Human–Agent Team Dynamics: A Review and Future Research Opportunities

ABSTRACT

Humans teaming with intelligent autonomous agents are becoming indispensable in work environments. However, human-agent teams pose significant challenges as team dynamics are complex arising from the task and social aspects of human-agent interactions. To improve our understanding of human-agent team dynamics, we conducted a systematic literature review. Drawing on Mathieu et al.'s (2019) teamwork model developed for all-human teams, we map the landscape of research to human-agent team dynamics, including structural features, compositional features, mediating mechanisms, and the interplay of the above features and mechanisms. We reveal that the development of human-agent team dynamics is still nascent, with a particular focus on information sharing, trust development, agents' human likeness behaviors, shared cognitions, situation awareness, and function allocation. Gaps remain in many areas of team dynamics, such as team processes, adaptability, shared leadership, and team diversity. We offer various interdisciplinary pathways to advance research on human-agent teams.

Keywords: human-agent teams, human-AI collaboration, intelligent agents, team dynamics, literature review

I. INTRODUCTION

As artificial intelligence (AI) and machine learning continue to evolve, the interdependent interactions between intelligent agents (IAs), such as Chat-GPT, Siri, Alexa, and Google Assistant, are becoming increasingly integral to daily life [1]. This growing prevalence has led to the emergence of Human-Agent Teams (HATs), where IAs perform a variety of roles, such as task automation, augmentation, and decision-making [2, 3]. These evolving roles are transforming the nature of work and redefining the dynamics between humans and technology [4]. Consequently, there's an imperative to rethink team structure and composition, processes, and evaluations for enhanced HAT effectiveness. Apple's 1987 Knowledge Navigator video [5] serves as an early conceptualization of the dynamic interplay between HATs. Also, in video game settings, such as Fortnite, we have seen IAs assist human players by performing specific tasks. They offer a glimpse into a future where technology is intricately woven into human endeavors. We are now on the verge of realizing this vision in our daily work. For instance, in surgical settings, a collaborative triad emerges among human surgeons, dedicated support staff, and autonomous robotic systems, illustrating a dynamic partnership that allocates responsibilities across a spectrum of intricate tasks and meticulous oversight [6]. Research has shown that HATs can be more effective in task completion and can have slightly better team satisfaction than all-human teams [7]. HATs will soon be a significant feature in work environments, augmenting task and social aspects of human-agent collaboration [8, 9]. Nevertheless, the road to integrating Intelligent Assistants (IAs) into the future of work is fraught with multifaceted challenges—ranging from technical and social to ethical and organizational [10, 11]. For example, an excessive dependence on the recommendations provided by IAs can inadvertently perpetuate biases, leading to unforeseen outcomes [12]. To successfully collaborate with IAs, employees will need to cultivate a new set of competencies that they currently lack [13].

Klein, et al. [14], in their seminal paper on HATs, envisaged agents in future to be fellow team members, akin to a novice worker, with humans. Early research on IAs was predominantly geared toward augmenting their autonomous and intelligent capabilities, often eclipsing the nuances of the human dynamics aspect [14], by fostering IAs' capabilities through design frameworks such as the Belief–Desire–Intention of agency [15] and Knowledgeable Agent-Oriented System [16]. One notable initiative was the CALO (Cognitive Assistant that Learns and Organizes) project, launched by the Defense Advanced Research Projects Agency (DARPA) in 2003, aiming at developing IAs capable of collaborating with humans in complex tasks [17]. Early HAT researchers [e.g., 18] proposed that a paradigm shift in the development of IAs was required for effective HATs. Along this line, autonomous and multi-agent research communities have called for investigating sophisticated and interdependent interactions between humans and agents [e.g., 18, 19, 20], where IAs and humans exhibit adaptive and dynamic cognition and behavior. Since then, AI has matured manyfold. Recent breakthroughs in deep learning and natural language processing (Open AI Five, Chat-GPT, Dall-E) have allowed AI systems to expand beyond repetitive or computational tasks and perform complex and creative tasks more accurately and efficiently. These technological strides, while significant, are insufficient to address the multifaceted nature of dynamics in HATs [21]. The endeavor to integrate agents as functional "team players" in these dynamics remains fraught with challenges, such as fluid and adaptive task and role demands, and complex social relationships [1, 9, 22, 23]. Given the escalating prominence of IAs and their increasing roles in teams, coupled with the diverse landscape of existing research, a thorough review is warranted to unify our understanding. We, therefore, conduct a narrative review [24] to provide a nuanced examination of the current landscape, with a special emphasis on the interplay between social and technical elements in HATs.

Drawing on extensive human teamwork literature, we explore how this knowledge can inform the design and functioning of HATs. As IAs attain higher levels of sophistication, they are increasingly perceived as comparable to human team members. Thus, we employ Mathieu et al.'s teamwork model [25] as an analytical model to evaluate the structural features, compositional features, mediating mechanisms, and their interplay in HATs. This model serves as a holistic lens for understanding the intricate, recurring exchanges in teamwork. It is well-suited for assessing human-agent teamwork given its dynamic, human-centric focus, considering team formation, teamwork design, contexts, team processes, and team emergent state. It differs from agent-centric frameworks [e.g., 26], emphasizing instead the pivotal role of humans and team interactions in team dynamics. While agents can be designed to understand contextual affordances and constraints and act accordingly, IAs also risk engendering negative attitudes [27] and algorithmic anxiety [28]. Hence, despite the careful design of agents, human perceptions and attitudes toward human-agent interactions can change the whole dynamics. A dynamic, human-centric perspective can help researchers and practitioners reflect on what we know and need to know about optimizing human-agent team (HAT) dynamics. Based on a review of 101 articles published between 2004 and 2021, we have highlighted several research opportunities to improve HAT dynamics in work environments. This study synthesizes and discusses the nature, theoretical perspectives, and patterns of HAT dynamics. It is hoped that researchers and practitioners can pay more attention to value creation in the adoption and management of HATs in organizations, which has been lacking in the current research around human-AI collaboration [29].

The rest of the paper is structured as follows. In the second section, conceptual foundations for the main elements of this research, i.e., agents and the nature of HATs, are laid. Section 3 describes the methodology for this study, and the findings are explained in Section 4. Section 5 discusses the implications of the findings and proposes an agenda for future research.

II. CONCEPTUAL FOUNDATIONS

A. Agents

Agents are computer systems situated in an environment capable of autonomous actions to fulfill designated objectives within that setting [30]. To quality IAs, they must exhibit agentic characteristics such as reactivity, proactivity, mobility, goal-orientation, communication, cooperation, coordination, character and the ability to learn [2, 30-32]. Originating from the fusion of Artificial Intelligence (AI) and distributed programming, the concept of IAs has evolved significantly since the 1950s, with major advancements occurring in the 1990s [33]. Recent advancements in machine learning, computational power, natural language processing, and the availability of big data have further refined IAs [34]. There has been substantial work recently in the area of reinforcement learning, an area of machine learning that has helped optimization of IA's behavior by training them to randomly explore the environment and increasingly exploiting the knowledge already learned from experiences [35].

IAs can contribute to a breadth of processes, from natural language processing for communication, knowledge discovery, knowledge representation, and automated reasoning to augment decisions to the optimized control of complex processes [36]. These agents have found applications across diverse sectors, including healthcare, military operations, and urban search and rescue[35]. However, a notable gap remains in optimizing their collaborative interactions with humans, a critical aspect for the successful deployment of IAs in team settings.

B. Human-Agent Teams

The increasing complexity of modern organizational tasks has led to a growing reliance on teams as a strategic approach to problem-solving [37]. This trend has been further amplified by technological advancements that facilitate the integration of IAs into human teams, where IAs and humans work together interdependently to achieve a common goal [32]. The literature on HATs is still nascent, and the definition and understanding of HATs are still evolving. We propose the following definition of HATs by adapting definitions from Mathieu, et al. [25] and O'Neill, et al. [38]. A HAT (a) consists of one or more humans and one or more IAs who (b) socially interact (face-to-face or virtually); (c) possess one or more common goals; (d) exhibit interdependencies with respect to workflow, goals, and outcomes; and (e) have distinct roles.

C. Opportunities and Challenges for Human-Agent Teams

Distributed work between human and non-human entities (e.g., animals) is not a new phenomenon [39]. However, human teams with artificial members (e.g., IAs) bring a unique set of opportunities and challenges. HATs offer a complementary set of abilities: humans excel in areas such as perception, judgment, induction and improvisation [40], whereas IAs bring computational power, speed, and the ability to perform simultaneous operations. The synergy can be particularly advantageous in complex, volatile environments where human teams may struggle. For instance, in situations where human teams face complex problems and multitasking, IAs can leverage their computational capabilities to reduce complex problem spaces to more manageable dimensions [41].

The intricate dynamics of HATs are compounded by a multitude of social factors, such as trust and fairness [42]. Potential challenges for HATs include difficulties in adaptation for humans to work with IAs as team members, coordinating interdependent activity, establishing, and maintaining common ground among team members and recovering from individual or team breakdowns. The challenge also stems from IAs' limited natural languages and shared cognition capabilities [43]. Given these complexities, there is a pressing need for frameworks that can harness the potential benefits of HATs while mitigating their inherent challenges.

III. METHODOLOGY

The research design for this study includes three main components. The first component is the identification of relevant literature. Section 3.1 delineates how the literature search was conducted and how it was narrowed down. The second component is a bibliometric analysis of the identified literature described in section 3.2. The third component is the concept-centric analysis based on [44]. The results of this analysis are presented in Section 4.

A. Data Collection

The literature review was conducted using the main elements of the evidence-based approach: Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) Protocol [45, 46]. The data collection was administered using a four-step process (Figure 1) to ensure objectivity, transparency and reliability [47]. Consistent with prior review studies in information systems research [e.g., 48], we conducted our search in the Scopus database. This database was chosen as it provides a comprehensive database of information systems, computer science, artificial intelligence conference proceedings and journals. Moreover, these databases index other potentially relevant databases for our search, such as ACM, IEEE and Springer.

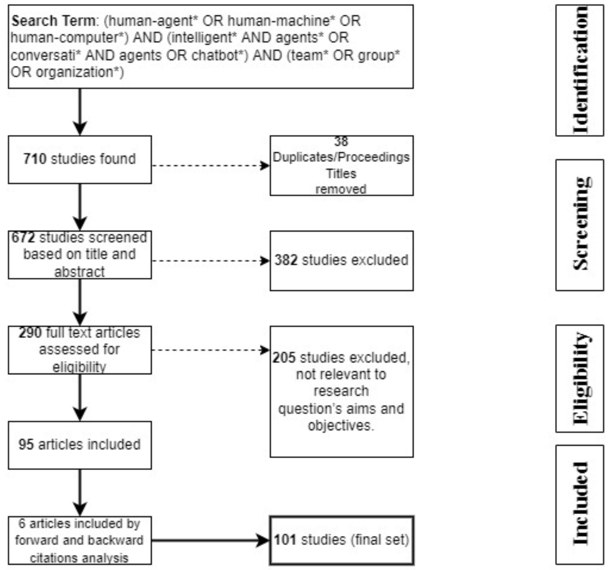

Figure 1. Article identification and selection process

In the first step, we identified the keywords for our search by focusing on the seminal publications in the field. These keywords, depicted in the first box of Figure 1, were adapted to align with our research objectives. The search included different types of academic publications such as journal articles, conference papers, book chapters, and workshop papers. We excluded all non-academic publications. We confined our search to publications from 2004 onward, as autonomous and multi-agent research communities mainly began research in understanding IAs' role in teams and developing automated systems with sophisticated team player qualities in the early 2000s. Two of the most cited publications [14, 18] in the field are from 2004. The initial search resulted in 710 articles. After removal of duplicates and entries that were not research output, we screened 672 articles by reading the titles and abstracts of these papers. Any case that was not clear was discussed amongst the research team, and inclusion/exclusion decisions were made together.

