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Tip Your HAT to Your New Teammate

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ABSTRACT
As the evolution of human-AI teams (HATs) progresses, it will cause a paradigm shift of previously accepted group dynamic and social exchange principles. Though the broad context of HAT development encompasses three dimensions: job displacement, job augmentation, and job creation, we focus on job augmentation, where AI (Artificial Intelligence) and humans will work best in collaboration. We investigate the impact on theory and implications to practice as the unique challenges and opportunities presented by these new collaborative interactions and exchange dynamics arise.

Keywords
Artificial Intelligence, Group Dynamics, Social Exchange, Job Augmentation, Human AI Teams

1 INTRODUCTION

As AI technology continues to transform the management landscape, scholars have only just begun to research and discuss the potential changes and concerns. We have identified numerous fields that will most likely utilize HATs more extensively. Fields such as medicine, law and engineering are examples of industries where humans have already begun working and interacting in HAT type environments and the work team dynamics are evolving at rapid speed. Concerns include both ethical and technical considerations. Likewise, emotional issues can arise when a human relies on a machine for work and moral support. Though some technology is anthropomorphized to make humans feel more comfortable with its uses, this is not a one size fits all solution. Cultivation of trust in this technology is, and will continue to be, an obstacle faced by management when asking employees to delegate their work to or collaborate with machines.

HATs have the potential to surpass the capabilities that humans or AIs alone can achieve (Seeber et al., 2020). Social exchange theory (SET) has helped to explain the dynamics of interpersonal relationships based on mutual benefits and costs (Cropanzano & Mitchell, 2005). As AI advances and is more deeply integrated into organizations through the evolution of HATs, there is a growing need to explore the implications on the related SET constructs of interdependence, reciprocity, trust, fairness, equity, social influence, and team norms.

Human teammates typically possess inherent social and emotional intelligence, which contributes to the formation of trust and the reciprocation of favors within relationships (Seeber et al., 2020). In contrast, currently, AI teammates lack human-like qualities, and the machines lack the ability to exhibit the emotional nuances necessary for effective reciprocity (Cropanzano & Mitchell, 2005), thus impacting the overall balance of benefits and costs in social exchanges. Human teammates display subjective judgments of fairness, often considering factors such as effort, contribution, and personal preferences. AI teammates, on the other hand, adhere to predefined algorithms and rules, potentially leading to more objective decisions, but can potentially produce undesired results that can be perceived as unfair or not based on all the facts. This shift in the perception of fairness has implications for the maintenance of cooperative relationships and the long-term viability of social exchanges within HATs.

Additionally, humans are highly susceptible to conformity and normative behaviors, often shaping their actions based on the observed behavior of others (Rusbult & Lange, 2003). AI teammates, being driven by algorithms and data, may have a different set of "norms" and decision-making processes, potentially influencing the expectations within the team.

2 HUMAN_AI TEAMING

There are several ways in which humans and AI can interact in an organizational setting. Raisch and Karkowski (2021) define augmentation as the interdependent collaboration between humans and AI to create optimal work performance (Raisch & Krakowski, 2021). This concept is juxtaposed to automation which refers to a machine taking over the job role completely without oversight. The HAT has already been shown to outperform human-only teams in many industries (Textor et al., 2022). Textor further explains that trust in the machine is crucial for humans to learn to rely on these team dynamics and give access and permission for AI to take on responsibilities.

AI has been used to make life and death decisions in many fields such including medicine and the military. Sawant (2022) points out that AI's capability to remove human-nature emotions from decision making allows for more strategic decisions (Sawant et al., 2022). Humans are prone to over-confident decisions and biases, where AI can follow a set of rules without any "white noise." Despite this superior capability, humans are often weary of working with AI and delegating responsibilities (Bendell et al., 2021). AI can learn some micro social cues and social etiquette, but it is beyond its capability to act human-like in a way that that can be considered sufficient to human standards. Human beings are variable, and AI needs a concrete set of rules to follow in any given situation.

To utilize AI successfully, it has been shown that organizations must use both automation and augmentation. These opposing strategies can each be used in various situations and may need to be used cyclically to complete a set task in an optimal way (Raisch & Krakowski, 2021). These two AI tactics are interdependent and there are obvious and nuanced reasons to choose one over the other at any given time. The 2021 study explained that these two processes are opposing because only one strategy can be used at a time. Automation is desired by management to increase efficiency and save money. It should be identified where and when this tactic is applicable and little human oversight would be necessary such as mundane tasks. Augmentation is desired when the human brain's capability to reason or think outside a prescriptive set of rules is necessary. Radiologists are using AI to take a first look at X-rays, but a human has been deemed necessary to then review each image as well. These strategies, though opposing, should both be used. Management must decide which responsibilities can be delegated to AI entirely and which require HATs to ensure optimal work is performed.

