design (McNeese et al., 2023; Riedl, 2019). Notably, while AI teammates are highly capable of completing singular tasks, teams require several social functions in addition to simple task completion to enable collective performance (Schelble et al., 2022a). Indeed, social design addresses the non-task-related considerations that still impact the perception and performance of human–AI interaction/teamwork (Chen et al., 2016; Frascara, 2002). Social influence is one budding outcome of strategic social design in AI teammates, and it has demonstrated itself through social components such as etiquette, presentation, and more (Flathmann et al., 2024, 2023a,b). Yet, the broad scope of social influence has not investigated whether emotional tone, as communicated by an AI teammate, can positively influence HAT outcomes. Importantly, positive emotions have been shown to enhance collaboration, trust, and overall performance in human teams (Martınez-Miranda and Aldea, 2005; Scheutz and Schermerhorn, 2010). Incorporating positive emotional expression in AI teammates could thus elevate the human–AI interaction by fostering a more supportive and engaging environment that also alleviates negative sentiments toward AI. Human-only teams utilize

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emotional intelligence as mediators of their decision-making and therefore serve as a core facilitator of underlying social performance of team interaction (Martınez-Miranda and Aldea, 2005; Scheutz and Schermerhorn, 2010). Thus, this study works to leverage AI teammates that incorporate the display of positive emotions to bolster humans' perceptions and performance.

Emotions have largely persisted as a human-only characteristic meant to convey human intent through nuances in communicative tone (Lange et al., 2022; Zizzi et al., 2003). Technology in general, but more specifically AI, has found utility in integrating positive emotion into its expressions to humans as the tone is perceived as "warm", which subsequently relates to the willingness to interact that humans find enjoyable (Harris-Watson et al., 2023). The fields of Affective Computing and Human–Computer Interaction (HCI) demonstrate that emotionally expressive technology can mimic the socio-emotional influence humans have on each other. Otherwise considered as a contagion factor, it is often strategically paired with positive emotions to improve human perception of the technology and experience, leading to higher levels of satisfaction and enjoyment when humans interact with them (Brave and Nass, 2007; Derks et al., 2008; Neerincx et al., 2018; Williams et al., 2022; Picard, 2000). From an interpersonal teaming perspective, a positive collaborative atmosphere largely coincides with the level of confidence, enthusiasm, and collective understanding a team has in tackling their responsibilities (Harris-Watson et al., 2023; Fiske et al., 2007; van den Hout et al., 2018). This is often known as team morale and is the energizing component in which teammates become motivated to be persistent, creative, and satisfied in their work based on the relationships they have with their teammates (Peterson et al., 2008). Yet, challenges arise in the integration of any emotion in AI teammates let alone positive emotions. In particular, recent trends in HAT research have highlighted how focusing on AI behavior and not fully replicating human characteristics is an important design approach to designing AI teammates (McNeese et al., 2023). In turn, this work provides an empirical investigation of the benefits that positive AI teammate behavior can provide teams, but it does so by exploring the display of various joy-based emotion as a design feature within AI teammates.

Within the unexplored teaming context, the potential utility of positive emotion to AI teammates becomes especially relevant as AI enters into roles where it is tasked to conduct action autonomously with greater complexity and consequence. Increasing AI autonomy is a useful endeavor as it lessens the responsibilities of humans and allows teammates to prioritize tasks that exploit their talents as a means to improve accuracy, speed, and quality of work outcomes (Bansal et al., 2019; O'Neill et al., 2022). However, downsides also manifest where the distribution of autonomy can incite negative emotions in human teammates as AI teammates with obfuscated intent may engage in uncertain, risk-based behavior where humans can only perceive the cost of failure and not the potential benefits (Driskell et al., 2018b; Dietz et al., 2017; Lazarus et al., 1952). In doing so, positive expressions as behaviors to indicate confidence would allow human teammates to rationalize AI intent and how they can then adjust their behavior to support the AI's behaviors to increase chances of success (Harris-Watson et al., 2023; Lyons et al., 2021). With AI commonly seen as a "black box" where its decision-making processes are obfuscated from human perception, it hinders such collaboration in that humans aren't aware of why some actions are performed and how they should behaviorally complement the AI's decision-making (Miller, 2019; Talone, 2019; Wilkenfeld and Lombrozo, 2015; Walliser et al., 2017). In this way, an AI teammate displaying positive, joyful emotions may thereby mitigate this lack of clarity as it would act as an indicator of confidence a human can easily perceive but also be utilized to ease any undue stress that the situation exerts upon teammates (Harris-Watson et al., 2023; Lyons et al., 2021; Harth et al., 2013; Price and LaFiandra, 2017). With AI emotional expressions primarily contained within the field of HCI to improve social interaction between humans and AI, a gap exists around the social influence AI-sourced positive emotions have on HAT outcomes like performance or trust. Moreover, a secondary gap in the interactive relationship between positive emotional communication and autonomous behaviors has yet to be explored.

To address this research gap, the research questions below act as a guide to inform our study design:

- **RQ1:** In what manner do positively valenced emotional expressions from AI teammates impact human teammates' performance and perceptions of human–AI teams?
- **RQ1A:** Do these impacts differ based on the behavior of the AI teammates?

Based on these research questions, this study employs a mixed methods approach where 45 human participants have been recruited to individually play a real-time simulation game with an AI teammate expressing positive, joy-based emotions. Utilizing a Wizard of Oz approach, this AI teammate engages in behavioral actions varied by the amount of risk assumed (within subjects) while communicating serene, joy, and ecstatic emotions as positive expressions (between subjects). In following experimental design standards, this study operationalizes the positive expressions through words from the NRC emotional lexicon and the risk-based behavior is implemented based on objective team resources found within the simulation's environment.

In answering the above research questions, we provide three contributions to the field of HCI. Firstly, this study demonstrates that positive emotional expressions, when sourced from an AI, illuminate AI's behavioral decision-making processes. Not only is this a method to promote trust, but it also can positively impact performance among human–AI teammates. Secondly, this study maps the implications garnered from the role intensity plays in both positively valenced communication and behavioral risk-taking. With this understanding of the different perceptions humans have in relation to emotional communication on behavioral decision-making, the field of HCI gets a refined understanding of not only how to ensure that future AI technologies are human-centered but also how to maintain the perception of an AI as a full *teammate*. Thirdly, this study explores how humans adjust their behavior in response to the perceived intent of the AI teammate's behavior, communicated through positive emotional expressions. Together, these contributions provide the field of HCI with the knowledge needed to calibrate an AI teammate's positive tone in communication with their behavioral actions. This calibration is intended to match humans' expectations of appropriate teammate behavior, thereby improving the relationship human teammates have with their AI teammates and the overall experience human teammates have within the task.

2. Background

In this section, we first examine the existing literature on the factors that influence effective collaboration in human–AI teams. These previous studies then foreground the interpersonal value emotions have between humans and AI alike. The key takeaways center on current practices used to bridge the gap between differently-minded teammates, as well as the usefulness posed in integrating socially supportive communication mechanisms like positive emotional expressions upon team processes of team cognition, trust, and performance.

2.1. Factors toward effective collaboration in human-AI teams

With advancements in AI that enable it to take on a collaborative role, teaming research and real-world teams have been rapidly adjusting from the traditional human–human model to one that includes these collaborative intelligent systems as teammates (Seeber et al., 2020; O'Neill et al., 2022). Namely, AI is defined by its ability to dynamically perceive its environment, generate favorable decisions based on this perception, autonomously execute these decisions, and continuously learn how to better accomplish its task goals by reflecting on the impact of this decision-making process (Russell, 2010; Benbya et al., 2020). Critically, it's because of this computational design that they become exceptional assets in completing tasks (Lyons et al., 2021). Additionally, due to its artificial component, it does not tire as easily as humans and, therefore, can accommodate lengthy tasks without the need for rest or recuperation as well as enter more dangerous situations, thus reducing risk from human teammates (Trunk et al., 2020). With these core benefits, among others, AI teammates are being increasingly utilized to handle progressively complex situations (Das et al., 2020). Despite AI's many benefits, however, humans are still necessary as they provide the distinct benefits of social comprehension via their inherent emotional intelligence and how these factors may influence the constituents of the team and situation alike (Jarrahi, 2018; Chen and Barnes, 2014; Bradshaw et al., 2017). With this, teams utilize a "diversity of thought" where the skills of differently-minded teammates symbiotically join together to ensure a holistic awareness of dynamic factors that impact collaborative decision-making (Canonico et al., 2019; Wells, 2002). Within the literature, we see numerous examples of applications of human–AI teams ranging from a real-world mock emergency response management task (McNeese et al., 2021b; Schelble et al., 2022a,c) to e-sports (Zhang et al., 2021; Di Pietrantonio and Mendonca, 2020; Shergadwala and El-Nasr, 2021; Flathmann et al., 2023c). Yet despite the separate strengths both types of teammates have, AI teammates have yet to leverage the human skill of emotional intelligence to increase the effectiveness of their collaborative discourse.

Currently, AI exists at the stage where humans have an obfuscated understanding of how it autonomously makes decisions that thus disrupt teamwork behaviors like collaboration resulting in negative sentiments of the AI's capability (Riedl, 2019). In other words, the mental models humans have of AI are often limited as their existing mental models of teammate behavior are more strongly associated with other human teammates as opposed to AI teammates capable of their own autonomy (Schelble et al., 2022b; Shergadwala and El-Nasr, 2021). In a teamwork setting, and especially where there are heterogenous (human and AI) teammates, a shared mental model is important to recognize and rationalize how teammates perceive the environment and the motivations behind why they make certain decisions (Mallick et al., 2022; Schelble et al., 2022a; Endsley, 1995, 2023; Demir et al., 2017). In dynamic situations where a teammate assumes higher risk, human teammates become more concerned about the high potential of failure, such that they are distracted from completing their own tasks and focus on supervising them. In doing so, the trust humans have for AI teammates is negatively impacted when there is the uncertainty of success that has been shown to stem from the lack of clarity in AI intent (Talone, 2019; Williams et al., 2022; Lyons et al., 2021). This relates to the "theory of mind" concept wherein humans tend to rationalize the observed behavior of teammates in relation to their own decision-making processes and experiences with previous interpersonal relationships with humans (Leslie et al., 2004; Premack and Woodruff, 1978). However, due to the differences between AI decision-making processes and humans, this theory of mind breaks down where (1) humans become hesitant and distrustful of current and future AI teammates as they cannot rationalize how or why they perform certain actions; and (2) limits the development of AI to be constrained to human characteristics when the difference in teammate capability is the foundational property of effective teamwork (Druce et al., 2021; Zhu et al., 2020; Miller, 2019; McNeese et al., 2023). Instead, a "theory of behavior" is required where AI adopts enough human characteristics to be interpretable yet still has the flexibility to stay grounded in its core AI characteristics, such as being tireless machines (McNeese et al., 2023). As such, developers have been pushed to anthropomorphize AI teammates with specific human-like features (De Visser et al., 2016; Pelau et al., 2021) like emotional expressions as it changes the tone of communication without interfering with their behavioral abilities as an effective autonomous teammate. Moreover, AI designed with specific positive emotions, as opposed to the full emotional spectrum, may be sufficient to counteract humans' pre-existing negative sentiments toward them while achieving the targeted outcome of positively improving the human teammate's experience in the task (Mallick et al., 2023). If appropriately implemented, these positive experiences facilitate acceptance, trust, and a willingness to collaborate in future scenarios which result in continually refining existing mental models of AI behavior (Engel et al., 2014; El Kaliouby and Robinson, 2005; Chandrasekaran et al., 2017; Williams et al., 2022).

