Red Rover, Red Rover, Send an F-35 Right Over: Assessing Synthetic Agent Trust in Humans to Optimize Mission Outcomes in Mosaic Warfare

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ABSTRACT

The research presented here builds on an existing multi-domain robotic teammate framework by exploring the bilateral nature of Human Machine Team (HMT) trust to optimize mission outcomes in a Mosaic-like warfare paradigm. Currently, the scientific community is focusing on measuring human trust with synthetic agent teammates, and the importance of building and sustaining well-calibrated trust to promote HMT interactions necessary for successful mission outcomes. Measuring trust objectively and in real time is a difficult problem, and solving it is essential to support a future warfare requiring rapidly reconfigurable multi-platform HMTs to address the mounting challenges of peer threats. However, the time sensitive nature of these reconfigurable, multi-domain, multi-platform kill webs assumes reliance on synthetic agents, driven by sophisticated Artificial Intelligence (AI), to make split-second decisions on how best to configure and reconfigure these kill webs. Those critical decisions will necessarily need to take into consideration the extent to which a synthetic agent can trust a human operator's ability to complete mission tasks. This paper explores and defines HMT relationships across synthetic agents' personas within our existing multi-domain robotic teammate framework to (a) identify human's psychophysiological constraints across HMTs that can impact the synthetic agent's trust in humans, and (b) promote the concept of a synthetic Mosaic agent that uses trust to rapidly assign tasks across HMTs to optimize mission outcomes. Theoretical findings are presented within an anti-satellite strike and response applied use case to highlight the bilateral nature of trust in HMTs as a key enabler of mission success.

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INTRODUCTION

With the Artificial Intelligence (AI) revolution well under way (e.g., Makridakis, 2017; Walsh, 2017) there is a renewed urgency to augment AI-driven synthetic agents' capabilities to support the development of highly effective Human-Machine Teams (HMT). The urgency is driven in part by future warfare demands (see Figure 1) to meet and defeat peer and near-peer threats (e.g., Bornstein, 2015), and the need to solve complex communication and collaborative problems that arise from teams composed of both human operators and synthetic agents (e.g., Scielzo and Kocak, 2021). As a result, a massive multi-disciplinary undertaking has begun across the scientific community to rapidly frame HMT's Research & Development frameworks, guidelines, and requirements necessary to yield validated technologies that translate to the operational environment (see National Academies of Sciences, Engineering, and Medicine, 2021).

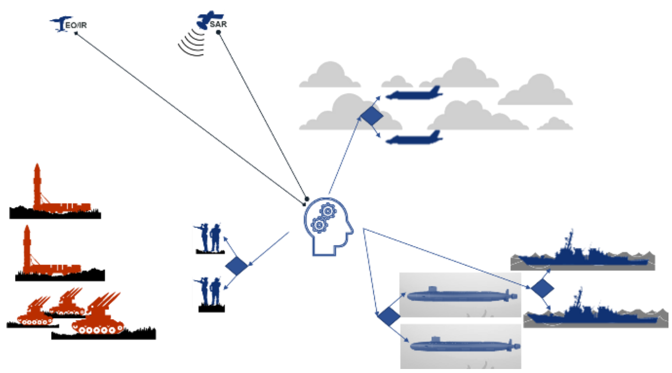


Figure 1. Trust in Human-Machine Teams

The concept of trust as a complex socio-affective construct is rapidly becoming one of the foundational factors driving HMT dynamics (e.g., Scielzo and Kocak 2021, Scielzo and Kocak, 2020). If HMTs are to be truly effective, it is paramount to capture key characteristics of high-efficiency human-human teams, such as trust, and translate them to HMTs. This paper extends our multidomain HMT framework by exploring the concept of bilateral trust whereby not only it is critical to gauge human trust in synthetic agent teammates, but it is also imperative to digitize trust so that a synthetic agent can ascribe its own level of trust in a human operator when the agent is relied upon to make split-second decisions aimed to increase the probability of mission success.

To achieve this aim, we review the accelerating paradigm shift transforming automation from a tool to teammate status and detail key aspects of HMT trust within the context of future warfare. A description of our current multidomain HMT framework is then provided, outlining key factors and processes to model, maintain, and facilitate HMT trust. Finally, a taxonomy of synthetic agents is presented, underlining the bilateral nature of trust that is required to achieve mission goals. Theoretical implications of the bilateral nature of HMT trust are then explored within a future warfare anti-satellite strike and response scenario.

