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Teamwork and Communication Methods and Metrics for Human–Autonomy Teaming

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NOTICES

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14. ABSTRACT

Communication is at the center of the most-critical research and developments in human–autonomy teaming (HAT) because it provides insights into how information is gathered, exchanged, and utilized by the team. The goal of this report is to discuss HAT applications of models, theories, and methodologies in existing literature on teamwork and communication to inform the development of a new method for capturing team communication in real time. To reach this end, this report first highlights the challenge areas in the development of communication in HAT specific to the research areas of humans understanding autonomy, autonomy understanding humans, and joint human–autonomy teamwork. Then we review models and theories of communication and teamwork to clarify current research needs related to communication in HAT. We follow this by reviewing methods for analyzing communication: qualitative coding, computational approaches, network analysis, and voice analysis. In discussing these methods, we additionally highlight their strengths and shortcomings. Finally, to address some of those shortcomings, we present a new tool for capturing team communication in real time, called Realtime Flow, Event, and Coordination Tool (REFLECT), and discuss the HAT applications of REFLECT.

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Summary

Communication is a critical element of human–autonomy teams because it provides insights into how information is gathered, exchanged, and utilized by the team. Team communication also provides crucial insight into the many aspects of team performance. However, since human–autonomy teaming (HAT) constructs and capabilities are still being developed, it is important to turn to the well-developed theories and models from human teams to help develop needed metrics for understanding and evaluating these developing human–autonomy teams (HATs). While these models and theories may not be representative of every factor needed to develop effective and appropriate HAT, this review provides insight into explaining team performance and developing effective team trust, team cohesion, and shared situation awareness (SA).

Throughout this report we highlight the fundamental importance of communication in HATs and focus on the ways in which these constructs, paradigms, models, and theories can inform communication research. To create adaptive HATs that can succeed in dynamic adversarial environments, multidirectional, networked communication among humans and autonomy will be needed to coordinate effectively. The three most important research thrusts pertaining to communication in HATs include humans understanding autonomy, autonomy understanding humans, and joint human–autonomy teamwork. We then provide a theoretical framework for understanding those challenges by discussing models and theories of teamwork and communication that can be applied to HAT. Successful integration of humans and autonomy will demand application of those models and theories to more fully understand performance and coordination in these evolving teams. Therefore, we advance our review as a foundation for understanding these types of integrated teams.

Following this theoretical underpinning of the current state, we review the current metrics and methods for measuring team communication, including qualitative coding, computational approaches, network analysis, and voice analysis. These methodologies provide insights into what information could be shared and how that information should be exchanged during HAT. These insights will be critical to developing effective teaming because communication is directly related to performance, coordination, team cohesion, and appropriately calibrated team trust. As future HATs are developed, we can use communication analysis tools to understand how the capabilities of humans and autonomy can be better integrated as well as how the autonomy can be designed to improve human understanding, trust, and SA. To this end, we also highlight some limitations of current communication analysis methods, paving the way for future analyses and

associated metrics. To synthesize our theories and frameworks of teamwork and communication, and to address the need for developing metrics and real-time communication assessment methods for HAT, we introduce a new tool for capturing team communication flow: the Realtime Event, Flow, and Coordination Tool (REFLECT). To maintain overmatch in changing adversarial environments and against emerging threats, future HATs must be characterized by dynamic, naturalistic interactions to perform, adapt, and succeed. REFLECT is aimed at capturing those interactions to reveal the unique coordination characteristics of those teams. Ultimately, if we are to build more effective HATs that exhibit appropriate trust, team cohesion, and SA, it is fundamentally important to understand their communication, and this report focuses on the importance of communication in many aspects of HAT.

1. Introduction

Advances in autonomy-enabled systems are anticipated to shape the battlespace of the near and far future. The Army expects autonomy to serve as a force multiplier, extending the ability of warfighters to impact the battlespace, reducing the number of warfighters in harm's way, and providing new ways of operating that should improve the flexibility and capabilities of teams (US Army 2017). Intelligent systems will reshape the way teams gather information, make decisions, identify threats, and engage with the environment. Much ongoing research is targeted at designing adaptive, intelligent systems with which operators can interact fluidly and naturalistically to achieve the mission (Barnes et al. 2017; DeCostanza et al. 2018a; Marathe et al. 2018). At the core of all these research efforts is communication. To build more advanced systems and better human–autonomy teams (HATs), it is fundamental that we understand how team communication affects, and is affected by, autonomy.

The motivation for evaluating team communication in human–autonomy teaming (HAT) is clear: communication is integral to most team processes and emergent states and, by extension, to performance (Marks et al. 2001; Mesmer-Magnus and Dechurch 2009; Salas et al. 2009; de Jong et al. 2015). An issue complicating the task of understanding communication in HAT is that human communication and human–autonomy communication have parallels, but they are not the same. Even for the most advanced intelligent agents, there is progress to be made in making their communication capabilities (whether verbal, text-based, gesture-based, etc.) more fluent and naturalistic. Ultimately, communication between humans and autonomy forms the basis for calibrating expectations and behavior within the team, and while good calibration can result in appropriate levels of trust, miscalibration can result in failures in teamwork.

Problems with team communication have been linked to team failures in critical situations in aviation, military operations, and more. For example, Macrae (2009) found that about 40% of situational factors in naval groundings were accounted for by poor communication. Sexton and Helmreich (2000) posited that 70%–80% of all aviation accidents in the 20 years preceding their work could be attributed to communication errors. In a prominent example of communication error, two US Army Black Hawk helicopters were shot down in a friendly fire incident during Operation Provide Comfort in 1994; misunderstandings and miscommunications were cited as important factors in the accident (Snook 2000). Conversely, team communication that is clear, complete, and on time can improve a team's ability to manage the situation, allowing teams to perform more effectively under duress, such as in crisis situations (Mckinney et al. 2005).

Three important areas of active research in developing effective HATs are humans understanding autonomy, autonomy understanding humans, and joint human–autonomy teamwork. Focusing on communication within each of these areas provides a clear means to describe current research and needed areas of future research to support coordination between humans and autonomy, resulting in better performance of HATs. Achieving a thorough understanding of how team characteristics affect those three areas is paramount. However, we define the terminology in this report before addressing these larger issues.

1.1 Definitions

It is important that readers of this report have a common understanding of the terms we are using. Therefore, we begin by defining and briefly describing several of the relevant constructs for teamwork, communication, and the various agent technologies.

1.1.1 Teamwork

In human teams, teamwork has been defined as "the means by which individual task expertise is translated, magnified, and synergistically combined to yield superior performance outcomes, the wisdom of the collectives" (Salas et al. 2009, p. 43). Salas et al. (2007) further describe teamwork as the "dynamic, simultaneous, and recursive enactment of process mechanisms which inhibit or contribute to team performance and performance outcomes" (p. 190). Morgan et al. (1993) emphasize that teamwork focuses on shared behaviors, cognitions, and attitudes.

Teamwork is different from taskwork, which involves "the performance of specific tasks that team members need to complete in order to achieve team goals" (Salas et al. 2015). Taskwork relates to "the work-related activities that individuals or teams engage in as an essential function of their organizational role" (Wildman et al. 2012; Salas et al. 2015). DeCostanza et al. (2018a) suggest that for HATs, the focus is on "team-level states and processes that influence performance and effectiveness […] rather than individual taskwork". Thus, teamwork in the context of HAT can be defined as *the mechanisms by which a group of people and/or agents moves toward goals,* whereby agents can be computer-based aids, software agents, machines (e.g., robots), or a combination.

1.1.2 Communication

Communication is the vehicle through which team members can resolve disagreements, synchronize information from multiple sources, align toward goals, or distribute critical information to team members (Salas et al. 2005). Team communication can be defined as *the exchange of information between two or more team members using verbal or nonverbal channels* (Adams 2007; Mesmer-Magnus and DeChurch 2009). For the purposes of this report, we extend this definition by understanding that the exchange of information can be between humans or between humans and autonomy.

1.1.3 Agents and Robots

Agents are intelligent systems and can exist either as software or as hardware with a physical form (Chen et al. 2018). According to Wooldridge and Jennings (1995), agents have some amount of control over their actions and internal state. Further, agents are reactive to their environments, proactive with goal-directed behavior, and interactive with other agents and possibly humans (Wooldridge and Jennings 1995). Robots are physically embodied agents that can interact with the environment (Prendinger and Ishizuka 2004; Russell and Norvig 2016). In this report, "robot" always refers to an embodied agent.

1.1.4 Autonomy and Automation

Automation refers to the whole or partial replacement of human-controlled tasks with computerized or mechanical processes (Parasuraman et al. 2000), although automation still requires human supervision or control (McNeese et al. 2018). In comparison, autonomy refers to an agent's ability to govern its own actions, goals, processes, or states. Systems with autonomous capabilities are, in a sense, more adaptable, capable, and independent than traditional automation and can arguably represent evolved forms of automation (Endsley 2015; Endsley 2017; Hancock 2017).

1.2 Characteristics that Affect Communication in Human–Autonomy Teaming

Communication involves the transmission of information both within and across teams (or other external individual or organization), and as such there are a multitude of factors that affect how well a team communicates. In HAT, the autonomy introduces unique capabilities and challenges into a team, and much of that challenge stems from how team communication is affected by autonomy. Human teams are naturally able to leverage communication to share information (Mesmer-Magnus et al. 2011), set goals (Marks et al. 2001), self-correct (Salas et al. 2008), and engage in teamwork. Many autonomous systems in task-oriented team environments cannot yet engage in naturalistic communication, but a critical focus of ongoing HAT research and development involves bidirectional communication. Bidirectional communication is an approach to developing effective, human-like communication practices in HATs by facilitating mutual understanding between humans and autonomy (Marathe et al. 2018). In effective HATs, Chen and Barnes (2014) argue that "agents must be able ask questions as well as answer them" and suggest that such interactions do not necessarily have to be verbal since other communication modalities are a focus of ongoing research as well (see Sections 1.2.1.3 and 1.2.2.1). Therefore, the characteristics addressed in this section are organized into three current challenge areas in the development of bidirectional communication in HAT: humans understanding autonomy, autonomy understanding humans, and joint human–autonomy teamwork.

1.2.1 Humans Understanding Autonomy

The research into humans understanding autonomy seeks to identify any dissonance between the human's expectations and the system's actions and determine how to balance the expectations and actions. For the HAT to work effectively, the human must have a clear and accurate understanding of how the autonomy operates (Phillips et al. 2011). Any mismatch between expectations and behavior, whether founded or not, can lead to a miscalibration of trust in the team. Therefore, good communication (and associated metrics and techniques for measurement of communication) associated with actions, intentions, goals, and general reasoning of the autonomous systems are needed for effective teaming to take place. The system's reliability, transparency, and user interface design all play a role in how well a human can interact with it, and in a team context, those system factors will be vital to the team's ability to coordinate, cooperate, and communicate.

1.2.1.1 System Reliability

A system's reliability plays a large role in a human's decisions about whether to use and trust that system. Reliability generally refers to how well a system completes its tasks, as well as the level of accuracy or the amount of error inherent to the system (Baker et al. 2018). Humans tend to trust automation that performs reliably (Lee and See 2004; Hancock et al. 2011). More-reliable automation is more likely to lead to better human–autonomy performance, and unreliable automation can induce performance decrements on the team by increasing the amount of workload on the human (Yeh and Wickens 2000; Rovira et al. 2007). Increasing reliability is not a panacea for the types of problems that can occur in HAT. When reliability increases, operator situation awareness (SA) may decrease as a result, which can decrease an operator's ability to quickly respond to alerts (Endsley 2017). However, effective system design can help mitigate those decrements by communicating information to the operator about the state of the systems and the environment. For example, Dzindolet et al. (2003) found that participants who were provided explanations for errors made by an automated decision aid showed more appropriate trust of the system, whereas participants who did not receive such explanations demonstrated poorer calibration, sometimes even distrusting a reliable aid. In a more general example, Wang et al. (2009) found that participants who were informed about the limitations of the system related to reliability level of an automated combat identification system were better able to calibrate appropriate use of the system at the appropriate time. Having transparent communication about the capabilities of the autonomy throughout the interaction is critical trust, because simply instructing a user that the system is reliable will not always directly translate into appropriate use of the system at the appropriate time even if the system is operating at optimal capacity (Schaefer and Straub 2016).