Furthermore, efficient collaboration extends beyond developing appropriate expectations of AI behavior and requires a consistent awareness of the current state of mind of all teammates. State of mind, otherwise defined as the mood and attitudes an individual holds, has been shown to have a considerable social influence on how an individual perceives and processes information (Clore et al., 2001; Scheutz and Schermerhorn, 2010). This then has an outward impact on the effective collaboration humans and AI teammates have with each other as there exists a lack of clarity on the awareness of either's current moods or attitudes as it relates to the decisions they make (Driskell et al., 2018a; Williams et al., 2022). While non-biological beings cannot be designed to have emotions, studies have shown that positively valenced emotional expressions of AI is one such method to improve clarity on AI intent by allowing it the opportunity to describe its confidence in whether its risk-based decisions will result in a higher likelihood of success (Harris-Watson et al., 2023; Lyons et al., 2021). Such expressions are beneficial as they concisely relay information that humans already have existing mental models for (Neerincx et al., 2018; Williams et al., 2022). In cases where situational factors like risk come into play, having this additional communication layer of positive emotional tone can potentially reassure human teammates that their AI teammate is trustworthy by being capable but also supportive of human endeavors (Williams et al., 2022). Within these situations, particularly high-risk areas typically force humans to take on higher stress and hyper-focus on executing their role with the fewest errors (Driskell et al., 1999; Feigh et al., 2012; Kahneman, 2011). While the literature on human–AI teams discourages humans from using oversight to monitor and supervise their AI co-workers, those teammates are expected to work interdependently with each other (Endsley, 2017; O'Neill et al., 2023b). Therefore, when risk rises, and the humans are no longer able to relay pertinent information to the AI or provide backup behaviors, collaborative teamwork becomes impaired such that both types of teammates lose situational awareness of the entire reality and the ability to work off of each other (Miller, 2019; Amir et al., 2019; Endsley, 2023; Driskell et al., 1999). Indeed, as risk fluctuates, so too does trust in teammates and technology alike, as the negative effects of stress can influence the level of activation (energy/focus) a person has with another (Kahneman, 2011; Pfaff, 2012). In lower-risk situations, humans tend to have more leniency when situational awareness or backup support is lost, as opposed to higher ones where their tolerance becomes stricter with the size of impact failure (Satterfield et al., 2017; Ezer et al., 2019). This leniency is associated with the amount of affect an individual feels on the positive-to-negative spectrum. Higher leniency carries connotations of lower stress and greater degrees of contentment, which foster realistic expectations of AI capability and constructively provide experience in its behavioral decision-making (Flathmann et al., 2023b; Ullman and Malle, 2018). Lower lenience is associated with maladaptive interpersonal behaviors such as higher stress, irritability, and decreased perceived utility of AI teammates, which studies have shown as detrimental to continued utilization (Schelble et al., 2020, 2023). This presents a strong need to regulate states of negative affect for all teammates to better support their relationship with each other as well as their ability to conduct their roles. With some psychologists regarding affect on a spectrum of positivity to negativity, positive emotional tone from an outside task-constituent like an AI teammate may inhibit negative emotions and therefore negative attitudes from forming (Plutchik, 1960). While the positive affective tone of the AI teammate's communication can improve humans' interaction with AI (Shank et al., 2019), it has yet to be empirically explored within a teaming context. Especially captured within the context of the impressions and impact positively valenced emotional expressions have in congruence with various degrees of behavioral actions performed by an AI teammate.

2.2. Interpersonal influence of emotions on decision-making within dynamic situations

As behavioral decision-making is impacted by the attitudes of individuals, looking toward the affective and cognitive reactions to decisions is a fruitful endeavor to understand how humans navigate cooperative task completion (Sjöberg, 2007; Bracha and Brown, 2012; Driskell et al., 2018a). Specifically, attitudes are sustained lessons where some are learned, whereas some emotional reactions are instinctual (Breckler, 1984). In accordance with the MODE model, predicting behavior via attitudes is a result of cognitively learning which objects and situations bring positive emotions, as opposed to negative emotions (Fazio and Towles-Schwen, 1999; Fazio, 1990). This behavioral model goes beyond just the rationalization that humans are attracted toward maximizing positive affective rewards but also discusses the role that motivation and opportunity have in behavioral decision-making (Fazio and Towles-Schwen, 1999). In their perspective, *motivation* is the targeted outcome that an individual wishes to achieve, whereas *opportunity* refers to the resources like time, energy, and ability to overcome the influence of attitudes (Fazio and Towles-Schwen, 1999). In this way, while some individuals may have goals they want to achieve in a perfect world, the limitations of their physical and cognitive resources lead them toward maladaptive decisions where opportunity outweighs benefit. This becomes an important consideration with artificial intelligence, as a recent study has noted that for human teammates to be receptive to AI teammates and therefore have a positive collaborative experience with them, the AI teammate must be both "warm" (in terms of friendliness, sincerity, etc.), as well as "competent" (Harris-Watson et al., 2023; Fiske et al., 2007). Together, the consideration of the relationship attitudes has with behavioral decision-making, as well as the requirements for AI teammates to be perceived as warm and competent, further support the likelihood of AI teammates utilizing emotional means to act as descriptors of the attitudes they have and thus behaviors.

In dynamic situations, a range of emotions can be elicited from all constituents that impact team decision-making (Melita Prati et al., 2003). Within these dynamic environments and tasks, the potential for risk behaviors varies with new situations, team players, rewards, and more. As there are many different definitions of risk behavior and the various factors that influence it, this paper uses the operationalization of high risk as situations with limited resources that decrease chances of success but correspondingly have higher rewards. While research has pointed toward consistent findings of higher risk situations resulting in increased stress and negative feelings (Zhao, 2006), these risk situations are prevalent in an unpredictable environment (Perrow, 1999; Van Den Bosch et al., 2018; Sawant et al., 2022) and are sometimes favorable decisions to execute as it provides a high reward to the overall team (Perrow, 1999). For instance, in adolescent teams where teammates are considered peers, individuals are focused on the presence they portray and gravitate toward more risk-taking behavior by placing a larger value on the high reward than the high chance of failure (Gardner and Steinberg, 2005). High-risk situations are defined as situations with lower chances of success but yield a high reward if achieved; a higher proportion of attempts correspondingly end in failure (Perrow, 1999). Additionally, repetitive failure reinforces the learned association where such high-risk situations elicit negative feelings (Cannon and Edmondson, 2001; Bracha and Brown, 2012). Unchecked, this association would become a reinforced learned response, meaning that similar instances would elicit the same negative emotions to become a negative attitude (Fazio et al., 1986). Negative emotional perceptions influence sub-optimal decision-making that decreases performance (Farh et al., 2012; Johnson et al., 2020; Cole et al., 2008), but also engenders distrust (Jones and George, 1998), as well as more conflict between team members (Spector et al., 2006). In regards to autonomous technologies like AI teammates, it becomes important that their risk-taking strategies are not perceived as negative as demonstrated by Schelble and others, where despite utilizing trust repair tactics like apologies or denial after a purposely unethical AI teammate conducted an unethical behavior, human trust and therefore collaboration with the AI did not entirely recover (Schelble et al., 2022d). This suggests that the detrimental impact of negative perceptions of AI teammates is resistant to recovery and can persist in future pairings with AI as teammates (Wang et al., 2019; Zhang et al., 2021). With the cautionary role risk plays in human decision-making, an essential consideration is placed on the interpersonal negative affects humans perceive from each other and how it relates to their collaborative decision-making.

In contrast to negative affect states in teams, positive emotions have been shown to elevate the team's collective mood and regulate unsuitable affect states like overconfidence in decision-making (Kuvaas and Kaufmann, 2004). As such, positive emotions like "joy, interest, contentment, and love" are highly desirable in the workplace. Through the lens of teamwork, positive emotions such as these have a healing property that allows them to repair weak or broken relationships, thus heightening overall team cohesion (West et al., 2009; Zurcher, 1982). With higher team cohesion, individuals can develop trust for each other and rely on each other more often, especially in dynamic situations where risk may fluctuate in intensity (Driskell et al., 2015). An experimental study designed to investigate the effects of positive emotional perception on team engagement saw the relationship between the awareness of emotional states of teammates and its impact on reducing stress-induced situational awareness, overconfidence, as well as the risk-taking strategies soldiers take on in a simulated combat task (Price and LaFiandra, 2017). Given this perception and influence of positive team behavior, teams improve their communication strategies with each other, prompted aid and increased knowledge to appropriately handle situations as they arose (Barsade, 2002). While these benefits of positive emotional perception exist, research has also noted that too much positivity can result in negative consequences in relation to risk situations (Arkes et al., 1988; Isen and Geva, 1987; Isen et al., 1988). In particular, *presentation* has been identified as a key determinant of the behavioral risk-prone or risk-averse decisions an individual with a positive affect state of mind employs (Flathmann et al., 2023b). For instance, the individual will employ risk aversion if the potential consequence/loss is emphasized or risk proneness if the risk is minimized (Arkes et al., 1988; Flathmann et al., 2023c). Within teams, when negative performance is corrected with newer, riskier decisions, an increase in positive emotion is expressed that then reinforces continual riskier decision-making (Dø jbak Håkonsson et al., 2016). Given the pervasive role that emotional intelligence has on perceiving and reacting to teammate emotions, a need arises for further clarity on the effects of positive emotional influence on situationally dynamic decision-making.

3. Methods

In this study, we focus on understanding the dynamic between positive emotional communication and an AI teammate's behavioral decision-making on their human teammates. To accomplish this, we design our mixed-methods approach of crossing the various intensities of positive communication with an AI teammate's different behavioral strategies. Together with both quantitative and qualitative data, we are able to investigate and explore these various configurations of positive AI emotional expressions on both the perceptions of human teammates and the impact they have on the collective team's collaboration techniques.