From Tools to Teammates

The current pace of technological advancement is affording a dramatic change in the way we operate and perceive synthetic agents by augmenting the level of decision-making these synthetic agents can make, thereby operating in a realm traditionally relegated to humans' cognitive capabilities. In fact, synthetic agents are increasingly able to sense, decide and act like a human. Recently, an AI-driven synthetic agent defeated an expert human pilot in a dogfight using human mental heuristics (e.g., Hitchens, 2020). Thus, the relationship between humans and synthetic agents is rapidly changing from a rigid and outdated model where humans and synthetic agents perform discrete tasks across different levels of automation, to a model where both humans and synthetic agents work as a team to accomplish mission objectives (e.g., Scielzo, Fiore, Jentsch, and Finkelstein, 2006). As a result, we are moving away from machines seen as subordinates and tools that support human operators to a paradigm where humans and synthetic agents work collaboratively as peers to meet mission objectives, and where trust plays a foundational role (e.g., Scielzo and Kocak, 2021).

Human-Machine Teaming and Trust

Traditionally, the concept of trust between a human operator and a machine was described in terms of trust in automation across levels of task control. This field of inquiry has existed for decades, led by human factors scientists, and culminating in taxonomies describing the various levels of automation across human information processing and decision-making stages (e.g., Endsley and Kaber, 1999). Applying these taxonomies resulted in the development of systems that could minimize human error while maximizing trust and situation awareness by promoting appropriate levels of automation and keeping human operators in the loop (e.g., Kaber, and Endsley, 2004).

However, HMT trust is far more intricate given the complex team dynamics at play. As a result, HMT trust needs to be viewed similarly to trust in a human-human team. From a social science standpoint, trust suggests the willingness to depend on someone else or to be vulnerable (e.g., Mayer et al., 1995; McKnight et al., 1998), and to cooperate as a way to manage risks and uncertainty in a team (e.g., Gambetta, 1988; Jones & George, 1998). Thus, team trust mostly rests on the extent to which team members can meet each other's evolving expectations as shared experiences among teammates accumulate. These expectations largely fall under behavioral observations across team dynamics such as communication, collaboration, context awareness, and team performance. As a result, building and sustaining trust between human and synthetic agents based on these observations becomes foundational to HMT operations.

Future Warfare and Human-Machine Teams

The rapidly accelerating shift towards future warfare paradigms, such as the Defense Advanced Research Projects Agency (DARPA) Mosaic warfare, is driving the need for high-performance HMTs. For example, with DARPA's Mosaic warfare, adaptive kill webs are composed of rapidly reconfigurable human operated and AI-driven automated platforms that can work collaboratively as a team (e.g., Grayson, 2018). Figure 2 illustrates part of the Mosaic warfare paradigm, showing the required interconnectedness between sensors and shooters. To reach that desired end state of highly effective HMTs, proper multidomain frameworks need to be in place to develop and validate next generation HMT technologies. Such a framework was introduced by Scielzo and Kocak (2021), which provided critical guidelines to build, sustain, and maintain well-calibrated HMT trust.

Figure 2. Connecting All Sensors to All Shooters

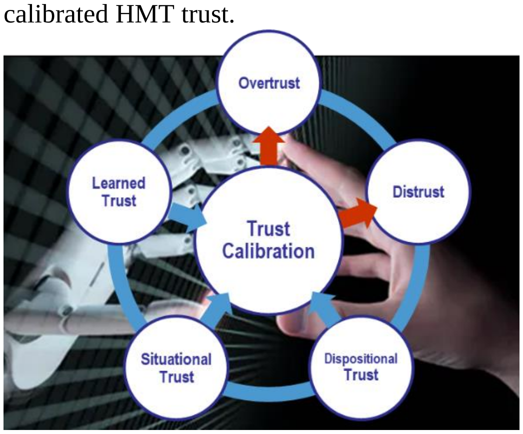


Figure 3. HMT Trust Calibration Factors

Figure 3 shows the main factors associated with human operator trust calibration, which are dispositional trust, situational trust, and learned trust. Dispositional trust indicates individuals' predispositions to trust machines (i.e., their biases). Situational trust is more intrinsic to an operational environment, which considers external variability factors (e.g., system complexity, task difficulty, weather impact) and internal variability factors (e.g., level of expertise). Finally, learned trust reflects how trust changes over time based accumulated experiences and observations. A failure to properly calibrate HMT trust invariably leads to either overtrust (i.e., human trust exceeds synthetic agents' capabilities) or distrust (i.e., lack of human trust prevents full use of synthetic agents' capabilities) (e.g., Lee and See, 2004).