In the third phase of the process, we assessed the remaining 290 articles for full-text eligibility. In this step, we excluded 205 articles that did not fulfill the criteria for HATs that we defined in Section 2.2. This led to the exclusion of articles that focused on agent-only teams or only dealt tangentially with human involvement. Studies that solely explored interpersonal dynamics between a human and an agent—such as affection or gaze—were also omitted. Notably, a significant portion of these studies originated from the healthcare sector. These studies were excluded as they do not meet the working definition of a HAT (i.e., no common goal and not performing organizationally relevant tasks). Subsequently, a thorough review of the remaining studies (N = 95) led to the inclusion of 6 additional papers based on cross-references. This final body of literature for our review amounted to 101 articles dating from 2004 to 2021.

B. Bibliometric Descriptors

The literature on HATs has been steadily growing over the last two decades, with a marked surge in recent years, as seen in Figure 2. In terms of research outlets of the reviewed publications, most of the papers were published in conference proceedings (51 papers, 50.5%), followed by journal articles (37 papers, 36,6%), workshops & symposiums (11 papers, 10.9%), and book chapter (2 papers, 2%). The preponderance of conference proceedings as the primary outlet underscores both the emergent nature of Human-Agent Team (HAT) research and the exploratory scope of existing studies, many of which present work-in-progress or preliminary findings. This trend suggests that the volume of literature on this subject is poised for further growth.

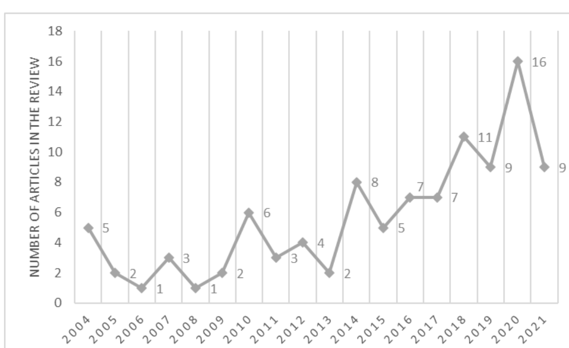

Figure 2. Development of HAT literature over the years

The reviewed papers included a diverse mix of empirical (n = 68, 67.3%) and conceptual (n = 33, 32.7%) research. Notably, the military and defense sectors dominate the empirical landscape, accounting for over half of such studies. Gaming and pedagogy follow as the next most prevalent domains, the three domains collectively making up over 70% of empirical research. The remaining domains, such as rescue operations, are less represented. Methodologically, the majority of studies (n = 46, 67.3%) employ experimental designs, while 25% focus on implementation and prototypes (n = 17). This suggests a design-centric research orientation aimed at advancing agent technology for HATs. Three papers adopted the case study approach (4.4%) and two papers utilized interviews (2.9%).

IV. FINDINGS

Most of the traditional research on teams (human-only) has predominantly been guided by IPO (Input-process-outcome) and lately by IMO (Input-mediating mechanisms-output) frameworks. However, as the nature of teams evolves, teams are now widely viewed as dynamic, multilevel, and complex systems [25], which can be attributed to factors such as team members' characteristics (e.g., attitudes, behaviors, and cognitions), interactions, how interactions evolve, and how contexts change [49]. Mathieu, et al. [50] proposed a new research framework to cater to the temporal nature and dynamic, multilevel, and complex view of the teams. This framework conceives mediating mechanisms, and structural and compositional factors as overlapping and co-evolving aspects in teams. Following Mathieu et al.'s framework, which accounts for these complexities, this review employs a concept-centric approach [44] to analyze HATs. Our analysis matrix, based on predefined units from Figure 3, serves as the foundation for this review and subsequent analyses of the highly dynamic and complex nature of HATs.

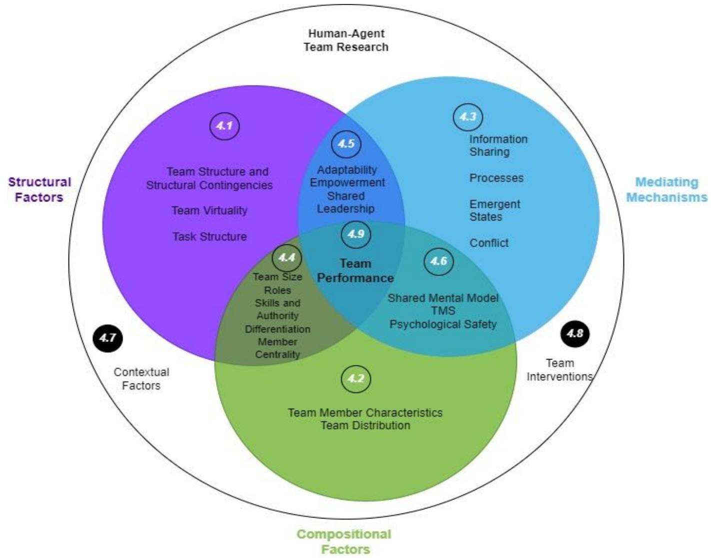

Figure 3. Teams Framework

A. Structural Factors

Structural factors encompass both team and task structure. Mathieu, et al. [25] define team structure as the "*means by which the team breaks down a large or complex task that exceeds the capacities of any one individual into smaller parts" (p.455).* Means include the formal structure of the team and the implicit structure concerning interdependencies among team members, tasks, and outcomes. Team virtuality adds a third dimension to the structure. In our review, we identified 20 studies that either focus on or incorporate these structural factors as critical elements in HATs. These studies primarily explore function allocation, various team structures (e.g., functional, divisional), task distribution, and the role of virtuality in HATs.

Team Structure and Structural Contingencies

Research underscores the significance of team structure in influencing various teamwork outcomes such as cohesion, trust, interdependence, and confidence within HATs [9]. A system design method has been proposed to break down the task goals and capabilities of both humans and IAs to establish a robust team structure [51]. Contingency theory has also been adopted to suggest that external factors determine the team structure, implying no one-size-fits-all structure [52]. Teams that can adapt their structure to the uncertainties of tasks and environments are more likely to result in better team performance. Regarding the specific structure, empirical studies indicate that functional HATs generally outperform divisional teams, except in uncertain conditions [53, 54]. Gao's experiment revealed that a shared pool team structure resulted in lower workload ratings compared to a sector team structure, albeit without a significant difference in task performance [55]. In the shared pool structure, human participants shared the responsibility of coordination with all agents, while in the sector structure, human participants were responsible for coordination with their sector (human participants were responsible for their own allocated agents).

Function allocation, defined as “the design decision in which work functions are assigned to all agents in a team, both human and automated” [56], is crucial for effective team coordination. Despite its importance, this area remains underexplored. Existing research primarily focuses on design requirements and measurements for effective function allocations, such as workload, interruptions, and stability of the human work environment [57]. Function allocation is a challenging aspect in the design of HATs as many issues arise only in actual operations and cannot be predicted by simulation. Moreover, concerns and unpredictability inherent in human-agent interactions further complicate the challenge of effective function allocation [56]. In the current research, function allocation has only been studied in the context where humans are responsible for function allocation.

Task Structure: Scope, Complexity, and Interdependence

The team structure is contingent on the task structure. When task scope and complexity increase, a team requires more complex configurations to address task demands. Few studies have focused on task scope, complexity and interdependence. Smets, et al. [58] argue that for the effectiveness of HATs, organizational structure should not impede the autonomy of the participating agents and agents should be able to disobey a policy. Agents who are not bound to predefined policies all the time are essential in complex task environments, as the changing scenarios might not be covered by the policies. In response to task complexity, Pico-Valencia, et al. [59] developed an ontology for HATs using a human-agent collective approach to optimize tasks with agile teaming sub-ontology. Johnson, et al. [60] caution that increasing agent autonomy without addressing task interdependence can compromise team performance.

Research on task allocation within HATs remains sparse [61]. Flushing, et al. [62] propose a task allocation solution for HATs with multiple agents, specifically designed for long-duration mission scenarios requiring shift work. Dynamic tasks involving spatial and temporal complexities, such as disasters, present another challenge for task allocation. Khani, et al. [61] developed a dynamic task allocation algorithm to allocate tasks of human-agent rescue teams to improve rescue time and space. Waa, et al. [63] introduced the concept of team design patterns for dynamic task allocation in HATs in the context of moral decision-making. They identified different team patterns for moral decision-making, identifying various patterns ranging from human-only to autonomous decision-making by IAs.

Team Virtuality

The concept of team virtuality explores alternatives to face-to-face interactions among team members. Research in this domain primarily focuses on the deployment of virtual agents and mixed-reality environments within HATs. Van Diggelen, et al. [64] have formulated an approach that leverages a virtual learning environment, wherein IAs contribute to team training. Barange, et al. [65] have investigated both task-oriented and pedagogical behaviors of agents in virtual environments, aiming to enable proactivity and improve engagement. Similarly, Barange, et al.

[66] developed an architecture for agents operating in collaborative virtual environments with the ability to coordinate their activities using natural language communication. Recent advancements also include research on hybrid physical-virtual environments; for instance, Phan, et al. [67] designed a testbed for experimenting with geographically dispersed HATs, showing that a wide variety of physical spaces could be interconnected for collaboration.

B. Compositional Factors

Team composition, which concerns team member characteristics and the impact of diverse characteristics on team processes and outcomes [50], has been relatively underexplored in the context of HATs. Our review identified seven studies focusing on this aspect. Johnson, et al. [68] developed a taxonomy for human-agent interactions within military settings, emphasizing the interplay between structural and compositional factors like skill and authority differentiation. However, they fell short of specifying which member characteristics warrant attention. Our review found that the limited team composition research has considered member attributes and functional diversity in HATs. Hanna and Richards [69] examined the influence of personality traits on team productivity, while Silva, et al. [7] empirically demonstrated the advantages of hybrid HATs in role-playing game scenarios, implicitly showing the benefits of team diversity. Their findings suggest that hybrid teams outperform human-only teams in task completion and are rated higher in terms of satisfaction, dependability, and reliability. This is corroborated by studies that have explored functional diversity, such as expertise, as a determinant of improved work allocation [70, 71]. More diversified teams performed better; however, the context may moderate the relationship [70]. Li, et al. [72] further substantiate this by showing that complementary policy adaptation enhances team performance. Damacharla, et al. [73] have outlined guidelines for effective HAT composition, including role identification, rule establishment, and specialized training for human members, etc.

C. Mediating Mechanisms

Mediating mechanisms serve as the linchpin that elucidates the intricate relationships among team composition, structural factors, and team outcomes. It explains how and why teams operate differently, given similar team compositions, and task, technological, and organizational structures. Information sharing, emergent states, and team processes underlie mediating mechanisms. Scholarly attention to these mediating factors is on an upward trajectory. Our comprehensive review unearthed 36 studies that delve into these pivotal mechanisms.

Information Sharing

Information sharing in HATs is significantly reduced compared to human-only teams [64]. For effective teamwork and to maintain common ground in teams, team members should actively share relevant pieces of information. Demir, et al. [74] compared the information sharing in HATs to human-only teams and found that HATs had lower levels of information sharing in terms of pushing and pulling information than the all-human teams. In their study, pushing information involved sharing general status updates with team members, and suggestions and information about planning ahead. Pulling information involved requesting information before acting and inquiring about the status of other team members in the task. They argue that the member of HATs has insufficient need anticipation ability due to lower levels of pushing information compared to members of the all-human teams. The timing of the information sharing by agents has also affected the performance of the HAT and the behavior of the human actors within this team. Therefore, it is suggested that the timing of information sharing by IAs be manipulated to modulate human engagement within a HAT [75].