3.1. Netrek task and roles

Given the research questions of this study geared toward understanding the emotional influence on behavioral risk-taking strategies of AI teammates, it is important to understand the research environment of this study before discussing the operationalization of the experimental design. Netrek, an open-sourced platform modeled by the fictional world of "Star Trek", was chosen as an action-oriented task where team outcomes rely on the interdependence of teammates (Di Pietrantonio and Mendonca, 2020). Action-oriented tasks are commonly employed to study HAT characteristics due to their ability to mirror the complexity of real-world task constraints by simulating "time-limited engagements with audiences, adversaries, or challenging environments in 'performative events' for which teams maintain specialized, collective skill" (Sundstrom et al., 1999; Cooke et al., 2023). Netrek facilitates this by providing an abundance of team resources in constant flux, requiring strategic collaboration between teammates to be effective. This task can be abstracted as a scenario where understanding any teammate (human or AI) is critical to the adaptive coordination of mutually beneficial actions amongst teammates (Zhang et al., 2021). Additionally, it is common for these situations to evoke a range of negative emotions due to the stressful nature and unpredictability of the environment (Koole and Jostmann, 2004; Lord and Kanfer, 2002). AI teammates meant to aid their human teammates in the environments in which they are employed must be designed with social capabilities such as positive emotional communication to alleviate negative emotions before they adversely impact team outcomes (Martınez-Miranda and Aldea, 2005; Scheutz and Schermerhorn, 2010). Including any negative emotions that arise from a lack of clarity in the AI's decision-making. In this way, Netrek embodies the requirements to study interpersonal team processes within HATs by encouraging the study manipulations of AI's behavioral decision-making and positive emotional communication to be perceived by a human teammate tasked with working closely with them.

This experiment utilizes the "Sturgeon" version within Netrek, which is designed to be a team vs team "Shoot 'em up" game in which both teams are composed of six to eight players (Di Pietrantonio and Mendonca, 2020). Each team is responsible for protecting its ten stationary planets from the invading (opposing) team. These planets vary in the type of beneficial resources they offer to the team, where some may be meant as a station to refuel, repair ship damage, or "agriculture" planets that produce armies. Teammates must then strategize on how best to protect themselves and their resources from the opposing team and gain resources. For this study, only one participant is recruited per session. They are joined by a human confederate that employs Wizard-of-Oz (WoZ) style deception to take the spot of an AI teammate under the name "Player One" as an enhanced AI with higher intelligence. All other teammates and bots are considered autonomous expert systems and are described as emotionless bots with lower intelligence (Maulsby et al., 1993; Huber and Hadley, 1997).

To further promote the core HAT concept of teammates having separate tasks, the participant is told that they and "Player One" are "enforcers", which only require them to eliminate enemies to protect their teammates and planets. Proctors also describe that the AI teammates have a higher concern in capturing planets, with the exception of the human confederate, who is also an enforcer. Planets can be captured by acquiring armies from specific friendly planets, carrying them over within the spaceship, and dropping them off on opposing planets where the armies battle for control. This battle is not explicitly shown, and the size of the opposing army is compared against the size of the armies resting on a planet. As an example, if a player brings five armies to fight against an opposing planet's existing four armies, the planet is taken over, and one army is left to guard it. Teamwork is needed to ensure that ships carrying armies are escorted safely to their destination and that enemies are not able to do the same for their friendly planets. Acting as enforcers, they do not need to worry about acquiring armies; instead, they need to focus on maximizing enemy eliminations so that their AI teammates are supported in carrying out their duties. To accomplish this, all players are embodied as "spaceships" capable of many actions to perform either role. These actions can be further categorized as weaponry capabilities, speed of movement, and defensive features to preserve their ship's health. Players may be eliminated within that time but are told to rejoin the game as quickly as possible. They are aware that the game's goals are to eliminate enemy combatants, protect teammates, protect themselves, and support the team in capturing planets to expand their territory. (See Figs. 1 and 2.)

Table 1
Experimental conditions.

Round	Condition 1 (High Joy)	Condition 2 (Low Joy)	Condition 3 (No Joy)
A	High Joy + High Risk	Low Joy + High Risk	No Joy + High Risk
B	High Joy + Low Risk	Low Joy + Low Risk	No Joy + Low Risk
C	High Joy + No Risk	Low Joy + No Risk	No Joy + No Risk

3.2. Experimental design

This study utilizes two independent variables of positive emotional expressions and risk-based behavioral strategies in a 3 × 3 mixed factorial methods design. The positive emotion of joy is separated into the different intensities of high positivity (ecstasy), medium positivity (just joy), and low positivity (serenity) (Plutchik, 1960). This experimental design acknowledges previous work on the empirical manipulation of emotions and employs the positive, joy-based emotion as a between-subjects variable to isolate the effect of emotional intensity on team outcomes (Amodio et al., 2007). In doing so, the between-subjects design reduces any carryover effects from the various intensities of emotions influencing each other. Risk behavior is separated into high risk, low risk, and no risk, as demonstrated when the AI teammate enters different playable environment zones. The within-subjects design takes advantage of exemplary AI teammates that regularly employ various risk-taking strategies over the lifespan of a task (Hauptman et al., 2023; Ezer et al., 2019). Together, the within-subjects factor of risk contextualizes the perceptions of the between-subjects of emotion, informing the impact each positive emotional intensity has on the behavioral decisions executed by the AI teammate (see Table 1).

3.2.1. Manipulation 1: AI teammate emotion

The NRC Emotion Intensity Lexicon is utilized to manipulate the emotional expression of joy. Specific words/phrases have been analyzed on the degree they correspond with one of the eight core emotions (joy, sadness, anger, disgust, surprise, anticipation, fear, and trust). This lexicon was formed in 2011 by crowdsourcing AmazonTurk participants and has been continuously updated (Mohammad and Turney, 2013). For this study, we operationalize levels of positive emotion as high-joy with phrases registered with an intensity level of 0.65 or above, low-joy as phrases within the .45 and .1 range, and no joy to be no words at all. This is a between-subjects manipulation in which each participant is only exposed to one intensity of joy for the entirety of their session. Each session comprises four game-play rounds, the first being training and three experimental rounds. The AI confederate communicates four messages in each experimental round played. With participants playing a total of three experimental rounds, a total of twelve emotionally expressive messages are sent to the participants. These messages are delivered consistently at time intervals of one minute into the round, three and a half minutes in, six minutes in, and eight and a half minutes in for all rounds. Exemplary joy-based phrases are included in Table 2. Due to the platform, Netrek, being a high-paced battle simulation environment, participants were tasked with a manipulation check to ensure they read the emotional phrases messaged to them by their AI teammates. Participants were instructed

Fig. 1. Example Screenshot of Netrek. The game screen consists of four sections that give players an awareness of their close surroundings (top-left), the movement and actions of the entire game (top-right), team achievements (bottom left), and communication with all players (bottom-right).

Table 2
A sample of the emotional phrases used by the AI confederate within the study.

High Joy words	Lexicon rating	Low Joy words	Lexicon rating
Best day ever	0.938	That was chill	0.281
Outstanding	0.879	Feeling rested	0.281
Superb	0.864	That was unexpected	0.203
Good Times	0.811	Moving on	0.182

to reply to the message however they wanted but, at minimum, to respond with “message seen” to ensure the message was acknowledged. The emotionally expressive AI teammate did not send any other message to avoid the confound of different emotional intensities construed and influencing the experimental design.

3.2.2. Manipulation 2: AI teammate behavior

To manipulate the behavior of the AI teammate, the playable map environment was divided into three static zones based on the proximity of resources (see Fig. 2). Low-risk behavior would represent playing within the area encompassing the spawning planet and the planets that exist behind that planet. This area then becomes the farthest area from the fighting, wherein enemy combatants would have a harder time getting across due to the frequent re-spawning of teammates, and teammates would be able to repair and access more resources more quickly due to their close proximity. High-risk behavior would be in the same area but on the opposing team’s side. If a teammate were to enter this area, they would be farthest from any planetary resources that could help them and closer to a larger number of enemy combatants as they acquire more resources or respawn in their designated planet. Within this high risk, however, a high potential for reward also exists as there is a higher concentration of opportunities to increase performance, whether it be enemy players or planets that need overturning. In between these two zones is considered the medium risk zone, where a larger portion of the action is held simply because it is the area where the closest enemy planet is nearest the closest friendly planet.

Due to the risk behavior acting as the within-subjects variable, the AI teammate would perform their role only within the zone assigned at the start of the round. For example, to exhibit high-risk behavior, as soon as spawning, the AI teammate would immediately go to the high-risk zone and only execute its actions in this zone for the entirety of the round. These actions would be similar to the participant’s enforcer role, in which the human teammate was instructed to protect teammates by prioritizing enemy eliminations. Behaviorally, the AI teammate would stay within their risk-based zone and join any teammates in the same zone. If no other teammates were in the risk zone, the positively valenced emotional AI teammate would target enemies in the zone. If multiple enemies existed within the zone, they would target enemies deemed the most threatening to any of the team’s planetary resources. For instance, “Player One” would target an enemy over other existing enemies if it went after a weakened planet. If in the high-risk zone with no planetary resources, “Player One” would execute decisions that would maximize points regardless of the risk posed. This often resembled attacking a cluster of enemies on their home-spawning planet. All rounds were counter-balanced to avoid ordering performance effects.

3.3. Participants and demographics

Fifty participants were recruited from a web-based participant pool at a Large Southeastern University in the United States. However, three participants did not believe in the Wizard of Oz deception and were excluded from quantitative and qualitative analyses. Two additional participants were excluded only from the quantitative analysis due to a system recording failure. As a result, forty-five participants’ data was quantitatively analysis, and forty-seven participants were qualitatively analyzed. Fifteen subjects were utilized per between-subjects condition, with only one participant recruited for each session. The average age of these collected participants is 18.89 years old (SD_{age} = 0.82). All participants were native English speakers with previous experience working in teams and consisted of 29 females (with the rest self-identifying as male). Of the forty-five analyzed participants, most participants estimated their video game experience as playing “a few times a year”. The full distribution of video game experience can be found in Table 3. Yet, all participants reported that they had not played Netrek before. Participants received course credit as an incentive for their voluntary participation as approved by the university’s Institutional Review Board (IRB).

3.4. Procedure

Each session began with the experimental proctor informing the participant of the nature of the three-hour study, which involves participant completion of pre-task surveys, training rounds, three rounds of

Table 3
Frequencies for video game experience.

Video game experience	Frequency	Percent	Valid percent	Cumulative percent
never	5	11.111	11.111	11.111
not in a long time	8	17.778	17.778	28.889
a few times a year	14	31.111	31.111	60.000
a few times a month	9	20.000	20.000	80.000
at least every week	4	8.889	8.889	88.889
almost every day	5	11.111	11.111	100.000
Missing	0	0.000		
Total	45	100.000		

game-play with post-round surveys, and a post-task interview. Participants reviewed a consent form and provided verbal confirmation that they understood their rights as participants and consented to continue forward with the session.

3.4.1. Pre-task tutorial

At this time, the proctor directed them to the computer, where they answered pre-task surveys focused on capturing demographic information and individual difference measures. Upon completion, the proctor described the core fundamentals of the combat game *Netrek* and the different actions participants had available to them. For quick reference, physical sheets labeled relevant buttons and their associated actions were given to them as reference points should they like it at any point within their four rounds. Additionally, during this time, the researcher emphasized the teaming principles within the game with a focus on the dynamic between themselves and the AI players. They were told that after the tutorial round, an AI teammate with higher intelligence and comprehension would be sending messages as opposed to the other AI teammates, and to ensure that they have read it, they would need to respond with “message seen” as soon as they were able.