From the standpoint of the synthetic agent, AI-driven machines need also to be able to quantify trust in human operators, or "synthetic trust," allowing them to express level of confidence of the actions and behaviors of their human teammates. In fact, the Department of Defense (DoD) Communities of Interest (CoI) are outlining key areas of investigation in automation, such as machine perception, reasoning, and intelligence to endow synthetic agents with "existence, intent, relationships and understanding in the battle space relative to a mission" (Bornstein, 2015). The process to achieve synthetic trust is analogous to how humans form trust—a process laid out in our multidomain HMT framework.

A MULTIDOMAIN HUMAN-MACHINE TEAMING FRAMEWORK

The multi-domain HMT framework presented here (Figure 4) represents an abridged version from previously published work (see Scielzo and Kocak, 2021) and juxtaposes selected HMT guidelines. This framework provides the basis for assessing, calibrating, and maintaining trust over time via domain-specific Man-Machine Interfaces (MMI) aimed to support team coordination between humans and synthetic agents. This HMT framework emphasizes three principal components: (1) modeling trust to guide the development of domain-specific objective measures of HMT trust; (2) Maintaining optimal trust by quantifying HMT shared situation awareness (SSA) needs and corresponding adaptive displays; and (3) facilitating trust via robust multimodal interfaces to promote HMT communication and coordination. Each of these components is reviewed in turn.