1.2.1.2 Agent Transparency and Communication of Intent

Transparency is the degree to which the inner processes and decision-making logic of an agent is known to a human (Seong and Bisantz 2008). It is an emergent property that results from the interaction of human and system (Ososky et al. 2014). Transparency is important to effective HAT because it allows humans to have a better understanding of the agent's intentions, actions, and decisions. This better understanding promotes trust (Chen and Barnes 2014; Schaefer et al. 2015). Transparency can be unique between users, as each user can have a different level of knowledge of the system, making the same system transparent to one user and opaque to another (Karsenty and Botherel 2005).

Predictability of the agent's choices, actions, and capabilities is important to the human side of the team, such that as the human's understanding of the autonomy's purpose and abilities increases, so does the potential performance of the team (Chen et al. 2018). Transparency can impact the team's communication by allowing a human operator to have a better understanding of the states and intentions of the system, increasing the quality of information possessed by the operator and allowing the user to better share relevant information with teammates. Transparency stems from the information provided to the user that increases their understanding of the system, its current state, and its underlying reasoning process for decision making.

Humans do not always need to have complete transparency of the agent's decisions or behaviors; the key is to find an appropriate balance between enabling transparency while avoiding information overload (Miller 2014). This balance will depend on the operational context of the team and the role of the agent. While intelligent agents can play different roles within a team (Sycara and Lewis 2004), Miller (2014) posited that human–autonomy interaction characterized by delegation of objectives to the agent can serve as a framework for improved comprehension of the agent, better communication of appropriate information from the agent, and thus better transparency. The agent's ability to communicate appropriate information about its states and intentions to the human is also important for bidirectional communication. Recent research has revealed some insights into how communication from autonomy can shape effective HAT.

One way is through user display technology and communication of context-specific information to convey intent. Through a review of multiple research programs, Schaefer et al. (2017) suggest that appropriately designed displays can facilitate shared SA and better communication of intentions and reasoning during decision making, while limited communication can lead to increased discomfort or degraded trust. They note, however, that some of the larger technological challenges that must be solved in effective display design involve perception and intelligence on the part of the autonomy. In other words, to communicate appropriate information, the autonomy must understand its environment and tasks, but intelligent systems are still not able to perfectly make sense of the world, and it is therefore difficult to convey to the users of the autonomy.

A second insight into how communication from autonomy can shape effective HAT is the connection between communication and human mental models. In another example, Perelman et al. (2017) investigated how human spatial mental models changed after receiving assistance from algorithm-generated solutions. In this study, participants attempted to create optimized routes and then received assistance from a route-planning interface that used algorithms to display suggested routes. The authors found that the algorithm's communication of a route did not necessarily lead a participant to change their mind about a route. Instead, they found that user trust of the algorithm predicted the likelihood that the participant would change their mind about a route. This implies that communication from autonomy is not enough to warrant utilization of the information, and that trust is partially responsible for one's acceptance of communications from an intelligent system. Thus, by visualizing differences between human-generated and autonomy-generated solutions to spatial problems, the system could allow operators to better understand and resolve those differences.

Overall, these research avenues suggest that autonomy can support the autonomy-to-human portion of bidirectional communication by conveying information relevant to its intentions and states to the human. Much work remains to be done to design systems that can make sense of the world, but that capability will allow systems to communicate with humans in a more naturalistic manner and improve the human's understanding of the tasks and the environment.

1.2.1.3 Multimodal Communication and User Interface Design

In the context of HAT, several modalities—visual, speech, auditory (i.e., nonverbal), gesture, and tactile or haptic—can be used to communicate between humans and autonomous intelligent systems (Hill 2017). Traditionally, human–autonomy communication has used computer interfaces or remote controllers (e.g., TALON explosive ordnance disposal [EOD] robot's operator control unit; Army Technology 2018), which rely primarily on visual modality to convey information. However, researchers have continued to investigate the utility of, and even implemented into working systems, the less-used dimensions of gesture and tactile or haptic interfaces (Barber et al. 2013, 2015; Hill 2017). Some speech and auditory interfaces have been developed, and research continues in using these modalities for human–agent communication. Naturalistic human–agent communication is one option that could support HAT research as a means to minimize human training requirements and increasing understandability by building interfaces based on how humans communicate with each other. However, we expect computer and handheld control interfaces will remain a popular modality for interfacing with intelligent agents for at least the near future given that more-naturalistic communication is still under considerable research and development (Bisk et al. 2016).

Nonverbal communication through displays or controllers is another active area of communication research. For example, unmanned aerial vehicles (UAVs) under human supervision can be controlled with a computer interface from long-distance geographic separation, while EOD robots have been typically controlled with teleoperated physical controller units, using physical input devices such as joysticks along with some visual displays (Army Technology 2018). Using touch-based interfaces often occupies two of the senses (touch and vision), so team communication when using these interfaces may be cognitively burdensome when also attending to other tasks that may require those senses (Wickens 2002; Wickens 2008). Some current research directions are investigating the effectiveness of using speech interfaces for load carrying robots (Taylor et al. 2017) and intelligence, surveillance, and reconnaissance tasks (Harris and Barber 2014; Kattoju et al. 2016), which would reduce some of the cognitive burden on Soldiers by freeing up the hands and eyes. Choosing not only what to communicate, but also how to communicate using various modalities, is the subject of continuing research and development.

In general, future HATs are expected to incorporate multimodal communication to improve the quality of teamwork and communication. To address that expectation, current research seeks to understand when and how to use more than one modality for communication (e.g., using speech, gesture, and touch; Schaefer et al. 2019).

Work in this domain will lay the groundwork for HATs that can transmit information most effectively using a mix of communication modalities.

1.2.2 Autonomy Understanding Humans

Just as humans must be able to understand the capabilities and intentions of their autonomous systems, there are instances where those systems will need to be able to either have direct communication from human team members or access to information about the human team members. The larger goal of this research area is to develop adaptive solutions that incorporate understanding and prediction of human behavior. If the intelligent system better understands the state of the human, the system can adapt to the changing state of its human teammate; this capability should improve performance as well as increase the flexibility of the team. For HAT-based communication research, this means a better understanding is needed of how intelligent systems can make sense of human inputs, whether those inputs involve speech, text, user interface inputs, or even physiological states.

1.2.2.1 Human-to-Autonomy Communication

The means by which humans can communicate information to intelligent systems depends on both the intended purpose of the systems as well as the user interface of the system. As discussed in Section 1.2.1.3, the interface can use a single modality or even multiple modalities for the user interface. Some ongoing work seeks to develop our understanding of how humans can use naturalistic language when communicating with robots. Bisk et al. (2016) studied the linguistic difficulties encountered when human participants tried to command a robotic teammate to move and reorganize blocks in a spatial task. The authors highlighted the importance of grounding to this coordination and introduced algorithms to help agents understand potentially ambiguous commands. A similar effort is underway by Army researchers to evaluate how human operators communicate with robotic teammates to develop new communication algorithms for human–robot dialogue (Marge et al. 2016, 2017; Bonial et al. 2017). One of the goals of this work is to produce a classification system that can allow the automated system to interpret and understand the operator’s intentions from their communication, which would eventually inform the development of more-naturalistic robotic communication algorithms and improve bidirectional communication between human and robot.

Other ongoing work has evaluated the feasibility of using gestures to communicate information to autonomy. Generally, two types of technologies are used to capture gestures for communicating with autonomy: instrumented recognition systems (e.g., gloves with sensors) and camera-based recognition systems (i.e., systems that recognize using computer vision; Hill 2017). Barber et al. (2013) described an instrumented recognition approach that utilized inertial measurement units embedded in gloves designed to detect changes in hand positions and shapes. Using these gloves, the authors used 21 different hand gestures to convey information to robotic platforms, which interpreted the gestures at accuracy levels greater than 95%. Barber et al. (2015) described a prototype multimodal interface for communicating with a robot using speech and gestures. This robot used a camera-based recognition system to detect gestures. Participants in the initial field assessment of the system reported that the gesture recognition needed to be improved, as did the training on how to interact with the robot using gestures. However, the authors noted positive impressions from participants regarding the flexibility of the communication with the robot.

These approaches demonstrate some of the progress being made in allowing humans to communicate information to autonomy in various modalities. Further development of these research areas will eventually yield autonomy that can better understand the human's states and intentions, enabling more-fluent bidirectional communication between humans and autonomy and increasing the operational flexibility of HATs.

1.2.2.2 Wearable Technologies

One critical challenge in developing advanced autonomy for HAT is the integration of the human element into that team. Therefore, HAT on a broad scope will benefit from accounting for the dynamic strengths and vulnerabilities of human team members. As such, future research will need to include 1) precise observations or inferences of individual and team states, processes, and performance over time, 2) a clear understanding of dynamic events in the operational environment and within the hierarchical and lateral structure of the teams, and 3) the ability to seamlessly and synchronously allow for adaptation while maintaining effective collaboration, coordination, and dynamic control among humans and agents (DeConstanza et al. 2018a). Real-time physiological assessments of human team members (e.g., heart rate or electrodermal activity) may be able to provide insights useful to joint operations and trust within HATs (Schaefer et al. 2019a). Current research efforts are looking into how data from wearable technologies can be used to communicate information about human state (e.g., stress, trust, and workload; Drnec et al. 2016; Gamble et al. 2018) to other team members including autonomy.

Given that humans' current state can influence the information they need and can interpret, this research can be used to facilitate transparency and shared SA in accordance to each specific humans' capabilities and informational needs. Further, this additional information about the human team members can influence team operations and joint decision-making behaviors. Another advantage of using sensing to infer human states and intentions is that it reduces the burden of forcing the human to communicate with the autonomous agent (whether communication is written, verbal, or gesture-based). Instead the agent will be able to infer task-relevant states without adding to humans' cognitive loads. However, sensing of a human through wearable technologies is insufficient to meet the need for improving human-to-autonomy communication because only so much information can be gathered by wearable sensors. Machine learning and artificial intelligence will need to be integrated to compute real-time information regarding the wearer's state over time, and this integration will support real-time management of HAT in the context of dynamically varying trust in autonomy (Metcalfe et al. 2017). For example, multisensor fusion architectures provide a method for estimating expected and actual performance of humans and autonomy team members during a joint task. By taking this approach it is possible to mitigate human bias and miscalibrated trust in autonomy through real-time visual feedback to a human team member (Nothwang et al. 2016; Marathe et al. 2018; Gremillion et al. 2018). These types of approaches make it possible to develop interventions to modify behavior of the appropriate team member at the appropriate time; to sense shifts in environmental or socio-cultural influences and mission goals; to determine relevance to the team mission; and to develop technologies capable of balancing among different types of states and processes within the team (DeConstanza et al. 2018a).

1.2.3 Joint Human–Autonomy Teamwork

Effective HAT will require coordination of appropriate information between all team members at the appropriate time (Sycara and Sukthankar 2006). A focus of current research seeks to maximize the strengths and minimize the weaknesses in both humans and autonomous teammates to achieve effective teaming (Marathe et al. 2018). To do that requires careful consideration of the capabilities of humans and autonomy when they are joined in teamwork. The successful integration of humans and intelligent agents will support new team structures that can perform effectively in dynamic adversarial environments (US Army 2017). To achieve that level of performance, HATs will need to exhibit a shared understanding of their tasks, teamwork, and environment (Ososky et al. 2012). The design of effective HATs will also benefit from emphasizing principles coactive design that incorporate grounding and interdependence between humans and agents (Bradshaw et al. 2009; Johnson et al. 2014).

As systems become more capable and as we gain a better understanding of how humans can function in HATs, our understanding of how team communication relates to other teaming characteristics will evolve as well. The factors highlighted in this section address characteristics that affect joint communication between humans and their autonomous teammates.

1.2.3.1 Shared Cognition

Knowledge within a team shapes communication by affecting the way that the team thinks, coordinates, shares information, and engages with tasks (Cooke et al. 2004, 2007; Sycara and Sukthankar 2006). Shared mental models (SMMs) comprise organized knowledge about teamwork and taskwork (Cooke et al. 2000; Mathieu et al. 2000), which allow team members to accurately understand tasks and expect team members' behavior (Espinosa et al. 2002). SMMs are long-lasting and remain fairly stable over time (Cooke et al. 2000), and have been shown to enable effective coordination among team members by allowing them to understand their teammates' needs and activities (Cannon-Bowers et al. 1993). This is because teams with good SMMs can better understand the context and implications of their communications (Evans et al. 2017). At the same time, SMMs have also been noted to support team coordination in situations where communication is hampered; it is thought that better SMMs help teams to communicate implicitly when explicit communication becomes challenging (Cannon-Bowers et al. 1993; Stout et al. 1996; Cooke et al. 2000). Indeed, these lines of research have also suggested that task-related SMMs can make team communication more efficient by decreasing the amount of communication needed to achieve a given purpose (Langan-Fox et al. 2004).