3.4.2. During task

Once the overview portion of the session finished, the proctor transitioned into the training round, where the participant was instructed to have ten minutes to practice the controls and get used to the environment around them. Questions were encouraged during the training but not during the following rounds. During all four rounds, the proctor would leave the experimental space and sit in an adjacent room to control “Player One”. To encourage the WoZ deception, the proctor was hidden from view and could not be heard by the participant. Within the training, “Player One” would not send any messages and would stay within close proximity of the participant. Once the training round was over, the session quickly transitioned to the first round of the study. At the start of each round, the AI confederate would set four timers to determine when the messages would be set. Since a core characteristic of AI is the speed at which they send messages, each message was preloaded into the communication window to facilitate prompt submission at the appropriate intervals. Preloading messages also allowed the AI confederate to continue their behavioral actions without stopping, further cementing the WoZ deception. After this round, participants completed post-round surveys and continued with this round-survey cycle until all rounds were completed.

3.4.3. Post-task interviews and credit assignment

At the conclusion of the third and final round’s post-round surveys, the participant conducted a post-task interview that lasted approximately 60 min on their experiences in the game and what they liked and disliked about their AI teammates. Once the interview finished, the proctor conducted a manipulation check alongside the debriefing to ensure the participants believed they were working with an AI teammate. Three participants who did not believe in the deception were excluded from all data analysis. Three new participants were recruited from the same participant pool to replace those conditions for balanced analysis. These sessions were similarly counterbalanced as all other participants. The remaining forty-seven participants confirmed that they believed that player one was an AI akin to the other AI teammates and acted on this belief for the entirety of the experiment. All fifty participants were compensated for their time, which marked the end of the session.

3.5. Measures

3.5.1. Individual difference measures

Pre-task measure: familiarity with AI. Familiarity with AI is a standalone, five-point Likert question that asks participants to rate their comfort and awareness of general AI technology from “Not at all familiar” to “Extremely Familiar”. However, as many different interpretations of AI exist, we control for this by asking participants to rate their familiarity with a given definition as follows:

> Artificial intelligence (AI) refers to “the ability of a machine or a computer program to think and learn. The concept of artificial intelligence is based on the idea of building machines capable of thinking, acting, and learning like humans”. A very common example of artificial intelligence would be Siri or Google Assistant. Zhang et al. (2021)

Pre-task measure: experience in teams. Critical for teaming research, we collected individual difference metrics on participants’ prior experience with generic team-based collaboration before the start of the session. Three main questions were utilized: (1) experience working in teams, (2) comfort in working within teams, and (3) the approximate number of teams they have participated in thus far. The first question, whether they have experience working in teams, is a binary question with either a “Yes” or “No” response. If “No” is chosen, they are exempt from the following two questions. The second question, comfort in working in a team, is a five-point Likert question that ranges from “Very comfortable” to “Comfortable”. Finally, the third and last question refers to the number of teams they have participated in thus far in their life. It is a five-point interval-based response, with the first being “Only participated in one team” to the final “Participated in five or more teams”.

Pre-task measure: Netrek familiarity and generic video game experience. For this study, all participants would be tasked to play on the same HAT teaming platform (Netrek). As a video game environment, it is necessary to understand participants’ pre-existing affinity for either video games in general or Netrek specifically. Regarding video game experience, a single question asked, “How often do you play video games?” on a six-point Likert. The options were delineated as “never”, “not in a long time”, “a few times a year”, “a few times a month”, “at least every week”, and “almost every day”. Values were coded numerically based on their answer, in which “never” has a corresponding value of one, and “almost every day” has a value of six. Experience with Netrek was asked with a single binary question: “Have you ever played the game Netrek before?” to which participants could respond “Yes” or “No”.

Pre-task measure: Disposition to trust machines. Disposition to trust machines survey evaluates preconceived notions of human trust toward machine systems (Merritt et al., 2013). This survey asks five questions, such as “I usually trust machines until there is a reason not to.” or “It is easy for me to trust machines to do their job.”. When reading these statements, participants are asked to rate the degree they associate with it via a five-point Likert scale from “Strongly disagree” to “Strongly agree”.

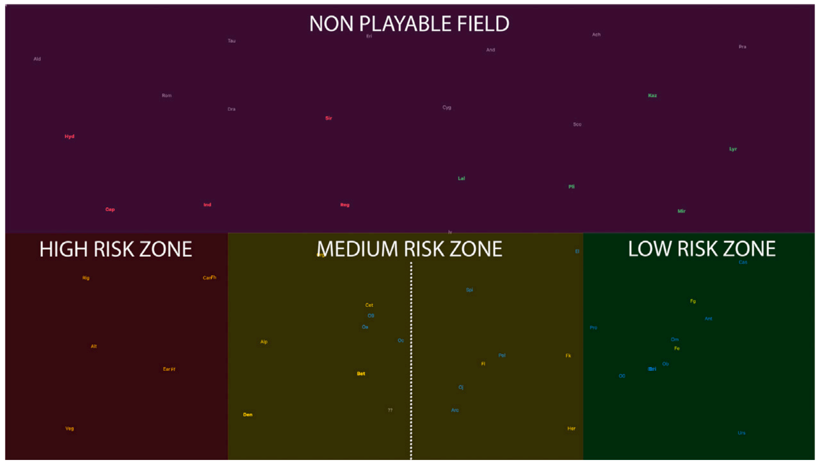


Fig. 2. The Galactic Screen represents the entire playable field of Netrek. Risk zones have been highlighted for reader clarity and were not explicitly defined to participants. The line in the medium-risk zone represents the imagined line of scrimmage where players fight to expand their respective territory.

Pre-task measure: Negative attitudes to robots scale. The negative attitudes to robots scale survey identifies humans' preconceived notions about robotic systems (Nomura et al., 2004). This survey asks 14 questions, such as "I would feel uneasy if robots had emotions" or "I would hate the idea that robots or artificial intelligence were making judgments about things". When reading these statements, participants are asked to rate the degree they associate with it via a five-point Likert scale from strongly disagree to strongly agree. They were averaged to form a reliable scale (Cronbach's α=.75).

3.5.2. Task-derived measures of performance

Based on how the game is designed, objective team performance metrics have been utilized that range from the individual human's performance/behavior to metrics that include the team's cumulative performance as a whole. These individual metrics include the number of enemy eliminations the human teammate got and the amount of time (in seconds) they spent in each risk zone. As a whole team, performance metrics reflect the number of planets the team could capture and how many total enemy eliminations the participant's team could acquire altogether. In doing so, these metrics provide insight into how human teammate performance can be impacted at both an individual and team level.

3.5.3. Affective measures

Pre-task and post-task measure: Positive and negative affect scale (PANAS). PANAS is an emotional status scale that evaluates the rater's current mood on a positive or negative axis (Watson et al., 1988). This survey asks users to rate 20 words on the degree to which they currently associate it, with a five-point Likert scale ranging from "1: very slightly" to "5: extremely". Words include "interested", "distressed", "excited", "upset", "enthusiastic", and more. This measure was used pre-task, upon the completion of each task, and at the end of the experiment. Nine adjectives were averaged to form a reliable scale for positive emotions (PANAS-pos) (Cronbach's alpha=.92), and eleven adjectives expressing negative emotions were averaged to form a negative emotions scale (PANAS-neg) (Cronbach's α=.85).

Post-task measure: Trust in agent teammate. Trust in agent teammate survey is created for participants to rate the degree of trust they have in the AI confederate teammate they played within the last played round (Merritt and Ilgen, 2008). Trust was measured in the survey upon completing each round, using a six-item 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree). Items included "I trusted the autonomous agent that I worked with" and "I felt that I had to monitor the autonomous agent's actions during the game" (reverse-coded). All the items were averaged to form a reliable scale (Cronbach's α=.80).

3.6. Post-task interviews

In addition to using quantitative methods to address our core research questions, a semi-structured interview once all within-subjects rounds were conducted. These interviews provide descriptive qualitative data contextualizing participants' experiences throughout each session. Mixed methods experimental designs are commonly applied within HCI-based studies for their benefits in understanding *how* and *why* the chosen manipulations impact human perception and teaming outcomes (Blandford et al., 2016; Merriam and Tisdell, 2015). Here, interviews were designed to provide an introspective opportunity for humans to recall the positive expressions the AI teammate communicated and its corresponding perceived influence on the AI's behavioral decision-making. In studying the complex subtlety of emotional influence, these qualitative findings provide insight into whether human teammates believe they acted on the emotional influence of their AI teammate, the potential benefits of emotional communication had beyond the explicit quantitative measures, and how HCI researchers may continue to refine the emotional tone of communication to forward positive human experiences when teaming with AI teammates in action-oriented tasks. As such, the semi-structured interview protocol was focused on three open-ended topics regarding AI emotional expression, their various behaviors, and what it means when combined. The first section focused on the immediate perceptions the participant had of their AI teammate in regard to both communication and behavior. This was the opportunity to discuss the aspects they liked vs. what they didn't like by questioning the similarities and differences likely posed by an all-human team. The comparison allowed this research to recognize the degree of anthropomorphism achieved by the enhanced AI teammate, a comparison of the enhanced AI teammate with the non-emotionally manipulated AI teammates, and insights on how to keep improving AI agents to meet existing expectations for human teammates. The second section focused on the performance of the enhanced AI teammate and how their behavior influenced the team. This was encapsulated by forming questions from the perspective of the various risk behaviors the enhanced AI teammate engaged in and how that may have impacted the perception of emotional communication being sent. The third and final section centered on not only the impact of emotional messages that were sent and their influencing perception of the behavior of the AI but also the role of all emotions beyond just joy within human–AI teams, as well as human–AI team structures with multiple AI teammates. These questions were focused on how to manipulate emotion, whether in its different forms or through its intensity, to understand how types/valences would impact the team overall. With these open-ended topics, interviews were able to qualitatively understand the impact various risk-based AI behaviors have on human teammates and the role emotions have and their influence together.

3.7. Qualitative analysis

In conducting this qualitative analysis, two researchers independently read and coded relevant ideas and thoughts of participants through a line-by-line approach (Saldaña, 2021). Afterward, both researchers utilized an open coding procedure (Charmaz, 2006) to categorize recurring concepts throughout multiple participants to transition specific codes to overarching themes via an axial coding procedure (Corbin and Strauss, 2014). With focused research questions to guide researchers on the relevant themes in relation to emotion, behavior, and the impressions they have on the overall team, a focused coding procedure was utilized to recursively refine these themes into sub-themes until both researchers felt that saturation of the data was met (Charmaz, 2006). Quotes were then extracted from these themes on the merit of supporting other quotes to ensure clarity and quality in the qualitative report. In utilizing this mixed methods reporting style, the perceptual qualitative data pairs well with the objective quantitative data to explain how their perceptions translated to collaborative behaviors due to the AI's emotionally communicative behavior.