Replacing humans with agents that respond faster improves team performance in time-constrained environments. Goodman, et al. [75] argue that the development of further awareness of the role of agent timing within dynamic team environments can positively influence the design of future HATs. Research has been undertaken to improve information sharing in HATs. Yazdani, et al. [76] developed an infrastructure that enables IAs to share information and support other teammates in performing joint actions. Cook, et al. [77] investigated the impact of the visual features intended to improve information access in HATs. Hanna and Richards [78] emphasized the importance of designing IAs capable of using multiple methods of communication (verbal and non-verbal) with humans. The results from their experiments show that multiple methods of communication impact the overall performance of human-agent teamwork. Moreover, non-verbal communication from IAs was more effective than verbal communication because of the limited natural language processing abilities of IAs.

Technologies that help agents in sharing information with human team members, such as user displays that are tailored with context-specific information foster the development of common ground among team members in HATs [79].

Schaefer, et al. [79] examined the advantages and limitations of user displays to communicate an IA's decisions, intent and the factors considered by the agent in coming to a decision. Their research suggests that custom-designed user displays, tailored to the specific dynamics of the team, can significantly enhance the ability of IAs to convey their intentions. When integrated with conventional audio-visual communication tools, these displays can further optimize collaborative efforts. The study scrutinized four distinct types of user displays, each suited to different team configurations. For instance, one such display was engineered for teams comprising a single human and a single agent, enabling the agent to transparently communicate its decision-making process. Flathmann, et al. [80], on the other hand, introduced a comprehensive framework that accommodates both natural language and data-centric communication. This multi-layered framework consists of IA interaction, human integration, and a layer of supporting technologies, thereby ensuring seamless collaboration between human and agent team members.

Team Processes

Team processes reflect the interplay of team members' "cognitive, verbal, and behavioral activities directed towards organizing taskwork to achieve collective goals." [25] These processes are categorized into three dimensions: transition, action, and interpersonal processes [81]. Transition processes refer to the transition between previous taskwork and upcoming work. Examples of transition processes include mission analysis, goal specification, and strategy formulation. Action processes occur during the execution of taskwork, including monitoring of progress, system monitoring, team monitoring and coordination. Interpersonal processes are related to teamwork, encompassing conflict management, motivation, and affect management. Wynne and Lyons [82] argue that these team processes will significantly influence perceptions of IAs, whether viewed as partners or tools. Bradshaw, et al. [83] advocate for more adaptive team processes needed for HATs. Instead of adhering to policies set for the system, they suggest enabling IAs to reason about relevant trade-offs and take appropriate measures in situations for enhanced team performance.

Research on human-agent transition processes remains scant, although Van Diggelen, et al. [84] introduced reusable team design patterns to address the gap. Team design patterns, consisting of behavior patterns, positive and negative effects, conditions to use, and design rationale, can inform team members to cope with common challenges arising from team transition processes. The authors noted that more research is needed for artificial team members to recognize team design patterns and adapt their behaviors.

Coordination and collaboration are important facets of the action and interpersonal processes. The concept of collaboration is the means of realizing HATs to assist with decision-making and overcome the physical separation between humans and agents. Schneider, et al. [85] developed a framework for understanding coordination in HATs and suggested while designing IAs for HATs; designers should consider coordination mechanisms (i.e., tools used by the team to coordinate, such as plans and expectation-setting used in preplanning and debriefing), moderators of coordinating behaviors (e.g., training and team building), and internal models (e.g., shared mental models) used to coordinate. Coordination in HATs should be considered across the full spectrum, ranging from fully explicit to fully implicit. Multiple ontologies for coordination and collaboration have been proposed by Pico-Valencia, et al. [59] to help agents understand taskwork and teamwork and facilitate action and interpersonal processes.

The specific ways that humans and agents interact with each other, known as interpersonal processes, are key to how well they work together in HATs. Neef [86] has delineated a comprehensive taxonomy for HAT collaborations, identifying eight distinct types based on the nature of collaboration and coordination mechanisms. Four of these types — static division of labor, adjustable automation, mixed-initiative collaborations, and adaptive automation — are intrinsically linked to task design and the interpersonal dynamics between human and agent team members. Extant research on interpersonal processes has mainly focused on mixed-initiative collaborations [58, 66, 69, 87-90], where humans and agents negotiate who will do what [86]. Other types, such as static division of labor [9, 74], adjustable automation [83, 91] and adaptive automation [92], have not received considerable attention. Static division of labor implies that there is a permanent division of tasks between humans and agents. *Adjustable automation* means that the level of autonomy can be adjusted by human team members. *Adaptive automation* is the situation where the agent can alter its level of automation in response to the performance and state of the human operator [92]. One such example is the communication breakdown between humans and agents during a team task studied by Yusuf and Baber [93] in the scenario of forest fire searching by a team of humans and an IA. As HATs evolve, more research needs to be tailored to these three types, particularly adjustable and adaptive automation, given their increasing prevalence in emerging technologies.

Emergent States

Emergent states are “cognitive, motivational, and affective states of teams [that are] . . . dynamic in nature and vary as a function of team context, inputs, processes, and outcomes.” [81]. Trust and member likeness (e.g., human-like decision-making for IAs) received considerable attention in HAT research; however, it has mainly focused on human trust in IAs [94]. Hou's IMPACT model [95] delineates six pivotal elements—Intention, Measurability, Predictability, Agility, Communication, and Transparency—that underpin human trust in IAs. Empirical studies corroborate that trust enhances the congruence of mental models between humans and IAs [96]. Drnec, et al. [88] found that trustworthiness tends to be improved and workload reduced when humans’ psychophysiological signals were incorporated to help build shared mental models in HATs. Fan et al. [97] conducted research that demonstrated how developing an understanding of when to trust and when not to trust the recommendations of IAs can lead to better decision-making, situational awareness of the critical issues associated with agents’ errors, and trust in the agents. This, in turn, helps establish better trust in IAs. Ulfert and Georganta [94] offer a comprehensive model of team trust, incorporating both human and IA perspectives, and identify ability, integrity, and benevolence as antecedents. Trust repair mechanisms, such as effective explanations and expressions of regret, are posited as essential for sustaining inter-member trust after a mistake by offering an effective explanation of the issue and expressing regret [98]. On the other hand, human team members' over-trust in the IAs leads to complacency [99]. Over-trust is the condition where an individual, either intentionally or out of habit, places greater trust in another person or entity than is justified based on a rational and unbiased evaluation of the circumstances [100]. The examination of over-trust remains predominantly unexplored.

Transparency is crucial for building trust in HATs. When IAs elucidate their reasoning processes, they not only bolster human trust [101, 102] but also enhance group identification [102], resulting in improved team performance. Chen, et al. [26] argue that as agents are transitioning from tools to artificial teammates, there needs to be bidirectional transparency where both humans and agents understand each other's decision-making processes. To facilitate this, they introduced control mechanisms that allow humans to provide input to agents [26]. Similarly, Calhoun, et al. [103] used a chat box for the operator to input information to the agent. A simple addition of a conversation channel (chat box) between operators and agents can increase perceived transparency. Stevens and Galloway [104] propose a measure of uncertainty, designed to empower IAs with the capability to discern whether a human team member or the entire team is grappling with uncertainty, thereby signaling the need for enhanced IA transparency.

There has been limited research on mediating mechanisms, such as conflict resolution, within the interpersonal dimension of HATs. Existing studies predominantly concentrate on resolving conflicts among human team members [53], leaving the dynamics of conflict resolution between humans and IAs largely uncharted territory.

In the context of emerging states, development in IAs has been restricted in terms of studying human likeness in agents. Wynne and Lyons [82] introduce the concept of autonomous agent teammate-likeness (AAT) as perceived by a human operator. They suggest that perceived AAT be positively related to HAT performance/effectiveness. AAT can be fostered when agents show transparency [102], especially when the agents utilize a tit-for-tat or an individualistic strategy instead of a cooperative strategy while interacting with human team members. Wang's simulation study [105] reveals that agents employing regret-based decision-making, which is more human-like decision-making (member likeness), may compromise team efficiency but enhance human-agent rapport.

D. Compositional and Structural

Compositional and structural factors represent variables that overlap with both compositional and structural features, such as skills and authority differentiation [25]. In the context of HATs, team roles [71, 106], team size [53, 54, 107], and skill and authority differentiation [107] have been studied.

Team roles are defined by the characteristics of the position itself, or by the person in the given position [108]. Figueroa, et al. [106] equipped IAs with abilities to identify team roles based on team member interactions, aiming to maintain an adequate balance of roles in teams. Schulte, et al. [71] further studied the core and peripheral roles of IAs within HATs, offering design patterns to specify responsibilities for those roles.

Authority and skill differentiation are both vital issues in HATs. While humans predominantly hold decision-making power in current HATs, studies like that of Paruchuri et al. [107] demonstrated the negative impacts of human biases on resource allocation; decisions made by IAs for resource optimization proved to be effective for medium to large-sized teams. This suggests IAs may be suitable to hold authority for specific task situations. Authority differentiation, "the degree to which decision-making authority is vested in one single individual or is distributed among team members" [50] is, therefore, a factor to consider when composing a human-agent team. Skill differentiation has been shown to affect the performance of HATs, with empirical evidence suggesting that teams comprising skilled human members are less susceptible to inappropriate IA recommendations [97]. Allocation of experts seems beneficial for human-agent collaboration, where IAs can focus on what they are good at.

When it comes to team size in HATs, research has so far mainly focused on scenarios with a single human and single agent. While some studies have ventured into exploring larger team configurations [e.g., 53, 54], coordination between members in these studies remains rudimentary. According to Neef [86], the coordination dimensions proposed include standardized, human, controlled, joint and agent-controlled coordination. Most research to date on HATs involves humans in command, as shown in Table 1. The research so far has not considered an agent in command scenarios in HATs. Many studies do not explicitly mention who the leader is in a team, barring exceptions such as [70], but it is implied that a human is in command of the team. Mixed initiative coordination (situation-driven control, hybrid command) is mainly studied in the space context, with most research in this category related to experiments for human-agent missions in space. The reviewed articles included only two studies that had situation-driven control coordination and one study with hybrid command.

Table 1. Types of coordination in HATs

Standardized Co-ordination	Human Controlled Coordination	Joint Coordination	Agent Controlled Coordination
Situation Driven Control: function allocation between agents and humans in accordance with situations [56, 57]	Human in Command • 1 human and 1 IA [71, 79, 96, 97, 101] • 1 human an 2 IAs [105, 109] • 3 humans and multiple agents in large teams [110] • Multiple humans and 2 IAs [70] • 2 humans and 2 IAs [60, 76]	**Hybrid Command** independent human and agent with a common main goal but different sub-goals [79]; some	Agent in command (i.e., agent as a team leader)

	• 3 humans and multiple agents in large teams [55] • 1 human and multiple agents [26, 53, 77, 111]	processes are managed solely by IAs and some processes require approval from humans (Wright et al., 2014)	

E. Structural Factors and Mediating Mechanisms

Structural and mediating variables simultaneously represent part of structural team features and the mediating mechanisms [25]. The research on structural and mediating factors is not well established in HATs and has scarcely dealt with team adaptability and shared leadership. Other structural and mediating variables, such as boundary spanning and team empowerment, are mainly unexplored so far.

