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Examining the impact of varying levels of AI teammate influence on human-AI teams

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ABSTRACT

The implementation of AI teammates is creating a wealth of research that examines how AI teammates impact human-AI teams. However, AI teammates themselves are not static, and their roles and responsibilities in human-AI teams are likely to change as technologies advance in the coming years. As a result of this advancement, AI teammates will gain influence in teams, which refers to their ability to change and manipulate a team's shared resources. This study uses a mixed-methods experiment to examine how the amount of influence AI teammates have on a team's shared resources can impact the team outcomes of human teammate performance, teammate perceptions, and whole-team perception. Results indicate that AI teammates that increase their influence on shared resources over time can stagnate the improvement of human performance, but AI teammates that decrease their influence on shared resources can actually encourage humans to improve their own performance. Additionally, AI teammates that are highly influential on shared resources can make humans perceive a greater cognitive workload. However, qualitative results indicate that these impacts on human performance and perception do not consistently impact the acceptance humans form for AI teammates. Rather, humans form acceptance for AI teammates if said AI use its influence to manipulate resources to benefit the personal goals of human teammates. These results have critical implications for human-AI teaming as it shows that the influence AI teammates have on shared resources can be designed in a way that improves human performance. However, future research is going to need to focus more critically on how the personal goals humans have, which may not align with a team's overall goals, are going to mediate the effectiveness of the AI teammate influence.

1. Introduction

The rapid progression of Artificial Intelligence (AI) has created a technology with so much potential that a multitude of new applications are being created every single day (Dick, 2019). Among these, human-AI teaming is a domain that is rapidly gaining traction in research domains, with past work empirically showing the potential for human-AI teams to benefit the performance of modern workforces (McNeese et al., 2018). However, more than just performance, AI teammates can contribute to critical teaming factors such as trust and shared understanding, which ultimately allows teams to produce even higher levels of performance due to greater efficiency as a team (O'Neill et al., 2020). These critical research efforts have created initial designs for human-centered AI teammates, which are an extension of rapidly advancing research in human-centered AI (Xu et al., 2022). Ultimately, the transition of AI into this teammate role is based on the creation and research of these human-centered AI teammates.

As AI systems begin to transfer to teammate roles, they will gain a unique influence over the shared resources and tasks of their assigned team (Ye et al., 2022). Specifically, this influence refers to an AI teammate's ability to control, manipulate, and contribute to the shared resources and environment that their team is responsible for (Helboe Pedersen, 2013). Within teams, the effective use of influence is critical as teammates can influence outcomes of shared resources, shared goals, and even other teammates (Manz et al., 2009). When used efficiently, teams are able to share complex workloads amongst each other and heavily outperform the sum of individual workers (Heinzel, 2022). However, the effective use of influence is not a given as influence is in and of itself a shared resource, where a teammate attempting to be more influential on a shared outcome can in fact reduce the influence another teammate has on a shared outcome (Carson et al., 2007). Thus, teams have to understand how to organize influence

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in an efficient way to efficiently share workloads. However, past research has mostly focused on the outcomes of influence, such as team performance (McNeese et al., 2018) or trust (McNeese et al., 2021), and not the underlying influence AI teammates that contribute to said outcomes. Thus, the following research gap exists: Despite being critical to teams, the shared nature of influence in human-AI teams and the varying amounts of influence AI teammates could have has yet to be empirically studied.

Moreover, the continued advancement of AI teammates that will be driven by continued advancement in AI technology in the coming years will also increase their utilization in real-world teams alongside humans (Cichocki and Kuleshov, 2021; Seeber et al., 2020). In turn, this increase in capability and utilization would escalate AI teammates' aforementioned influence on team outcomes. Thus, the balance between human and AI teammate influence would gradually change over time, and human and AI teammates would have to dynamically balance the shared influence in a human-AI team. Given that AI teammate influence has not been examined in general and AI teammates are likely to not have consistent levels of influence, the following research gap can also be derived: the impact of AI teammate influence being dynamic has not been empirically examined by research yet.

This study addresses the above-mentioned research gaps using a mixed-methods experiment that examined how varying levels of AI teammate influence change the outcomes of human performance and perception to answer the following research questions:

- RQ1 How does the amount of influence an AI Teammate has on their team's shared task and resources change human performance and perception?
- RQ2 How do variations in the amount of influence an AI teammate has on a task change human performance, human perception, and team outcomes?

Critically, these research questions heavily contribute to our understanding of influence in that the amount of influence an AI teammate has over a shared resource or goal could directly impact the influence humans have over said resources and goals. In turn, these shifts in influence could create frictions in human-AI teams that would impact human teammates' perceptions of their AI teammates, human teammates' perceptions of their team, or even their own ability to perform. Moreover, these research questions ensure that our understanding of influence's impacts is not made under the assumption that influence is static, which is highly unlikely given the dynamic nature of technology. Thus, answering these research questions provides a fundamental understanding of the construct of influence in human-AI teamwork.

Additionally, the contributions to the field of human–computer interaction (HCI) created from answering the above research questions are three-fold. First, the influence AI teammates have is going to increase in the coming years as their utilization in teaming environments rises. Without properly understanding the impacts of their impending deployment, it would be extremely difficult to predict how real-world workers will be impacted by the inclusion of AI teammates. Second, human-AI teaming is a rapidly advancing field in human-AI interaction and, more broadly, HCI, and the findings stemming from this study provide a greater understanding of how AI teammates can influence various teaming outcomes. In turn, this understanding will increase researchers' ability to create actionable design recommendations for the creation of human-centered AI teammates. Finally, while the influence examined in this study is scoped within a teaming environment, influence exists outside of a teaming environment, and this study can help inform those environments. The existence of shared goals and resources is not unique to teams, and this study's findings on the importance of humans' personal motivations to human-AI teaming provide critical insight into general human-AI interaction where humans and AI may share a level of influence.

2. Background

Before discussing the methodology and results of this research, it is pertinent to further discuss past research that provides both motivation and context. Two specific research fields are discussed in detail: influence in teams and human-AI teams. The merger of these two sections provides a strong motivation for why the consideration of critical teaming factors is necessary for creating human-AI teams that leverage influence in a human-centered way.

2.1. The relevancy of influence to teams and technology

One of the largest challenges facing research in influence is that the research domain is broad and lacks a universal definition (Helboe Pedersen, 2013). For instance, in communication domains, the concept of influence can more heavily focus on social networks and how one can influence human behavior (Anagnostopoulos et al., 2008), but research in political influence is often much more focused on the concept of power and control (Becker, 1983). This lack of definition can make it difficult to not only operationalize the concept but also build on previous research. However, influence can be more concretely outlined when its application in specific scenarios is discussed. Thus, rather than continuing to provide a broad review of influence, the following provides a review of how influence manifests in teamwork domains and how technology has mediated said influence over the past few decades.

Within teaming, influence is often viewed in a similar to its representation in politics, as the concept of power over the resources and outcomes of a team, group, or organization play a critical role in teams' shared resources, and outcomes (Fiorelli, 1988; Tallberg et al., 2018). Specifically, within teams, this power means teammates get to control the use, purpose, and state of said resource (DiPalma, 2004). Importantly, these resources do not have to be limited to physical resources, as simply controlling the flow of information can be an extremely potent utilization of influence (Pettigrew, 1972). Personnel resources can even be included in this concept as social influence is the specific application of one's power to change other humans' thoughts and behaviors (Yuan et al., 2005). Regardless of the resource in question, however, the balance of this influence in teams is of utmost importance to long-term team performance (Farber, 1994; Arai et al., 2021). When influence is balanced correctly, teams are able to achieve greater levels of interdependence and performance (Appelbaum et al., 2020). For instance, when teams allow diverse individuals to have greater levels of influence in their teams, they often see a greater level of team performance due to the unique perspective provided by these individuals (Perry, 2021).

However, there can be a negative side to influence as well. Leaders can negatively influence resources like information in a way that harms the work of individuals by restricting said resources (Tost et al., 2013). Moreover, in addition to the application of influence, the imbalance of influence can also cause negative outcomes in teams. For example, teams with multiple highly influential teammates can often experience power struggles where said two teammates are conflicting in how they utilize their own influence (Greer, 2014). The result of these struggles is not only infighting, but team performance can often significantly drop when teams are too busy resolving conflicts over influence to complete work (Greer et al., 2011; van Bunderen et al., 2018). Given this importance and the potential negative impacts of influence, researchers and real-world teams have worked to better understand how influence should be used positively in teams (Hoegl and Parboteeah, 2006). In fact, learning how to better influence team resources and teammates is often one of the most critical components of learning to be an effective leader (Fiedler, 1972; Cartwright, 1965). Human-AI teams would not be an exception from this importance either, as the balance of influence in these teams is going to be present, and it could negatively impact a team if not balanced correctly. However, learning how AI teammates might possess and impact influence in teams requires an understanding of how general technology impacts influence as well.