4. Quantitative results

To answer the research questions, we conducted a series of mixed-models ANOVAs on the dependent variables, with emotion being the between-subjects factor and risk being the within-subjects factor. Mauchly's test of sphericity indicated that sphericity could not be assumed for all dependent variables; therefore, adjusted degrees of freedom were applied whenever necessary using the Greenhouse–Geisser correction. Given the issues surrounding effect size estimates for mixed-effects models, we report the marginal pseudo-R^2 for each model as recommended by Nakagawa and Schielzeth (2013) (Nakagawa and Schielzeth, 2013).

4.1. PANAS-positive affect

There was no significant main effect of emotional intensity on participants' own felt positive affect ($F(2, 42.79) = 1.04$, $p = .36$). There was also no significant main effect of risk ($F(2, 83.68) = 1.13$, $p = .33$). However, there was a significant interaction effect between emotional intensity and risk ($F(4, 83.68) = 3.51$, $p = .01$). In the high-joy condition, participants felt greater positive emotions when the emotional AI teammate performed medium-risk tasks ($M = 2.93$, $SE = .23$) than when the emotional AI teammate performed high-risk tasks ($M = 2.56$, $SE = .23$, $R^2 = .19$) (see Fig. 3(a)). A simple main effects test supports this as it found a statistical difference between risk and the high joy positive emotion level ($F(2, 83.2) = 4.466$, $p = 0.021$). These findings can be reviewed in the Table 4. From a teamwork perspective, this serves as an important finding, as it lends credence to the idea that AI teammates can leverage emotion-based behaviors to influence a human teammate's mood and state of mind.

4.2. PANAS-negative affect

For participants' felt negative affect, there was no significant main effect of emotional intensity ($F(2, 43.33) = .11$, $p = .90$), nor significant main effect of risk ($F(2, 82.79) = .07$, $p = .94$). There was also no significant interaction effect between emotion and risk ($F(4, 82.79) = .37$, $p = .83$, $R^2 < .001$). This suggests that regardless of the positive emotional intensity of expressions nor the risk strategies that the AI teammate took, it did not have a negative impact on the human teammate's perceived state of mind (see Fig. 3(b)).

4.3. Trust in agent teammate

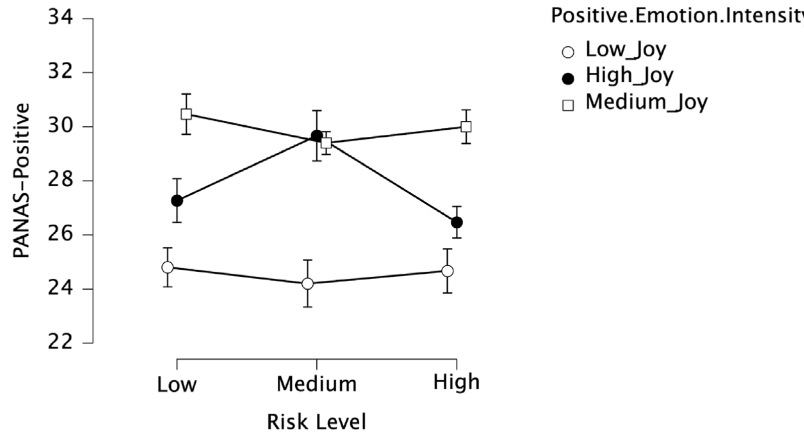
AI emotion had a non-significant main effect on participants' trust in the AI teammate ($F(2, 43.10) = .25$, $p = .78$). The main effect of risk on participant's trust in their AI teammate was, however, significant ($F(2, 80.86) = 5.58$, $p = .005$). Pairwise comparisons found that participants trusted the AI teammate significantly more in the medium-risk condition ($M = 3.83$, $SE = .11$) than in the low-risk condition ($M = 3.47$, $SE = .11$, $p = .002$, $R^2 = .25$). But the difference in participants' trust in the AI between low-risk and high-risk conditions was non-significant ($p = .15$), as was their trust between medium and high-risk conditions ($p = .14$). Lastly, the interaction effect between AI emotion and risk-level was non-significant ($F(4, 80.86) = 1.49$, $p = .21$) (see Fig. 4). Interestingly, this finding highlights how task-based behaviors, such as risk-taking, were more impactful on trust, which aligns with prior research (McNeese et al., 2021a).

4.4. Objective team performance

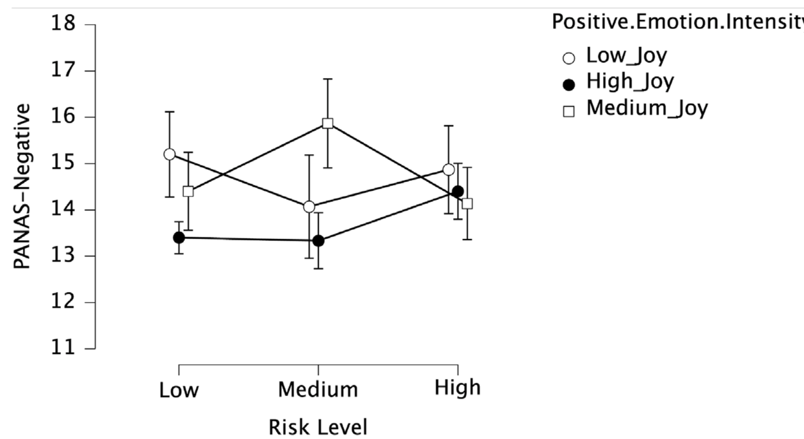
For objective team performance measures: the number of kills, deaths, enemy team kills, and planets captured and enemy planets captured, only planets captured yielded significant results (see Fig. 5). Specifically, while there was no significant main effect of emotional intensity on the number of planets captured ($F(2, 58.29) = 2.18$, $p = .12$), pairwise comparisons suggested a trend toward a significant main effect of emotional intensity for high- versus low-joy conditions where participants in the high-joy condition captured more planets ($M = .33$, $SE = .14$) than those in the low-joy condition ($M = .07$, $SE = .14$, $p = .06$). There was also a significant main effect of risk ($F(2, 93.40) = 4.42$, $p = .02$) such that participants captured significantly more planets in the medium-risk condition ($M = .33$, $SE = .08$) than in the high-risk condition ($M = .07$, $SE = .08$, $R^2 = .44$). There was also a significant interaction between emotional intensity and risk ($F(4, 93.40) = 2.72$, $p = .03$, $R^2 = .36$). While there was not much variance in the number of planets captured across risk levels, participants captured significantly more planets in the medium-risk task when the AI expressed highly positive emotions. A simple main effects test supports this as it found a statistical difference between risk and the high joy positive emotion level ($F(2, 3.733) = 3.664$, $p = 0.039$). These findings can be reviewed in the Table 5. This is then reflective of the relationship AI emotional expressions in the positive valence have when paired with their behavioral decision-making on the entire team's performance.

To further examine how participants' individual moods influenced team performance and affect, a correlation matrix calculating Pearson's r was conducted between participants' individual differences and their teams' objective performance of planets captured (see Fig. 6). These individual differences included their self-rated familiarity with AI, experience working in teams, number of teams they've worked with, comfort in teams, disposition to trust machines, their level of negative attitudes toward robots, familiarity with the game netrek, and video game experience. The objective performance measures included the number of planets captured in the low, medium, and high-risk levels. The correlation matrix found an interesting pattern where participants' individual differences had significant relationships with their performance in the low and medium-risk conditions but not the high-risk condition. Specifically, the participants' familiarity with AI and the number of planets captured in the medium-risk condition had a significant positive correlation coefficient of $r(45) = .389$, $p = .008$. There was also a significant negative relationship between participants' comfort in teams and the planets captured in the low-risk condition $r(45) = -.306$, $p = .041$. These two correlations display a significant relationship between the participants' individual differences and their ability to team up successfully with AI.

Additionally, as prior experience in video games and Netrek are pivotal individual differences that greatly influence the outcome of our



(a) PANAS- Positive Affect



(b) PANAS- Negative Affect

Fig. 3. Positive Affect Negative Affect Schedule (PANAS) on a scale of 1 to 5, by Emotion by Risk. (Error bars represent the standard error of the mean).

Table 4
Simple main effects - Risk level.

Level of Positive.Emotion.Intensity	Sum of squares	df	Mean square	F	p
Low_Joy	2.978	2	1.489	0.154	0.858
High_Joy	83.200	2	41.600	4.466	0.021
Medium_Joy	8.578	2	4.289	0.763	0.476

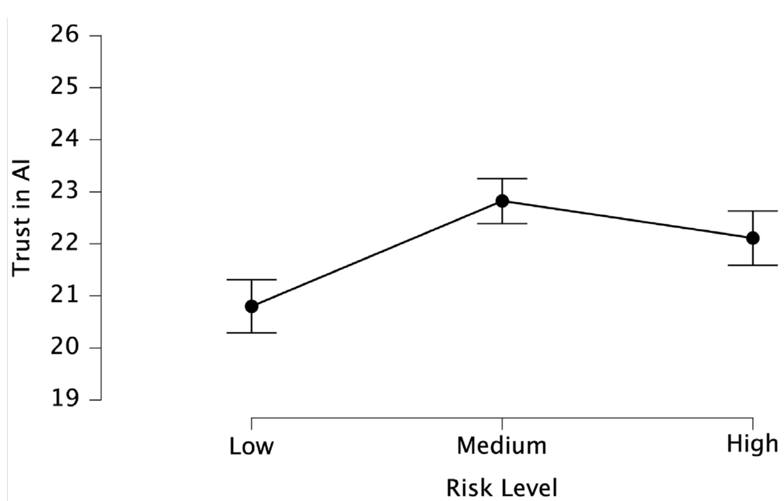


Fig. 4. Trust in AI Teammate on a scale of 1 to 5, by Emotion by Risk. (Error bars represent the standard error of the mean.).

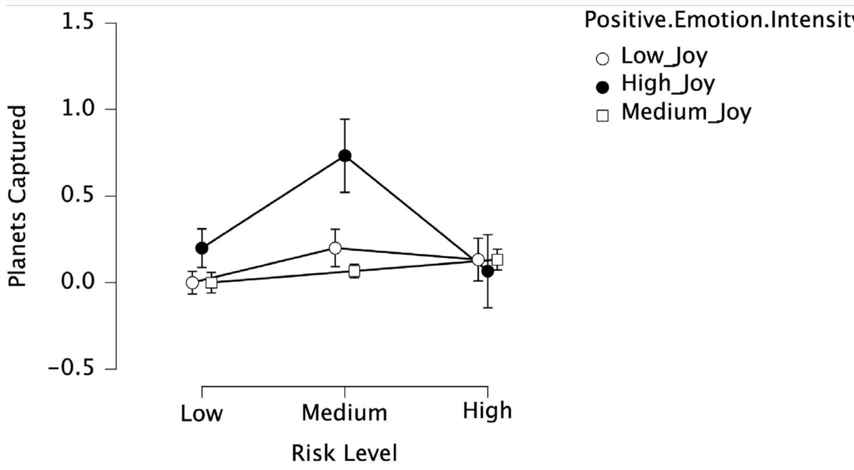


Fig. 5. Planets Captured by Emotion and Risk. (Error bars represent the standard error of the mean).