Previous research on team adaptability has primarily focused on the adaptability of IAs. Specifically, researchers have studied the concepts of agent autonomy, adjustable autonomy, and policy adaptation in HAT research. Adjustable autonomy, for instance, enables agents to assume control over resource-intensive tasks when human members are overwhelmed, thereby allowing humans to focus on tasks where a human's role is indispensable [92]. Wright, et al. [110] categorize automation levels into Fully Autonomous and Semi-Autonomous, with the former capable of adapting to the environment and assisting the team in accomplishing tasks. Preliminary work by Tweedale [112] aims to enhance automation levels by developing interoperable and scalable cognitive architectures. These architectures are designed to support multiple agents in complex environments by incorporating rules and functionalities. Li, et al. [72] found that teams with adaptive agents outperform those with static agents, particularly in dynamic settings. In highly dynamic environments, mutual adaption based on the characteristics of other team members improves team performance in HATs [72].

Shared leadership research in HATs deals with shared responsibility and leaderless teams where influences are distributed to humans and agents. Van Diggelen, et al. [90] propose a solution for a leaderless HAT with the introduction of IA as an ad-hoc leader for a limited time based on the requirements or needs of the team. This can create a peer-to-peer team structure, devoid of permanent leadership, where agents collaboratively formulate plans and strategies.

F. Composition Factors and Mediating Mechanisms

The interplay between mediating mechanisms and team composition is represented by variables that embody both these factors or the interconnection between them. Key variables include psychological safety, transactive memory systems, shared cognition and shared mental models. Our review identified 38 studies that predominantly focus on these variables. Shared cognition and transactive memory systems have been somewhat explored in HATs, but we found no research related to psychological safety.

Shared Mental Model

Shared mental model (SMM) refers to a shared understanding of team tasks, roles, goals, and individual and team abilities [25]. In HATs, when IAs have a grasp of human team members, they can provide accurate and timely support, resulting in reduced human cognitive load and better team performance [92]. Many studies on HATs have found a positive correlation between the development of an SMM between team members and team performance [113-115]. However, there is still a lack of consensus among researchers on whether teamwork (interpersonal requirements, such as an understanding of team member skills) or taskwork (e.g., an understanding of common work goals and performance requirements) SMM is more strongly associated with team performance [113].

Several studies have contributed to the development of agents for enhancing SMM. van Zoelen, et al. [116] developed IAs that employ proactive communication strategies that evolve as they learn from human team members. Barange, et al. [87] found that proactive agents, not only learn human members' beliefs from dialogues but also anticipate human members' needs, accelerate the development of SMM and reduce humans' efforts to share knowledge. Schneider and Miller [115] took it a step further by creating IAs that maintain a computational representation of human intent for multi-agent teams. This semantic representation of human intent in a team can facilitate an improved understanding for both humans and IAs. This was expanded upon by Schneider, et al. [117], who captured the changing intent of the human members during task execution and used machine learning to update this understanding in real time, leading to more effective task execution. Hughes, et al. [118] found a similarly positive effect on team performance, with IAs capturing the changing intent of human team members. Jonker, et al. [114] build a mental model ontology by investigating which concepts are relevant for shared mental models and modeling how they are related by employing Unified Modelling Language.

Transactive Memory System

Transactive memory system (TMS) is defined as a "collection of knowledge possessed by each team member and a collective awareness of who knows what" [25]. In HATs, the TMS has been mainly explored through the lens of situation awareness (SA). Enhanced understanding of each team member's situational awareness—be it human or autonomous—amplifies individual efficacy within the team [79, 119]. In Mercado et al.'s [41] experimental study, the situation awareness-based transparency (SAT) model supported by agents' transparent reasoning and recommendations improved performance effectiveness without incurring additional time or workload costs. The information that IAs should convey to human team members for them to have proper SA of the agent in its tasking environment, includes the agent's planning process, the rationale of suggestions (e.g., feasibility, trade-offs between alternatives), the to-be situations (e.g., expected outcomes, the likelihood of errors) [21, 120]. Roth, et al. [121] corroborated that increased agent transparency positively influences SA and overall HAT performance, provided the presentation and identification of transparency information aligns with human factors principles. However, indiscriminate sharing of all transparency information by IAs can lead to cognitive overload of human team members [122]. For example, in specific contexts, conveying only the objectives proved more efficacious than detailing both goals and beliefs [111]. Recent advancements include the design of IAs for better SA. Ding, et al. [123] developed an IA to accelerate human-agent collaboration in tactical and strategic battlefield decision-making by improving the SA of the pilot. Das, et al. [124] developed a framework for the rapid development of SA in unknown and/or dynamic environments. Besides the agent's awareness, successful operations require human members to have SA of both the changing situation and the IAs' decision-making processes [125].

G. Contextual Factors

Mathieu, et al. [126] classify contextual factors into internal and environmental factors. Internal factors originate from within the team's organization (e.g., organizational culture and leader exist), whereas environmental factors originate outside the organization (e.g., national culture, industry environments). These contextual elements can either augment or impede team processes and shape the values—such as efficiency versus creativity—that teams prioritize. While HATs are also subject to these contextual factors [63], existing research has so far mainly considered contextual influences emanating within the team, and the effect of the environment is less explored. Our review revealed a conspicuous absence of studies that specifically investigate the impact of contextual factors on HATs.

H. Team Interventions

While team interventions like team building, training, and the utilization of preparatory tools to facilitate role allocation and work processes can pose positive impacts on teams [25], our review found that only five studies focus specifically on team interventions in HATs. Walliser, et al. [9] empirically demonstrated that team-building interventions focusing on social interactions help connect team members (both humans and IAs) and significantly impact team performance. This study also highlighted a need for comparative research on different team-building interventions (e.g., social interaction focused, team coaching, team training). Phan, et al. [67] went a step further by creating a test bed specifically designed for training HATs, aiming to improve human-agent interactions and help humans acclimate to working with IAs. Van Diggelen, et al. [64] also contributed to this area by developing an IA designed to train human team members, with the primary objective of enhancing human participants' team skills. Johnson, et al. [127] conducted experiments on entrainment-based coordination training (i.e., training for "a spontaneous coupling and synchronization of the timing and content of teammate communication") and trust calibration training in HATs, revealing improvements in task efficiency and trust building compared to the control group. Brewer, et al. [128] investigated the role of after-action reviews in HATs, suggesting that these reviews can be instrumental in enhancing communication, shared situational awareness, and trust among team members.

I. Team Performance

Measuring the performance of HATs is a complex task that can be approached in various ways. Common models often look at individual contributions, the overall team setting, and both individual and collective group performance [73]. Our review has identified as many as 28 different dimensions used to measure HAT performance, including commonly used measurements such as team effectiveness, task performance, mission performance, mission success, human workload, average efficiency, and performance perception. Notably, there are no standard models to evaluate HATs. This highlights the need for the development of standardized evaluation methods to facilitate effective learning and ongoing improvement in HATs. Damacharla, et al. [73] suggest that a well-rounded evaluation of HATs should include three types of metrics: those that measure human performance, machine performance, and overall team performance.

J. Summary

HAT research has been mainly concentrated on the mediating mechanisms, compositional and mediating, and structural factors, with a specific focus on certain areas. Within the mediating mechanisms, information sharing has been a focus area. The research on information sharing has considered the effect of verbal and non-verbal communication within the HATs and recommends non-verbal communication as the more effective method of communication. Moreover, the timing of agent-initiated information dissemination has been identified as a critical design consideration. Trust and member likeness (e.g., human-like decision-making for IAs) have also been extensively studied. Transparency has a positive effect on human's perception of trust, group identification, and human likeness. Studies have shown that when agents are transitioning from tools to artificial teammates, bidirectional transparency is necessary to support teamwork paradigms. Human-like decision-making (member likeness) can lead to suboptimal teamwork (in terms of observation cost and workload), but better acceptance by the human team members during collaboration.

In the compositional and mediating factors, shared mental models and transactive memory systems have emerged as significant areas of inquiry. Teams incorporating IAs with shared human cognition have demonstrated superior performance. The situation awareness-based transparency model exemplifies a cognitive framework that enhances performance without incurring additional time or workload costs.

Regarding the structural factors, function allocation remains pivotal. When assigning tasks and responsibilities to IAs, factors like task scope, complexity, and team virtuality warrant careful consideration. Moreover, a nuanced balance between agent autonomy and task interdependence is recommended. As HATs increasingly become integral to organizational structures, there is an urgent need to elevate our understanding of HAT dynamics to the level of a human-only team. Table 2 provides a summary of the current literature's focus and highlights the challenges that lie ahead.

Table 2. Summary of the findings from the literature

Research Area	Main Focus	Challenges and Gaps
Structural factors	Function allocation [56], types of team structure [53, 54], task allocation [61, 62], and virtuality in HATs [67].	• Effective function allocation considering the unpredictable and evolving nature of human-agent interactions. • Absence of recommendations on optimal team structures. • Further exploration required for task scope, complexity, and interdependence. • Limited research on virtuality in HATs.
Compositional Factors	Team member characteristics [69, 72] and functional diversity [70, 71]	• Further exploration is needed on team composition factors in the context of HATs. • Limited investigation of specific team member characteristics.
Mediating Mechanisms	Information Sharing [74, 75], Team Processes [82, 90], Emergent States [88, 98]	• Limited research on information sharing in HATs. • Need for more research on the timing of information sharing by IAs. • Examination of over-trust remains predominantly unexplored.

Compositional and Structural	Team roles [71, 106], team size [53, 54, 107], skill and authority differentiation [107]	• Limited investigation of skill differentiation. • Limited research on larger teams and coordination dimensions. • Limited research on team adaptability and shared leadership
Structural Factors and Mediating Mechanisms	Team adaptability [72, 92] and shared leadership [90]	• Research required on boundary-spanning, and team empowerment factors
Composition Factors and Mediating Mechanisms	Situational awareness (Jiang et al., 2021; Schaefer et al., 2017), shared mental models [113-115]	• Limited research on the development of IAs for enhancing situation awareness of the team. • Few studies have focused on frameworks for the HAT for better situational awareness in unknown and/or dynamic environments.
Contextual Factors	Internal contextual factors [63]	• Most research has focused on internal contextual factors, with less exploration of the effect of environmental factors. • Absence of research with an exclusive focus on the examination of contextual factors
Team Interventions	Team building [9], team training [127]	• Limited research on the effects of team interventions in HATs. • Need for comparative research on different team-building interventions.
Team Performance	Various dimensions used to measure team performance in HATs.	• Lack of standardized approaches and models for the evaluation of HAT performance.

V. FUTURE RESEARCH OPPORTUNITIES

Mathieu's framework unveils intricate dimensions that pave the way for interdisciplinary research avenues, particularly in understanding the dynamics of HAT. In this section, we discuss potential interdisciplinary pathways in the areas of mediating mechanisms, compositional factors, and structural factors.

A. Mediating Mechanisms-related Factors

Team mediating concerns raised in this analysis, in particular the timing of information sharing, transactive memory, and methods or channels of communication, provide an opportune avenue for multidisciplinary perspectives on HATs to better understand the interpersonal and sociocultural context of these interactions. The field of Human-Robot Interaction (HRI) in particular offers multi-disciplinary insights and critiques on intercommunication, reciprocity and cooperation between humans and agents.