The concept of transactive memory systems (TMSs) is closely related to, but distinct from, SMMs. Transactive memory is information that helps us understand "who knows what", and a TMS involves the group's engagement with managing, updating, and coordinating such information (Wegner 1987; Ren and Argote 2011). Thus a TMS is characterized by knowledge about which team members possess specific information and active coordination of that knowledge, whereas SMMs involve additional information about team strategies, goals, taskwork, and so on (Cooke et al. 2000; Lewis 2003; Wildman et al. 2014). Both TMSs and SMMs are important facets of team cognition that support effective teamwork.

Team cognition, communication, and performance are innately linked such that teams communicate information while performing tasks. The literature has consistently identified team information sharing as a driver of team performance (Mesmer-Magnus and Dechurch 2009), although not all information sharing is equal. Teams can share information that is already commonly held among team members, or information that is uniquely held by one member (Stasser and Titus 1985). Generally, teams share common information to bolster team cohesion, improving the social aspect of working as a team, though it may sometimes be detrimental to performance if teams share too much common information; the tendency for teams to do so is known as the common knowledge effect (Gigone and Hastie 1993; Gruenfeld et al. 1996). In contrast to sharing common information, teams share unique information to increase the amount of knowledge available to the team, improving the team's ability to solve problems and work on tasks (Mesmer-Magnus and Dechurch 2009). Generally, communication is important to the development of transactive memory during early team interactions (Ren and Argote 2011). For example, in a study of business consulting teams, Lewis (2004) found a relationship between communication frequency in the planning phase and the development of a TMS.

In the HAT context, shared cognition encompasses a mutual understanding held between the human and autonomy team members regarding the individuals' and team's status and goals. As with human teams, HATs can have SMMs corresponding to teamwork and taskwork. However, the communication that shapes shared cognition in human teams is sometimes abstract, and given that current agents lack the ability to understand nuanced communication, this presents a barrier to measuring shared cognition in HATs (Evans et al. 2017). Regardless, research into this area is ongoing, and researchers continue to shed light on the links between automation transparency, human–agent shared cognition, and team performance (Chen et al. 2018). As cognition is a term that encompasses more-specific constructs (e.g., information sharing and decision making), research has also been conducted on those finer aspects of cognition, including shared SA.

1.2.3.2 Shared Situation Awareness

Shared SA reflects the extent to which the SA possessed by each team member overlaps (Endsley and Jones 2001). Shared SA is dynamic and relates to the environmental situation around the team (Cooke et al. 2000). This is in contrast with SMMs, which are considered to be more structured and stable over time and relate to understandings developed among the team (Wildman et al. 2014). For shared SA, Endsley (2015) argues that "team members do not need to share everything they know, which would constitute overload, but only those informational needs that they have in common, as a function of their overlapping goals" (p. 23). Because SA is a cognitive construct, shared SA can be considered a shared cognition.

Shared SA is critical to how well teams can coordinate actions, goals, and intentions, as long as the appropriate amount and quality of information is being shared among the correct team members. In HAT, shared SA is critical to goal alignment, function allocation, communication of decisions and intentions, and coordination of taskwork (Endsley 2015). Shared SA in HATs also involves components of transparency, as illustrated by the Situation Awareness-based Agent Transparency (SAT) model (Chen et al. 2018). The SAT model defines the information that is needed to have SA of an agent. The model involves three levels of information: 1) current actions, plans, and status (Level 1), 2) general reasoning process and intentions (Level 2), and 3) projections and predictions about future outcomes (Level 3). Thus, the SAT model illustrates how information provided by autonomy can support human SA (Chen et al. 2018). This is critical to coordinating teamwork processes and should be considered essential to effective communication. Ultimately, communication helps to moderate what information is held by which members, and effective communication helps to ensure that the team's shared SA is calibrated to the demands of the task.

1.2.3.3 Implicit Communication

When discussing communication, much work considers communication that is actively and explicitly performed, but implicit communication is also a useful means of transmitting information. Implicit communication can be characterized by nonverbal cues such as posture and facial cues, but some have noted that implicit communication can also involve verbal components such as sighs or grunts (Lackey et al. 2011). In human teams and HATs, implicit communication can allow teams to share more information without usually occupying more communication bandwidth (see Section 1.2.1.3 for more discussion about multimodal communication). This is illustrated in Barnlund's (2008) transactional model of communication: The sending and receiving of messages happens simultaneously, such that while two people are speaking, verbal and nonverbal cues are being exchanged as well. Nonverbal cues can involve face and head movements, which are visible if two parties are co-located and communicating verbally, and they allow the parties to engage in social functions using this implicit channel while speaking in the explicit channel (Hecht et al. 1999).

Some research has evaluated how robot design can facilitate nonverbal communication. In one study, Baraka et al. (2016) implemented lights to allow a robot to persistently display its state in relation to its environment and tasks, such as when it believed itself to be blocked by an obstacle. In another study, Kühnlenz et al. (2013) found that when a robotic head's facial expressions were made to mirror participants' emotional states, the participants demonstrated more prosocial behavior. In human teams, the multichannel interactions characteristic of nonverbal communication are complex, and nonverbal communication is not commonly evaluated in analyses of teamwork (Tiferes et al. 2016). Thus, more work must be done to understand implicit communication in human-only teams if we are to apply those principles to HATs.

2. Relevant Models and Theories for Human–Autonomy Team Communication

To shape current and future HATs, and to address the challenges of humans understanding autonomy, autonomy understanding humans, and joint HAT, a clear theoretical foundation must be laid based on teamwork and communication. This section provides such a theoretical foundation by detailing several models and theories of teamwork and communication. While the models and theories described represent a broad a range of contexts, they should not be considered exhaustive. They were selected based on their explanatory power and applicability to different domains both within and outside of HAT. There are virtually unlimited numbers of possible configurations of teams involving humans and autonomy-enabled systems, and autonomous capabilities will continue to evolve, so an approach that seeks to generalize across a range of contexts is most useful for this review.

2.1 Teamwork Models and Theories

A large variety of teamwork models have been designed to account for different aspects of teamwork, but many are context-specific and are thus less generalizable. The models and theories presented in this section describe the general aspects of teamwork processes and emergent states and are thought to be applicable to a variety of scenarios and team compositions.

2.1.1 Inputs, Processes, and Outputs (IPO) Model

One of the early teamwork models to gain widespread acceptance conceptualized teamwork with three stages: inputs, processes, and outputs (IPO Model, Fig. 1; Steiner 1972; McGrath 1984; Hackman 1987). The IPO Model is important because it provides researchers with a framework for understanding how team inputs (e.g., knowledge, skills, and attitudes) lead to processes (e.g., backup behaviors or nonverbal communication), which then lead to outcomes (e.g., performance or accuracy). The introduction of the IPO Model was a step forward in modeling teamwork, as prior research on group interactions was primarily focused only on how inputs resulted in outputs, with very little research into processes (Hackman 1987).

Fig. 1 IPO Model

However, the IPO Model has several shortcomings. First, it only accounts for processes as a linkage between inputs and outputs, and thus it does not account for emergent states (Ilgen et al. 2005). Processes involve the nature of the team's interaction and reflect things that team members *do*, such as closed-loop communication (Salas et al. 2015). Emergent states, in contrast, refer to the cognitive or affective states that emerge from a team's experiences (including processes) (Marks et al. 2001). One example of an emergent state is trust (Ososky et al. 2014). Emergent states can serve as mediators between team inputs and outcomes. Thus, this limitation in the IPO model restricts its ability to account for the breadth of mediators that can link team inputs to team outputs.

Second, the IPO Model does not account for the cyclical nature of teamwork (Ilgen et al. 2005). It models the way that inputs lead to outputs via processes, but it does not explain how outputs can affect subsequent inputs. For example, after-action reviews are used to review team performance following tasks to identify failures and improve subsequent performances. In this manner, team outputs (e.g., performance) ultimately will affect their inputs the next time they engage in those tasks. Within the constraints of the traditional IPO Model, this team development over time cannot be easily represented.

Third, the IPO Model moves linearly through each step. Research has suggested that relationships between each set of influences (inputs, processes, emergent states, and outputs) can occur nonlinearly, conditionally, or in other manners (Ilgen et al. 2005) rather than in a linear procession from inputs to processes to outputs. This implies that a different model is needed to account for nonlinear transitions between the influences.

2.1.2 Temporally Based Taxonomy of Teamwork

To address some of the shortcomings in the IPO Model's characterization of teamwork, Marks et al. (2001) argued that the IPO Model was better represented in brief "episodes and sub-episodes, rather than the entire life cycle of the team" (p. 360) and posited that the IPO Model could be repeated many times, with outputs from one "episode" feeding into inputs from another (Fig. 2).

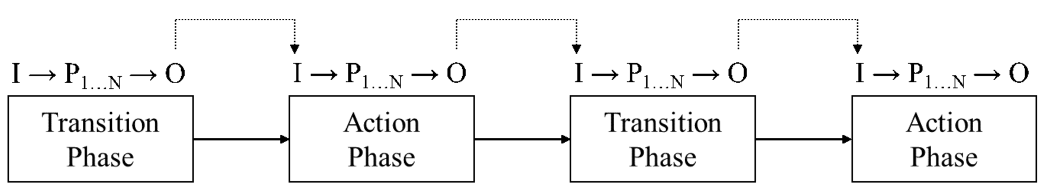

Fig. 2 Example breakdown for a single task over time (adapted with permission from Marks et al. [2001])

While this is one potential solution, it fails to address the fact that the IPO Model does not account for emergent states, a shortcoming that was underscored by the authors. In their work, Marks et al. (2001) highlighted the importance of distinguishing between team processes and emergent states, but ultimately sought to produce a team process taxonomy rather than a broader teamwork taxonomy that accommodated both processes and emergent states. Thus, while the taxonomy advanced by Marks et al. served as a refinement of the initial IPO model, later authors proposed a model that accounted for a fuller picture of teamwork, which we discuss in the following section.

2.1.3 Input-Mediator-Output-Input (IMOI) Model

In response to the IPO Model and the taxonomy of teamwork discussed, Ilgen et al. (2005) proposed the IMOI of teamwork (Fig. 3). The IMOI Model represents teamwork in an improved manner relative to previous models through their use of a second input phase after output to reflect the cyclical nature of teamwork. Second, their replacement of *processes* (used in the IPO Model) with *mediators* is meant to capture a greater extent of variables and constructs that can link inputs to outputs. Finally, they argued that the IMOI Model accommodates potential interactions between its phases rather than serving as a solely linear flow from inputs to outputs, as in the IPO Model and the team process taxonomy (Marks et al. 2001). The IMOI Model has considerable explanatory power and has remained useful since its conception, providing utility in modern research including for HAT. For example, You and Robert (2018) proposed an IMOI framework of human–robot teamwork to describe the developmental process of human–robot teams.

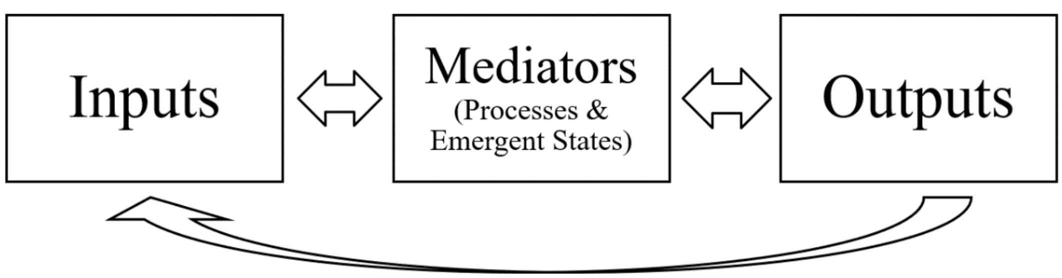

Fig. 3 Example IMOI model

2.1.4 Big Five Model

To build on the previously developed theoretical models of teamwork, Salas et al. (2005) produced the Big Five model of teamwork. This model unified previously disparate teamwork literature to identify five core components of teamwork: team leadership, mutual performance monitoring, backup behavior, adaptability, and team orientation. It also identified the importance of three coordinating mechanisms to teamwork: shared mental models, closed-loop communication, and mutual trust. In this way, Salas et al. (2005) linked what a team does (five core components) with how it coordinates (three coordinating mechanisms).