In the modern era, the influence teams have has become mediated by technology, allowing influence to change shape as technology becomes more strongly intertwined with teams. For instance, the introduction of internet technology like email and groupware has enabled more asynchronous and non-collocated teaming (Olson and Olson, 2000). These digital teams are able to influence resources, including personnel, across distances and time zones (Hertel et al., 2005). Moreover, the majority of resources that exist within modern teams are in and of themselves digital, meaning one can influence these resources regardless of their location as long as they have an internet connection (Songer, 2007). Effectively, technology has lowered barriers that prevent humans from influencing their team's resources and outcomes (Cantoni et al., 2001). However, AI is also unique in that it, as technology, can also influence various resources without human involvement (Monod et al., 2022). As such, it is critical to explore how the construct of influence can impact teams when it is presented by teammates that are not human.

2.2. Human-AI teaming

As AI technology has rapidly advanced, humans' utilization of it has increased. With applications of AI technology ranging from recommender systems to AI-powered robotics systems (Knijnenburg et al., 2012; von Braun et al., 2021). Unfortunately, this rapid application of AI technology has not traditionally left time for humans to be critically understood and considered when designing AI (Wienrich and Latoschik, 2021). These errors ultimately resulted in the creation of AI technology that, while technically sound, ends up being harmful to humans, such as racist Twitter bots that actively post hate speech (Wolf et al., 2017; Neff, 2016). As a result of these errors, research has shifted toward the creation of human-centered AI, which refers to the balancing of human compatibility with the performative abilities of AI systems (Shneiderman, 2020). Using this human-centered perspective, large strides have been made in creating AI systems that are both computationally capable while also benefiting the humans they collaborate with, ultimately leading to long-term performance and acceptance from humans (Xu, 2019; Riedl, 2019).

Human-AI teaming serves as a direct application of human-centered AI that merges the aforementioned research domain with the historically robust research domain of teamwork (Dubey et al., 2020). For this article, the following definition is used for human-AI teaming: one or more AI teammates working with one or more human teammates interdependently to complete a shared goal (McNeese et al., 2018). The benefit of these teams is that they leverage the unique computational strengths of AI systems with the unique strengths of humans to accommodate for each others' weaknesses and create high levels of performance (Zhang et al., 2021). However, the potential benefit of these teams is also met with an increase in complexity in their evaluation. Evaluating team performance is not a simple examination of task performance but rather a complex story of teaming outcomes, including human performance, AI performance, team performance, and other teamwork outcomes like trust or workload (O'Neill et al., 2020). Thus, for human-AI teams to be effective, they must inherit the complexity of human-centered AI mentioned above and the complexity of teaming. As a result, research has worked to identify where human-AI teaming can be applied, how AI teammates must be advanced for these applications, and how these advancements ultimately impact the various teaming outcomes that dictate effectiveness.

In application, human-AI teams are poised to benefit from a variety of real-world domains and contexts. For instance, human-AI teams have already shown great deals of promise in the field of medical diagnosis, with these teams bolstering higher diagnosis rates than human experts or AI-only systems (Hosny et al., 2018). Additionally, military organizations are highly interested in the computational capabilities of AI teammates (Fazekas, 2021), and research has reflected this by actively designing AI teammates for unmanned aerial vehicle teams (Ball et al., 2010). Moreover, military organizations have even begun explicitly funding research in human-AI teaming due to the perceived benefit (Vorm, 2020). In addition to these domains that are already seeing some application of human-AI teaming, other domains are predicted to heavily utilize human-AI teams in the coming years. For example, surgery groups predict a large potential benefit from human-AI teaming due to the computational accuracy AI teammates can achieve compared to humans (O'Sullivan et al., 2020). Other domains that have also seen explicit interest in human-AI teaming include patient care (Lai et al., 2021), software development (Weisz et al., 2021), and even manufacturing (Haindl et al., 2022), just to name a few. However, work still needs to be done to advance AI teammates to accommodate some of the prospective applications. For instance, adaptive AI research needs to advance to ensure the safe implementation of AI in surgery groups (O'Sullivan et al., 2020), and extensive strides need to be made in natural language processing for AI to be effectively used in patient care (Sujan et al., 2019).

While the construct of influence has not been explicitly examined by research, there are a variety of other constructs that can be derived from influence that have been examined in human–robot and human-AI teams. For instance, leader–follower dynamics (Kucukyilmaz et al., 2012), mutual adaptation (Nikolaidis et al., 2017), performance (Bansal et al., 2019), and workload (Kobayashi et al., 2020) all represent constructs highly related to and derived from influence in human-AI teams. Looking at the construct of performance more closely, past work has demonstrated that greater levels of AI teammate influence can decrease the performance of human teammates (Bansal et al., 2019), and influence, which can create performance, could potentially follow a similar trend. Similarly, when examining the concept of assigned workload, one can see that assigning AI with a greater task load can, in turn, reduce the task load of humans (Pacaux-Lemoine and Trentesaux, 2019), but this work and task load are often assigned prior to interaction. As such, these constructs do not entirely represent influence, as performance represents the positive or negative result of influence and workload organization removes the shared nature of influence that teams have to self-organize. Thus, while one can hypothesize that increasing the influence of AI teammates can, in turn, reduce the influence of humans, the impact of AI teammate influence on human influence, the aforementioned constructs, and the impact of influence on various other human factors that are critical to human-AI teams, such as trust (McNeese et al., 2021), still need to be empirically examined.

3. Methods

Utilizing a mixed-methods approach, this study investigates varying levels of AI influence that are either dynamic or static over time in an electronic sports (esports) context. This experiment manipulates both influence level and whether or not influence is dynamic in AI teammates over the course of three rounds, which answers RQ1 and RQ2, respectively.

3.1. Participants and demographics

Participants were recruited using a web-based university subject pool in a Large Southeastern University, where participants would sign up for a specific time slot for the study. Only one participant was allowed for each time slot. Participants received extra credit in their courses for participation in this study. Participants received eight total extra credit points, one for every 15 min spent in the experiment. Participants were allowed to stop the experiment at any time if they felt uncomfortable playing the game, but no participants stopped early. The mixed-effects design of this experiment allowed a greater power to be achieved with a lower number of participants, and in total 32

Fig. 1. Example screenshots from Rocket League, which include an AI teammate. Included is also an example scoreboard that would be shown at the end of a game.

participants were recruited; however, one participant's quantitative data was lost due to a computer glitch so an extra person was recruited, which totals 32 participants for the quantitative analysis and 33 for the qualitative analysis. Full participant demographic information can be found in Table A.3.

3.2. Research platform

Before discussing the actual experiment that was designed and conducted, it is first important to understand the research platform participants interacted with. To promote reproducibility, a popular esports title was used, but some slight modifications were made to better align it with the goals of this study.

3.2.1. Rocket league platform

For this experiment, the popular gaming platform Rocket League (Shown in Fig. 1) was chosen. Rocket League is a team sports video game that has two teams (often consisting of two teammates) competing in a soccer-like game. However, in this game, the players control cars and drive around a soccer stadium striking the soccer ball with their cars instead of playing the game as normal people. Teammates are generally tasked with driving these cars around a large shared arena to move a ball into the opposing team's goal, while also preventing the opposing team from scoring on their goal. Participants were placed on a team with one AI teammate; however, a modification to the task was made. Instead of playing against two opposing teammates, participants and their AI teammate played against a singular goalie that simply worked to prevent a participant's team from scoring. This modification slowed down the overall task, especially for participants new to Rocket League, and also allowed participants to more heavily focus on their AI teammates rather than their opponents.

Importantly, Rocket League games consist of three distinct phases that each provides an opportunity for teamwork (characterized by interdependence) to manifest: (1) kickoff, (2) ball handling, and (3) shooting and scoring. In Phase (1), kickoff, teams are placed around the arena, a ball is placed in the center of the arena, and a countdown is performed. Once the countdown has ended, teams can rush the ball to gain possession of it. Teamwork during the kickoff stage often manifests as one teammate rushes the ball quickly to simply hit it somewhere, and then their other teammate will follow up and try to recover the ball after this initial hit. Phase (2), ball handling, occurs after the kickoff and has teammates work to move the ball toward the goal. This phase can consist of passing the ball between teammates, dribbling the ball toward the goal, and even holding the ball while teammates get into position. Teamwork manifests during this phase when teammates interdependently cover different positions of the field, such as left or right or front or back, and this teamwork is beneficial as ball control is difficult and teammates often have to recover bad dribbles or passes. Phase (3), shooting and scoring, has teammates attempt to hit the ball into the goal of the opposing team. In the event that a teammate scores, the game resets back to Phase (1), but if a shot is either blocked or misses, then the game resets back to Phase (2). Teamwork is most critical during this phase, with one teammate trying to shoot the ball, and another teammate will follow up in case the shot is blocked or missed in hopes of scoring with the rebound.

Given the above, it is clear that teamwork is not only a characteristic of Rocket League but also a hallmark of highly efficient Rocket League teams. For the purpose of this experiment, teams It is also important to note that while Rocket League benefits from teammates having roles, roles are not explicitly given to teammates, and it is up to the discretion of the team to assign teammate roles. As such, effective teamwork and interdependence in Rocket League are achieved through team coordination and adaptation.