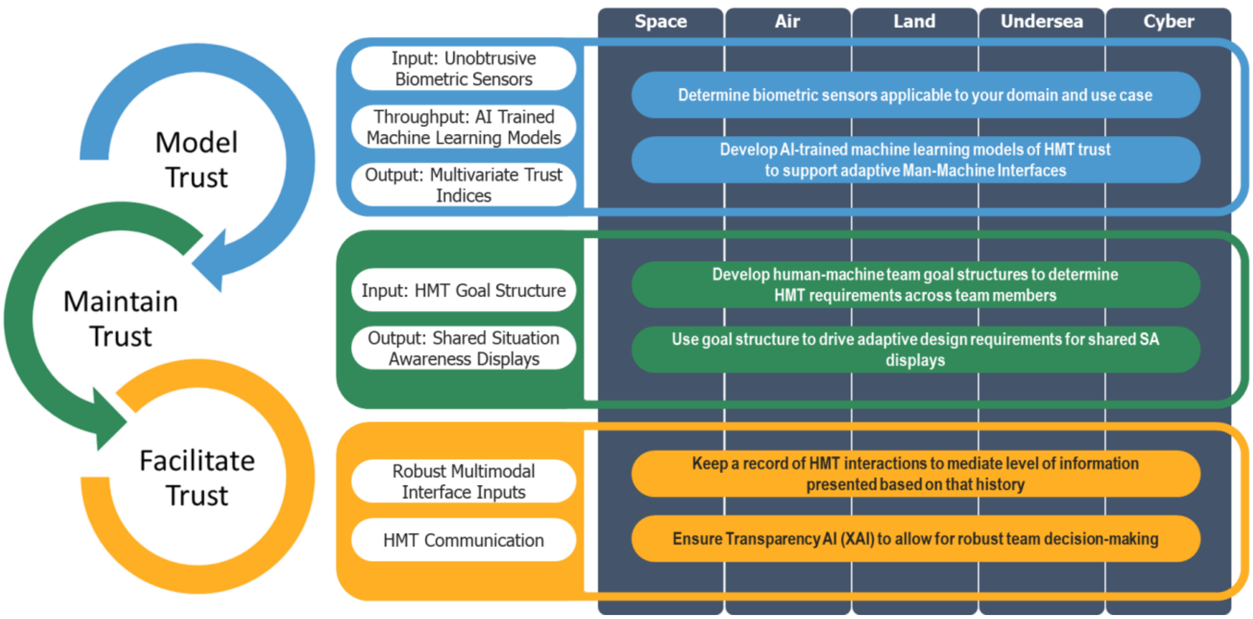


Figure 4. Abridged Multidomain HMT Framework with Selected Guidelines

Modeling Trust

Modeling trust assumes the ability to measure in real time the construct of trust, directly or indirectly (e.g., Harrivel et al., 2017). Measuring HMT trust automatically is necessary to inform next generation machine-driven AI level of transparency into its decision-making process, and to mediate the level of MMI information displayed. This is possible thanks to advances in the unobtrusive use of biometric sensors and the development of corresponding Machine Learning (ML) classifiers to assess with high accuracy both cognitive and affective constructs (e.g., Scielzo et al., 2020; Wilson, Nair, Scielzo, and Larson, 2021; Wilson et al., 2020).

Modeling trust adopts an input/throughput/output model. Input to the model begins with determining the domain at hand and its user roles to determine the type of biometric sensors that can be used to measure HMT trust. For example, while the air domain can allow multiple in-cockpit biometrics sensors, this is not the case with domains that have significant constraints, such as the undersea domain. As a result, biometric sensor selection is both domain and use-case dependent. When biometric sensor data is accurately mapped to operational demands, trust modeling can be generated via ML.

The outputs are HMT trust indices which can be either performance-based or affective-based. An example is the operator crosscheck ratio as a performance-based indicator of trust, determined the ratio of the operator's visual gaze fixations between primary task MMI elements and synthetic agent controlled MMI elements. Affective-based trust metrics can be derived by prosody (pitch, intensity) and other affective constructs (stress, frustration).

Maintaining Trust

Real time HMT trust indices' primary role is to drive adaptive MMIs. Moreover, to build, calibrate, and maintain HMT trust, it is key to capture and quantify the team's goals and decision points, which would also drive the reconfigurable and adaptive aspect of MMI (i.e., presenting context and time sensitive information to support team decision making). The construct of shared SA, defined as "the degree to which team members possess the same SA on shared SA requirements" (Endsley & Jones, 2001, p. 48), is needed to define shared informational requirements needed for HMTs to accomplish individual and shared tasks. This method has been effectively used in many domains, from Army Brigades (e.g., Bolstad et al., 2002) to maritime operations (e.g., Sharma et al., 2019). Overall, shared SA exposes HMT requirements common and unique across team members. Thus, shared SA displays' adaptivity can be driven by HMT's goal structures. Together with real time trust indices, next generation MMIs can be developed to promote both HMT trust and shared SA.

Facilitating Trust

Facilitating trust and overall HMT communication and coordination needs to occur via robust multimodal MMIs tailored to vehicle, operational, and domain constraints. In addition, to support HMT interactions and decision making it is necessary to adopt emerging AI capabilities such as conversational AI, transparency AI (XAI), or neuro-symbolic AI. Conversational AI allows for effective exchange of information and the synthetic agent's responses can be tailored based communications history to increase trust. Finally, XAI and neuro-symbolic AI are critical to support transparent decision-making across HMTs. For example, XAI capabilities are designed to support AI transparency across the Observe, Orient, Decide, and Act (OODA) decision making continuum (e.g., Angerman, 2004, Scielzo and Kocak, 2021) and allow human operators to remain in the loop and support team decisions, thereby increasing overall trust.

HUMANS AS SYNTHETIC AGENTS' TEAMMATES

This paper thus far introduced the concept of HMT trust, its importance to support future warfare needs, and a framework to develop and validate next generation HMT technologies that can build and maintain HMT trust. However, the focus was predominantly on human operators and their need for appropriately trusting synthetic agents. This section of the paper introduces and explores the concept of "synthetic trust," where the construct of trust is digitized so a synthetic agent can quantify its own level of trust in human operators. Thus, a synthetic agent teammate would consider its own trust towards other human operators in its team, which can be critical to make appropriate split-second decisions to save a human life, asset, or simply to ensure the probability of a successful mission outcome.