The primary contribution of the model is that it is easily translated to many contexts and scenarios. The model accounts for some of the major teamwork factors and links team processes and states to coordination and communication factors. However, there are a few limitations of the model. First, it should not be considered fully diagnostic. While it accounts for five core components and three coordinating mechanisms, there are a multitude of teamwork constructs that are not accounted for by the model, such as SA and team cohesion. Second, the relationships within the model are not necessarily complete. In the model, mutual trust is only linked to mutual performance monitoring, and closed-loop communication is not related to any other constructs. Additional research will help to better specify other relationships among the constructs in the model. While this model is not perfect, it represents a major attempt to produce a model that captures essential teamwork and coordination constructs in a manner that is both parsimonious and generalizable. The Big Five model of teamwork (Salas et al. 2005) remains a useful framework for considering important contributors to teamwork.

2.2 Taxonomy of Classifying Teams

Previous sections presented some of the models of teamwork that describe how teams function. In this section we discuss the classification of team characteristics. In an attempt to create a generalizable taxonomy for classifying and describing teams, Hollenbeck et al. (2012) devised a method for describing teams on three dimensions: skill differentiation, authority differentiation, and temporal stability. Hollenbeck et al. argued that the lack of consensus on how to define and classify teams presented challenges when trying to compare results and aggregate findings across studies of teams. All three dimensions provide insight into the communication patterns of the team, so the discussion of each dimension briefly addresses how it relates to team communication.

2.2.1 Skill Differentiation

Skill differentiation refers to the extent to which the skills held by each team member are shared or unique. Some teams are characterized by a high degree of specialization among their members; consider surgical teams in which the lead surgeon cannot do the anesthesiologist's job, for example. Other teams have little differentiation, as in a crew of service technicians where members may be cross-trained on each other's roles. This method for classifying teams provides insight into the communication of the team because the overlap between team member skill sets relates to how much skill-based knowledge is shared by team members. With less skill differentiation, team members can assume a shared base of knowledge (see Section 1.2.3.1 regarding shared cognition), whereas a higher degree of skill differentiation implies that some discussions may need to involve reaching a common ground of understanding (see Section 2.3.5 regarding grounding).

2.2.2 Authority Differentiation

Authority differentiation describes the extent to which leadership or influence is balanced across the team or concentrated in one or a few members. Teams with high authority differentiation may be hierarchical, relying on the team's leadership to make decisions or set goals. This is the structure typically employed across various levels of the US Army and other military organizations. On the low end of this dimension, a team with low authority differentiation would engage in team processes in a more democratic fashion, allocating tasks in a manner that allows for more shared participation and opportunity for different members to contribute to decision making. For example, this might characterize design teams that focus on creative problem solving. The authority structure of a team directly affects the communication patterns that can be exhibited within a team. Teams with looser authority differentiation and more shared participation can have more dispersed communication between team members, whereas teams with clear authority differentiation have rigid hierarchies and thus similarly rigid communication structures. Ultimately, different contexts will require different structures for authority (and thus, different communication patterns) based on mission needs.

2.2.3 Temporal Stability

Temporal stability represents the expected lifespan of the team (i.e., how long the team is expected to remain intact). Team temporal stability affects many other factors such as trust and shared mental models, so this dimension is an important consideration for the analysis of teamwork. Teams with high temporal stability have very little turnover between projects and rely on a consistent set of team members over time. In contrast, teams with low temporal stability may be formed for a sole purpose and then reformed or disbanded, as with ad hoc virtual teams that are assembled to complete tasks rapidly (Crisp and Jarvenpaa 2013). Team temporal stability affects team communication primarily due to how those constructs relate to shared cognition. More temporal stability means more time to build shared cognitions, trust, and team cohesion using communication. Teams with little temporal stability may instead be formed rapidly to address tasks in a limited time frame, but they may not have time to engage in enough communication to fully develop trust and team cohesion.

The use of dimensions provides better granularity for understanding teams and their communication patterns. However, there are a few drawbacks to this approach. There is not an exact way to operationalize where a team lies on a dimension; in other words, it is a subjective matter to decide whether one team has more skill differentiation than another and to identify the extent of that difference. Thus, finer distinctions of teams remain difficult. Another issue lies in the number of dimensions used. While Hollenbeck et al. (2012) argue that the explanatory power of the three dimensions is considerable, authors have suggested that this approach may need to be expanded to account for the wide variability in the compositions, functions, and performance of modern teams (Benishek and Lazzara 2019). Further, other dimensions may account for variance in team performance that is not explained by this model. For example, a dimension of virtuality (i.e., the extent to which a team is geographically separated and reliant on technology-mediated communication) may be warranted given the recent consensus that team virtuality is measured dimensionally rather than dichotomously (Schweitzer and Duxbury 2010; Hollenbeck et al. 2012). In the context of HAT, it is also possible that another dimension of the model could reflect the extent to which the team makes use of autonomous assets, though as discussed with previous limitations, operationalizing exactly where a team falls on dimension could prove challenging. Despite this limitation, methods for describing and classifying HATs will be continually useful given the ever-evolving capabilities and implementations of intelligent agents.

2.3 Communication Models

There is a vast field of research into many aspects of communication due to its importance to any kind of group interaction. Due to the breadth of this research, a variety of theories and models of communication have risen to prominence over the years. This section outlines a selection of prominent theories and models of communication, and discusses the relevance of the communication theories and models to teamwork, and specifically HAT, where applicable.

2.3.1 Shannon's Model of Communication

Shannon (1948) published the first widely adopted model of a communication system in an effort to characterize how communication systems such as the telephone transported information. Figure 4 depicts this model of communication. Shannon's model has a few parts:

- Source: the object, system, or person from which the message originates.
- Transmitter: the system or mechanism that produces and encodes the message for transmission.

- Signal: the information being sent from source to destination.
- Noise source: refers to anything that introduces noise into the system, potentially affecting the quality of the transmitted message; for example, background sounds, electrical interference, and the like.
- Received signal: the signal after considering the effects of noise.
- Receiver: something that receives and decodes the message.
- Destination: the final location for the message.

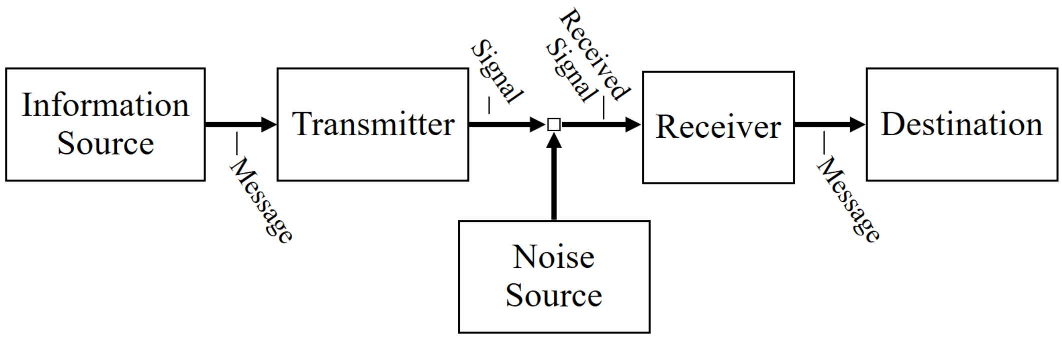

Fig. 4 Model of information transmission (adapted from Shannon [1948])

Notably, while Shannon's model was designed to represent technological systems such as phones or radio, it was eventually applied to other contexts, such as person-to-person communication, because it represents the conceptual process of information transmission. However, this reveals one of the limitations of the model: it ends at receipt of the message and does not account for any other processing of the information. This processing could, for example, involve a Soldier interpreting a superior's order based on their positions in the battlespace. Another limitation of the model is that it becomes unwieldy in situations involving group, one-to-many, or back-and-forth communication. Like the IPO Model, this model does not account for the cyclical or reciprocal nature of interaction, in this case communication. To address this shortcoming, Marko (1973) extended Shannon's model to involve two sources exchanging information. In this bidirectional communication theory, Marko (1973) argued that information exchanges between humans, animals, or other "multivariate complex systems" could be described. Further discussion on communication as a reciprocal interaction can be found in Section 2.3.3.

The limitations of Shannon's model necessarily stem from the original purpose of Shannon's work, which was to characterize telephone and radio communication. Despite its drawbacks, the model remains effective at conceptually outlining the process of transmitting information between two points.

2.3.2 Berlo's Sender-Message-Channel-Receiver (SMCR) Model

In response to some of the limitations of Shannon's model of communication, Berlo (1960) created a communication model that better accounts for the human aspect of communication. Berlo's SMCR model contains the following four components:

- Sender: source of the message.
- Message: information being transmitted from sender to receiver.
- Channel: medium used to transmit the message.
- Receiver: person receiving the message.

Further, each component involves several subcomponents. Sender encompasses one's characteristics such as attitudes, culture, knowledge, and communication skills. Message involves the structure, content, and purpose of the message. Channel invokes the ways in which the senses are used to transmit the message: sight, hearing, touch, and so on. Receiver encompasses the receiver's attitudes, knowledge, culture, communication skills, and so on, similarly to how these subcomponents play a role for the Sender.

Compared with Shannon's model of communication, the SMCR model is better able to explain aspects of human communication, such as purpose, prior knowledge, and emotional content. Further, unlike Shannon's model, the SMCR model can account for the greater context of the communication via the Source and Receiver factors of attitudes, social systems, and culture. Because they capture a broader perspective of human communication, these features allow for better applicability to team communication work. However, some limitations to this model are worth considering. First, like Shannon's model, the SMCR model does not account for the reciprocal nature of communication and is not able to effectively represent feedback processes or one-to-many communication. Second, unlike Shannon's model, the SMCR model does not consider or represent the effects of noise (i.e., unwanted signal or interference) on the communication channel, and many forms of noise can affect communication. Despite these limitations, the SMCR model was a significant step forward for models of communication because it highlighted the importance of psychological and contextual factors to communication.

2.3.3 Turn-Taking

Whereas communication can be conceptualized as the transmission of information (as outlined in the preceding two sections), a conversation involves a back-and-forth exchange of information between two (or more) parties. Research by the contemporaries of Shannon (1948) and Berlo (1960) focused on the former perspective, and this eventually gave way to research that sought to develop the latter perspective and advance an analytical view of language as a reciprocal interaction between parties. One line of work in this movement sought to establish the importance of turn-taking to conversation. Sacks et al. (1974) noted that turn-taking allows us to communicate effectively by dictating how we shift speakers during a conversation. They argued that communication comprises utterances marked by transition-relevance places (TRPs), which indicate conversational boundaries that allow speakers to exchange turns. TRPs allow conversation to flow between speakers. Jurafsky and Martin (2007) summarize what happens at each TRP as follows:

- If during this turn, the current speaker has selected A as the next speaker, then A must speak next.
- If the current speaker does not select the next speaker, any other speaker may take the next turn.
- If no one else takes the next turn, the current speaker may take the next turn.

This system of turn-taking uses TRPs to flow between speakers during a conversation. It is a considerable advancement of the science of communication from the models of Shannon and Berlo because it provides a foundation for understanding the exchange of information between two (or more) speakers as opposed to those models that represent communication as a one-way transmission. If we adopt the perspective of Sacks et al., we can begin to understand communication as a joint coordination activity between two or more parties, which provides a theoretical basis for the importance of communication to teamwork. The view of communication as a two-way exchange of information was also echoed by Barnlund's (2008) transactional model of communication, originally published in 1970. In this model, Barnlund considered a conversation to be a multilayered feedback system in which two speakers exchange information both verbal and nonverbal.

In a recent extension of the turn-taking concept, Gibson (2003) proposed a framework for analyzing conversations based on "participation shifts". These shifts capture how a conversation shuffles between speakers and recipients. Each participation shift incorporates a temporal element by capturing two consecutive communication acts (e.g., A talks to B, then B talks to A; or A talks to B, then A talks to Y). Gibson tested this framework by analyzing meetings of managerial groups and was able to identify sequential patterns in speakers that governed "who could speak and be addressed in a given turn".

From these perspectives, communication involves a fundamental level of coordination to share information, so if this process encounters problems, other teamwork processes (which rely on coordination) are more likely to subsequently experience problems. Communication and teamwork are thus interlinked. Consider the following hypothetical example of this link. A fire team leader might spot a target and call on one of his riflemen to confirm visual on the target. If the next person to speak is instead the radio operator with information about a transmission, the expected turn-taking order was violated. This could potentially lead to a decrement in SA if the rifleman needed immediate clarification from the team leader, and could also potentially affect the team's response time when dealing with the target.