3.3. AI teammate selection

Another affordance provided by Rocket League is that there is a large repository of custom AI teammates made by passionate fans of the game. AI teammates made by this group are published in a public repository hosted on an MIT license (LINK). Each AI teammate included in the repository was evaluated by researchers who worked on this article. AI teammates were evaluated on their skill level, teamwork capabilities, and code readability, which allowed for needed modifications. Through iterative observations, it was determined that the AI teammate named "Botimus Prime" served as the most appropriate option for this study as it had a python codebase, which the research team is familiar with, a superb performance history in 2v2 tournaments, and its teamwork decision making happens in a well written and separate python file, which makes it easy to modify.

3.4. Defining and operationalizing influence in the chosen task with the chosen teammate

As a reminder, this study generally defines influence as the ability to control, manipulate, and contribute to the shared resources and environment that their team is responsible for managing (Helboe Pedersen, 2013). Using this definition as a guide, this study operationalized influence from a task perspective and then worked to understand how this operationalized definition could be designed for the AI teammate. Starting with task operationalization, this study focused on (1) the shared resources and (2) the goals of the task. For focus (1), the shared recourse in this task was the soccer ball, in which teammates work together to move. For focus (2), both teammates share the goal of moving and hitting the ball toward the opposing team's goal. In intersecting these two considerations, this study operationalized influence within this task as "the movement of the soccer ball (shared resource) toward the opposing team's goal (shared goal)".

Leveraging this operationalization, it was determined that modifying the frequency at which the AI teammate determined to go for the ball would modify the frequency in which it had influence, in turn changing the overall amount of influence the teammate has. To change this frequency, this study first modified the decision-making algorithm

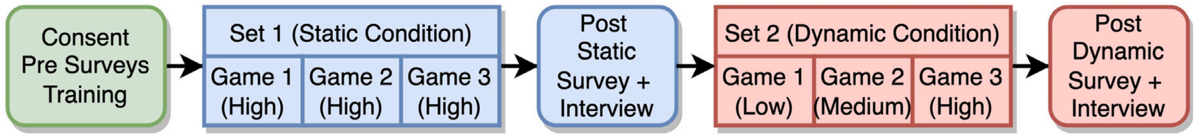

Fig. 2. Example experimental procedure for someone in the high between condition who also did the static within condition first. The between condition (High or Low) as well as which within condition participants would complete first were both randomly selected before participants arrived.

the AI used to determine if it or its teammate should go for the ball. Specifically, the AI teammate calculates a line between them and the ball and their teammate and the ball; if their line is shorter, then they go for the ball. Our study modified this algorithm to always make the AI teammate's line appear either shorter or longer than it actually was, in turn increasing or decreasing influence, respectively. Additionally, when the AI teammate's teammate is going for the ball, it will stay back and play defense. Positioning the AI teammate further in the backfield decreased influence as it would often be further from the ball, but positioning it closer to the midfield would have the opposite effect and increase influence. Leveraging these two design considerations, this study made three modified AI teammates based on the selected AI teammate: (1) an AI teammate with higher levels of influence, (2) an unchanged AI teammate, and (3) an AI teammate with lower levels of influence.

3.5. Experimental design

This study utilized two different experimental manipulations: (1) the level of influence an AI teammate has in the third game; and (2) whether or not that influence was static or dynamic prior to the third game. Each of these conditions has two condition levels, resulting in a basic 2 × 2 experimental design. However, participants played three games of Rocket League, and performance was gathered for all three games and used as a repeated measure, resulting in a 2 × 2x3 experimental design when including round.

3.5.1. Manipulation 1

For Manipulation 1, this study uses a between-subjects manipulation to examine high and low amounts of influence applied by an AI teammate. The assigned between-subjects condition explicitly dictates what influence level the AI teammate would have in the third and final game played with the human. The assignment of these conditions was fully randomized across all participants. Participants either played game three with the highly influential or lowly influential teammate. The assignment of these conditions was randomized, but it was split evenly with 16 participants being placed into each condition.

3.5.2. Manipulation 2

For Condition 2, this study looks at whether an AI teammate's influence level is consistent in game one and game two or if they vary. Specifically, there were two conditions within this manipulation. Condition 1, static, had the first two games played to match the between subject condition assigned. Condition 2, dynamic, had an influence increase or decrease across game one from game two to game three of the assigned between conditions was high or low, respectively. This is a within-subjects manipulation, so each participant played three games with static influence and three games with dynamic influence. As an example, if a participant was in the between high condition for game three, then their dynamic condition would have them play with a low, medium, and highly influential teammate in games one, two, and three, respectively. On the other hand, when they did the static condition, they would play games one, two, and three, all with a highly influential AI teammate.

3.6. Task procedure (represented in Fig. 2)

3.6.1. Informed consent & pre-surveys

Upon arriving at the experimental room provided to them by the online sign-up portal, participants were immediately provided with an informed consent letter. This letter, along with the following procedures, was approved by our University's Institutional Review Board. Participants were asked to read and agree to the letter, participation was voluntary, and the experiment was not allowed to proceed without this agreement. The informed consent letter also noted the presence of manipulations, but it did not specify them to prevent participant bias. Once participants agreed to the informed consent letter, they completed a variety of pre-task surveys, including demographics, video game experience, and various preexisting perceptions of AI technology.

3.6.2. Tutorials & training

After pre-surveys, participants completed a two-part tutorial on the Rocket League Platform. Part one of this tutorial included a full button tutorial based on the actual tutorial provided by the Rocket League platform. In this tutorial, participants got accustomed to the controls and the design of the game. The second part of the tutorial tasked participants with a three-minute free play session, which allowed participants to practice moving the ball.

3.6.3. Game block one

The first game block consisted of three games. The AI teammate used during each of these games was based on a combination of their assigned between-subjects and their current within-subjects condition. Each individual game lasted for five minutes. There was about a one-minute break in between each game. In total, game block one lasted a little under 20 min. After each game, the experimenter then recorded the scores from the Rocket League-provided scoreboard.

3.6.4. Surveys & interview one

After the final game of block one, participants took a short collection of surveys that asked about their experiences and perceptions. This survey block was only concerned with the final game they played in this block. The following interview lasted about fifteen minutes and had a much broader focus, discussing all three games and the differences between them.

3.6.5. Game block two

Game block two followed an identical procedure to game block one, but the choice of AI teammate changed based on the within-subjects condition. This block also lasted a little under twenty minutes.

3.6.6. Surveys & interview two

Survey block two was identical to survey block one in regard to procedure. The only difference in this survey block was the actual questions asked during the interview. However, the interview timing and survey questions were the same.

3.7. Measures

Given that this study consists of a mixed-methods experiment, both quantitative and qualitative data collection methods were used.

Table 1
Quantitative measures.

Pre-Task Measures
Demographics: Age, Gender, Race, Education **Video Game Experience**: Prior Video Game Experience and Experience with Rocket League
Task-Derived Measures
Game Score: Rocket League provides a score at the end of each round for each teammate, which considers (1) positive ball movements, (2) goals scored, (3) assists, and (4) blocks. Items (2), (3), and (4) provide large, skewing point values that bias goal scoring over general teamplay. As such, the points for items (2), (3), and (4) are removed from the Rocket League provided score to create the measure Game Score. Thus, Game Score denotes the positive movement of the ball. **Improvement**: Improvement denotes the difference between Game Score from Game 1 to Game 3, which quantifies how much a participant either improved or worsened throughout the task.
Post-Task Measures (Measures are Summed & Provided Via Qualtrics)
Perceived Teammate Trust (Merritt et al., 2013): 6, 5-point Likert, Higher score denotes more trust in AI teammate [a]**Perceived Social Influence** (Sagrestano et al., 1999): 5, 7-point Likert, Higher score denotes more perceived power by participant

[a]Scale was modified for relevancy to AI systems.

3.7.1. Quantitative measures

For quantitative data, since six games were played, surveys were only provided after each block of three games to reduce survey fatigue. This choice also meant that surveys were designed to only elicit feedback on the final game participants played (which refers to their between-subjects condition). This method ensured that each participant's survey data was relevant to the between-subjects condition and its interaction with the within-subjects condition, but the qualitative data more heavily targeted experience during the first two games and the differences between the three games played. This data collection methodology provided a holistic view of participant experiences while reducing fatigue and confusion among participants. Quantitative measures are shown in Table 1.

3.7.2. Post-task interview

After post-task quantitative measures were completed, participants conducted a fifteen-minute interview about the three games they just completed, which means they completed two interviews each. Each interview was designed for the within-subjects condition they had just completed. As a reminder, the within-subjects conditions were randomized, which helped normalize any bias between interviews, and the content of the interviews differed to further reduce any bias being carried over from one interview to another. Static condition interviews centered around their adaptation to AI teammate influence, if they felt this adaptation would change if they did a different task, how they would change their AI teammate to improve them, and how well their team improved over time in terms of performance and team cohesion. The post-dynamic interview focuses more heavily on how participants handled changes in their AI teammates, why they would or would not prefer their AI to continue changing their influence, how comfortable they were adapting to these changes, and if these changes are more or less beneficial in a human teammate compared to their AI teammate.