The Bilateral Nature of Trust

Although at first glance synthetic trust may be perceived as an unwarranted anthropomorphic ascription of machine affective states, the notion of a synthetic agent experiencing trust is essential. It is also imminently achievable given the HMT framework presented earlier; This framework outlined methods and processes to quantify trust objectively and in real-time. Thus, synthetic trust can be defined as *a continuous multivariate algorithmic solution based on both real-time and historical observations of contextual and behavioral information*.

As described earlier, trust is primarily expressed in terms of dispositional, situational, and learned trust factors. When combined, the overall perception of trust can be well calibrated, or, when not properly calibrated, can lead to distrust or overtrust. Table 1 provides an overview of how each of these trust factors are defined from both human and synthetic agent standpoints. Thus, it is imperative to accurately operationalize each of these factors and leverage the HMT framework presented here to develop real-time human and synthetic trust metrics.

Table 1. Trust Factors Defined from both Human and Synthetic Agents Standpoints

Trust Factor	Human Standpoint	Synthetic Agent Standpoint
Dispositional	Human predispositions to trust machines (e.g., cultural biases)	Synthetic agent predispositions to trust humans (e.g., hard coded robotics laws, zero trust architectures)
Situational	Trust in the synthetic agent mediated by intrinsic elements of an operational environment across external (e.g., weather) and internal (e.g., expertise) factors	Trust in the human mediated by intrinsic elements of an operational environment across external (e.g., sensor data) and internal (e.g., AI maturity) factors
Learned	Trust in the synthetic agent changes over time based accumulated experiences and observations	Trust in the human that changes over time based on historical data and human behavioral observations
Distrust	Lack of human trust prevents full use of synthetic agents' capabilities	Lack of synthetic trust prevents full use of human capabilities
Overtrust	Human trust exceeds synthetic agents' capabilities	Synthetic trust exceeds humans' capabilities

Finally, synthetic trust must also take into consideration the synthetic agent role and hierarchy within a team. Just as human teams have well-defined hierarchies, from small units to teams or teams of teams, the same analogy needs to be applied to synthetic agents in terms of taxonomic and hierarchical relations.

A Taxonomy of Synthetic Agents

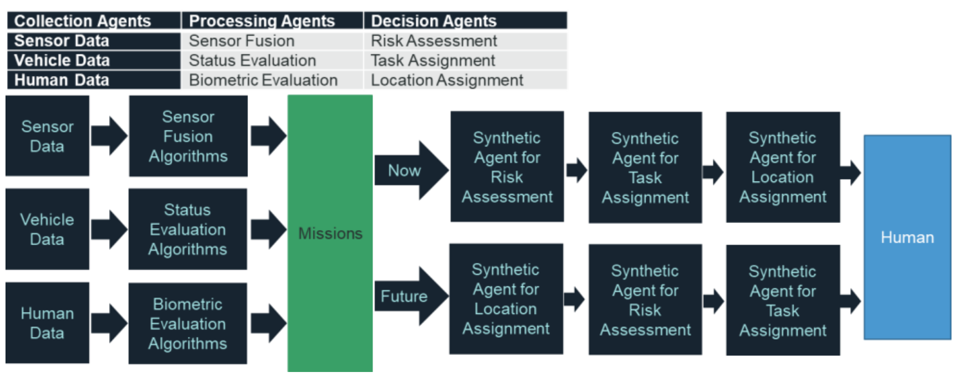


Figure 5. Taxonomy and Organization of Synthetic Agents with Stove-piped Assignments

Based on the information presented above, Synthetic agents' roles will need to be determined and ultimately trained to support future Warfighter embedded in HMTs. Adding these synthetic agents, or agents, into the targeting process to establish kill chains will utilize each platform in efficient and effective ways (see Figure 5). This simple taxonomy and organization illustrates the need for specialized synthetic agents, understanding their roles and functions. However, this paradigm does not take advantage of the Mosaic warfare concepts of connecting every sensor to every shooter. To break the stovepipe of this tasking paradigm, a new agent must be created and empowered.

The Need for a Mosaic Warfare Synthetic Agent

Enabling mosaic warfare at the Speed-of-the-Fight will require artificial intelligence algorithms to process, sort, and evaluate the vast swaths of data coming from every sensor on the battlefield. This resulting information flow will require specialized synthetic agents trained to convert that data into information to feed to the Mosaic warfare synthetic agent. This agent will evaluate the incredible complexities on the battlefield to determine, select, and assign which pieces of which platforms to connect to create a web of connected kill-chains.