However, turn-taking violations are not always indicators of poor team communication practices. For example, in an interaction between a doctor and two nurses regarding a patient, if the first nurse asks the doctor about the dosage for an antibiotic that should be provided to the patient, but the second nurse interrupts by clarifying that the patient's records indicate an allergy to that antibiotic, we would likely conclude that this was a necessary and helpful violation of expected turn-taking. In brief, the turn-taking mechanics proposed by Sacks et al. (1974) provide a critical link between the theories of communication and teamwork. This perspective allows us to understand communication within a team as a coordinated sequence of information exchanges, and the ability of a team to effectively navigate those exchanges plays a role in how well it can perform in different scenarios. Other publications from this era advanced and expanded this view, a selection of which is detailed in the following two sections.

2.3.4 Grice's Maxims

In the body of research on language, another landmark effort developed an analytical view of conversation. Grice (1974) argued for the existence of guidelines that governed how conversations worked. Grice posited that efficient conversations would follow four maxims:

- Manner: those in conversation should speak logically and in an orderly fashion.
- Quality: conversational information should be based in fact.
- Quantity: those in conversation should say only what is needed.
- Relation: those in conversation should say only what is relevant.

Together, the four maxims comprise Grice's "cooperative principle". It was Grice's belief that, when engaging in conversations, individuals should "make their conversational contribution such as is required, at the stage at which it occurs, by the accepted purpose or direction of the talk exchange in which they are engaged". The four maxims offer a method for understanding the mechanisms that underpin a conversation. For example, consider a situation in which two team members are searching for a simulated enemy in a building. Following Grice's maxims, a team member should not offer information about their dinner plans in response to a question about the last known location of the enemy, as this would violate the maxim of relation. While this seems intuitive, there was not previously a theory that outlined functional aspects of communication in a manner that prescribed aspects of successful conversation.

While Grice's maxims represent a landmark in communication research, they are not all-encompassing. For example, they do not provide insight into defining the concepts; for example, "what is relevant" can mean different things to different people looking at the same situation. Therefore, this theory provides a set of general heuristics for understanding what makes conversations effective, and not a concrete methodology. However, it remains a scientific contribution that offered a framework for understanding what makes certain conversations more effective than others.

2.3.5 Grounding

Another seminal area of research in communication involves the concept of grounding, a collaborative effort between speaker and listener that involves shared information about what is known, what is said, and what is intended. In conversation, to ensure that future utterances will be understood, speakers need evidence that listeners are attending to and understanding what they are saying (Goodwin 1981; Clark and Schaefer 1987). As such, when communicating we use grounding to establish and maintain a common understanding (Clark and Brennan 1991).

During a conversation, speakers use coordination techniques to ensure that they are on the same page. Using speech or nonverbal cues, speakers can indicate their understanding of the current conversation (e.g., by nodding the head) as well as problems arising from a lack of common ground (e.g., by furrowing the brow or asking a question). If a squad leader says "Vehicle at our 3 o'clock", he is assuming that the squad shares the common understanding that 12 o'clock is at a certain orientation relative to the squad and thus bases his comment on that assumption. In most cases, these assumptions are effective and allow us to exchange a vast amount of information quickly. How to achieve grounding between humans and intelligent systems remains an active area of research (Boularias et al. 2015; Chai et al. 2016), and the construct of transparency has been noted to be important to human–

autonomy grounding (Stubbs et al. 2007; see Section 1.2.1.2 for discussion on transparency). The goal of having humans communicating efficiently with intelligent agents using normal, unconstrained speech is still a ways off, partly due to problems with getting synthetic agents to understand humans' intentions based on their speech (Demir et al. 2015). However, researchers have highlighted the importance of grounding to effective human–autonomy coordination in efforts to improve the effectiveness of interdependent HATs (Bradshaw et al. 2009; Johnson et al. 2014).

Like the collaborative nature of conversational turn-taking, grounding also involves collaboration between those in conversation. While the concept of turn-taking accounts for mechanics of conversation, the concept of grounding serves as a clearer link between conversation and psychology. It accounts for how we derive understanding from communication. Thus, by considering turn-taking and grounding together, we can gain a broader perspective on how communication influences aspects of coordination and teamwork.

2.3.6 Synthesizing Communication and Teamwork

Given the conceptual and practical links between communication and teamwork, researchers have devoted considerable attention to understanding the interplay between the two. Broadly, team communication factors can be broken down into factors of content, quality, timing, and type. Content relates to what is said; quality relates to how it is said; timing relates to how quickly, how often, or how much it is said, and also encapsulates the order in which things are said; and type refers to the purpose for saying what is said (e.g., to share general knowledge or to elaborate on existing information). Problematically, researchers often inconsistently operationalize these factors, complicating efforts to synthesize findings across studies of team communication.

In a recent meta-analysis of communication and teamwork, Marlow et al. (2018) sought to address this inconsistency and evaluate the relationships between various team communication characteristics and team performance. Their findings suggested that there is less of a relationship between the frequency of communication and performance, but rather it is in the quality or type of communication (depending on team familiarity and proximity) that can positively or negatively affect a change in performance (Fig. 5). However, additional research is needed to quantify communication as a whole rather than individual variable effects on performance.

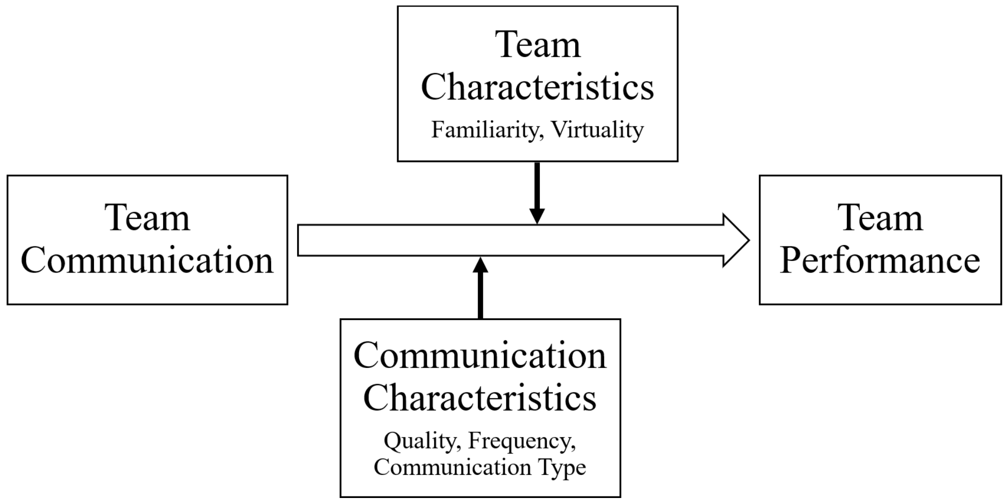

Fig. 5 Meta-analytic model of team communication and performance with moderators (adapted with permission from Marlow et al. [2018])

The broad perspective on team performance taken for this meta-analysis represents the current and future directions of research into team communication; that is, to better understand team performance, researchers need a broadly informed understanding of the team's communication. This driving force is especially important in HAT contexts where the communication abilities of agents are under constant development and involve rapid technological advancement. Efforts are underway to build new models of human–autonomy team communication that can accommodate these factors, but more work is needed to synthesize data gathered from the many disciplines involved in this area (Evans et al. 2017). With respect to the model provided in Fig. 5, it is possible that another set of moderators, agent characteristics, could be added to account for the unique considerations of intelligent agents. Again, more research will continue to shed light on a possible model of human–autonomy team communication.

2.4 Human–Autonomy Team Applications of Models and Theories

Given the increasing complexity of intelligent agents and autonomous systems, better methods and metrics are needed for understanding team communication in HAT, given that communication shapes critical aspects of teamwork, performance, cohesion, and trust. To achieve this objective, we need to build our understanding on a foundation of both teamwork and communication. The models and theories discussed in the preceding sections represent a broad cross section of theoretical scaffolding for understanding how teams work. The models and theories identify a variety of constructs critical to effective teamwork and represent aspects of teaming and coordination in different ways. Although HAT is complex, we can blend different models and theories to gain deeper insights. To understand the dynamics of interactions within HATs, it will be appropriate to combine the programmatic information theory approaches (e.g., Shannon 1948; Berlo 1960) with the cognitive-based approaches (e.g., Grice 1974; Clark and Brennan 1991). By drawing from several models and theories, the multimodal interactions that will characterize HATs can be better explained and understood. For example, we can conceive that each step of turn-taking during a conversation involves an individual transmission involving a source, a message, a channel, and a receiver, blending Berlo's approach with that of Sacks (1974) and offering a deeper way to think about *why* turn-taking might result in certain team outcomes whether or not the team involves autonomy. This broader theoretical foundation can thus provide a framework for understanding how communication results in other psychological phenomena, such as team trust, team cohesion, and SA.

The theories discussed in the preceding sections can be leveraged to gain new perspectives on the ways in which team composition and team communication are affected by intelligent agents. The team taxonomy advanced by Hollenbeck et al. (2012) can provide insight into critical aspects of the dynamics between humans and agents. Paralleling the taxonomy's dimension of authority (see Section 2.2.2), much ongoing research in HAT involves some aspects of control authority and task allocation, especially given the increasing functionality of intelligent agents (Chen and Barnes 2014). The dimension of temporal stability is also relevant to HAT. Because future HATs will need to be adaptive and flexible in the face of evolving threats, teams may need to reorganize their membership in emergent situations, which places stress on team communication and coordination. For example, there may be a need for increased communication of intent or general reasoning at the start of a new team's interaction to build a shared understanding of their tasks and roles, underscoring the extent to which a team's taxonomic characteristics impact its communication patterns. Diverse mission environments and novel situations will challenge teams, and no matter how complex such teams become, a strong theoretical basis for understanding their interactions and performance can be found in these principles of teamwork and communication.

3. Communication Metrics and Analysis Methods

The complexity of HAT requires that a variety of metrics and methods be used to capture different aspects of teaming. This requirement extends to communication. While there are many methods for analyzing and evaluating team communication, each method has certain considerations regarding its utility. This section discusses several modern communication analysis methods and, where applicable, their utility to examining HAT topics.

3.1 Qualitative Coding

Qualitative communication coding is an approach used to systematically derive information about team communication. To code communication data, the first step usually involves transcribing audio recordings into text. Once transcribed, it can then be coded by manually sorting portions of language-based data into categories based on predefined criteria. Alternatively, if categories are not defined a priori, a set of categories may be defined organically during review of the data set. In any case, the process of coding derives an explanation of meaning from communication data (Charmaz 2001). There are many approaches to qualitative coding depending on the design and goals of the research at hand (for a thorough review of qualitative coding, see Saldaña 2013). Regardless of the approach used, qualitative coding can provide rich insights into team processes and emergent states.

Qualitatively coded data can offer researchers information about what teams are saying, when, and why, which can allow researchers to better understand other teaming concepts such as the team's shared mental models, goals, attitudes, and more (see the Appendix for a review of some studies that used qualitative coding). However, this method is not without its drawbacks. Qualitative coding of communication data is time-intensive. While exact time requirements are highly variable and depend on the amount of data being gathered and the coding scheme used, estimates can sometimes reach as high as 30 min of effort to code 1 min of communication (Tiferes et al. 2016).

While coding can be done manually, software programs designed for qualitative coding have been developed, such as NVivo (QSR International 2019), MaxQDA (VERBI GmbH 2019), and ATLAS.ti (ATLAS.ti Software Development GmbH 2019). These programs are typically called computer-assisted qualitative data analysis software, or CAQDAS. These types of software facilitate the storage, organization, management, and reconfiguration of data throughout the analysis process (Saldaña 2013). Using CAQDAS, a researcher can more efficiently manage a data set and perform qualitative coding. CAQDAS programs can also have features that allow the user to visualize the qualitative data in different ways, such as by displaying color labels or graphical representations of relationships between codes. While CAQDAS programs make qualitative communication analyses more efficient, the task of coding still ultimately falls to the researcher, meaning that qualitative communication coding remains a time-consuming process (for more discussion of CAQDAS programs, features, and methods, see Saldaña 2013).

Given the laborious nature of qualitative coding, researchers have sought to shift the task of coding data from humans to algorithms. In doing so, researchers hope to more efficiently tap into communication data using computational methods to evaluate the structure and function of team communication.

3.2 Computational Approaches

To tackle the complexities of communication analysis, advanced algorithms, mathematics, and computation have been used to derive information from team communication far more quickly than would be possible with human interpretation alone. Computational approaches are very diverse and highlight the flexibility of algorithmic applications. In this section, we highlight several computational approaches to team communication analysis, although this is not intended as an exhaustive list.