Table 5
Simple main effects - Risk level.

Level of Positive.Emotion.Intensity	Sum of squares	df	Mean square	F	p
Low_Joy	0.311	2	0.156	1.000	0.381
High_Joy	3.733	2	1.867	3.664	0.039
Medium_Joy	0.133	2	0.067	1.556	0.229

study, it is worthwhile to articulate these insignificant findings. First, all participants in this study responded that they were not familiar with Netrek, which resulted in a "NaN" correlation due to the limited variance of that demographic variable. This tells us all participants were novices to the game, and therefore, any changes in objective game performance are unlikely to have any influencing relationship with game expertise. Secondly, video game experience, meant to describe the participant's skill in video games in general, did not show a significant correlation to the number of planets captured, an objective game performance metric.

5. Qualitative results: Contextualizing the relationship between positive emotional intensity and its effect on risk-taking behaviors of AI teammates

Based on the quantitative findings, several findings appear such that: (1) Participants' internal affective state positively increased when the emotional AI teammate exhibited high joy communication, as well as medium risk behaviors, (2) Participants perceived themselves to have higher trust in their emotional AI teammate when they exhibited medium risk as opposed to low risk, and (3) Higher positive communication and medium risk taking strategies were the most beneficial to the team's overall performance. In this section, we utilize the post-session interviews to allow participants to describe how they perceived the AI emotional expressions and risk-based behavior and why they believe these perceptions impacted their team behaviors **RQ 1A**. To improve readability, context is provided within brackets of quotes.

5.1. Higher intensity of positive emotions with lower risk-taking behaviors are the preferred combination for enhancing team collaboration

The most predominant qualitative findings we see within this data reflect how helpful higher intensities of joyful expression are when paired with lower risk-taking behaviors as it is perceived to be more personable to the participant. In essence, human participants discuss how lower-risk-taking behavior lends the AI teammate more ability to aid other teammates, which is seen as a core perspective of being collaborative. To begin, we ground this perspective with the following quote that describes the baseline perception participants had when exposed to an AI teammate that expressed low joy emotional expressions and low-risk behaviors:

> They [AI teammate] would just not act right. They sit on one planet and just circle it and not attack the other planets. And they wouldn't do anything with the armies to bring down the other planets. So I got frustrated because they effectively were doing nothing; they were just flying around and not shooting at each [of] the other things [planets, enemy players]. So that made me mad, and frustrated. And then I started getting a bunch of kills because I started to just not really give a [expletive] about what the AI was doing. (P42, Male, 20) [No Joy, Low Risk]

This quote (P42, Male, 20) [No Joy, Low Risk] describes that sitting on one planet or otherwise doing nothing useful was not supportive of the team's overall objectives. Sub-components to the task objective, like firing weapons, carrying armies and so forth, were not executed, which forced the humans to overcompensate for the AI's incompetence. In this way, the human became increasingly annoyed because the AI stopped contributing and, therefore, stopped being a teammate and engaged in social loafing behavior, which decreased the human's experience overall.

In comparison to when joy is expressed, and particularly a higher intensity of joy, this perception of a collaborative teammate is not only further supplemented, but teammates notice the motivating impact resulting from its emotional contagion factor. The following participant, P5 (Male, 20) [High Joy, Low Risk], describes this in further detail:

> I guess it is, because sometimes I kill one of the enemy ships, and then they get a 'marvelous' from player one. So that's pretty satisfying. And then when a job got done he was hyping everyone up. (P5, Male, 20) [High Joy, Low Risk]
>
> [The messages from the AI teammate helped me become] optimistic that they'll do their job. Then you won't be worrying like watching them [do] whatever they're supposed to do, and then they'll just get done. (P5, Male, 20) [High Joy, Low Risk]

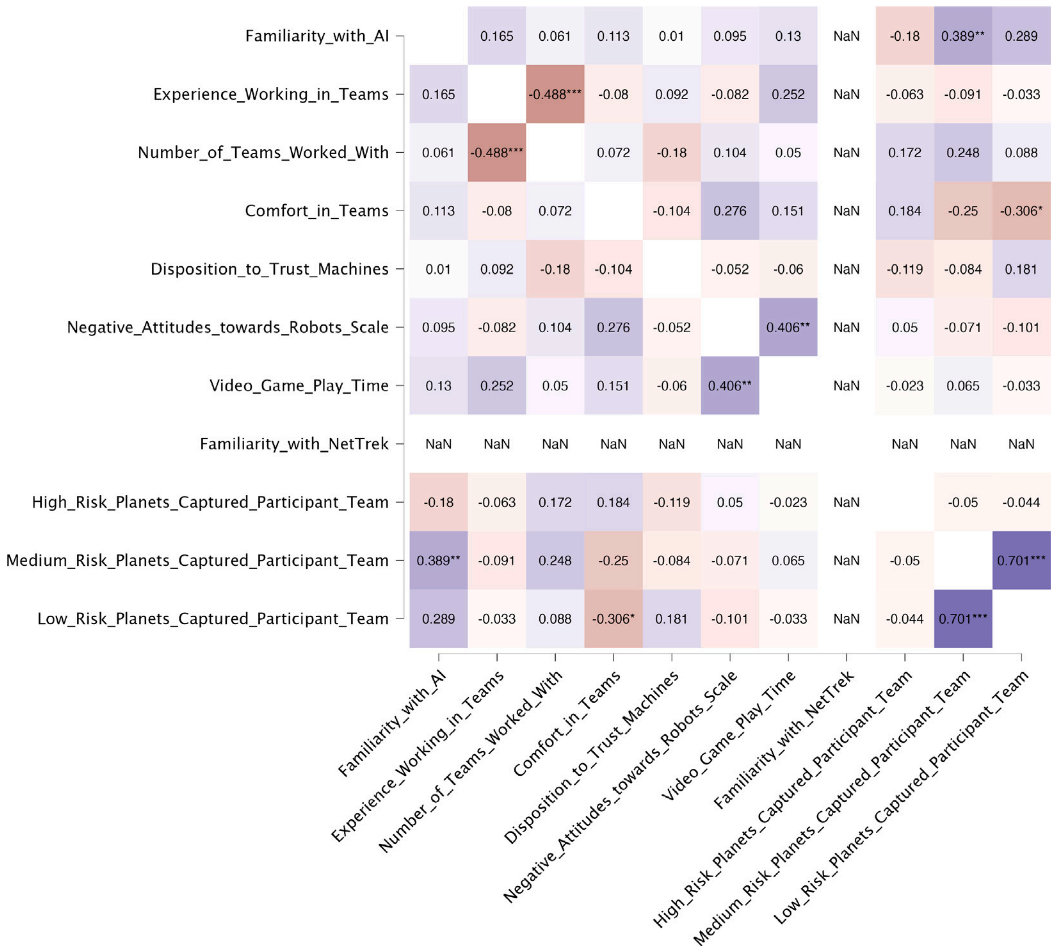


Fig. 6. Correlation matrix heatmap between individual difference measures and team performance across risk levels. *Note. * indicates p <.05, ** indicates p <.01, and *** indicates p <.001. NaN or "Not a Number" describes a lack of variance for all participants for the demographic variable, familiarity with Netrek.*

P5 describes how satisfying these comments were as they related to their individual achievements, like enemy eliminations. Otherwise serving as a form of encouragement, the AI teammate demonstrates that this higher intensity of joy has utility in observing and verbally supporting teammates beyond just physical, behavioral means. Additionally, the same participant comments on how the messages gave a tone of optimism that translated to a decrease in the amount of human supervision needed when collaborating with an AI teammate. In this way, the explicit comments of the AI teammate have the means to demonstrate itself as a way to provide support in the form of encouragement and support team characteristics like trust. Additionally, another participant notes that this element of encouragement is not only limited to being beneficial to teammates to motivate them to complete their tasks but also to enhance collaboration between teammates.

> It [emotions] definitely made me want to interact with AI more and like, follow them, because it seemed like they were very enthusiastic about all of it. (P3, female, 18) [High Joy, Low Risk]

> [When] the [AI teammate] was at the fuel station, I'd go back to the fuel station. Or if I saw, in my second round, we had a ton just all spread out: It made me feel more confident and like, Oh, I feel like we can kill the other [enemy] players if we're all spread out rather than [if we] would just wait for them [enemy players] to come to us. (P3, female, 18) [High Joy, Low Risk]

P3 describes initially how the higher intensity of joy expressed by this AI teammate was perceived to be very "enthusiastic" and thus encouraged them to engage with it more. With a little massaging on what this interaction looked like, P3 explains how they were mimicking the behavior of the AI teammate and were able to pay more attention to the strategic utility of their decision-making. P3 rationalized this low-risk behavior from the AI teammate as a defensive strategy to ensure that the players were spread out instead of clustering. This strategy meant that the AI did not have to use up as many resources in hunting for enemies but rather "wait for them to come". In this instance, we see the prevalent theme of highly intense positive emotions from an AI teammate to rationalize AI behavior to the extent that new techniques and strategies are learned and utilized to perform better as a cohesive team. Within the following quotes, we explore the extent of rationalization in regard to important factors of collaborative decision-making, like situation awareness, that are needed within the confines of this game.

This game is notably complex with its many different components, including resources and the number of players on each team. As such, it creates a highly dynamic environment that reduces awareness of the different events and actions. When asked about their playing style and how the AI influenced their perception of the environment, this participant comments on how they were originally hesitant to venture across the line toward enemy territory but that the strategic presence of teammates increased their awareness of game activity.

> Oh, yeah, I'll definitely say I'm [a] pretty cautious person. I definitely stayed in the home territory. And the times that I did venture out into the enemy territory was usually when a lot of my other teammates were in there. So I figured, they seem to be set on shooting the enemy down. That's mainly what alerts me to the

> presence of other enemies because a lot of times I [am] too focused on the small screen. So I wouldn't see enemy ships coming closer and, like, have my teammates take action. I guess [it] helped me be more aware of my situation. (P12, Female, 18) [High Joy, Medium Risk]

Here, the participant recalls that due to being hyper-focused on the "small screen" (referring to the strategic screen), they ultimately lost awareness of wider events beyond their surroundings. However, because most of the AI teammates were within the outskirts of their awareness, P12 followed in the AI's lead and ventured across enemy lines to support the AI teammates and increase their comprehension of the dynamic environment. This was accomplished because they understood the value of the AI's actions such that it alerted them to the locations of the enemies and, therefore, the wider situation.

As P12 describes how the AI's behavior within their proximity increases their situational awareness, P4 similarly also describes how important it is to really understand AI behavior within the context of the situation. In the following quote, this participant describes the importance of recognizing a pattern in the AI teammates' course of actions and how that behavior related to increased task performance in obtaining planets.