3.7.3. Qualitative analysis

A thematic approach was used to analyze the qualitative interviews collected (Braun and Clarke, 2012; Guest et al., 2011). First, two researchers read through all of the transcripts of the interviews. Based on these initial reads, both researchers independently made codes to describe the data. Both researchers met, along with an additional researcher, and discussed the initial codes found. With these in mind, a second round of coding was performed by the two initial researchers. Then, all three researchers met again to perform a final discussion of the codes created. During this meeting, themes were created based on the identified codes. However, given that these themes were identified as part of a larger experiment, an additional step was taken to create subthemes that expand on these themes in light of specific experimental conditions. For instance, a theme identified by this process regarded the importance of personal motives, and the additional subtheme creation detailed which personal motives best aligned with which condition. After this final round of discussion and subtheme creation, the writing of this article began.

4. Results

4.1. Quantitative analysis

Because repeated measures were nested within participant, observations were unlikely to be independent. We computed the intraclass correlation coefficient (McGraw and Wong, 1996) for each dependent variable using participant as a random effect. Across the dependent variables, the average intraclass correlation coefficient was .44. Thus, because there was evidence of clustering by participant, each dependent variable was analyzed using multilevel modeling (Fox, 2015).

The marginal distribution of each dependent variable was examined. Based on q-q plots as well as the Anderson and Darling (1954) test of normality (Anderson and Darling, 1954), each dependent variable closely approximated a normal distribution with one exception—score. Participant's score was a strictly positive count and was heavily positively skewed. Although score ranged between 2 and 641, the median (50th percentile) was 81 and the mean was 112. As further confirmation, using score, D'Agostino's (1970) skewness test was statistically significant ($z = 8.45$, $p < .001$) (D'Agostino, 1970). Thus, all dependent variables were analyzed using a linear mixed effects model with a normal probability distribution except for score, where we used a generalized linear mixed effects model with a Poisson distribution (Gelman and Hill, 2006). The Poisson distribution is often used to model count data, which is typically positively skewed (Fox, 2015; Gelman and Hill, 2006). For linear mixed effects and generalized linear mixed effects models, there are no general agreed upon measures of effect size with some indices based on deviance, log-likelihood, and reduction in residual variance. However, because many of these indices suffer from problems including being negative or not increasing monotonically when predictors are added, we report the marginal pseudo-R^2 recommended by Nakagawa and Schielzeth (2013) that is less susceptible to common problems of other pseudo-R^2 indices (Nakagawa and Schielzeth, 2013).

All data were analyzed using R (R. Core Team et al., 2022) and the lme4 package (Bates et al., 2014). For all models, participant was included as a random effect and we controlled for prior gaming experience. In addition, for all models, we also examined whether the covariate (i.e., prior gaming experience) interacted with our independent variables. Unless otherwise noted, gaming experience did not interact with any of our manipulated independent variables. Residual analyses were conducted for all models to ensure the tenability of model assumptions (Fox, 2015; Rosopa et al., 2013).

Because of the complexity of linear mixed effects and generalized linear mixed effects models, including fixed effects, random effects and intraclass correlation, a simulation-based power analysis was conducted. Using parameter estimates from our models, we simulated power associated with the model comparison of having the larger model of interest (e.g., with two-way interaction) compared to a reduced model (e.g., exclude the two-way interaction). We used the simr package (Green and MacLeod, 2016) and 200 simulations per model. Assuming α = .05, the mean simulated power for the main effects was .904. The mean simulated power for the interactions was .596. Importantly, it was the tests of the interactions when predicting the perceptual outcomes that were underpowered. Thus, the results of statistical tests and effect sizes involving interactions associated with the perceptions will be conservative.

The quantitative results are presented by dependent variable. This section addresses two major dependent variables of influence, first, the effect of influence on performance variables like score and participants improvement over time, and second, human factors under the category of perceptions like trust in the AI teammate.

4.1.1. Performance

Score. A 2 (AI influence: low, high) ×2 (AI variability: dynamic, static) ×2 (Round: 1, 2, 3) Poisson generalized linear mixed effects model was conducted to assess the effect of AI influence (between-subjects), AI variability (within-subjects), and round (within-subjects) on participants' score while controlling for prior video game experience (see Table 2 for descriptive statistics). There was no main effect of AI influence or AI variability. However, there was a main effect of Round, $\chi^2(2) = 57.66$, $p < .001$. Post hoc analyses suggested that the average score at Round 2 (M = 94.63) was significantly greater than at Round 1 (M = 85.63). The average score at Round 3 (M = 96.54) was significantly greater than at Round 1. However, there was no significant difference in the average score between Round 2 and Round 3. The marginal model R^2 = .59.

There were statistically significant two-way interactions between AI influence and AI variability, $\chi^2(1) = 47.03$ ($p < .001$), AI influence and Round, $\chi^2(2) = 50.67$ ($p < .001$), and AI variability and Round, $\chi^2(2) = 93.34$ ($p < .001$). Fig. 3(a) depicts the nature of the AI influence ×AI variability interaction. When AI influence-variability was low-static (M = 115.58), the average score was significantly greater compared to when low-dynamic (M = 83.93) and high-static (M = 60.95). In addition, the average score was significantly greater when AI influence-variability was high-dynamic (M = 91.84) compared to high-static. Fig. 3(b) depicts the AI influence ×Round interaction. The linear effect of round was significant, and the pattern of effects on the average score changed when AI influence was low vs. high, suggesting a disordinal interaction. Fig. 3(c) depicts the AI variability ×Round interaction. This was an ordinal interaction such that the average score was greater when AI variability was static compared to dynamic. However, the difference diminished by Round 3. The marginal model R^2 = .659.

When controlling for all lower-order terms, there was a statistically significant three-way interaction between AI influence, AI variability, and Round, $\chi^2(2) = 139.63$ ($p < .001$). In Fig. 3(d), it is evident that when AI variability was dynamic, the two-way interaction between AI influence and Round was disordinal. In contrast, when AI influence was static, the two-way interaction between AI influence and Round was ordinal such that average score was always greater when AI influence was low compared to high. The marginal model R^2 = .664.

Table 2
Descriptive statistics for score.

Round	Between	Within	*M*	SD	N
Round 1	High	Dynamic	118.88	79.55	16
		Static	66.50	60.77	16
	Low	Dynamic	88.88	91.14	16
		Static	142.38	84.93	16
Round 2	High	Dynamic	110.38	67.18	16
		Static	92.88	98.25	16
	Low	Dynamic	103.88	98.67	16
		Static	153.44	134.13	16
Round 3	High	Dynamic	107.81	151.49	16
		Static	80.75	70.59	16
	Low	Dynamic	144.69	115.24	16
		Static	136.63	109.51	16

Improvement. A 2 (AI influence: low, high) ×2 (AI variability: dynamic, static) linear mixed effects model was conducted to assess the effect of AI influence (between-subjects) and AI variability (within-subjects) on the participant's performance improvement while controlling for prior video game experience. There was a statistically significant main effect of AI influence on improvement, $\chi^2(1) = 5.68$ (p = .017). The average improvement across the rounds was significantly greater when AI influence was low (M = 24.84) compared to high (M = −8.97). The marginal model R^2 = .10.

There was a statistically significant two-way interaction between AI influence and AI variability on improvement, $\chi^2(1) = 20.11$ ($p < .001$). When AI influence was low and AI variability was dynamic, this resulted in the greatest improvement (M = 55.65) and this differed significantly from low AI influence with static AI variability (M = −5.91) and high AI influence with dynamic AI variability (M = −33.92). The marginal model R^2 = .31. See Fig. 4.

4.1.2. Perceptions

Perceived social influence in comparison to the AI teammate. A 2 (AI influence: low, high) ×2 (AI variability: dynamic, static) linear mixed effects model was conducted to assess the effect of AI influence (between-subjects) and AI variability (within-subjects) on the participant's perception of the AI teammate's level of social influence while controlling for prior video game experience. There were no statistically significant main effects or two-way interaction between AI influence and AI variability when predicting perceived social influence. However, there was a statistically significant three-way interaction between prior gaming experience, AI influence, and AI variability when predicting perceived social influence, $\chi^2(1) = 4.91$ (p = .027). The marginal model R^2 = .32. In Fig. 5, as gaming experience increased, there was a general increase in perceived social influence in comparison to the AI teammate when AI influence is low compared to high. However, this rate of increase was more pronounced when AI variability was static compared to dynamic. Although all three simple slopes in Fig. 5 were positive and statistically significant, the simple slope for gaming experience was not statistically significant when AI variability was static and AI influence was high.