The variety of computational approaches to team communication is as diverse as the variety of algorithms that can be written; this is not intended as an exhaustive list of all computational methods for analyzing communication. In general, while these methods can be mathematically very complex and sometimes limited in adoption, they can provide unique, rich insight into team communication and coordination processes. Because computation methods can often analyze data much more quickly than human-reliant methods like qualitative coding, we believe these methods will be extremely useful to analyzing HATs in lab settings as the capabilities of intelligent systems evolve.

3.2.1 Latent Semantic Analysis

Latent semantic analysis (LSA) is a theory and method in computational linguistics that derives meaning from the context and pattern of word usage irrespective of word meaning or syntax (for reviews, see Landauer et al. 1998; Dong 2005). LSA focuses on word co-occurrence and assumes that words that occur more frequently together are conceptually linked. LSA can be used as a way to annotate team communication (Foltz and Martin 2008) and has been applied to analysis of other communication content such as task relevance and topic shifting. Gorman et al. (2003) used LSA to evaluate communication in three-person teams that operated simulated Predator UAVs. The authors found that team communication density was related to performance, and that LSA was useful in distinguishing high-performing and low-performing teams. Further, they tested an automated communication annotation system by using it to tag a data set that was then compared with a human-tagged data set. Their automated system performed only 10%–20% poorer than human taggers, suggesting that their method could be refined to save some of the time investment required for automated tagging. Ultimately, the authors noted that their method still required a significant time investment to produce the communication transcripts that form the basis of the tagged data but suggested that speech recognition software might eventually prove useful to automate transcription as well. In a final example of research using LSA, Gorman et al. (2013) analyzed communication among teams in submarine training simulations, finding that LSA was able to differentiate experienced and less-experienced crews. In addition, their LSA data were found to be cross-correlated with a metric of team neurophysiological synchrony, suggesting that future work might further develop a paradigm for understanding team performance through a framework involving team communication and team neurophysiology.

3.2.2 Dynamical Analysis

In this computational approach, Gorman et al. (2012) developed a method for dynamically analyzing communication events to detect unexpected critical events in team communication. In their method, the dynamical stability of team communication is measured using advanced algorithms to reveal fluctuations and perturbations in communication in real time. These perturbations consisted of prompts by a confederate that interrupted the normal flow of communication within three-person teams in a simulated UAV environment. Team members attempted to maintain their usual communication patterns during the interruptions, but the demands of the confederate necessarily impacted these patterns. The authors noted that their method was able to reveal the normal dynamics of the team's information flow as well as the effects of the perturbation, and these are measures that cannot be captured by a human observer. However, the authors note that this method is not diagnostic and cannot provide meaning for the perturbations; in other words, this real-time dynamical analysis can identify unexpected critical communication events, but these events could have been due to entirely routine changes within the team rather than maladaptive ones. Therefore, this approach can offer insight into the relative stability of team communication, but it should be complemented by others to gain a fuller picture of how the team's communication resulted in performance.

3.2.3 Computational Approaches for Analyzing Linguistic Features

Linguistic features such as word choice, sentence structure, and word counts can be analyzed to reveal similarities and differences between two or more pieces of text (or speech that has been transcribed to text), linking communication to cognitions, attitudes, or behaviors. Software such as LIWC (Linguistic Inquiry and Word Count) can be used to analyze text and reveal these features (Tausczik and Pennebaker 2010; Pennebaker et al. 2015). The measurement of similarities in the communication between two or more people is sometimes called language style matching (LSM), and it has been shown to predict cohesiveness and performance in some groups (Gonzales et al. 2010). This is because cohesive groups tend to converge in the ways in which they communicate, such as by using similar words or phrases (Tausczik and Pennebaker 2013). LSM, and by extension other text analysis methods, can therefore be a useful way of measuring team cohesion.

3.3 Social Network Analysis (SNA)

SNA is a growing field that involves the measurement and analysis of relational structures to provide insight into team communication, coordination, and consequently evaluating performance. SNA is built upon graph theory, where in a communication network the individual entities are represented by vertices or nodes, and the relationships or interactions between the entities are represented by edges (Butts 2008; Newman 2010). Representing these underlying relationships or interactions as matrices allows for novel ways of analyzing qualitative data. For example, Pokorny et al. (2018) proposed a method of importing qualitative coding data into statistical software and conducting network analysis on the data to graphically represent the qualitative aspects of the communication, whereby the nodes represent the qualitative code labels and the edges represent the locations of the codes relative to each other in the source data. This method is promising because it synthesizes the qualitative approach to team communication with the computational strengths of the network analysis approach

These relational structures can vary vastly in scale, from intrapersonal networks of known concepts to networks involving large organizations (Butts 2008). For example, Reagans and Zuckerman (2001) analyzed research and development teams and found a link between network heterogeneity (i.e., team demographic diversity), network density (i.e., frequency of team communication), and team productivity. In another study, Wolf et al. (2009) applied SNA to software development teams and found that communication structures predicted the success or failure of software build integration. In a human–robot interaction paradigm, Litaker and Howard (2013) used SNA during a 2-week field study involving two NASA Rovers to better understand the communication networks of the interlinked ground control, flight, and planetary science crews. Through this process the researchers were able to identify two distinct communication structures and thus revealed the need for a more stable communication network among the crews. As a final example of SNA, Army researchers recently modeled the communication structures between individuals before and after a simulated mass casualty event, revealing critical insights into the factors that affected the organization's response to the situation; some of these factors involved a person's SA, self-reporting as more cooperative or motivated, or occupation of a coordinative role (Fitzhugh and DeCostanza 2018). Given the predicted complexities of future HAT, SNA is promising as a means for representing and analyzing communication patterns in

HAT, as it can account for diverse group structures and offers potential for future research into team communication.

SNA is a method that provides unique information about a team's communication, and researchers are increasingly leveraging SNA to analyze teams in a variety of contexts (Schaefer and Cassenti 2015; Serrat 2017). It has considerable flexibility in the types of data that it can be used to model, as it can be used on verbal or text-based communication, and it can even be applied to survey-type data. However, the data type selected can sometimes cause issues with the analysis if self-report is involved, because participants may not accurately remember details about their networks (Krackhardt 2014). For example, if the focus of a study involves modeling the social network of an organization by asking employees who they communicate with, they might forget someone who they only speak with occasionally, which will affect the validity of the network analyses. For this reason, some advocate relying on behavioral logs (phone, email, transactions, etc.) to mark interactions rather than relying on individuals' perceptions of their networks (Butts 2008; Kitts 2014). Another difficulty with SNA stems from defining the boundaries of a network. When using SNA the analyst must decide what gets included and what gets included within the network, a task that is sometimes complicated by the phenomenon being studied. Generally, the analyst will either use boundaries that populations impose on themselves (all members of a classroom, all members of an organization, etc.) However, SNA can also be applied to custom-defined populations, such that all people that meet a certain criterion will be included in the network (e.g., all organization members who sent more than three e-mails per day in a 2-week period). The selection of a boundary has implications for the generalizability of the network, and analysts must be cognizant of how a boundary's definition can affect the data set.

Despite these considerations, we expect SNA to be useful in the study of HATs because we expect that these teams will use multimodal interaction as a bridge between computer screens, teammates, and intelligent agents, and SNA can model complex, multimodal interactions in networks of varying sizes. SNA is also valuable in evaluating the structure of team communication because of the network analysis results in visual representation of the team member relationships that can be used for description and comparison in a number of different ways. With measures and methods at the individual and network-level, SNA offers a multitude of avenues for analyzing relational data.

3.4 Voice Analysis

Voice analysis techniques are aimed at measuring vocal characteristics, such as pitch and intensity, to derive insights into communication. When we communicate with others, our voice characteristics change in relation to what we are saying and how we have to say it. The goal of these analyses is to capture those fluctuations to relate them to how we are working together. If one team shouts commands and another calmly speaks them, the loudness of their conversation can relate to a variety of possible causes. We might imagine that the former team might be coordinating less effectively, dealing with degraded communication channels, experiencing frustration, or simply are in a noisy environment. Additionally, the semantic content of the speech used between team members may interfere with effective coordination and team cohesion. For example, Neubauer et al. (2016) found that teams that used more language (i.e., the semantic content) relating to emotion performed less cohesively than teams that used language relating to cognitive processing and problem solving. In this context, overly emotional language usage may interfere with effective communication and, in turn, team cohesion.

Generally, the information that can be derived using vocal cues is limited in scope, so research using these cues tends to fall into analyses of stress patterns (Kuroda et al. 1976; Harnsberger et al. 2009; Olguin et al. 2016), though some other work has evaluated vocal patterns of deception (Harnsberger et al. 2009). More specifically, fundamental frequency (f_0), an indicator of prosody and its relationship to human expression of emotion, has been the most extensively studied feature in vocal analysis (Kuroda et al. 1976; Scherer 1981). Here, a typical finding is that an increase in f_0 tends to reflect an increase in the emotional load of a speaker regardless of the verbal context (Hecker et al. 1968; Scherer et al. 1984). For example, Williams and Stevens (1969, 1972) found significant increases in f_0 in the cockpit recordings of pilots during inflight emergencies and the voice of a radio announcer describing the approach of the Hindenburg when it burst into flames. However, the data obtained from real-life emergencies were limited with regard to the quantity of speech samples and the number of voices recorded. While the majority of research on the vocal expression of emotion focused on pitch, other researchers have explored the role of vocal quality in the expression of emotional states (Gobl 2003). Results indicate that the changes in vocal quality (e.g., a whispered, breathy, or tense voice) can create differences in perceived speaker affect. Additionally, these researchers found that a breathy voice was perceived by listeners as expressing boredom or fear, while a harsh voice expressed stress or anger.

Typically, voice analyses are used in conjunction with other physiological analyses of body signals, such as electrocardiography or galvanic skin response, to reveal more information about team members during a task. For example, the primary determinant of f_0 is the result of passive stress on the vocal fold cover that is created by elongating the vocal fold via cricothyroid muscle activity. Because physical activation is necessary to produce speech signals, there is some evidence that vocal features, and specifically f_0, are related to the autonomic nervous system due to the fact that the laryngeal muscles are innervated by the vagus nerve. For example, one Army initiative found that vocal tension and cardiovascular measures varied together as a function of psychological stress during a task (Neubauer et al. 2017). Given the limited scope of the data that can be extracted from voices, this is not a large area of group research, and these analyses are often used to complement other physiological and psychological measures. Despite the limited scope of voice analysis, we expect that this method will be useful in the study of HATs, as it provides an unobtrusive avenue for assessing psychological states such as stress. A better understanding of the multimodal interactions that characterize HATs is needed, and voice analysis can help reveal how psychological states change during the course of those interactions.

3.5 Current Research Gaps for Human–Autonomy Teams

The communication methods described in previous sections can be applied to the HAT context with several considerations, as follows:

- **Qualitative coding** provides rich insights into communication data, but if spoken communication is to be analyzed, it must be transcribed prior to coding. When done manually, transcribing audio into text can take upward of 4 h for each hour of audio (Britten 1995; Patton 2002), and this figure rises when audio recordings involve multiple speakers or poor audio sources. However, transcription software such as Google's Cloud Speech API can be a means for rapidly and automatically transcribing audio (Ziman et al. 2018). Once the transcription is obtained, the resulting data are then analyzed, and depending on the method of coding used, this can require extensive amounts of additional time. This means that qualitative coding, while rich, can be considerably (and sometimes prohibitively) time intensive. Further, future team communications may not always use spoken or text-based communication, given that users can interact with intelligent agents (and each other) via interfaces that use touch or point-and-click. This will limit the utility of qualitative coding and require other methods (e.g., event logging) to capture those interactions.

- **Computational methods** are highly diverse, and we expect them to continue to be explored and developed. Approaches such as those outlined in Foltz and Martin (2008) can automate coding, but this also requires transcription and the automated system is not yet as accurate as a human annotator. The dynamical approach discussed in Gorman et al. (2012) provides real-time communication analysis insights, which offers a significant improvement over qualitative coding in that it does not have a considerable time investment. However, the data produced by this method are far more limited, as they can reveal unexpected critical events in communication but cannot diagnose those communication events for cause, context, or content. Latent semantic analysis can shed light on the links between communication content and teamwork (Gorman et al. 2003, 2013). A variety of other computational methods exist. Generally, computational approaches require specialized software/hardware and training, which can sometimes limit their applicability to different contexts.

- **SNA** is promising and offers fewer limitations. In addition to its applicability to spoken communication, it can also be applied to text-based data such as e-mails or instant messages as well as to survey data. SNA data can also be used to evaluate and visualize information transmission or communication throughout a network that can be either very small or very large. However, it is sometimes difficult to define the boundaries of the network depending on the phenomenon being studied. In addition, if self-report data forms the basis of the network analysis, participants' self-report biases and poor recall can impair the quality of the resulting network.