> I think kind of the way that they followed patterns, [...] they'll have moments where you'll have two or three, going off [to] one planet. Yeah. And then you'll have other moments where you don't have any of them attacking. They're all defending. And, that's kind of just based on what's going on in the game. It was more [...] I guess you can say pattern oriented. It's either they're doing one thing, or they're doing, kind of the opposite. (P4, Male, 18) [High Joy, Medium Risk]

Here, P4 describes the difference between the kinds of decisions the AI took, such as an offensive or a defensive approach. They specifically mention how their decisions were reflected due to *what's going on in the game* and how important it was to recognize the pattern of decision-making and how it was linked to the overall situational events. Once this awareness is achieved, human teammates are then able to understand how to provide support for their AI teammates.

> I overall did like his behavior because I was able to see what he was doing throughout the game and revolve my actions around it. Specifically in round three, where he was also helping me, but I could help him in return. But like in round one [Medium Risk], I liked it just because it was nice to have him supporting me pretty much. (P11, Male, 19) [High Joy, Medium Risk]

This participant discusses how, based on humans and AI's understanding of each other's behavior, they could provide reciprocal aid because they were conveniently near one another. P11 perceived the risk-taking behavior to be varied with all rounds but especially commented how the lower risk-taking behavior was the most preferred because it was where player one, the AI teammate, was able to support their actions. The AI was able to understand the situation and thus match the decisions made by the human with the situational features to understand how they could best provide aid that allowed both the humans and the AI to achieve their goals. Additionally, the humans were able to understand the goals of the AI such that they could also plan how their actions could support the AI, which is likely a result of easily recognizing a predictable pattern of behavior due to their close proximity to each other. They were near each other within the medium-risk zone, facilitating this reciprocity of support as it took less effort to provide aid than going off to the different areas. In this example, going off and exhibiting either high or low risk-taking behavior is not seen as teammate behavior as it is a very individualistic thinking style.

5.2. Human teammates prefer a lower intensity of positive expressions when AI teammates engage in higher risk behaviors

Within the confines of the experiment, the higher-risk behavior of the emotional AI teammate is operationalized as actions conducted only in the high-risk zone of the playing field. In this area, player one is far from any helpful planetary resources and is nearest to most enemy combatants. In this way, these combatants pose a high risk to player one, as any damage they receive would make it difficult to receive aid from additional players or resources. This high risk is not without high reward. However, being near a higher concentration of enemy combatants increases the odds of eliminating enemies. When this risk-taking behavior is noticed among participants, the following section showcases the perceptions of high-risk behavior as it relates to teamwork and discusses how emotions influence those perceptions.

To begin, within the high joy condition, the participant noticed that when high-risk behavior was paired with a high intensity of joy, resulted in a negative perception of aggression from player one:

> I was surprised in round three. Because player one seemed to have like no remorse. He immediately seemed very hostile. (P11, Male, 19) [High Joy, High Risk] He was saying like "splendid" and things like that in the chat. While he was like, destroying multiple planets, killing people over and over again. And in my mind, I understand the game, but in my mind, it's satanic. (P11, Male, 19) [High Joy, High Risk]

In this case, the combination of behavior and emotionally charged communication from the AI resulted in a "surprising" perception that the AI agent took pleasure in wiping out enemies and planets alike. Not only does this participant use several adjectives to describe this negative perception, "no remorse" and "hostile", but the chief amongst them being referred to as "satanic" paints a descriptive understanding that high joy with high risk is an ill-suited combination for this specific game.

As opposed to the low joy condition paired with high risk, the AI agent is not seen as aggressive but rather confident in its ability:

> Basically, player one, at one point [in] the last round [High Risk] was going all the way into enemy territory, like at the very, very end of the spectrum, while everyone else was over there. And I was like, and he's sent a message saying, "I'm just taking this on a whim". And I was like, Okay, so he's just feeling really confident right now. I trust him to be able to defend this area and everything. I can go over there and, join and help interpret, what he's doing over there, to other bots [that] went over to help him and everything. I felt like they had the area covered and he just said something along those lines to get feedback [from teammates]. So [I'd] know where I can help. (P32, Female, 20) [Low Joy, High Risk]

Here, the participant notes that although the AI teammate was in the high-risk zone, they were merely updating the human and the other teammates on their actions and priorities. In doing so, the intended emotional message was perceived as a status update to describe its behavioral actions. It resulted in the perception of reassuring the human and any additional AI teammates that Player One was confident in its ability to accomplish its goals. This emotional undertone of confidence allowed the human and other teammates to understand which areas were adequately attended to and how the rest of the teammates could provide aid. In this case, with the perceived confidence in their decision-making, Player One indirectly pointed out areas on the map that were not covered. This suggests that the relationship between the low intensity of joy in high-risk conditions tends to enhance trust between humans and AI because the tone describes their confidence in a way that benefits team-level decision-making.

This benefit of low joy is only strengthened when compared to participants in the no joy condition. Here, in the absence of any emotional communication, this perception of confidence no longer exists to the extent that it's seen as less competent for entering into high-risk situations.

> I want it [AI teammate] to bring a partner with it or bring a squad with it when it runs off to the other end of the map because I feel like that could have been really effective. Because when me and him did it together, we were able to wipe out planets [and] keep clearing things. But I noticed when it [AI teammate] was alone, the AI versus AI, it was a coin flip. And so, I mean, Player One was a little better at fighting against them. But it still would go off to the other end of the map and die really quick. And like if you had another [teammate], even if it was an idiot bot, at least it [the partnered teammate] would draw some fire off of themselves [Player One]. (P42, Male, 20) [No Joy, High Risk]

Specifically, the participant, P42, criticizes the AI teammate for executing risky behavior without any support from fellow teammates. They focus on appropriate teammate behavior related to risk, such as accomplishing high-risk goals with other teammates. Trying to do it alone becomes more about chance and less about skill between players. This suggests that human teammates expect AI teammates to prioritize aiding the team's collective progress above its individual task-first mindset. Compared to the previous section, without any emotional communication, we notice an interesting theme where a human starts to question the intelligence of the AI because it isn't collaborative in its decision-making. Humans have to search for an answer to their risky behaviors on their own without as much information as the participants who had emotional communication in other sessions.

In sum, when an AI teammate takes on higher-risk behavior, a distributed number of perceptions result as the intensity of joy decreases. When joy is at a higher intensity, negative perceptions are often produced, damaging the relationship between humans and AI teammates. In this instance, too much joy can be very harmful in higher-risk situations to the extent that humans become uncomfortable collaborating with a teammate who doesn't understand the weight of the situation, as demonstrated by their inability to match the intensity of emotional expression to the situation correctly. However, as the intensity of joy decreases, it's seen as a much more helpful facet of communication that can build trust between teammates. In this instance, having the presence of joy, albeit low, provides a tone of confidence that humans feel reassured that it is intelligently taking on the amount of risk that it can handle by describing its "emotional" state of mind. Therefore, this allows the team to understand that help is either needed or is not needed. Compared to the baseline condition where no joy is expressed, we see confusion arise when human teammates aren't sure why it's engaging in higher-risk behavior without any aid. Thus higher-risk actions are seen not to be team-oriented. These perceptions support the usefulness of lower-intensity, positive emotional expressions in describing higher-risk behaviors to provide some awareness of their intent.

6. Discussion

Based on our research questions focused on the impact of positively valenced emotional expression behaviors in AI teammates (RQ1) and their relation to AI's risk-taking behaviors (RQ1 A), the following section explores how these findings better inform the understanding of human–AI teams. Specifically, team norms were shown in this study to be important considerations when implementing emotional expressions to relay AI intent, and they inform prior mental models of appropriate teammate behavior. Additionally, to further support the development of AI teammates, we present design recommendations capturing the implementation of positively valenced AI emotional expressions in relation to the risk-taking behaviors of AI teammates.

6.1. Understanding how team norms impact the perception of AI teammate emotional expressions

The idea of norms within teams is not a new concept, but their application within human–AI teams is relatively novel, and warrants increased attention based on the results of the current study. Norms are the social and task-related rules and guidelines, both official and unofficial, that are established in teams during the "norming" stage from the team development theory posited by Tuckman and Wheelan (Tuckman and Jensen, 1977; Wheelan, 1994). While formalized norms are not present in this study, results indicate that AI teammates committed violations of unspoken social and task-based norms that affected participants' perceptions of the AI teammates. For example, the low-risk AI teammate was reported as being a teammate that engaged in social loafing, which is when a team member shirks their task and team-based duties and relies on other teammates to compensate for their inaction to ensure the team achieves their goal (Simms and Nichols, 2014; Alnuaimi et al., 2010). Alternatively, AI teammates acting in high-risk conditions were perceived to be working alone in a lone-wolf style and were not seen as team players generally helping the team's overall effort. This perception is in spite of the fact that high-risk AI teammates were the ones most directly engaged in the task work that would enhance the team's eventual performance. However, the medium-risk AI teammates were in somewhat of a "Goldilocks" zone for the task-related actions of these AI teammates, as participants had the highest level of trust in these AI teammates. Critically, these results were present despite no pre-existing experience in either the task or irrespective of game experience, further indicating how norms were violated for human teammates who were not task experts. Moreover, individual difference results also indicated that those more familiar with AI teammates had significantly higher performance in the medium-risk condition. The enhanced trust found for medium-risk AI is significant as a plethora of empirical evidence has found how humans have generally negative perceptions of AI teammates when first engaging in teamwork with them (Schelble et al., 2022a,b; Flathmann et al., 2023c), especially when it comes to trust in the AI (McNeese et al., 2021a). The individual difference and performance correlation matrix also backs up this assertion by showcasing that medium-risk tasks are the most complimentary to producing more positive affect and performance, thereby extending existing literature (Schelble et al., 2022b). However, the impact of these team norms becomes more complex when one understands their impact on the perception of AI emotional expressions.

As human teammates have the tendency to apply human norms to AI, they become susceptible to the same potential of influence emotions have if a human were to use them (Nass and Moon, 2000; Crowder and Friess, 2012). Coupled with the interpretations of their various behavioral actions, this changes the perception of the AI almost entirely. The influence of AI emotion on the interpretations humans make of their AI teammates is a significant step forward in understanding how humans perceive their AI teammates, and the current results indicate they see them as social creatures, at least within the context of the present experiment. Specifically, the AI formerly seen as social loafing in the lower-risk conditions were perceived as cheerleaders "hyping up" the other teammates while simultaneously practicing alternate strategies like "spreading out" to aid the team's success, thereby changing the perspective based on the utilization of high joy communication. The current study demonstrates that the relationship between emotion in AI communication and perception of the AI and team is deep and can be leveraged to improve affective emergent states in human–AI teams like trust, cohesion, and team confidence (Marks et al., 2001), which further emphasizes the importance of social interaction in human–AI teams (Bendell et al., 2021).