As an emergent phenomenon, human-agent interactions are still in the process of being defined and have the potential for a significant impact on social life. Our findings in 4.3.3 show that IAs are still novel and transitioning from tools to teammates. This is a significant challenge that has philosophical and sociocultural ramifications. The term ‘social robot’ is a prominent descriptor for both physical and screen-based agents that offer social interaction. Hakli and Seibt [129] have stated, “Social robots, if used pervasively in society, will change the fabric of human social interactions more profoundly than any other technology before” (p.v). Philosophical studies of IAs interrogate their ontological status, asking fundamentally, how we as humans see ourselves positioned relative to IAs and vice versa. The emerging field of ‘Robophilosophy’ encompasses such investigations, aiming “to come to terms with the very idea of artificial social agency” (p.v) by exploring “whether the notions of sociality and normativity, the hallmarks of human-human interactions, can be suitably extended to capture the phenomena of human interactions with so-called “social” robots.” [129]

Linguistic and communication studies contribute insights into the language and conversational mediation of interaction with IAs. Our findings in 4.3.1 highlight the critical role of timely and adaptive information sharing in enhancing the quality of human-agent collaboration. Modes and styles of communication could support information sharing by building positive rapport. To do so, it is necessary to consider the conventions of language within human-agent interactions. Linguistic exploration of robot interactions posits whether, when addressing agents, we talk *to*, or *about* them [130]. Close examination of language and conversational elements reveals the relationship between humans and agents. As Coeckelburg [130] reminds, “Our ‘robot talk’ is not neutral but interprets and shapes our relations with robots; it has a hermeneutic and normative function.” (p.64) Whether an agent is an ‘it’, a ‘they’ or ‘you’ speaks to its place relative to a human team member. Future research could consider the impact that pronouns, or a third- or second-person perspective has on teamwork and cohesion. Sandry [131] calls for a wider understanding of communication with robots, beyond privileging anthropomorphic interactions. While effective communication is often a matter of sharing common ground, “robots are intriguing communicators because they appear in such a variety of forms” (p.2).

Information sharing and trust are also impacted by social cues. The concept of polite computing [132] and human-computer etiquette [133] provide cultural and behavioural perspectives on an agent’s perceived display of ‘memory’, or timing of communication. Polite computing outlines the behavioral norms required of agents if they are to be accepted in social interactions. Whitworth [132] finds that politeness suggests consideration and choice, while impoliteness is characterized by dismissiveness, lack of choice, and forgetfulness. Whitworth’s seminal example is Microsoft’s Mr Clippy help agent, an infamously derided user interface. Clippy was rude, because it was ignorant, forgetful, domineering, and inappropriate. To Whitworth, politeness in computing leads to efficiency and aids security by engendering trust. This has relevance to our analysis in 4.3.3 showing that trust is incredibly important for HATs.

Art and design shape the appearance of agents. The experience of the visual interface or embodiment of the IA often precedes interaction, so appearance is arguably a formative moment of relationship building. Aesthetic design, therefore, is an area that could greatly impact the acceptance of agents as teammates, as discussed in 4.3.3. If an agent has a ‘face’ or is visually personified, a human teammate will relate differently than if interacting with a text-only agent [134, 135]. Chesher and Andreallo [136] argue that understanding faciality is a transdisciplinary endeavor encompassing philosophy, art, and science. Further, style is as important as specific features. Chesher and Andreallo [136] also contend that the face is particularly important as it plays a crucial role in how interactions with robots are mediated: “it is largely by reading the face that interactants will perceive the robot’s identity, character, style, communicative intent, emotion, and, indeed, its apparent virtuousness” (p.83). Also addressing appearance, Sparrow [137] argues that humanoid robots raise significant cultural and social tensions, as they are more likely to be ascribed with race, which ultimately leads to dangers in perpetuating stereotypes. Sparrow highlights that “the “default” race of humanoid robots today is indeed White” (p.544), and arguably perpetuates the racist view that human forms are associated predominantly with whiteness. Sparrow's work is a salient reminder that social and cultural studies provide crucial contextual understandings of human-agent engagements, particularly acknowledging that discreet interactions do not happen in a vacuum, but are informed by beliefs, norms, and values. As Julier [138], a design theorist, succinctly says: “No design object is an island. Rather, its meaning, function and value are dependent on a complex patchwork of other artifacts and people” (p. 14). Whether intentionally or not, humans will bring their life experiences to interactions with IAs, and this will shape how their relationships and teamwork unfold.

Another crucial aspect to consider is the ethical dimensions of HATs. Utilizing Floridi's concept of the 'infosphere' [139] as a lens, into HAT, ethical inquiries can be made into data privacy, transparency, and responsible information sharing between humans and IAs. Future research in this area could examine how ethical considerations manifest in the flow of information, ensuring that data shared and utilized respects individual autonomy and minimizes biases.

B. Structural-related Factors

Structural factors for HATs present multifaced challenges that call for a comprehensive and nuanced approach. Underpinning this inquiry is structural contingency theory, wherein team structure and task structure need to be configured corresponding to the task environments [52]. The theory is applicable in predictable work environments where standardized and formalized roles, responsibilities, rules, and procedures enhance mutual understanding of taskwork [140]. The alignment between team and task structures, therefore, enhances team performance [54]. However, as task uncertainty increases, greater coordination complexity demands more frequent communication among HAT members to adapt to changing conditions. Ongoing research is addressing this uncertainty by exploring the autonomy of autonomous agents [59] and dynamic task allocations [61], both of which offer promising avenues for future work.

Autonomy in HATs is premised on trust. Existing studies underscore the role of transparency in reasoning [101] and communication [103, 104] as key factors in fostering team trust. The burgeoning field of Explainable AI (XAI) offers promising avenues for future research in HAT settings. Beyond mere transparency, the quality of explanations provided by agent teammates is crucial for human comprehension [141]. Moreover, agents can gain trust by exhibiting [142] and Artificial emotional intelligence [143]. Emotional regulation remains a complex issue, particularly when agents' actions conflict with human expectations. Human team members can become emotional and resist working with IAs. Future research could explore strategies for early trust-building, emotional support, and empathy from agents. Ultimately, emotional bonds between agents and humans can help team identification and collaboration [144]. Additionally, the review reveals that team adaptability—dependent on organizational culture, flexible structures, and members' willingness to adjust [145]—has been relatively underexplored. The current research starts exploring dynamic task allocation, which is assigned to humans and agents corresponding to their skills and resources [61]. Furthermore, in response to changes, negotiation [14] and feedback [26] between agents and humans are essential for teams to maintain flexibility and adaptability. Both parties should be able to take the initiative, which can be oriented by agents or humans, change their behaviors, and achieve a team goal together [146]. As adaptation takes two to tango, future research can consider IAs' generativity [147] and improving IAs' sense-making ability using social and contextual knowledge [148], which goes beyond statistics-based sensemaking. Given the limitations of current technology, IAs cannot grow without human help. Quality control for inputs concerning agent development is essential to mitigate biases. Furthermore, we would be remiss to ignore changes required from human team members. It has proved that humans can be reluctant to change and fall into cognitive entrenchment [149]. Research from persuasive systems design [150] offers comprehensive design principles to boost human teammates' motivation and guide behavioral changes. Besides individual learning from humans and AIs, drawing on the "human-in-the-loop" perspective, building incremental and iterative feedback loops at the team level has the potential to ensure team adaptation at HAT [151]. From a theoretical standpoint, various types of learning cycles can be integrated into team learning frameworks to facilitate this adaptability [152].

C. Composition-related Factors

Team composition research on HATs is still largely in its infancy, predominantly focusing on team members' attributes and functional diversity. This leaves a fertile ground for future inquiries at the intersection of team dynamics and IAs. Firstly, the way team members behave towards each other is largely determined by surface-level attributes (e.g., age, race, gender). Once team members are familiar with such attributes, their collective dynamics could hinge on hidden assumptions relating to surface-level information about team members. How is an agent perceived by a human when it comes to easily detectable surface-level attributes, and what does it entail in the collective exchange of information for the team? This can be an interesting starting point to examine the impact of team composition within different human-agent settings.

Similarly, deep-level attributes that comprise a HAT have a long-lasting impact on team performance [153]. Values and attitudes are good examples of deep-level aspects that often shape team member interactions over time. While we are largely familiar with these psychological characteristics as applied to humans, it is imperative to understand how (if any) such areas are understood within an IA. Moreover, what are the implications on team performance when there is significant diversity in deep-level attributes within human-agent interaction?

Team composition can impact the affective states of teamwork [154]. The overall team's mood provides an illustration of an affective state. A team's mood is primarily shaped by the positive or negative predisposition of an individual's trait [155] and the spread of this individual mood through evolving interactions of the team members [156]. This complex interplay of team composition, dynamic affective states and resulting behavior of team members opens a critical area of inquiry when humans and agents strive for collective goals. Depending on the level of an agent's consciousness, will the team's affective states (e.g., mood) be a product of the human team members only? Or if an intelligent agent can also contribute to the mood. If the latter, how might the agent's presence affect the spread of positive or negative emotions within the team?

The context in which a HAT is operating will significantly determine the outcomes of team composition via behavioral processes. The presence of IAs within a team adds a layer of consideration for the work environment in terms of the nature of roles being held by team members at a given time as well as their corresponding network centrality [157], whether IAs should play informational or social roles and exert their influences [14]. This brings forth the question of the degree of autonomy when it comes to job design within a human-agent team. Holistically, it seems vital to examine the contextual determinants (external, internal (to a team) and psychological) having a varying impact on team composition attributes, which translate into behavior and performance of HATs. Another critical factor to consider in this regard is stress. While higher agent autonomy generally alleviates stress, some individuals have reported discomfort when agents operate at maximum autonomy, where the agent makes decisions without human confirmation [158]. This paradox may heighten stress levels, as humans grapple with the tension between relying on automation and retaining accountability. Separate research links high agent autonomy to a rise in technostress [159], suggesting that as agents become more autonomous, human stress levels may increase due to technological interactions. As agent autonomy grows, so does the potential for stress arising from technological interactions and decision-making processes. These complexities necessitate further studies to better understand stress factors in HATs.

The dynamic composition of HATs presents unique challenges, such as blurred team boundaries [160], changes in team membership and even multiple memberships. Such aspects would have direct implications on team composition. An example could be a change in membership where the incoming and outgoing team members hold diverse attributes toward working with agents within a team. Similarly, how does the learning attribute of an agent evolve with time when the membership is diffused in multiple teams? Coordination is particularly affected by these compositional shifts [161]. Consequently, future research could involve relative contribution models [162] in examining the dynamic composition of HATs.

VI. CONCLUSION

The research on IAs has evolved from being completely IA-design-centric to increasingly considering various socio-technical aspects of HATs. This paper draws on Mathieu's framework, concerning structural, compositional, mediating factors, and their interactions, to disentangle HAT dynamics. We suggest several potential ways forward and call for more research from multiple disciplines to contribute to the enhancement of HAT performance. As the future of work becomes increasingly dependent on effective HATs, understanding these dynamics is not just an academic endeavor but a societal imperative. It is our hope that the insights gained from this study will stimulate discussions around effective collaboration between humans and agents in the future.

REFERENCES

[1] T. Takko, K. Bhattacharya, D. Monsivais *et al.*, "Human-agent coordination in a group formation game," *Scientific Reports,* vol. 11, no. 1, pp. 1-10, 2021.

[2] A. Baird, and L. M. Maruping, "The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic IS Artifacts," *MIS Quarterly,* vol. 45, no. 1, pp. 315-341, 2021.

[3] S. Ahrndt, and S. Albayrak, "Joint human-agent activities: challenges and definition," *German Conference on Multiagent System Technologies*, pp. 105-112, 2016.

[4] S. K. Parker, and G. Grote, "Automation, algorithms, and beyond: Why work design matters more than ever in a digital world," *Applied Psychology*, vol. 71, no. 4, pp. 1171-1204, 2022.