Trust in the AI teammate. A 2 (AI influence: low, high) ×2 (AI variability: dynamic, static) linear mixed effects model was conducted to assess the effect of AI influence (between-subjects) and AI variability (within-subjects) on the participant's trust in the AI teammate while controlling for prior video game experience. Although there was no main effect of AI influence, there was a statistically significant main effect of AI variability on trust, $\chi^2(1) = 4.27$ (p = .039). The marginal model R^2 = .04. The average trust was significantly greater when AI variability was dynamic (M = 23.40) vs. static (M = 21.70). There was no statistically significant two-way interaction between AI influence and AI variability.

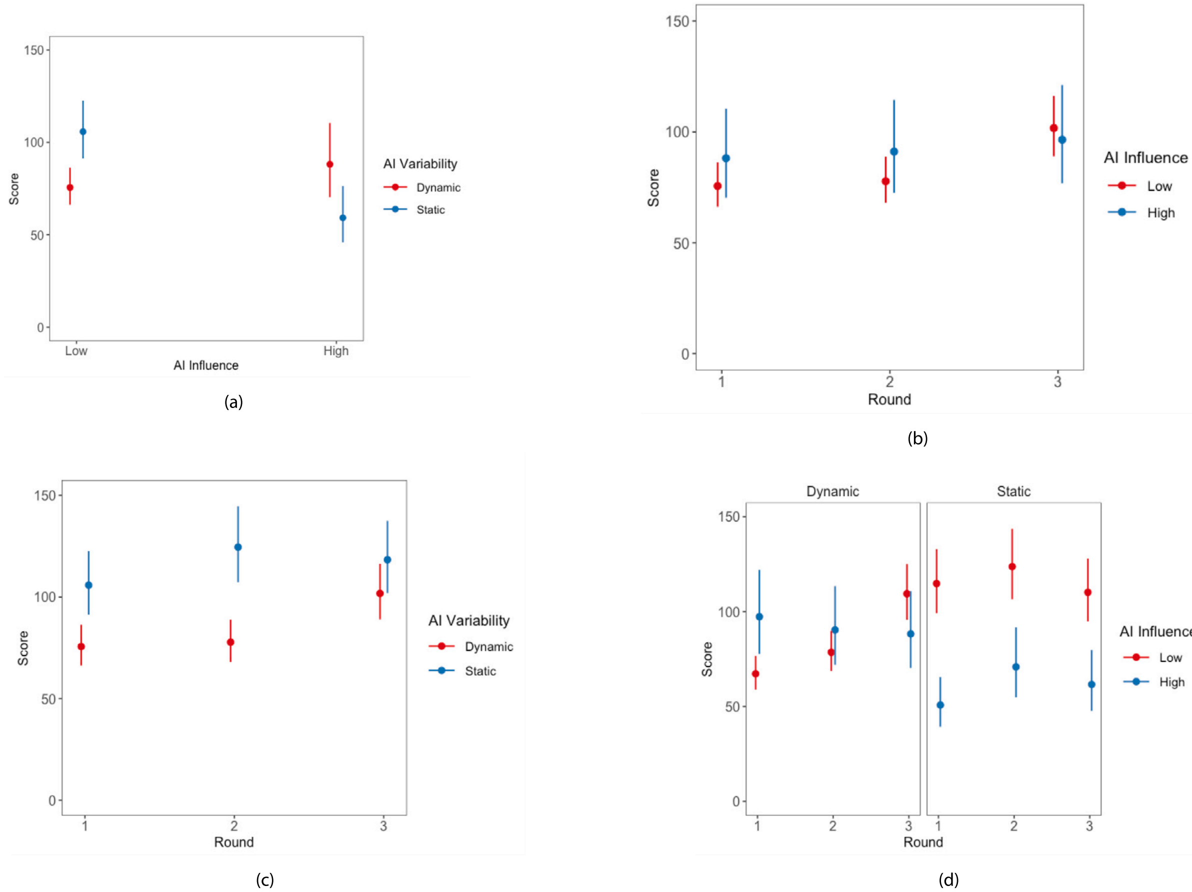

Fig. 3. AI Influence and variability's effect on participants' scores. Error bars represent 95% confidence intervals.

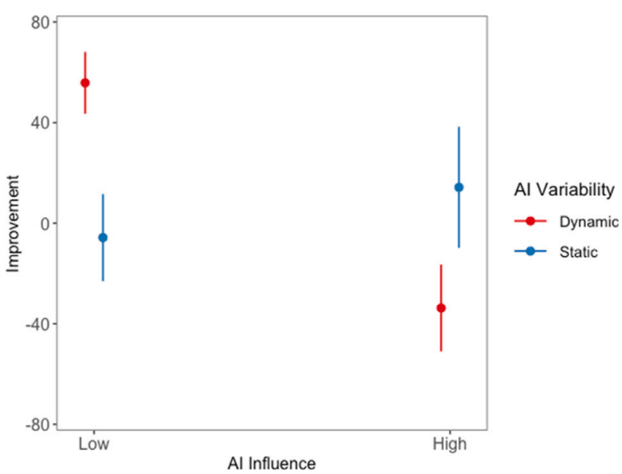

Fig. 4. The effect of AI influence on participants perceived influence. Error bars represent 95% confidence intervals.

4.2. Qualitative results: Why humans can perceive varying levels of AI influence differently

The qualitative results presented demonstrate that the perceptions humans form are not exclusively driven by the impacts influence has on human performance. Rather, the below results demonstrate that if an AI teammate uses their influence to benefit the personal goals of a human teammate, then humans will form acceptance for said AI teammate's influence. The following discusses the three prominent findings of the interviews conducted, including: (1) how humans use their personal motivations and goals to determine their ideal influence level of an AI teammate; (2) how humans use their personal motivations to determine their ideal for how AI teammates should change their influence level; and (3) factors humans will also consider when determining their ideal AI teammate influence level in real-world contexts. As a note, for this section, the following labeling will be given with each quote (PID, Between Condition, Post-Within Condition Interview).

4.2.1. The personal motive and goal of human teammates dictates their ideal level of AI teammate influence

The most predominant finding of the interviews conducted by this study is the importance of personal motivations in determining a human's preference for how much influence their AI teammate has. This finding helps explain the insignificance found in our perception results as the perceptions humans form are not solely determined by influence level but rather by the alignment of AI teammate influence with a human's personal motivation. In a team setting, this poses a complication as individuals and their team's goals may not be entirely the same. Participants, such as P28 and P33, explicitly noted that their preference for an AI teammate would change based on their personal motivation:

> I'm just thinking in terms of like, what I need to win. In that standpoint, I want teammate number three but say like, I wanted to practice I would probably want number one because I thought they had the least influence. -P28, High, Dynamic

> When I was trying to maximize winning, I wouldn't go to the ball, I would just let them do the whole thing, because I knew I wasn't very good at it. But then to maximize my enjoyment, I'd probably keep going and see how many times I could touch the ball even if it wasn't going in the goal. -P33, High, Static

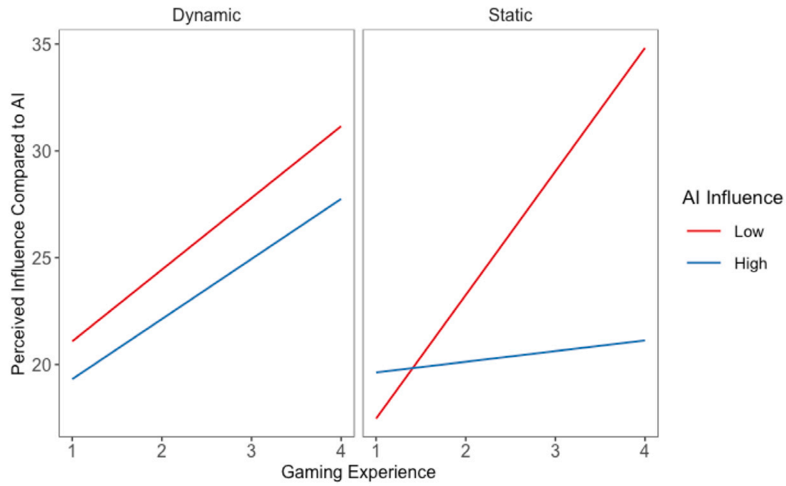

Fig. 5. The effect of AI influence on participants perceived influence. Error bars represent 95% confidence intervals.

In the short term, this misalignment is less important, as some participants even noted the importance of having a highly influential teammate in the early stages of teaming to help "set the tone". In the long term, however, if an alignment is not achieved between these motivations and AI teammate influence, then it will lead human teammates to lose motivation. Participant P02 echoed these sentiments when they signaled how they eventually gave up due to this misalignment:

> I noticed how in the beginning, they would always be really aggressive. And I think in like all three games, we scored a goal, like within the first 20–30 s, so I liked how it kind of like set the tone in that regard. So I think I would keep that... being aggressive and having that sort of mindset. -P02, High, Static

The findings discussed below will be organized to talk about (1) motivations that align with highly influential teammates, (2) motivations that align with lowly influential teammates, and (3) motivations that align with influence being relatively even between teammates. Ultimately, these findings demonstrate the three ways in which personal motive was found to link to influence level.