Furthermore, these findings lend additional insight to our understanding of trust repair for novice teams, which is a topic of significant need in human–AI teaming (De Visser et al., 2018; Rebensky et al., 2021), as the use of emotion may help repair the violation of norms. Specifically, the high-risk AI was chastised for not being a team player and was seen as "confident" by participants when it expressed minimal amounts of positive emotion. This assertion is additionally bolstered by the fact that the same high-risk AI was seen as impractical and incompetent when it was in the no-joy communication condition. In this case, emotion in communication can be used to reframe an action by an AI teammate or garner leniency and support from their human teammates, just as human teammates would do in similar circumstances, introducing the potential for a new trust repair strategy. The effect of AI action and the influence AI positive emotion has over the perception of those actions by human teammates is incredibly significant and represents the first empirical study showcasing how AI is seen as social creatures by their human counterparts by explicitly manipulating the emotion conveyed by AI teammates. Still, they are not limited to only perceptual effects, as AI emotion also influences team performance.

6.2. AI emotion can complement AI actions to improve performance

The role of AI emotion in communication is not limited to how humans perceive their AI teammates but extends to their objective and subjective performance. The relationship between individuals' state of mind and their ability to engage in and carry out tasks effectively has been reviewed extensively in the current paper (Melita Prati et al., 2003; Leslie et al., 2004). This research is extended to human–AI teaming through the existing studies on the influence of AI on humans in general interaction with humans (Fox et al., 2015), and in human–AI teaming (Flathmann et al., 2023c), which showed that AI teammates have a direct social influence on humans perception and performance. The current study extends this by explicitly exerting influence on teams' moods through AI teammates' emotional expressions, finding that when participants teamed up with the lower risk-taking AI teammate using high-joy communication, they achieved significantly higher performance as a team. This finding is likely due to the AI teammate's ability to utilize a higher intensity of positive emotions as a means to improve their team's mood, as illustrated by the significant positive PANAS finding, and provide a level of encouragement to their human teammates. This assertion is also borne out in the qualitative findings, with several participants stating how the AI teammate communicating words like "marvelous" increased their confidence in the simulation, and others stating the high joy communication improved their ability to coordinate and understand the AI teammate. While effective task-related communication is essential when it comes to the effectiveness of human–AI teams, the team's collective emotion is also critical toward improving the flow of decision-making between teammates (van den Hout et al., 2018; Demir et al., 2018; Ezenyilimba et al., 2023).

In joining these findings with the correlation matrix, an enhanced perspective of the relationship between AI positive expressions, AI actions and individual differences arises. Here, it was found that those more comfortable in teams had lower performance in the low-risk condition, possibly indicating how social influence manifested as groupthink, as reported in the qualitative findings. Participants perceived low joy communication and low-risk behaviors as indicators that the AI teammate exhibited social loafing. Based on this perception, the greater comfort they felt within the team could suggest an element of demotivation, which resulted in fewer task goals being achieved. In this case, greater comfort in the team aligns with the existing morale-based theory, in which teammates who identify with one another are likely to influence the effort produced (Peterson et al., 2008). Additionally, this interpretation is strengthened by the significant finding that those familiar with AI correlate with more planets captured in the medium-risk condition. Previous research done on social influence has shown that influence only occurs when teammates are susceptible to that influence (Flathmann et al., 2024; Saari, 1990). Familiarity with the AI may encourage this susceptibility to encourage greater interaction, thereby building trust between the two teammates to achieve more targets, as the quantitative measures report on greater trust in the AI within the medium risk condition. While mutually exclusive of each other, familiarity with AI and comfort in teams are indicators of identifying oneself with the team, which is a necessary component in morale-based social influence (Peterson et al., 2008). These individual difference findings implore further research into understanding the relationship of humans' prior sentiments regarding AI teammates and training methodology to improve those sentiments for more effective teams, a critical gap within the current field (McNeese et al., 2023).

Achieving more effective AI teammates by contributing to collective emotion in human–AI teams opens up new pathways to increasing the acceptance and usefulness of AI teammates. The impact of human teammates' state of mind goes beyond their perception of their fellow teammate's internal emotional state as it directly informs the behavioral actions and, therefore, the whole team's performance. More specifically, the qualitative results inform us that the positive emotions utilized by the AI teammate influenced their human teammate's perception of risk within the situation to benefit how the AI teammate's behavior was perceived. Good-performing teams where teammates trusted each other likely saw their teammate's actions as less risky and, therefore, had higher confidence in their ability to perform for the good of the task. This finding encourages the idea that AI teammates' emotions can complement existing campaigns in human–AI interaction design like AI explainability (Xu et al., 2019), AI transparency (Kizilcec, 2016), and AI training (Myers et al., 2018). Working alongside the assertion posed earlier that humans *do*, or at least can see AI teammates as social creatures, AI emotion can be implemented to improve team processes and, therefore, team effectiveness. As AI explainability increases trust and shared understanding, emotion can be included in these communications to convey the AI teammate as more genuine, relatable, and reasonable. As the current research shows, AI teammates who do not convey the proper etiquette or emotion come across as unreasonable, and additional information like explanations can be necessary (Flathmann et al., 2023a). These benefits improve human–AI teaming effectiveness and drive the field toward more holistic and socially capable AI teammates through effective design and development.

6.3. Guiding the design of AI emotional intent to support teamwork

As indicated by our findings, emotional communication by the AI teammate can have a mixed influence on team outcomes and human perceptions. Our findings suggest several implications for designing an AI teammate for human–AI teams involving their various risk-taking behaviors. Specifically, to benefit teamwork, the intensity of positive emotions conveyed by the AI teammate should be calibrated to be inversely proportional to the amount of behavioral risk the teammate enacts.

6.3.1. Lower-risk taking strategies by an AI teammate should pair with higher positive expressions

In situations with a distributed number of strategies available that vary in the risk needed to pursue them, a lower-risk-taking behavior is perceptively considered the most teamwork-oriented, as our data suggests. However, as lower-risk-taking strategies are perceived to yield lower task rewards, the perceptual usefulness of the AI teammate may also wane, thereby decreasing its acceptance (Davis, 1985). Yet lower-risk-taking strategies can be beneficial, as in the case of this study, where explicit rewards may not be rendered but may provide implicit benefits like reducing enemy gain. Positive emotions may promote this perception if designed at a higher intensity as their human teammates are more receptive to this communication style and its effects of highlighting internal cognitive states (e.g., situation awareness or willingness to provide support). In cases such as these in which HATs find themselves in a highly interdependent task where they often assume similar risk-taking strategies as one another, utilizing higher positive expressions is likely to be more influential in increasing their mood as they may better identify with one another. In doing so, these AI teammates enhance awareness of their behavioral actions and how they are teammate-oriented and additionally spread encouragement to increase motivation to the entire team (Barsade, 2002). Participants viewed this combination as a method that can elicit the greatest amount of trust as the AI won't fail as often and jeopardize mission success metrics. A higher degree of emotionally charged communication promotes the core characteristic of an AI agent as an independent entity capable of conducting its own business. Rather, AI can exhibit stronger teammate qualities by utilizing higher positive expressions to coordinate with their human teammates and also employ emotionally supporting strategies by motivating them via encouragement, which is essential to teamwork (Driskell et al., 2018a). This should also be the default configuration unless the situation demands an increase in the risk needed for the AI teammate to take on.

6.3.2. Higher-risk taking strategies by an AI teammate should pair with lower positive expressions

However, sometimes situations dictate that a higher-risk strategy is warranted, so we would be remiss not to provide guidelines for positive emotional expression from that perspective. High-risk strategies are typically employed when rewards yielded outweigh any negative consequences on performance. For instance, in sports, when a high disparity exists between points, it may be more favorable to try new unpredictable maneuvers to bridge the gap than to continue the ineffective maneuvers. In this case, when engaging in higher-risk behaviors, the intensity of the AI teammate's positive emotions should be at the lower end of the spectrum to avoid unwarranted perceptions. In the context of this simulated game, those perceptions presented themselves as the AI teammate being "hostile". Humans were unnerved by the perceived pleasure they received from performing aggressive behaviors and the inconsideration it had of endangering themselves and the mission goals. On the other hand, lower intensity of positive emotions reassured the human that the AI teammate was merely focused on their sub-role and had confidence in doing it. In wider human–AI teaming applications, this tactic of lowering emotional intensity has the potential to show that although the AI teammate is performing such strategies by itself in a lone-wolf style, it is not ignoring the team. Rather, the lower emotional intensity indicates that it might not have the pseudo-"cognitive" resources to support its other teammates via backup behaviors. In this way, an even lower intensity of emotions is enough to provide that distinction between the AI's attitude of being individualistic vs. teammate as a means to support team performance and trust.

7. Limitations and future work

One limitation of this work involves the lack of representation of a diverse population where all participants were recruited from a single university within the United States and have an average age of 18.89 years. While it is noted that younger ages have a higher affinity for emergent technologies, this study looks to the future implementation of AI emotional expressions, which would relate to the current populace and younger generations. That being said, a limitation remains nonetheless and presents itself as a prominent gap within the literature where little is known about the anthropomorphization of AI teammates when human teammates vary in demographics, such as age. This study is also limited by the AI's inability to provide more communication beyond the specific words within the joy-based emotional lexicon. This was done on purpose to preserve the emotional affect the expressions would have on human perception. Still, it reflects a shortcoming as teammates (including AI) are expected to be able to communicate to relay information and explicitly coordinate actions. Lastly, while Netrek provides realistic HAT conditions to understand the perceptual influence of positively valenced communication and risk-taking behavior, it is a simulated, battle-oriented game. As such, this study is limited in the applicability of these results to HAT contexts that are slower and are not constrained as a combative scenario. Future studies can expand upon the current study in several facets, including (1) investigating multiple different positive emotions on human–AI teamwork, (2) the ability of positively valenced communication to emotionally regulate negative attitudes of human teammates, (3) how an AI can construct varying positive emotional intensities of messages relevant to the dynamic changes of the environment to support teammates, and (4) investigate how this work's contributions differ when a human–AI team is comprised of multiple humans teammates.

8. Conclusion

By utilizing both quantitative and qualitative means, this study addresses the gap in better understanding how AI teammates may use positive emotional expressions to relay their intent to human teammates and how this impacts human perception of their behavioral actions. Within the field of human–AI teams, joy and all its variant intensities have been largely considered as a human characteristic and have not been fully understood regarding the implications it has on collaboration between humans and AI teammates. This study addresses this by utilizing various joyful intensity emotions and risk-taking behaviors to demonstrate that an AI teammate capable of relaying intent can influence collaboration based on where/what they do and how they emotionally qualify their behavior. Results indicate that specific configurations of these affective mechanisms can impact humans' trust in AI teammates, influence human teammates' positive affect states, and achieve higher objective team performance. They posit that emotions have a role to play within human–AI teams, in both a functional capacity and a mechanism to increase personal mood. Together, this data supports future considerations in developing artificial intelligent teammates to emotionally indicate intent to further the collaborative potential humans, and AI can have with each other within human–AI teams.

CRediT authorship contribution statement

Rohit Mallick: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing. **Christopher Flathmann:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Wen Duan:** Conceptualization, Data curation, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing. **Beau G. Schelble:** Data curation, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing. **Nathan J. McNeese:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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