[5] B. Colligan. "How the Knowledge Navigator video came about," https://www.dubberly.com/articles/how-the-knowledge-navigator-video-came-about.html.

[6] E. Fosch-Villaronga, P. Khanna, H. Drukarch *et al.*, "The Role of Humans in Surgery Automation: Exploring the Influence of Automation on Human–Robot Interaction and Responsibility in Surgery Innovation," *International Journal of Social Robotics,* vol. 15, no. 3, pp. 563-580, 2023.

[7] M. Silva, S. McCroskey, J. Rubin *et al.*, "Learning from demonstration to be a good team member in a role playing game," *FLAIRS 2013 - Proceedings of the 26th International Florida Artificial Intelligence Research Society Conference,* vol. 2, pp. 393-398, 2013, 2013.

[8] A. Deshmukh, S. A. McComb, and C. Wernz, "Agents as Collaborating Team Members," *M. P. Letsky, N. W. Warner, S. M. Fiore, & C. A. P. Smith (Eds.), Macrocognition in Teams*, pp. 107-25: CRC Press, 2017.

[9] J. C. Walliser, E. J. de Visser, E. Wiese *et al.*, “Team structure and team building improve human–machine teaming with autonomous agents,” *Journal of Cognitive Engineering and Decision Making*, vol. 13, no. 4, pp. 258-278, 2019.

[10] M. Ashok, R. Madan, A. Joha *et al.*, “Ethical Framework for Artificial Intelligence and Digital Technologies,” *International Journal of Information Management*, vol. 62, pp. 102433, 2022.

[11] Y. K. Dwivedi, L. Hughes, E. Ismagilova *et al.*, “Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy,” *International Journal of Information Management*, vol. 57, pp. 101994, 2021.

[12] S. Alon-Barkat, and M. Busuioc, “Human–AI interactions in public sector decision making: “automation bias” and “selective adherence” to algorithmic advice,” *Journal of Public Administration Research and Theory*, vol. 33, no. 1, pp. 153-169, 2023.

[13] C. Anthony, B. A. Bechky, and A.-L. Fayard, ““Collaborating” with AI: Taking a system view to explore the future of work,” *Organization Science*, in press.

[14] G. Klein, D. Woods, J. Bradshaw *et al.*, “Ten Challenges for Making Automation a “Team Player” in Joint Human-Agent Activity,” *IEEE Computer Society*, no. December, pp. 91-95, 2004.

[15] M. Georgeff, B. Pell, M. Pollack *et al.*, “The belief-desire-intention model of agency,” *International Workshop on Agent Theories, Architectures, and Languages*, pp. 1-10, 1998.

[16] J. M. Bradshaw, S. Dutfield, P. Benoit *et al.*, “KAoS: Toward an industrial-strength open agent architecture,” *Software agents*, vol. 13, pp. 375-418, 1997.

[17] G. Tur, A. Stolcke, L. Voss *et al.*, “The CALO meeting speech recognition and understanding system,” *2008 IEEE Spoken Language Technology Workshop*, pp. 69-72, 2008, 2008.

[18] P. Urlings, *Human–machine teaming*: University of South Australia, Adelaide, 2004.

[19] J. Allen, and G. Ferguson, “Human-machine collaborative planning,” *Proceedings of the Third International NASA Workshop on Planning and Scheduling for Space*, pp. 27-29, 2002.

[20] J. M. Bradshaw, P. J. Feltovich, H. Jung *et al.*, “Dimensions of adjustable autonomy and mixed-initiative interaction,” *International Workshop on Computational Autonomy*, pp. 17-39, 2003.

[21] M. R. Endsley, “Supporting Human-AI Teams: Transparency, explainability, and situation awareness,” *Computers in Human Behavior*, vol. 140, pp. 107574, 2023.

[22] J. van Diggelen, J. Barnhoorn, R. Post *et al.*, “Delegation in Human-machine Teaming: Progress, Challenges and Prospects,” *Proceedings of the 4th International Conference on Intelligent Human Systems Integration (IHSI 2021): Integrating People and Intelligent Systems*, pp. 10-16, 2021.

[23] M. H. Jarrahi, “Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making,” *Business Horizons*, vol. 61, no. 4, pp. 577-586, 2018.

[24] M. Templier, and G. Paré, “A framework for guiding and evaluating literature reviews,” *Communications of the Association for Information Systems*, vol. 37, no. 1, pp. 1-27, 2015.

[25] J. E. Mathieu, P. T. Gallagher, M. A. Domingo *et al.*, “Embracing complexity: Reviewing the past decade of team effectiveness research,” *Annual Review of Organizational Psychology and Organizational Behavior,* vol. 6, pp. 17-46, 2019.
[26] J. Y. C. Chen, S. G. Lakhmani, K. Stowers *et al.*, “Situation awareness-based agent transparency and human-autonomy teaming effectiveness,” *Theoretical Issues in Ergonomics Science,* vol. 19, no. 3, pp. 259-282, 2018.
[27] Y. T. Chiu, Y. Q. Zhu, and J. Corbett, “In the hearts and minds of employees: A model of pre-adoptive appraisal toward artificial intelligence in organizations,” *International Journal of Information Management,* vol. 60, pp. 1-16, 2021.
[28] S. Jhaver, Y. Karpfen, and J. Antin, “Algorithmic anxiety and coping strategies of Airbnb hosts,” in Proceedings of the 2018 CHI conference on human factors in computing systems, 2018, pp. 1-12.
[29] A. F. Borges, F. J. Laurindo, M. M. Spínola *et al.*, “The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions,” *International Journal of Information Management,* vol. 57, pp. 102225, 2021.
[30] M. Wooldridge, "Intelligent agents," *Multiagent Systems,* G. Weiss, ed., pp. 3-50, Cambridge: The MIT Press, 2013.
[31] E. Alonso, “AI and Agents: State of the Art,” *AI Magazine,* vol. 23, no. 3, pp. 25-25, 2002.
[32] M. Rieth, and V. Hagemann, “Automation as an equal team player for humans?–A view into the field and implications for research and practice,” *Applied Ergonomics,* vol. 98, pp. 103552, 2022.
[33] S. Balakrishnan, “An Overview of Agent-Based Intelligent Systems and Its Tools,” *CSI Communications Magazine,* no. 42, pp. 15-17, 2019.
[34] J. van Diggelen, J. S. Barnhoorn, M. M. M. Peeters *et al.*, “Pluggable Social Artificial Intelligence for Enabling Human-Agent Teaming,” *HFM-300 Symposium on Human Autonomy Teaming,* pp. 1-22, 2019.
[35] O. Meyer, and V. Gruhn, “Towards concept based software engineering for intelligent agents,” *IEEE/ACM 7th International Workshop on Realizing Artificial Intelligence Synergies in Software Engineering (RAISE),* pp. 42-48, 2019.
[36] S. Russell, and P. Norvig, *Artificial intelligence: A modern approach,* 4 ed., New York City, NY: Pearson Education, 2021.
[37] E. Salas, N. J. Cooke, and M. A. Rosen, “On teams, teamwork, and team performance: Discoveries and developments,” *Human Factors,* vol. 50, no. 3, pp. 540-547, 2008.
[38] T. O’Neill, N. McNeese, A. Barron *et al.*, “Human-autonomy teaming: A review and analysis of the empirical literature,” *Human Factors,* vol. 64, no. 5, pp. 904-938, 2022.
[39] E. Phillips, K. E. Schaefer, D. R. Billings *et al.*, “Human-animal teams as an analog for future human-robot teams: Influencing design and fostering trust,” *Journal of Human-Robot Interaction,* vol. 5, no. 1, pp. 100-125, 2016.
[40] J. M. Bradshaw, V. Dignum, C. Jonker *et al.*, “Human-agent-robot teamwork,” *IEEE Intelligent Systems,* vol. 27, no. 2, pp. 8-13, 2012.
[41] J. E. Mercado, M. A. Rupp, J. Y. C. Chen *et al.*, “Intelligent Agent Transparency in Human-Agent Teaming for Multi-UxV Management,” *Human Factors,* vol. 58, no. 3, pp. 401-415, 2016.

[42] A. Van Wissen, K. Gal, B. Kamphorst *et al.*, “Human-Agent Team Formation: An Empirical Study,” *BNAIC 2010: 22rd Benelux Conference on Artificial Intelligence,* pp. 1-8, 2010.
[43] M. Demir, N. J. McNeese, and N. J. Cooke, “Understanding human-robot teams in light of all-human teams: Aspects of team interaction and shared cognition,” *International Journal of Human-Computer Studies,* vol. 140, pp. 102436, 2020, 2020.
[44] J. Webster, and R. T. Watson, “Analyzing the past to prepare for the future: Writing a literature review,” *MIS Quarterly,* pp. xiii-xxiii, 2002.
[45] D. Moher, A. Liberati, J. Tetzlaff *et al.*, “Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement,” *Annals of Internal Medicine,* vol. 151, no. 4, pp. 264-269, 2009.
[46] D. Moher, L. Shamseer, M. Clarke *et al.*, “Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement,” *Systematic Reviews,* vol. 4, no. 1, pp. 1-1, 2015.
[47] A. M. Kranzbühler, M. H. P. Kleijnen, R. E. Morgan *et al.*, “The Multilevel Nature of Customer Experience Research: An Integrative Review and Research Agenda,” *International Journal of Management Reviews,* vol. 20, no. 2, pp. 433-456, 2018.
[48] J. Koivisto, and J. Hamari, “The rise of motivational information systems: A review of gamification research,” *International Journal of Information Management,* vol. 45, pp. 191-210, 2019.
[49] F. Delice, M. Rousseau, and J. Feitosa, “Advancing teams research: What, when, and how to measure team dynamics over time,” *Frontiers in Psychology,* vol. 10, pp. 1324-1324, 2019.
[50] J. E. Mathieu, J. R. Hollenbeck, D. van Knippenberg *et al.*, “A century of work teams in the Journal of Applied Psychology,” *Journal of Applied Psychology,* vol. 102, no. 3, pp. 452-452, 2017.
[51] M. E. Miller, J. M. McGuirl, M. F. Schneider *et al.*, “Systems modeling language extension to support modeling of human-agent teams,” *Systems Engineering,* vol. 23, no. 5, pp. 519-533, 2020.
[52] N. Dimotakis, R. B. Davison, and J. R. Hollenbeck, “Team structure and regulatory focus: The impact of regulatory fit on team dynamic,” *Journal of Applied Psychology,* vol. 97, no. 2, pp. 421-421, 2012.
[53] F. Gao, and M. L. Cummings, “Barriers to robust and effective human-agent teamwork,” *AAAI Spring Symposium - Technical Report,* vol. SS-14-04, pp. 36-41, 2014.
[54] F. Gao, M. L. Cummings, and E. Solovey, "Designing for robust and effective teamwork in human-agent teams," *Robust Intelligence and Trust in Autonomous Systems*, pp. 167-190: Springer, 2016.
[55] F. Gao, “Modeling teamwork of multi-human multi-agent teams,” *Proceedings of the 2013 Conference on Computer Supported Cooperative Work Companion*, pp. 47-50, 2013.
[56] A. R. Pritchett, S. Y. Kim, and K. M. Feigh, “Measuring human-automation function allocation,” *Journal of Cognitive Engineering and Decision Making,* vol. 8, no. 1, pp. 52-77, 2014.
[57] A. R. Pritchett, S. Y. Kim, and K. M. Feigh, “Modeling human-automation function allocation,” *Journal of Cognitive Engineering and Decision Making,* vol. 8, no. 1, pp. 33-51, 2014.