- **Voice analysis** is unobtrusive and can provide insights into the emotional characteristics of communication such as stress or fear, revealing physiological information that may not be captured by other communication measurement methods. However, the applications of voice analyses are limited in scope, as they primarily rely on pitch, loudness, or vocal quality (e.g., breathy vs. harsh). Therefore, this approach is best used in conjunction with others.

The listed measurement methods can be used in various capacities to address some of the most active research areas in HAT. This is because communication is at the root of three major thrusts in current HAT research: 1) how best to use bidirectional communication to improve trust, shared SA, and team cohesion, 2) how intelligent systems can be designed with a focus on transparency to improve how well operators can understand the intentions and decisions of those systems, leading to higher trust and better shared understanding of the tasks at hand, and 3) how independent, adaptive autonomy will introduce additional capabilities to HATs. To address all three thrusts, research and development efforts are focused on designing autonomy that can communicate effectively with the rest of the team to maintain optimal team performance, trust, and shared SA. Therefore, to support those design efforts, we require a better understanding of communication in HATs.

In research involving HATs, the best approach to analyzing team communication will depend on the constructs of interest, the goals of the analysis, and the resources available. Often one will be best served by using several measurement methods where possible, to capture a broader picture of a team's communication patterns. With good access to advanced software and hardware, computational methods can prove useful at capturing advanced communication dynamics. Comparatively, qualitative coding can provide rich data with fewer resources but requires more time. Therefore, new metrics and tools will need to be developed to directly support the critical nature of HAT. In the modern practitioner's toolbox, no current communication analysis method can be easily used in real time, requiring almost no resources, while still providing useful insights into team communication. The following section discusses a tool designed with those considerations, and the context of HAT, in mind.

4. Real-time Flow, Event, and Coordination Tool (REFLECT)

REFLECT is a software tool being designed to support analysis and evaluation of team communication in real time. Future HAT will be multidimensional and involve novel teaming structures between humans and intelligent agents. While we do not yet know what these future teams will look like, we will need effective methods of collecting and measuring how they communicate in order to understand and explain their performance. In the nearer term, these methods of measuring communication will support ongoing research and development of future HAT. To serve these needs, REFLECT is designed to be adaptable to teams of various sizes, functions, and capabilities, as well as to capture aspects of a team's coordination that reveal insights into other critical constructs such as SA and team cohesion.

The theoretical basis for REFLECT is derived from several of the models and theories outlined in Section 2. The models of Salas et al. (2005) and Marlow et al. (2018) conceptually link communication and team performance; aspects of communication can serve as both an inputs (e.g., what a teammate says) and mediators (e.g., the communication modality used) based on the IMOI model, leading us to study outcomes (e.g., team performance) and subsequent inputs. Grice's (1974) maxims provide guidelines for communication, and can be considered when evaluating the effectiveness, efficiency, and precision of team communication (Webster 2017). The theories of turn-taking and grounding shed light on the relationship between what teams say and how they think and process information, relating to concepts of shared SA and trust. The models of Shannon (1948) and Berlo (1960) are useful for understanding the relevant factors involved with a single transmission of information between a sender and a receiver, and when multiple transmissions are exchanged during a conversation, we scale back up to the higher-level conversation-based theories of turn-taking and grounding. The contributions of all of these can be summarized succinctly: If one wants to understand how a team performs, one must understand how it communicates. Indeed, Cooke et al. (2013) argued that team cognition is directly observable in the dynamics of team communication and coordination patterns.

The models and theories discussed in this report offer scientific frameworks for understanding the various constructs involved with teamwork and communication as well as how they relate to each other. Based on these frameworks, REFLECT is designed to capture data that can be used to map how communication flows within the team, which can provide insights into shared cognitions, team cohesion, and trust. Thus, the communication flow data captured by REFLECT can inform analyses of the relationships between team communication and performance.

4.1 Communication Flow Mapping

The communication patterns within a team reveal critical information about how the team works together to complete tasks, share information, and coordinate toward goals, offering a clear picture into the team's successful and unsuccessful coordination processes (Sacks et al. 1974; Kiekel et al. 2001; Tiferes et al. 2016). Communication flow, or the measurement of who speaks to whom throughout a team interaction, is a valuable way to evaluate team processes at the cognitive and the interpersonal level (Fischer et al. 2007). Communication flow can be modeled to reveal how teams coordinate and share information, which in turn reveals insights into aspects of team cohesion, trust, and team performance. During the development of HAT concepts and capabilities, it will be critical to understand how communication flow affects, and is affected by, intelligent systems, team structures, and task demands.

In one application of communication flow, Fischer et al. (2007) noted how often team members in a simulated search-and-rescue task responded to each other's communication to produce the flow diagrams in Fig. 6. These show structural differences in the communication patterns of successful and unsuccessful teams, revealing that successful search-and-rescue teams had a more equal distribution of communication, whereas unsuccessful teams tended to involve a few team members dominating the discourse.

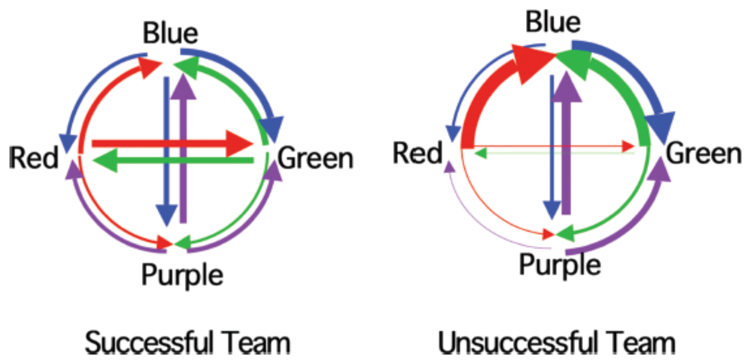

Fig. 6 Flow diagrams for successful and unsuccessful teams (reprinted with permission from Fischer et al. [2007])

In another approach to mapping communication flow, ARL scientists collaborated on development of the Automated Collaboration Collection Relationship Understanding Environment (ACCRUE) interface for automatically capturing communication data (including email, chat, phone, and face-to-face interactions) within military staff environments (DeCostanza et al. 2018b). ACCRUE is a software tool that was developed as an approach that seeks to improve unit training effectiveness by providing real-time access to performance-related data and analyses, collected via unobtrusive data collection methods. Using email logs and sociometric badges worn around the necks of team members, the ACCRUE system can log the flow of communication between team members interacting virtually or face-to-face and present the relevant information on the Command Operations Dashboard, which can then be used by observers or trainers to provide feedback. Development of the hardware and software is ongoing.

REFLECT is designed with a similar conceptual approach to that of Fischer et al. (2007) and the ACCRUE system (DeCostanza et al. 2018b). It is designed to allow a user to log communication flow in real time while observing a team's interactions. REFLECT diverges from the approach of Fischer et al. (2007) by identifying, rather than ignoring, communication that was not targeted at a specific team member. An example of such communication might be a statement like "Hey team, I am moving to point B". By accounting for this nontargeted communication to the crew, it becomes easier to capture information that team members might share with their team as a whole to improve SA and update shared mental models (Cannon-Bowers et al. 1993; Wildman et al. 2014). REFLECT also differs from ACCRUE by requiring no additional software or hardware beyond REFLECT. In this way, a single observer using a single computer or tablet can record team communication flow, whereas ACCRUE requires additional hardware and software, such as email traffic logs or sociometric badges that link with ACCRUE.

4.2 REFLECT Usage

The information captured by REFLECT provides valuable insight into the coordination characteristics of a team, revealing how the team uses, shares, and acts upon information. The user interface of REFLECT has three main panes: the logging pane on the left, the data pane in the center, and the editing pane on the right (Fig. 7). REFLECT is currently under development, and this section describes the initial features of the tool. It is currently aimed at supporting the capture of verbal communication in teams, whether or not those teams involve autonomy, but we expect future iterations to support additional communication modalities.

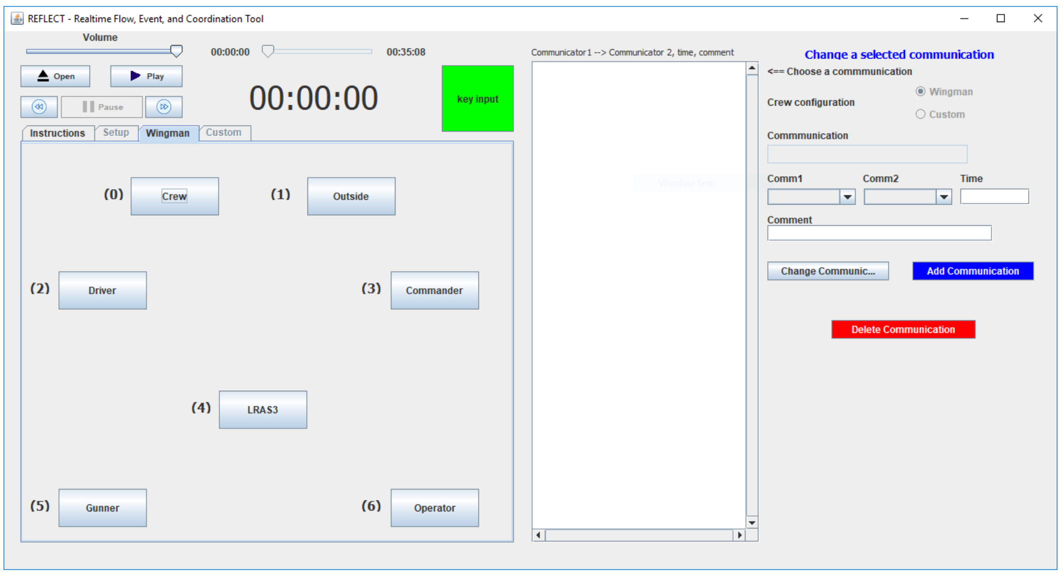

Fig. 7 REFLECT main window: left pane used for logging communication events; center pane displays communication events as they are collected; right pane used for appending comments or other text to communication events

Using the logging pane, the user first inputs the number of team members and labels for their roles. Then the user is able to log the source and destination of each verbal message heard during a team interaction. If the user is not observing a live interaction, an audio file may also be loaded and played within REFLECT as an alternative. Whether live or recorded, when someone begins speaking, the user clicks that person's role, which turns red. The user then clicks the intended recipient for the team member's communication, which turns blue. This completes one communication event. Each communication event is populated in the event pane in the middle of the user interface along with the timestamp (in milliseconds) of the communication event. The user continues logging communication events during the team's interactions until the scenario is complete.

The output produced by REFLECT can be parsed to identify the number of communication events experienced by each possible sender–receiver pair. This can then be organized to show which sender–receiver pairs account for greater proportions of the team's communication, as well as the overall flow of information between team members. The flow maps in Fig. 8 were created from communication logs of Army and Marine crews using the Wingman manned–unmanned teaming system (see Schaefer et al. [2019b] for more information about the system and the scenario).

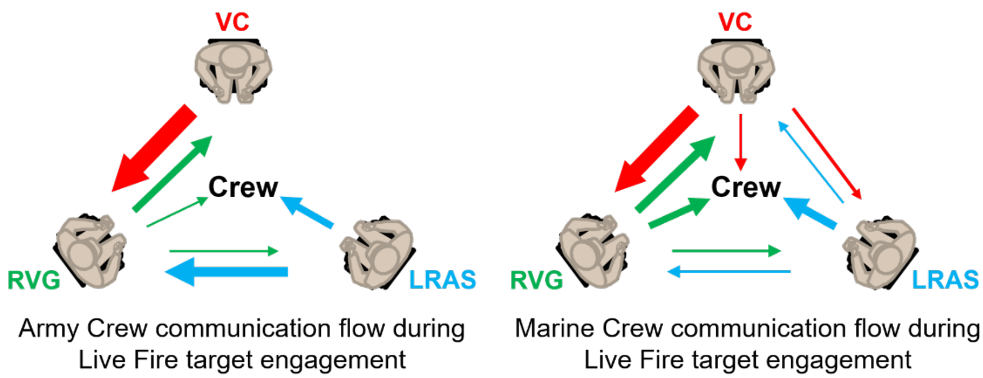

Fig. 8 After logging communication between team members, the output from the REFLECT tool can be used to produce communication flow maps. Thicker lines indicate more communication between that sender–receiver pair. Eventually, visualizations such as these will be produced automatically.