3 SOCIAL EXCHANGE THEORY

Social exchange theory provides broad constructs and models to predict numerous exchange relationships in an organizational context. These relationships are predicated on behaviors and rules that have been adapted, studied, and defined for decades (Cropanzano et al., 2017). To date, these definitions have defined the actors in the exchange relationships between humans. As AI advances towards artificial general intelligence—machines are able to replicate some of the cognitive abilities of humans to perform human-level tasks. As HATs become a more prevalent structuring of work groups, social exchange theory needs to continue to evolve towards models that can help predict outcomes of the new exchange relationships between humans and machines (Hashemi-Pour & Lutkevich, 2023). Specific areas of social exchange theory that warrant deeper discussion will be the interdependence of humans and AIs, the rules that govern exchange decisions between them, and affected norms of the HATs.

Interdependence is the foundation of an interconnected team which enables it to achieve organizational outcomes. The outcomes themselves are dependent on the collaboration and cooperation of team members rather than team members' individual efforts or complete reliance on a single team member's effort (Cropanzano & Mitchell, 2005). Within the HAT, the dyadic relationships between human and AI teammates could provide shifts in the interdependence structure. The outcome matrix described by Kelley and Thibault in their theory of interdependence described how outcomes in an interdependent relationship depend on the choices and actions of the exchange partner. That relationship power dynamic is derived from control based on those choices and actions (Kelley & Thibaut, 1978). What does that look like when outcome goals are aligned but the interdependence structure shifts towards the AI teammate because its choices and actions are algorithmically selected?

A further refinement of the theory can be taken from Rusbult and Lange's interdependence extension that introduces situational structure and provides a deeper definition of the needs of partners in a dependent relationship. Level of dependence, basis of dependence, mutuality of dependence, and covariation of interest have helped explain human interactions in an exchange relationship (Rusbult & Lange, 2003). Varying any of these dimensions provides predictive mechanisms for each exchange partner in the relationship. With the introduction of the AI teammate, there is an increase in levels of dependence, mutuality of dependence, and basis of dependence and less covariation of interest from the human to the AI. Assuming that the AI is not programmed to abuse its increased power in the relationship, what new dimensions might be needed to predict interaction behavior when a "benevolent" AI introduces higher levels of dependence with elevated levels of outcome alignment? How might the outcome matrix be reshaped to account for power imbalance and alignment of outcomes?

Exchange rules are generalizations used for pay-off assignment in the outcome matrix to the participants in the exchange. As interdependence increases between humans and AI, and specifically human reliance on AI, the rules once applied to the exchange relationships will shift to accommodate the change. Human-only exchange is driven by the application of rules affecting each participant's behavior in the exchange. Between two human participants, humans may apply several different exchange rules in valuing their own payoffs. For example, a rational exchange rule where one participant attempts to maximize their own pay-off or a competitive exchange where each participant is attempting to maximize the value difference in their pay-off relative to their exchange partner. It is unlikely that AIs will be definitionally rational in terms of maximizing its pay-off, that an AI would be competitive with a human or that an AI would look to promote its own status. More than likely, the application of exchange rules will help promote team gain or look to maximize the human's pay-off.

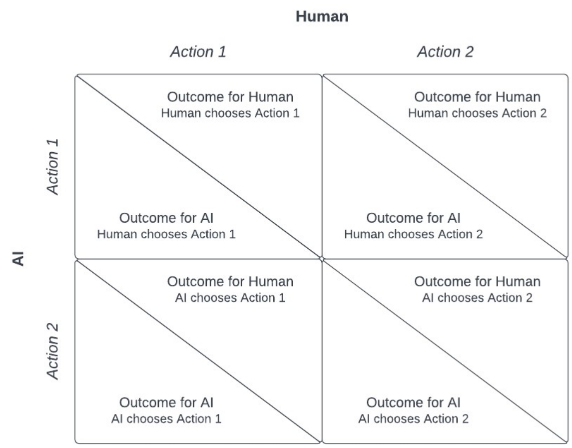

Figure 1. Outcome Matrix

Where does this leave reciprocal exchange rules where the exchange partners keep track of their exchange partners' contributions to their pay-off over time? AI is only constrained on "memory" by the configured limits of how much data it can store. It has the capacity to track every exchange with a human partner. While it can track the exchanges, the broader question is will it? Will the programming that tracks context apply logic or learning that establishes a reciprocal relationship with a human partner? Will the human partner apply reciprocal exchange rules rather than other self-maximizing exchange rules? There are broad implications to the application of these exchange rules and their further impact on team norms as teams include AI teammates and evolve their standards.

Team norms are standards for behavior within a team and apply to exchanges within the team. Meeker indicated that exchange rules can operate as team norms (Meeker, 1971). With the adjustment of rules to accommodate increased levels of interdependence on AI teammates, a corresponding adjustment will occur in team norms (Harris-Watson et al., 2023). Following this logic and the changes that will occur in human/AI exchange rules, norms such as fairness, reciprocal obligations, competition, and equity will evolve. This evolution will be shaped by the current normative foundations of the team and the degree to which the AI is viewed anthropomorphically. Teams that are highly competitive or low on reciprocity may become more so with the addition of AI teammates that do not necessarily compete nor require reciprocation, allowing human team members to push individual agendas more readily. Teams that are fair and highly collaborative may seek to train their AI teammates to be more assistant oriented in behavior to feed into the team's existing norms. Underpinning all of this will be the level to which human teammates ascribe human characteristics to their AI teammates. The more human-like the AI teammate, the more likely it will be for the humans to include the AI in their team norms.

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