4.2.1.1. An influence balance that favors AI teammates is preferred by humans who enjoy winning and prefer to learn by watching. While highly influential AI teammates can lead to greater levels of performance in human team members, personal motivations may be more critical than these performance gains in dictating preference for influence level. Specifically, participants noted two key personal motivations that directly aligned with high levels of AI teammate influence: (a) the desire to win; and (b) the desire to learn by watching.

For motivation (a), participants were mostly supportive of having highly influential AI teammates because they felt it best help them win. Specifically, participants explicitly link their enjoyment of the activity with whether or not they are winning, which ultimately motivates to prefer a highly influential teammate. For instance, P12 and P26 noted their preference for winning as it is their actual purpose:

> I'd probably take the one I just played with. Considering, you know, they won two games and tied one. -P12, High, Static

> I'd rather win than really have like an influence on the team. -P26, High, Static

Importantly, highly performative human teammates may actually be the exception to this trend as they see themselves as solely capable of fulfilling their desire to win. For instance, P18 echoed their preference for a lowly influential teammate while also mentioning the following importance of winning:

> Um, I think they're almost connected. If I know I'm doing really poorly, I just won't be having a good time. But because that can a thing of either you are hard on yourself or your teammates are hard on you. -P18, Low, Static

For motivation (b), learning was a common personal motivation participants had, and many of them prioritized learning through watching. These participants were heavily supportive of highly influential teammates as they could use their AI teammate as an exemplar who was constantly demonstrating skill. For instance, P12 and P22 noted that they mostly wanted to watch their AI teammate in order to improve:

> I feel like that would help. Especially, since I was learning as I went, I can be able to learn and see what they do and then try to react off that. -P12, High, Dynamic

> I think I'm still improving, and I think I'm learning some skills from the dominant players, like how to jump or flip or whatever. -P22, High, Static

The above two motivations show that there is a desire in human teammates to have highly influential teammates, even if that desire results in them having lower performance potential. However, the above also demonstrates that the reason for having a highly influential teammate is non-consistent from person-to-person, meaning that other contexts may actually see specific motivations align with different levels of influence due to the design of the task and team.

4.2.1.2. An influence balance that favors human teammates is preferred by humans who enjoy playing and prefer to learn by doing. Participants who prefer lowly influential teammates often place a greater sense of value on the actual experience and participation they have as teammates. Specifically, the following two motivations were commonly seen as reasons for wanting a lowly influential teammate: (a) the desire to have fun playing a game; and (b) the desire to learn by doing the task.

For motivation (a), participants felt that highly influential teammates prevented them from actually playing the actual game. Ultimately, highly influential teammates reminded participants of unpleasant "ball hogs" that made the game itself enjoyable, thus reducing the perceptions humans had of these teammates. Participants p04 and p15 were clear examples of this motivation as they enjoyed the game and felt the entire purpose of the game was to have fun and not to win.

> [Asked about having a highly influential teammate] No, not for me... I've grown up playing sports, and I don't like a ball hog. And you're on a team for a reason. -P04, Low, Static ...you also just don't want to feel like you're kind of like a side character and you're kind of just watching somebody do all the work. So I probably just pick the first one [low influence] still. -P15, High, Dynamic

For participants with motivation (b), learning was still really important, but the actual method of learning centered around participation rather than observation. Lowly influential teammates provided these participants with the room they needed to actually perform, make mistakes, and learn in a hands-on manner. Participants P08 echoed this sentiment in their interviews by explicitly mentioning the motivation to learn and the need to do it in a hands-on manner; Participant P17 even noted that this motivation to learn can increase over time, in turn decreasing the desire for high levels of AI teammate influence.

> I think when I was able to have more of a chance to play and interact with the ball and actually try to do it, I was more motivated to try to do well. But then as like, my teammate kept doing it and kind of taking the ball away from me, I just was like, oh, I could lay back a little bit. -P08, High, Dynamic

> I think it was a little bit worse. In the end, it might have been because I was getting better at it. So they didn't need to be everywhere as much. -P17, Low, Dynamic

The above results demonstrate that hands-on experience is a priority for a lot of humans working in human-AI teams. Whether that experience is used for learning or just to have a more enjoyable experience, the availability of that hands-on experience is critical to these people. However, highly influential teammates may deprive humans of this desired experience, especially if that influence level is maintained for a long period of time.

4.2.1.3. An even balance in influence is preferred by humans who prioritize healthy teamwork. While some participants tended to have a personal preference for high or low levels of influence in their AI teammates, some participants were actually more receptive toward having even levels of influence between both teammates. Generally, these participants were not as much concerned with the performance of their team but the balance of influence present. Both P01 and P19 mentioned their perceived importance of this balance:

> Sometimes you have to limit yourself to other people's like skill levels. -P01, High, Dynamic

> I liked the second one the most, because it was almost balanced, but to the point where I could rely on someone else. -P19, Low, Dynamic

Participants who have these strong beliefs about teamwork can even use these beliefs to override other personal motivations. For instance, winning may not be a priority if a participant feels like a team is trying their best and working cohesively. This sentiment was echoed by participant P16 (Low, Static): *"I'm completely fine losing, as long as we lose together"*.

Importantly, this does not mean that humans want the amount of AI teammate influence to be exactly the same as their own. Rather, they simply want a balance that allows responsibility to be shared in a way that is not one-sided. The following from P19 clearly illustrates how having a better teammate is not bad as long as that teammate is somewhat similar to the participant:

> Um, I would want them above me, but not super expert because I wouldn't want to feel like I'm totally being carried or anything. But, I still would like someone better than me so it's almost like a cushion. -P19, Low, Static

The above subthemes demonstrate how the ideal level of influence that an AI teammate has is a highly personal factor. While the performance of a team or individual ties into this preference, it is ultimately up the motivations of the individual in determining an ideal level of influence. Unfortunately, this may make it difficult to design AI teammates with an ideal level of influence as the prediction of these personal motivations will be unique from team to team, and the above does not represent an exhaustive list of all the potential motivations that exist.

4.2.2. Personal preference for the dynamic nature of AI teammate influence is also contingent on personal motive alignment

The level of influence an AI teammate has is not guaranteed to be static as environmental or technological changes may ultimately change the role these teammates play. In addition to determining the ideal level of AI teammate influence, the findings of this study also uncovered that the method of transition between influence levels is also tied to personal motivation. Specifically, the motivation of adaptation was prevalent amongst most users was a prevalent concern when determining their ideal method of influence transition. Participant P05 provide a clear example of how this motivation to adapt was impacted by changes in influence level:

> First game, compared to last game, difficulty adjusting... I thought it was probably harder in the beginning, because like, they were kind of hanging back a little bit more. They weren't actually taking control, but then when they were taking control the situation, it was easier for me to understand. -P05, High, Dynamic

While adaptation was a central motivation for participants' preference, participants' preferred methods of adaptation differed, which ultimately differed in their preference of how an AI teammate should transition between influence levels. Firstly, a considerable number of participants prioritize the importance of consistency in adaption. These participants wanted quick transitions that while jarring, would provide a greater amount of time with an AI teammate at a static influence level. In other words, these participants show a greater affinity for static AI teammates over highly dynamic teammates in environments where a change in influence is inevitable. For instance, when asked about whether they would prefer quick or gradual changes in AI teammate influence, P09 and P14 said the following:

> I wouldn't want it to keep changing, because I would have to adjust every time. So if I keep it consistent, then I can keep whatever my plan is consistent, which I feel would work out better. -P14, Low, Dynamic

On the other hand, some participants were much more receptive toward dynamic levels of AI teammate influence; however, their preference was for that influence to be dynamic in a much more gradual manner. This preference stems from the motivation to gradually adapt to AI teammates by making small, but frequent adjustments. Since this method of transition would provide participants with a less jarring and more iterative approach to adaptation, it was ultimately preferred by some participants in environments where a change in influence is inevitable. Participant P19 echoed this preference during their interviews:

> I feel like the gradual descent would make me a little better and get more comfortable because it's kind of the aggressive teammate allowing me to get used to it. And then slowly, I can move on to the more passive teammate so I can do more in the game and be better. -P19, Low, Dynamic

While a high degree of unique motivations that impact the preference for static or dynamic influence was not found, the importance of adaptation to humans shows a clear and personal preference. Humans who prioritize consistency are going to want faster, more visible change, but humans who thrive on gradual and slow-pace change are going to want the same in their AI teammates. However, the existence of these preferences in combination with the motivations found in the previous theme paint a highly complex and personal picture of the preference for AI teammate influence. Not only are humans unique in their preference for its level, but they are also uniquely different in their preference for how that influence should change over time.