[58] N. Smets, J. M. Bradshaw, J. van Diggelen *et al.*, "Assessing human-agent teams for future space missions," *IEEE Intelligent Systems*, vol. 25, no. 5, pp. 46-53, 2010, 2010.
[59] P. Pico-Valencia, J. A. Holgado-Terriza, and L. M. S. Martinez, "A Preliminary Ontology for Human-Agent Collectives," *International Conference on Practical Applications of Agents and Multi-Agent Systems*, pp. 176-187, 2019.
[60] M. Johnson, J. M. Bradshaw, P. Feltovich *et al.*, "Autonomy and interdependence in human-agent-robot teams," *IEEE Intelligent Systems*, vol. 27, no. 2, pp. 43-51, 2012.
[61] M. Khani, A. Ahmadi, and H. Hajary, "Distributed task allocation in multi-agent environments using cellular learning automata," *Soft Computing*, vol. 23, no. 4, pp. 1199-1218, 2019.
[62] E. F. Flushing, L. M. Gambardella, and G. A. Di Caro, "Robot rostering: Coalition formation for long-term missions with work shifts," *SSRR 2016 - International Symposium on Safety, Security and Rescue Robotics*, pp. 334-341, 2016.
[63] J. v. d. Waa, J. v. Diggelen, L. Cavalcante Siebert *et al.*, "Allocation of moral decision-making in human-agent teams: a pattern approach," *Engineering Psychology and Cognitive Ergonomics. Cognition and Design: 17th International Conference*, pp. 203-220, 2020.
[64] J. Van Diggelen, T. Muller, and K. Van Den Bosch, "Using artificial team members for team training in virtual environments," *Intelligent Virtual Agents: 10th International Conference*, pp. 28-34, 2010.
[65] M. Barange, J. Saunier, and A. Pauchet, "Pedagogical agents as team members: Impact of proactive and pedagogical behavior on the user," *Proceedings of the International Joint Conference on Autonomous Agents and Multiagent Systems, AAMAS*, vol. 2, pp. 791-800, 2017.
[66] M. Barange, A. Kabil, C. D. Keukelaere *et al.*, "Communicative Capabilities of Agents for the Collaboration in a Human-Agent Team," *The Seventh International Conference on Advances in Computer-Human Interactions.*, pp. 1-6, 2014.
[67] T. Phan, W. Honig, and N. Ayanian, "Mixed Reality Collaboration between Human-Agent Teams," *25th IEEE Conference on Virtual Reality and 3D User Interfaces, VR 2018 - Proceedings*, pp. 659-660, 2018.
[68] C. J. Johnson, G. J. Lematta, L. Huang *et al.*, "An interaction taxonomy of human-agent teaming in Next Generation Combat Vehicle Systems," *International Conference on Applied Human Factors and Ergonomics*, pp. 10-16, 2020.
[69] N. Hanna, and D. Richards, "Human-agent teamwork in collaborative virtual environments," *13th International Conference on Autonomous Agents and Multiagent Systems, AAMAS 2014*, vol. 2, pp. 1735-1736, 2014.
[70] F. Rehnmark, N. Currie, R. O. Ambrose *et al.*, "Human-robot teaming in a multi-agent space assembly task," *Robotics: Trends, Principles, and Applications - Proceedings of the Sixth Biannual World Automation Congress, WAC*, pp. 69-74, 2004.
[71] A. Schulte, D. Donath, and D. S. Lange, "Design patterns for human-cognitive agent teaming," *International Conference on Engineering Psychology and Cognitive Ergonomics*, pp. 231-243, 2016.
[72] H. Li, T. Ni, S. Agrawal *et al.*, "Individualized Mutual Adaptation in Human-Agent Teams," *IEEE Transactions on Human-Machine Systems*, vol. 51, no. 6, pp. 706-714, 2021.

[73] P. Damacharla, P. Dhakal, J. P. Bandreddi *et al.*, "Novel human-in-the-loop (Hil) simulation method to study synthetic agents and standardize human–machine teams (HMT)," *Applied Sciences (Switzerland),* vol. 10, no. 23, pp. 1-31, 2020.
[74] M. Demir, N. J. McNeese, and N. J. Cooke, "Team situation awareness within the context of human-autonomy teaming," *Cognitive Systems Research,* vol. 46, pp. 3-12, 2017.
[75] T. J. Goodman, M. E. Miller, C. F. Rusnock *et al.*, "Effects of agent timing on the human-agent team," *Cognitive Systems Research,* vol. 46, pp. 40-51, 2017.
[76] F. Yazdani, G. Kazhoyan, A. K. Bozcuoğlu *et al.*, "Cognition-enabled Framework for Mixed Human-Robot Rescue Teams," *IEEE International Conference on Intelligent Robots and Systems*, pp. 1421-1428, 2018.
[77] M. B. Cook, C. A. Rieth, and M. K. Ngo, "Displays for effective human-agent teaming: the role of information availability and attention management," *International Conference on Virtual, Augmented and Mixed Reality*, pp. 174-185, 2015.
[78] N. Hanna, and D. Richards, "The impact of communication on a human-agent shared mental model and team performance," *13th International Conference on Autonomous Agents and Multiagent Systems, AAMAS 2014,* vol. 2, no. Aamas, pp. 1485-1486, 2014.
[79] K. E. Schaefer, E. R. Straub, J. Y. C. Chen *et al.*, "Communicating intent to develop shared situation awareness and engender trust in human-agent teams," *Cognitive Systems Research,* vol. 46, pp. 26-39, 2017.
[80] C. Flathmann, B. Schelble, B. Tubre *et al.*, "Invoking Principles of Groupware to Develop and Evaluate Present and Future Human-Agent Teams," *Proceedings of the 8th International Conference on Human-Agent Interaction*, pp. 15-24, 2020.
[81] M. A. Marks, J. E. Mathieu, and S. J. Zaccaro, "A temporally based framework and taxonomy of team processes," *Academy of Management Review,* vol. 26, no. 3, pp. 356-376, 2001.
[82] K. T. Wynne, and J. B. Lyons, "An integrative model of autonomous agent teammate-likeness," *Theoretical Issues in Ergonomics Science,* vol. 19, no. 3, pp. 353-374, 2018.
[83] J. M. Bradshaw, H. Jung, S. Kulkarni *et al.*, "Toward trustworthy adjustable autonomy in KAoS," *Trusting Agents for Trusting Electronic Societies,* pp. 18-42: Springer, 2004.
[84] J. Van Diggelen, M. Neerincx, M. Peeters *et al.*, "Developing Effective and Resilient Human-Agent Teamwork Using Team Design Patterns," *IEEE Intelligent Systems,* vol. 34, no. 2, pp. 15-24, 2019.
[85] M. Schneider, M. Miller, D. Jacques *et al.*, "Exploring the Impact of Coordination in Human–Agent Teams," *Journal of Cognitive Engineering and Decision Making,* vol. 15, no. 2-3, pp. 97-115, 2021.
[86] M. Neef, "A taxonomy of human-agent team collaborations." pp. 245-250.
[87] M. Barange, J. Saunier, and A. Pauchet, "Multiparty Interactions for Coordination in a Mixed Human-Agent Teamwork," *International Conference on Intelligent Virtual Agents*, pp. 29-42, 2017.
[88] K. Drnec, G. Gremillion, D. Donavanik *et al.*, "The role of psychophysiological measures as implicit communication within mixed-initiative teams," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics),* vol. 10909, pp. 299-313, 2018.
[89] M. Harbers, J. M. Bradshaw, M. Johnson *et al.*, "Explanation and coordination in human-agent teams: A study in the BW4T testbed," *Proceedings - 2011 IEEE/WIC/ACM*

International Joint Conferences on Web Intelligence and Intelligent Agent Technology - Workshops, WI-IAT 2011, vol. 3, pp. 17-20, 2011.

[90] J. Van Diggelen, J. M. Bradshaw, M. Johnson *et al.*, "Implementing collective obligations in human-agent teams using KAoS policies," *Coordination, Organizations, Institutions and Norms in Agent Systems V: COIN 2009 International Workshops*, pp. 36-52, 2010.

[91] N. Schurr, J. Marecki, M. Tambe *et al.*, "Towards flexible coordination of human-agent teams," *Multiagent and Grid Systems,* vol. 1, no. 1, pp. 3-16, 2005.

[92] X. Fan, P. C. Chen, and J. Yen, "Learning HMM-based cognitive load models for supporting human-agent teamwork," *Cognitive Systems Research,* vol. 11, no. 1, pp. 108-119, 2010.

[93] S. M. Yusuf, and C. Baber, "Human-agents Interactions in Multi-Agent Systems: A case study of human-UAVs team for forest fire lookouts," *ICAART 2020 - Proceedings of the 12th International Conference on Agents and Artificial Intelligence*, vol. 1, pp. 347-354, 2020.

[94] A.-S. Ulfert, and E. Georganta, "A model of team trust in human-agent teams," *the 2020 International Conference on Multimodal Interaction*, pp. 171-176, 2020.

[95] M. Hou, "IMPACT: a trust model for human-agent teaming," *IEEE International Conference on Human-Machine Systems (ICHMS)*, pp. 1-4, 2020.

[96] B. S. Perelman, A. W. Evans, and K. E. Schaefer, "Mental model consensus and shifts during navigation system-assisted route planning," *Proceedings of the Human Factors and Ergonomics Society,* vol. 2017-Octob, pp. 1183-1187, 2017.

[97] X. Fan, S. Oh, M. McNeese *et al.*, "The influence of agent reliability on trust in human-agent collaboration," *ACM International Conference Proceeding Series,* vol. 369, 2008.

[98] E. S. Kox, J. H. Kerstholt, T. F. Hueting *et al.*, "Trust repair in human-agent teams: the effectiveness of explanations and expressing regret," *Autonomous agents and multi-agent systems,* vol. 35, no. 2, pp. 1-20, 2021.

[99] S. S. Rodriguez, J. Chen, H. Deep *et al.*, "Measuring complacency in humans interacting with autonomous agents in a multi-agent system," in Artificial intelligence and machine learning for multi-domain operations applications II, 2020, pp. 258-271.

[100] S. Goel, and R. Karri, "Entrepreneurs, effectual logic, and over–trust," *Entrepreneurship theory and practice*, vol. 30, no. 4, pp. 477-493, 2006.

[101] J. Y. C. Chen, and M. J. Barnes, "Agent Transparency for Human-Agent Teaming Effectiveness," *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015*, pp. 1381-1385, 2015.

[102] S. Tulli, F. Correia, S. Mascarenhas *et al.*, "Effects of agents' transparency on teamwork," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics),* vol. 11763 LNAI, no. September, pp. 22-37, 2019.

[103] G. L. Calhoun, H. A. Ruff, K. J. Behymer *et al.*, "Operator-autonomy teaming interfaces to support multi-unmanned vehicle missions," *Advances in Human Factors in Robots and Unmanned Systems*, pp. 113-126: Springer, 2017.

[104] R. H. Stevens, and T. L. Galloway, "Teaching machines to recognize neurodynamic correlates of team and team member uncertainty," *Journal of Cognitive Engineering and Decision Making,* vol. 13, no. 4, pp. 310-327, 2019, 2019.