These maps were created as a proof of concept for the visualizations that can be created using REFLECT data.[1] The maps are visually intuitive; thicker lines indicate more communication between a sender–receiver pair. Based on that information, differences between the flow maps for the teams are immediately apparent. The Army crew exhibited a more rigid communication pattern: the vehicle commander only spoke to the robotic vehicle gunner. This is notable because the Army team had previous experience and training with the gunnery tasks used in the experimental scenario, and the Army team exhibited better performance in these tasks. In contrast, the Marine team's communication pattern appeared to favor sharing information with the entire crew rather than speaking directly to certain crew members. The Marine crew had little prior experience with these types of gunnery operations, and thus the flow pattern suggests that the Marine crew attempted to build shared SA and a shared understanding of the task to work more effectively in a relatively unknown environment. However, this looser communication pattern came at a cost because the Marine crew exhibited, on average, a longer time before first firing on a target than the Army crew. While this

[1]For more information about the creation of these flow maps, we direct the reader to Schaefer et al. (2019a).

is partially due to the experience gap between the crews, the flow maps also imply that the stricter communication patterns within the Army team helped them fire on targets more quickly. This demonstrates an interesting perspective into the relationships among team experience, communication, and performance in the context of a manned–unmanned team.

4.3 REFLECT and Future HAT

Because the capabilities of intelligent systems are constantly evolving, scientists and practitioners will need multiple methods for understanding and analyzing communication in teams that integrate these systems. The communication patterns exhibited by teams will likely be different when interacting with agents in different roles. Sycara and Lewis (2004) distinguish between agents that support individual team members in completion of their tasks, agents that support the team as a whole, and agents that assume the role of an equal team member. Given the differences in responsibility allocated to each of those categories, it is expected that team members would communicate differently with an autonomous robotic asset versus a computer-based decision-making aid and versus a teleoperated vehicle given the extent to which those systems tangibly impact the way the team can operate. Multimodal interactions between humans and autonomy will add additional complexity to the communication patterns of the team, requiring a greater focus on how information flowing within the team shapes team cognitions, cohesion, and performance. Because REFLECT's data output is based on the sender, receiver, and timestamp of each communication event, it can be applied to a wide variety of scenarios involving HATs and is not limited to specific contexts or team configurations. While the initial work described in this report involved applying REFLECT to a HAT using a teleoperated vehicle for gunnery, we intend to test REFLECT on other team structures.

Ongoing design and development in HAT is focused on building intelligent systems that learn and adapt to situations in order to work independently or collaboratively with human teammates. To push the science forward, some of the most important frontiers being explored in the development of HAT involve bidirectional communication, individualized, adaptive technologies, and transparent systems (Evans et al. 2017; Chen et al. 2018; DeCostanza et al. 2018a; Marathe et al. 2018). Several major constructs impact those frontiers: trust, team cohesion, communication, and shared SA all influence the extent to which HATs can interact effectively.

Bidirectional communication within a team can foster trust and shared understanding (Marathe et al. 2018). Individualized, adaptive technologies will learn from situations and human interactions, allowing the intelligent systems to collaborate better with humans and improve team outcomes (DeCostanza et al. 2018a). Transparent systems engender a better shared understanding between human and operator, supporting bidirectional communication and spurring improved trust of the autonomy (Chen et al. 2018). Ultimately, if we are to achieve the objective of building more-effective HATs that demonstrate improved trust, team cohesion, and SA, it is of fundamental importance that we more fully understand communication in the HAT context, given that our review of models and theories has highlighted the critical importance of communication to teamwork. To this end, REFLECT can be used to capture data that sheds light on the communication patterns of HATs with different capabilities, team sizes, and mission needs, fulfilling some of the need for new communication metrics that will be useful throughout the development of next-generation HAT.

5. Conclusions

Communication is at the core of most of the ongoing research directives in HAT that seek to develop more-effective teams. The future of autonomy that interacts seamlessly with its human teammates is impossible to realize without understanding the extent to which communication impacts teamwork. To this end, analyzing communication in mixed HATs can offer unique insights into HAT. Current communication analysis methods such as qualitative coding, computational approaches, social network analysis, and voice analysis have different advantages, but all are expected to be useful in deriving performance insights from future HAT interactions.

Improvements in autonomy will dictate the ways that future teams can be structured, and the capabilities of those intelligent systems will shape how HATs communicate, coordinate, and cooperate. Some key obstacles in the development of effective HAT are the following:

- A shared understanding of the mission space must be developed, as well as a basic knowledge about the other teammates (Marathe et al. 2018).
- Multimodal input and output sources (gesture, tactile, display) will need to be integrated in a manner that does not impede effective communication.
- Communication of states and intentions between humans and autonomy must be bidirectional to support SA and lethality.

REFLECT, a new communication capture tool, can help address some of the limitations for communication data capture and analytic metrics. REFLECT is designed to capture verbal communication flow within a team, logging and timestamping the sender and receiver of each communication event. The flow of communication within a team reveals insights into team cognition, coordination, cohesion, and ultimately performance (Fischer et al. 2007; Tiferes et al. 2016). Thus, REFLECT is focused on capturing data that can be used to describe the flow of communication in HATs, which may have diverse structures, capabilities, and goals. REFLECT offers a unique utility in this domain as a means to capture data, which can be used along other forms of analysis.

As HATs become more multimodal, communication analysis methods will be necessary to capture complex multimodal interactions in teams. Advanced user interfaces will support improvements in transparency and shared SA in HATs, and thus the information flowing through those interfaces will supplant some amount of spoken communication within the team. Communication data collection, measurement, and analyses will need to capture those nonspoken interactions as another means of communicating information within the team. Ultimately, communication is a fundamental aspect of teamwork, and to achieve the Army's vision of a battlespace that integrates human, autonomy, and joint human–autonomy capabilities, much research is needed to understand how team communication is affected by capabilities and organization of the team's various members, both human and autonomous.

6. References

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Appendix: Qualitative Coding

Although researchers generally design their own coding schemes a posteriori to fit the research study of interest, some have argued that coding schemes should be standardized to improve applicability across contexts and domains.[1] Using standardized (i.e., a priori) coding schemes offers more consistency between research studies; however, since a posteriori coding schemes are customized to specific research contexts, such schemes may thus provide better insight into the factors of interest. While there are advantages and disadvantages to each approach, the key takeaway is that qualitative coding is of great use to teamwork researchers interested in communication. Table A-1 contains a selection of coding schemes found in the team communication literature, and identifies which schemes account for information flow, statement type, and communication content. Information flow accounts for the transmission of communication throughout the team, and schemes that account for this factor identify the source and destination of the communication. Statement type refers to the overarching function of the communication. For example, Burke et al.[2] identify whether a statement is a question, instruction, comment, or answer, and Fischer et al.[3] identify acknowledgments, disagreements, elaborations, answers, and missing responses. Content refers to the subject of the communication or its quality. For example, Tiferes et al.[4] differentiate between communication about equipment, patient condition, safety, education, and so on. Rockmann and Northcraft[5] code for positive reactions and negative reactions, among other features. Table 1 also identifies the relevant context of the coding scheme.

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[1]Tiferes J, Bisantz AM, Guru KA. Team interaction during surgery: a systematic review of communication coding schemes. J Surg Res. 2015;195(2):422–432.
[2]Burke JL, Murphy RR, Coovert MD, Riddle DL. Moonlight in Miami: field study of human-robot interaction in the context of an urban search and rescue disaster response training exercise. Hum–Comp Interact. 2004;19(1–2):85–116.
[3]Fischer U, McDonnell L, Orasanu J. Linguistic correlates of team performance: toward a tool for monitoring team functioning during space missions. Aviat Spa Environ Med. 2007;78(5):B86–95.
[4]Tiferes J, Hussein AA, Bisantz A, Kozlowski JD, Sharif MA, Winder NM, Allers AN, Cavuoto L, Guru KA. The loud surgeon behind the console: understanding team activities during robot-assisted surgery. J Surg Edu. 2016;73(3):504–512.
[5]Rockmann KW, Northcraft GB. Expecting the worst? The dynamic role of competitive expectations in team member satisfaction and team performance. Small Group Res. 2010;41(3):308–329.

Table A-1 Sample of qualitative team communication coding schemes in the literature as well as the factors accounted for by the schemes.

Citation	Information flow	Statement type	Content	Context
Tiferes et al. [1]	Yes	Yes	Yes	Surgical teamwork
Burke et al. [2]	Yes	Yes	Yes	Robot-assisted search and rescue
Fischer et al. [3]	No	Yes	Yes	Team search and rescue
Espinosa et al. [6]	No	Yes	Yes	Making maps in dyads
Rockmann and Northcraft [5]	No	Yes	Yes	Team negotiation task
Bales (1949) [7]	No	Yes	Yes	Group decision making
Scheidel and Crowell [8]	No	Yes	No	Group idea development
Riethmüller et al. [9]	No	Yes	Yes	Medical anesthesia training

[6] Espinosa JA, Nan N, Carmel E. Temporal distance, communication patterns, and task performance in teams. J Manag Inf Syst. 2015;32(1):151–191.
[7] Bales RF. Interaction process analysis; a method for the study of small groups. Cambridge (MA): Addison-Wesley; 1949 [accessed 2018 Nov 6]. http://archive.org/details/interactionproce00bale.
[8]Scheidel TM, Crowell L. Idea development in small groups. Q J Speech. 1964;50:140–145.
[9]Riethmüller M, Castelao EF, Eberhardt I, Timmermann A, Boos M. Adaptive coordination development in student anesthesia teams: a longitudinal study. Ergonomics. 2012;55(1):55–68.

Using such coding schemes, researchers can parse extensive communication logs to understand many constructs of interest. For example, the coding scheme described by Burke et al.[2] was designed to assess team communication and interactions during an urban search-and-rescue training exercise involving human–robot teams. To this end, the coding scheme allowed the researchers to conclude that the human–robot teams spent more time communicating about the state of the environment and the robot than they did navigating the robot. Further, the coded data provided evidence that the view screen used with the robot limited operator situation awareness (SA), and that operators attempted to counter this by communicating with team members located at the search site to improve their mental models of the environment.

Qualitative coding can provide rich insights into a variety of communication-related factors of interest to researchers, and determining what factors will be analyzed is up to the researcher and the research questions under investigation. Besides coding for aspects of task-related information exchange, Fischer et al.[3] also coded for interpersonal affect as positive (humor, praise, reinforcement, etc.), negative (blame, insult, etc.), or neutral (politeness, apology, etc.) to understand how team communication relates to team functioning. Rockmann and Northcraft[5] coded for strategy and tone on team members' statements during a negotiation task by identifying aspects of the statement. For example, the coding scheme seeks to identify whether, in each statement, a team member states an issue preference, demonstrates a positive/negative reaction, asks a preference question, and so on. This allowed the authors to better understand how teams' competitive expectations affected their cooperative behaviors.

Much remains to be understood about communication in human–autonomy teams (HATs), especially given that autonomous capabilities are under active development and technology evolves rapidly. Recall the three major thrusts of active human–autonomy teaming research discussed in Section 3.5 of the main report: 1) how best to use bidirectional communication to improve trust, shared SA, and team cohesion, 2) how intelligent systems can be designed with a focus on transparency to improve how well operators can understand the intentions and decisions of those systems, leading to higher trust and better shared understanding of the tasks at hand, and 3) how independent, adaptive autonomy will introduce additional capabilities to HATs. Qualitative coding can be applied to each of these areas to provide researchers with rich information about how communication relates to performance. Some sample research questions for qualitative coding studies in human–autonomy teaming are as follows:

- What aspects of team communication change when team trust increases or decreases?
- Do teams request fewer status/location updates when systems have more transparency? What aspects of system transparency affect the amount of information requests made by teams?
- What aspects of communication from autonomy improve team trust in high-stress situations?
- How can autonomy communicate uncertainty/unreliability while maintaining human trust?
- How is team decision making affected by the various capabilities of autonomy?

List of Symbols, Abbreviations, and Acronyms

ACCRUE	Automated Collaboration Collection Relationship Understanding Environment
CAQDAS	computer-assisted qualitative data analysis software
EOD	explosive ordnance disposal
f_0	fundamental frequency
HAT	human–autonomy teaming; human–autonomy team
IMOI	input, mediator, output, input
IPO	inputs, processes, outputs
LIWC	Linguistic Inquiry and Word Count
LSA	latent semantic analysis
LSM	language style matching
NASA	National Air and Space Administration
REFLECT	Realtime Event, Flow, and Coordination Tool
SA	situation awareness
SAT	Situation Awareness-based Agent Transparency
SMCR	sender, message, channel, receiver
SMM	shared mental model
SNA	social network analysis
TMS	transactive memory system
TRP	transition-relevance place
UAV	unmanned aerial vehicle

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