4.2.3. Real-world preference of AI teammate influence will be further mediated by context and risk

While the above two themes were heavily contextualized in the scope of the games of Rocket League played by participants, interviews also discussed preference for AI teammate influence in other contexts. Similar to the above result, it appears that the transition into the real-world will also provide competing motivations and preferences that will further complicate the ideal level of AI teammate influence. Specifically, participants were heavily motivated to minimize the risk AI teammates posed to themselves and society. The following quote from P27 provides an example of this motivation while also revealing that this motivation to minimize risk may actually be highly unique to AI teammates:

> I think it'd be the same. This is like a soccer game. I mean, it's like important, I guess, but like, not really that important. I'd be a little more reserved when it came to really important stuff working with the bot to teammate. -P27, High, Static

However, the challenge with the risk being a complicating factor is that it may actually be highly subjective to humans, meaning that while the risk is a consistent consideration there is a high degree of variance in this consideration, similar to the consideration of adaptation. For instance, participants are more inclined to attribute risk to the targeting of vulnerable populations, the potential consequences of a mistake, or even the impact it may have on personal comfort. Participants P12 and P14 all expressed their consideration of risk while providing different contexts and factors that contribute to risk:

> I think it is gonna affect their growth a little bit. Because I feel like it's very important to have that human connection when you're younger. -P12, High, Static

> I would rather my mom cooked me a meal or something like that. Not that the machine's not in control, but it's easier to let's just say you are cooking potatoes and be like "hey can you put not as much butter or something like that". Whereas the machine I feel like it would be harder to like, communicate something like that. -P14, Low, Dynamic

In addition to the motivations identified by previous themes, the concept of risk explored by this theme demonstrates that the transition from AI teammates into real-world settings will be further complicated by unique personal preference driven by the motivation to reduce risk. Moreover, the variance that exists in the concept of risk further complicates this matter as it would make it increasingly difficult to predict if a task is deemed risky by a human, in turn resulting in a preference for low influence in an AI teammate.

4.3. Summary of results

In summary, the results of this study are both promising and complex for the future of AI teammates. In answering RQ1, influence appears to have a complex relationship with the human teammate's performance, such that the effect of influence is changed as teams continue to work together (see Figs. 3(b),3(c)); however, these performance impacts do not seem to have a clear, quantitative connection to humans' perception and preference their AI teammate's level of influence. While perceptions heavily tied to influence, such as perceived influence, were impacted, perceptions more closely related to preference and quality, such as trust, do not see a significant effect of AI influence. However, an investigation of qualitative findings revealed that these perceptions are more closely linked to personal motivations that are unique to individual humans and further contextualize the main effects of AI variability. The results of this paper were able to identify 5 key motivations in humans that would ultimately lead to them having a preference for their AI teammate's influence level. While this answer to RQ1 is promising in that it shows humans can prefer highly influential teammates, the variance of these individual motivations will ultimately make it difficult to design AI teammates to align with every teammate's personal motivation.

Similar to RQ2, whether or not AI teammate influence was dynamic did significantly impact human performance in the form of an interaction effect. Humans who work with AI teammates that dynamically decrease their influence see a significantly higher level of improvement than other conditions (Fig. 3(d)). Moreover, given that the inverse was not seen in increasing levels of influence (i.e., significant worsening of performance), it can be derived that these performance increases are actually due to participants improving and not simply increases due to lowing AI teammate influence. This conclusion is further backed up by the qualitative findings that show how high levels of influence at the beginning of a task are welcome as they can help set the tone and motivate humans. However, the qualitative results also conclude that after setting this tone, AI teammates need to be cautious in how they transition to a different level of influence as humans may have highly personal preferences for how that transition should happen in addition to the influence level they are transitioning toward.

Additionally, the qualitative findings of this study help lend external validity to the answers of RQ1 and RQ2 by showing that personal motivations and their linkage to AI teammate influence preference will continue in the real-world. However, the motivations considered will become more complex due to the variance in context and risk present in real-world scenarios. Thus, while the above results are highly optimistic for the future welcoming of AI teammate influence, researchers, designers, and practitioners should read carefully to ensure AI teammates are well aligned with human motive, thus encouraging acceptance and usage.

5. Discussion

5.1. The potential of personal competing goals that complicate influence in human-AI teams

The qualitative results of this study highlight how complex human-AI teaming can become due to the existence of competing motivations within teams. Within teams, the complication of competing motivations is not new (Ramamoorthy and Flood, 2004). At their core, teams consist of individuals who have personal motivations, all working together to complete a team motivation or goal (Waitzberg et al., 2021; Nigam, 2018). Effective teaming is not the result of ignoring these personal objectives for the sake of only focusing on team performance, but rather balancing the completion of personal and team goals (Sohmen, 2013). In fact, this balance is so important that team leaders and managers often see the creation of this balance as one of their most important responsibilities (Clark, 2003; Sohmen, 2013). While past research has discussed how these personal motivations are still an important consideration for leaders in human-AI teams (Flathmann et al., 2021), the results of this study show how these motivations may actually be an important consideration for AI teammates themselves.

However, as also demonstrated by the results of this study, prioritizing a team's goal may unfortunately de-emphasize specific personal motives humans are going have. The result of this de-emphasis is a conflict of motivation, where the personal motivation of the AI could be viewed as the efficient prioritization of a team's goal, which may not be the motive of human teammates. Although humans may be able to iteratively balance personal and team motives when operating in a team, this would be a greater challenge for AI teammates as they will lack a level of general intelligence, especially in early cases of human-AI teaming (Flathmann et al., 2020; Pennachin and Goertzel, 2007). While this may not make AI teammates highly performative teammate from a raw performance perspective, we know that raw performance is not the only component that makes an effective and compatible team member (Salas et al., 2008; Brannick et al., 1993), even if they are an AI team member (Bansal et al., 2019). Thus, based on the results of this study, the concept of human-compatibility in human-AI teaming will need to be updated to include the consideration of potentially competing for personal motivations to ensure AI teammate influence does not work counter to personal motivation.

Like most challenges in human-AI teaming, the challenge of balancing performance and personal motivations needs to be tackled from both a human and computational perspective to be solved in an efficient and human-centered manner. From the human side, research work needs to prioritize the communication of AI teammates' motives while also teaching human teammates that AI teammates may not be able to actually help their personal motives due to design limitations. Although this may not be ideal for humans, having this knowledge is key to tempering expectations and not assuming an AI teammate is always going to help with their own personal motive (Amershi et al., 2019). From the computational side, work needs to advance the generalizability of AI teammate knowledge to be inclusive of the personal motivations human teammates have. This does not mean that AI teammates should be designed to only consider these motives, but rather that these motives need to become a consideration component, just like any other teaming component, such as trust (McNeese et al., 2021), ethics (Flathmann et al., 2021), or even team cognition (Schelble et al., 2022). If research focuses on both of these perspectives, a healthy and necessary middle ground can be achieved in early implementations of human-AI teams where humans are willing to compromise on the prioritization of their personal motivations by AI teammates.

5.2. The importance of healthy competition in human-AI teams

While personal motivation was critical to the long-term perceptions humans formed for their AI teammates, both the quantitative and qualitative results of this work show that high levels of AI teammate influence on a task are most welcome in the early stages of teaming. Not only was a large degree of participants unopposed to AI teammates "setting the tone", but this action ultimately led to performance improvements in human teammates. In explaining this outcome, one could look at the concept of competitiveness in teaming (Constantinou, 2014). Within teams, a healthy level of competition can exist where humans actively encourage each other to improve by setting an example of high performance (Julian et al., 1966). In fact, teams often find ways to promote this competitiveness as it not only helps performance but also other critical teaming factors like knowledge sharing and adaptability (He et al., 2014). Overall, competitiveness, when used correctly (Katz, 2001), can benefit teams in tangible ways. The results of this study suggest that AI teammates would have the ability to also promote this healthy competition in human-AI teams.

The ability of AI teammates to encourage improvement is not an unknown as past work has shown that AI teammates that initiate conversation improve teaming outcomes like team cognition (Schelble et al., 2022). Extending on this idea, both the quantitative results of this study show that the influence AI teammates have on a task can effectively goad humans into improving at the task level without harming long-term perceptions. While it may not be practical for AI teammates to decrease their influence over time in a real-world task, humans may go into real-world tasks with a higher level of performance if they are trained with an AI teammate which decreases influence, as suggested by the quantitative results of this study. This concept could relate to the perturbation theory of teams, which discusses how experience in isolated training benefits real-world performance (Gorman et al., 2010; Cooke et al., 2012). AI teammates could be designed to be more competitive and increase the efficiency in these perturbation exercises, thus better-preparing humans for real-world human-AI teaming.

However, the implementation of this competitiveness is not entirely intuitive. While an initial assumption might posit that the competitiveness provided by AI teammates should grow alongside human improvement, the actual results of this work suggest that AI teammates should start highly competitive but back off and give humans room to grow and improve (i.e. set the tone). If competitiveness is not implemented in this way, healthy competition becomes unhealthy, which can be detrimental to teams (Casadevall and Fang, 2012). The effects of this unhealthy competition are also evident in this study as well, as AI teammates that increase in influence ultimately stagnate the performance improvement of humans. Thus, both sides of this competitiveness can be seen through the results of this study, with results indicating how helpful healthy competition can be to human-AI teams.