[105] Y. Wang, “Regret-based Bayesian sequential decision-making for human-agent collaborative search tasks,” *Proceedings of the American Control Conference,* vol. 2015-July, pp. 5738-5743, 2015.
[106] H. Figueroa, R. Costaguta, M. L. A. De Menini *et al.*, “An automatic identification of team roles in forums,” *ACM International Conference Proceeding Series*, pp. 6-7, 2019.
[107] P. Paruchuri, P. Varakantham, K. Sycara *et al.*, “Effect of human biases on human-agent teams,” *Proceedings - 2010 IEEE/WIC/ACM International Conference on Intelligent Agent Technology, IAT 2010,* vol. 2, pp. 327-334, 2010.
[108] J. E. Mathieu, S. I. Tannenbaum, M. R. Kukenberger *et al.*, “Team role experience and orientation: A measure and tests of construct validity,” *Group & Organization Management,* vol. 40, no. 1, pp. 6-34, 2015.
[109] J. Y. C. Chen, A. R. Selkowitz, K. Stowers *et al.*, “Human-Autonomy Teaming and Agent Transparency,” in Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction, Vienna, Austria, 2017, pp. 91–92.
[110] J. L. Wright, S. A. Quinn, J. Y. C. Chen *et al.*, “Individual differences in human-agent teaming: An analysis of workload and situation awareness through eye movements,” *Proceedings of the Human Factors and Ergonomics Society,* vol. d, pp. 1410-1414, 2014.
[111] S. Li, W. Sun, and T. Miller, “Communication in human-agent teams for tasks with joint action,” *International Workshop on Coordination, Organizations, Institutions, and Norms in Agent Systems,* pp. 224-241, 2015.
[112] J. W. Tweedale, “Using Multi-Agent Systems to Enhance the Level of Autonomy in Unmanned Vehicles,” *Communications in Computer and Information Science,* vol. 246 CCIS, pp. 189-208, 2013, 2013.
[113] N. Hanna, and D. Richards, “The impact of virtual agent personality on a shared mental model with humans during collaboration,” *Proceedings of the International Joint Conference on Autonomous Agents and Multiagent Systems, AAMAS,* vol. 3, no. Aamas, pp. 1777-1778, 2015.
[114] C. M. Jonker, M. B. Van Riemsdijk, and B. Vermeulen, “Shared mental models,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics),* vol. 6541 LNAI, no. Section 2, pp. 132-151, 2011.
[115] M. F. Schneider, and M. E. Miller, “Operationalized Intent for Communication in Human-Agent Teams,” *Proceedings - 2018 IEEE International Conference on Cognitive and Computational Aspects of Situation Management, CogSIMA 2018*, pp. 117-123, 2018.
[116] E. M. van Zoelen, A. Cremers, F. P. M. Dignum *et al.*, “Learning to communicate proactively in human-agent teaming,” *Communications in Computer and Information Science,* no. July, pp. 238-249, 2020.
[117] M. F. Schneider, M. E. Miller, and J. M. McGuirl, “Tracking Operator Intent in Tactical Operations,” *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC),* pp. 3214-3220, 2020.
[118] D. Hughes, A. Agarwal, Y. Guo *et al.*, “Inferring non-stationary human preferences for human-agent teams,” *29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pp. 1178-1185, 2020.
[119] J. Jiang, A. J. Karran, C. K. Coursaris *et al.*, “A Situation Awareness Perspective on Human-Agent Collaboration: Tensions and Opportunities,” *Lecture Notes in Computer*

Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 13095 LNCS, no. July, pp. 437-444, 2021.
[120] J. Y. Chen, K. Procci, M. Boyce *et al.*, *Situation awareness-based agent transparency*, Army research lab 2014.
[121] G. Roth, A. Schulte, F. Schmitt *et al.*, “Transparency for a Workload-Adaptive Cognitive Agent in a Manned-Unmanned Teaming Application,” *IEEE Transactions on Human-Machine Systems,* vol. 50, no. 3, pp. 225-233, 2020.
[122] A. Bhaskara, M. Skinner, and S. Loft, “Agent transparency: A review of current theory and evidence,” *IEEE Transactions on Human-Machine Systems,* vol. 50, no. 3, pp. 215-224, 2020.
[123] W. Ding, S. Kim, D. Xu *et al.*, “Can Intelligent Agent Improve Human-Machine Team Performance Under Cyberattacks?,” *International Conference on Intelligent Human Systems Integration*, pp. 725-730, 2019.
[124] A. Das, P. Kol, C. Lundberg *et al.*, “A Rapid Situational Awareness Development Framework for Heterogeneous Manned-Unmanned Teams,” *Proceedings of the IEEE National Aerospace Electronics Conference, NAECON*, pp. 417-424, w, 2018.
[125] M. J. Barnes, J. Y. C. Chen, J. L. Wright *et al.*, “Human-Agent Teaming for Effective Multirobot Management: Effects of Agent Transparency,” *International Conference on Engineering Psychology and Cognitive Ergonomics*, pp. 169-178, 2016.
[126] J. E. Mathieu, M. T. Maynard, T. Rapp *et al.*, “Team effectiveness 1997-2007: A review of recent advancements and a glimpse into the future,” *Journal of Management,* vol. 34, no. 3, pp. 410-476, 2008.
[127] C. J. Johnson, M. Demir, N. J. McNeese *et al.*, “The Impact of Training on Human–Autonomy Team Communications and Trust Calibration,” *Human Factors*, 2021.
[128] R. W. Brewer, A. J. Walker, E. Pursel *et al.*, “Assessment of manned-unmanned team performance: Comprehensive after-action review technology development,” *International Conference on Applied Human Factors and Ergonomics*, pp. 119-130, 2019.
[129] R. Hakli, and J. Seibt, *Sociality and normativity for robots*, Heidelberg, Germany: Springer, 2017.
[130] M. Coeckelbergh, “You, robot: on the linguistic construction of artificial others,” *AI & Society,* vol. 26, no. 1, pp. 61-69, 2011.
[131] E. Sandry, *Robots and communication,* London, UK: Springer, 2015.
[132] B. Whitworth, “Polite computing,” *Behaviour & Information Technology,* vol. 24, no. 5, pp. 353-363, 2005.
[133] C. Hayes, and C. A. Miller, *Human-computer etiquette: Cultural Expectations and the Design Implications They Place on Computers and Technology*, 1 ed., Boca Raton, FL: Auerbach Publications, 2010.
[134] D. Benyon, and O. Mival, "Landscaping personification technologies: from interactions to relationships," *CHI'08 extended abstracts on Human factors in computing systems*, pp. 3657-3662, 2008.
[135] C. I. Nass, and C. Yen, *The man who lied to his laptop: what machines teach us about human relationships,* New York: Gildan Audio, 2010.
[136] C. Chesher, and F. Andreallo, “Robotic faciality: The philosophy, science and art of robot faces,” *International Journal of Social Robotics,* vol. 13, no. 1, pp. 83-96, 2021.

[137] R. Sparrow, “Robotics has a race problem,” *Science, Technology, & Human Values,* vol. 45, no. 3, pp. 538-560, 2020.
[138] G. Julier, *The culture of design*: Sage, 2013.
[139] L. Floridi, *The fourth revolution: How the infosphere is reshaping human reality*: OUP Oxford, 2014.
[140] J. A. Cannon-Bowers, and E. Salas, “Reflections on shared cognition,” *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior,* vol. 22, no. 2, pp. 195-202, 2001.
[141] D. Shin, “The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI,” *International Journal of Human-Computer Studies,* vol. 146, pp. 102551, 2021.
[142] R. C. Mayer, and J. H. Davis, “The effect of the performance appraisal system on trust for management: A field quasi-experiment,” *Journal of Applied Psychology,* vol. 84, no. 1, pp. 123-123, 1999.
[143] M. Krakovsky, “Artificial (emotional) intelligence,” *Communications of the ACM,* vol. 61, no. 4, pp. 18-19, 2018.
[144] S. You, and L. P. Robert, “Human-robot similarity and willingness to work with a robotic co-worker,” *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* pp. 251-260, 2018.
[145] M. T. Maynard, D. M. Kennedy, and S. A. Sommer, “Team adaptation: A fifteen-year synthesis (1998--2013) and framework for how this literature needs to “adapt” going forward,” *European Journal of Work and Organizational Psychology,* vol. 24, no. 5, pp. 652-677, 2015.
[146] B. Shneiderman, “Human-centered artificial intelligence: Reliable, safe & trustworthy,” *International Journal of Human-Computer Interaction,* vol. 36, no. 6, pp. 495-504, 2020.
[147] Y. Yu, N. Lakemond, and G. Holmberg, “AI in the Context of Complex Intelligent Systems: Engineering Management Consequences,” *IEEE Transactions on Engineering Management,* in press.
[148] V. Sarathy, “Learning context-sensitive norms under uncertainty,” *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 539-540, 2019.
[149] E. Dane, “Reconsidering the trade-off between expertise and flexibility: A cognitive entrenchment perspective,” *Academy of Management Review,* vol. 35, no. 4, pp. 579-603, 2010.
[150] M. Merz, and V. M. Steinherr, “Process-based Guidance for Designing Behavior Change Support Systems: Marrying the Persuasive Systems Design Model to the Transtheoretical Model of Behavior Change,” *Communications of the Association for Information Systems,* vol. 50, no. 1, pp. 13, 2022.
[151] T. Grønsund, and M. Aanestad, “Augmenting the algorithm: Emerging human-in-the-loop work configurations,” *The Journal of Strategic Information Systems,* vol. 29, no. 2, pp. 101614, 2020.
[152] M. C. Schippers, A. C. Edmondson, and M. A. West, "Team reflexivity," *The Oxford handbook of group and organizational learning*, L. Argote and J. M. Levine, eds., pp. 175-194, 2020.
[153] S. T. Bell, A. J. Villado, M. A. Lukasik *et al.*, “Getting specific about demographic diversity variable and team performance relationships: A meta-analysis,” *Journal of Management,* vol. 37, no. 3, pp. 709-743, 2011.

[154] S. T. Bell, S. G. Brown, A. Colaneri *et al.*, "Team composition and the ABCs of teamwork," *American Psychologist*, vol. 73, no. 4, pp. 349-349, 2018.
[155] R. S. Lazarus, "Progress on a cognitive-motivational-relational theory of emotion," *American Psychologist*, vol. 46, no. 8, pp. 819-834, 1991.
[156] J. R. Kelly, and S. G. Barsade, "Mood and emotions in small groups and work teams," *Organizational Behavior and Human Decision Processes*, vol. 86, no. 1, pp. 99-130, 2001.
[157] R. P. Tett, and D. D. Burnett, "A personality trait-based interactionist model of job performance," *Journal of Applied Psychology*, vol. 88, no. 3, pp. 500-500, 2003, 2003.
[158] S. Rebensky, K. Carmody, C. Ficke *et al.*, "Teammates Instead of Tools: The Impacts of Level of Autonomy on Mission Performance and Human–Agent Teaming Dynamics in Multi-Agent Distributed Teams," *Frontiers in Robotics and AI*, vol. 9, pp. 782134, 2022.
[159] A.-S. Ulfert, C. H. Antoni, and T. Ellwart, "The role of agent autonomy in using decision support systems at work," *Computers in Human Behavior*, vol. 126, pp. 106987, 2022.
[160] Y. T. Chiu, M. S. Khan, M. Mirzaei *et al.*, "Reconstructing the concept of team fluidity for the digitized era," *ISPIM Innovation Symposium*, pp. 1-9, 2017.
[161] J. K. Summers, S. E. Humphrey, and G. R. Ferris, "Team member change, flux in coordination, and performance: Effects of strategic core roles, information transfer, and cognitive ability," *Academy of Management Journal*, vol. 55, no. 2, pp. 314-338, 2012.
[162] M. A. Wolfson, and J. E. Mathieu, "Team composition," *The psychology of team working and collaborative processes*, E. Salas, R. Ramon and J. Passmore, eds., pp. 129-149, Hoboken: Wiley Blackwell, 2017.