However, work still needs to explore other ways AI teammates can "set the tone", and management/leadership research may point to a great starting place as motivation and the encouragement of competition is critical to those roles (Isaac et al., 2001; Naile and Selesho, 2014). For example, human-AI teams could utilize collaborative training where humans actively train alongside AI teammates to improve motivation (Jiang, 2010). More robust and specific communication strategies could also be designed that allow AI teammates to directly motivate human teammates through the use of competitive language (Zhu et al., 2013; Barratt, 2017). Even the use of gamification methods, which are fantastic for AI design and education (Sakulkueakulsuk et al., 2018; Méndez et al., 2020; Yordanova, 2020), could also create a level of healthy competition and motivation in teams (Sarangi and Shah, 2015). This work can already be seen in human-AI teaming from a theoretical viewpoint (Flathmann et al., 2021), but empirical explorations of these motivations are still needed. As such, the results of this study merit the further exploration of these concepts with the goal of ensuring AI teammates are not demotivating to the improvement of human teammates.

5.3. Design recommendations

5.3.1. When AI teammates are highly performative and share influence with humans, AI teammates should be highly performative when they first join human-AI teams

One of the most interesting interpretations created from this study's findings was the ability of highly influential AI teammates to both motivate and demotivate individuals based on personal motivation. However, demotivation was more likely to occur after repeated interaction. Moreover, the results of this study show that early instances of high AI teammate influence can benefit and encourage improvement in human performance. Thus, having AI teammates be highly performative and influential in the early stages of interaction will allow for potential motivation, but scaling back their influence during the middle stages of interaction will prevent demotivation while also allowing growth.

Critically, when this design recommendation should be implemented is also of note as the context and task in this study provided humans with a low-risk task, highly performative AI teammate, and influence that had to be shared. As such, the relevance of this design recommendation is critically dictated by the relevance of these three features to an AI teammate. Specifically, these factors present a context in which AI teammates can serve as an exemplar to humans without having to ensure task performance. Within teaming, this is a critical function of teammates as being an exemplar benefits team performance (Afota et al., 2019), but this should not be the focus of AI teammates when risk becomes a factor or human teammates do not need motivation or growth.

5.3.2. When AI teammate updates are optional, human teammates should schedule performance updates for their AI teammates

While the early and middle stages of interaction can follow the design recommendation above, the results of this study show that long-term influence from AI teammates has to be decided based on the personal goals of humans. Thus, long-term teaming in this task needed a more individualistic way of designing AI teammate influence. Specifically, this study found that humans' preferences differed for both the level of influence AI teammates have and how that level varies. Given this finding, human teammates should be able to select when the influence of AI teammates might change by personally scheduling their update cycles. Doing so would not only provide human teammates with a more preferred experience, but that preferred experience would lead to a greater perception of the AI teammate based on the results of this study.

Interestingly, this recommendation, which is derived from this work's findings, is somewhat contrary to existing literature that promotes more constant and incremental methods to updating AI teammates (Amershi et al., 2019). As such, it is important to note that this recommendation may not always be ideal or feasible for AI teammates. For instance, the low-risk task used by this study presents a context where updates to AI teammates' programming do not create negative consequences outside of the simulated environment. However, a high-risk environment, such as a human-AI cybersecurity or healthcare environment, would present a setting where real-world consequences can directly stem from the influence of an AI teammate. As such, designers should weigh the severity of AI teammate updates to the context their team operates in to determine if humans' preference for update cycles can and should supersede AI teammate performance updates.

5.3.3. Human's personal motives should be a minor consideration of AI teammates

As repeatedly mentioned in this study, personal motivation is one of the most critical factors when determining the acceptance of AI teammate influence. However, AI teammates are not designed with personal motivations in mind but rather team motivations, and this will be especially true in the early stages of human-AI teaming when AI teammates lack general intelligence. Thus, the performance feedback AI teammates receive from their human teammates should also include feedback on if AI teammate influence conflicts with any personal motivations. In doing so, AI teammates will gain team-specific knowledge and become better aligned with human teammates while still learning from general task feedback. Unfortunately, this recommendation will not perfectly align AI teammates with personal motivations as there can be many personal motivations, and AI teammates still have to ensure they are completing their assigned tasks correctly. However, this recommendation would still improve overall alignment and in turn, AI teammate acceptance.

While it would be nearly impossible to design AI teammates with personal motivation in mind before those teammates are assigned to human-AI teams, this ad-hoc consideration of personal motivations would provide a good compromise. Importantly, even in human-human teams, the alignment of personal motivations is difficult and not instantaneous or guaranteed with teams constantly dealing with conflict between personal and group motivations (Janss et al., 2012). However, the prioritization of these personal motivations in an AI teammate's decision-making calculus should be driven by their potential benefit compared to the potential negative of having an AI teammate reduce their prioritization of their team's objective. In the event that reducing an AI teammate's prioritization of a team objective creates harmful and demonstrable outcomes, then the consideration of personal motives should be minimized if not forgone altogether.

5.4. Limitations and future work

Most notably, this work presents three key limitations in light of its results and design: the team outcomes examined, the context and task used, and the population recruited. First, this study examined team outcomes often prioritized in human-AI teamwork, such as trust and performance (McNeese et al., 2021), but a variety of other team outcomes can be impacted by influence. Based on the results of this work, the team process and outcome of interdependence could be highly related to influence in human-AI teams. Most notably, the quantitative outcomes related to performance as well as the qualitative outcomes related to team synergy denote that behavioral and task interdependence, which are hallmarks of team performance, could be directly linked to AI teammate influence.

Second, the task, context, and AI teammate chosen for this study are critical limitations as the role of influence may change based on changes to these limitations. For instance, this study presented a low-risk task and a highly-performative AI teammate to humans, which might have helped some humans build positive perceptions of the AI teammate's performance and influence. As such, a task with a greater level of risk, such as human-AI surgery, or an AI teammate that was not as performative could have led to demonstrably more negative perceptions when it had greater levels of influence. Moreover, the qualitative results of this work may become less generalizable in other tasks as personal motivations could change and humans may become more skilled, which is why future work should also examine additional personal motivations that should be considered.

Finally, this work has a somewhat limited population in that it recruited college-aged participants that may have a different perception of technology than older individuals. Future work can provide a critical contribution to the examination of influence by exploring its perception in older adults or individuals with various cultural backgrounds. As future work continues to explore the concept of influence, the above limitations should serve as immediate ways to expand and build upon this work.

6. Conclusion

The findings of the current study shed critical light on the role of varying levels of AI teammate influence on human performance and perceptions. Specifically, the results of this study comprise the first explicit and empirical investigation of how the influence of AI teammates influence in human-AI teams and how said influence impacts human teammates. While humans are able to generally improve with AI teammates that decrease their influence overtime, the perceptions humans form for this influence are not directly predicated on performance benefits, with results showing that these performance benefits almost rarely matter. Rather, ensuring the influence AI teammates have is human-centered and accepted is a highly complex task that is heavily predicated by the benefit of that influence on humans' personal motivations. Moreover, as AI teammates' influence becomes dynamic, which is likely in the coming years, the personal preferences for this influence also become more complex with humans often having preferences for both the level of influence and how that influence should change if that change is necessary. The quantitative findings of this study suggest that AI teammates that decrease their influence throughout their interactions enable humans to better improve over time. This finding is further explained through the qualitative results of this work that show how humans enjoy working with AI teammates that display high levels of skill as long as those AI teammates provide room for humans to learn and grow. Based on these findings, AI teammates can be better designed to serve as teammates that help motivate the growth of their human teammates. These findings provide critical contributions to the field of HCI as the implementation of AI teammates, and in turn, the existence of AI teammate influence is expected to rise in the near future. This study provides empirical results and targeted design recommendations that will not only allow researchers to prepare for the said increase but also ensure it directly benefits human teammates.

Table A.3
Participant demographic information.

Gender identity		Age					Video game experience			
Male	Female	18	19	20	21	22	None at all	Some	A good amount	A lot
12	21	23	4	3	2	1	11	14	4	4

Race (multiple races counted for each)				
Caucasian	Latino or Hispanic	Black/African American	Asian	Pacific Islander
28	3	2	3	1

Rocket league experience				
Never	Not in a long time	Few times a year	Few times a month	Almost every day
18	11	2	1	1

Please note that the above tables only displays answers provided by participants and not all options available.

CRediT authorship contribution statement

Christopher Flathmann: Conceptualization, Methodology, Data collection, Writing – original draft, Writing – manuscript revision. **Beau G. Schelble:** Methodology, Writing – original draft, Writing – manuscript revisions. **Patrick J. Rosopa:** Writing – manuscript revisions. **Nathan J. McNeese:** Supervision, Writing – reviewing & editing. **Rohit Mallick:** Writing – original draft. **Kapil Chalil Madathil:** Writing – reviewing & 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 are unable or have chosen not to specify which data has been used.

Appendix. Participant demographics

Participant demographic information has been provided in Table A.3.

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