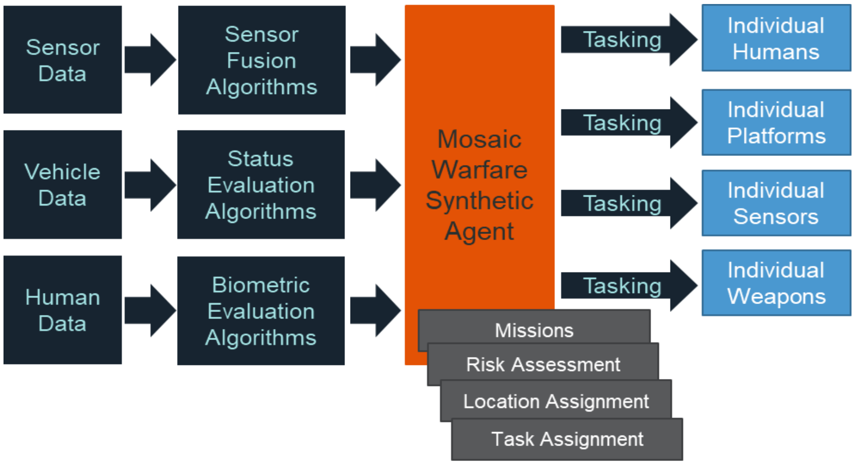


Figure 6. Organization of Synthetic Agents with Mosaic Agent Assignments

As part of this new connection strategy, the Mosaic agent will be required to evaluate every aspect of every component of every platform currently available in the joint operating area. Many of these choices will be straightforward, as some platforms will have the needed weapon, or the most precise sensor, or required dwell time over an area. Less straightforward choices involve the evaluation of the human who is currently in control or command of that platform. Thus, the Mosaic agent will need to use real-time operational data and historical data of previous task assignments and outcomes along with biometric information to correctly select the most trusted human to assign to the task. As a result, the Mosaic agent needs to effectively compute its own trust in human-operated assets and quantify trust levels for each human's ability to complete tasks across the main trust factors presented in Table 1, especially for situational and learned trust factors.

ANTI SATELLITE STRIKE USE-CASE

Synthetic agents that will be trained to support Mosaic warfare must be able to rapidly choose each of the parts of the kill chain to assemble into a kill web. The many pieces composing the kill web allows for best sensor, shooter, and sensor-to-shooter selection which will account for varying conditions or states of a platform (e.g., time, distance, fuel, weapons, sensors, mission task priorities, etc.). The Mosaic agent can easily and quickly be able to parse through the overwhelming data and provide additional confidence or course of action for the human teammate. In a narrow use case, the Mosaic agent may be presented with a choice between two assets that have the same capabilities, the same distance from the task, and the same availability. For these assets, the only differentiator will be the human in the cockpit, the Ship's Captain, or the team leader.

Situation

The following hypothetical situation is proposed (see Figure 7): tensions are brewing within the island of Kundu off the coast of California, which is divided by two independent nations Qumar (red) and US-backed Averna (blue). Qumar and Averna are currently in heated negotiations. There has been a tremendous build-up of military arms along the border and every unit is bracing for a misstep by either side that will initiate hostilities. While a pair of Next-Gen Fighter/Bombers maintain patrols along the border, two Expert Small Unit Teams have quietly infiltrated into areas to observe a pair of large transporter erector launcher (TEL) vehicles that are being raised to fire (see Figure 1). A pair of submarines silently shadow a pair of destroyers, providing mutual protection and support to friendly units.

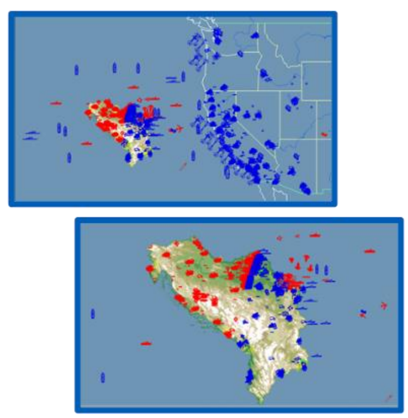
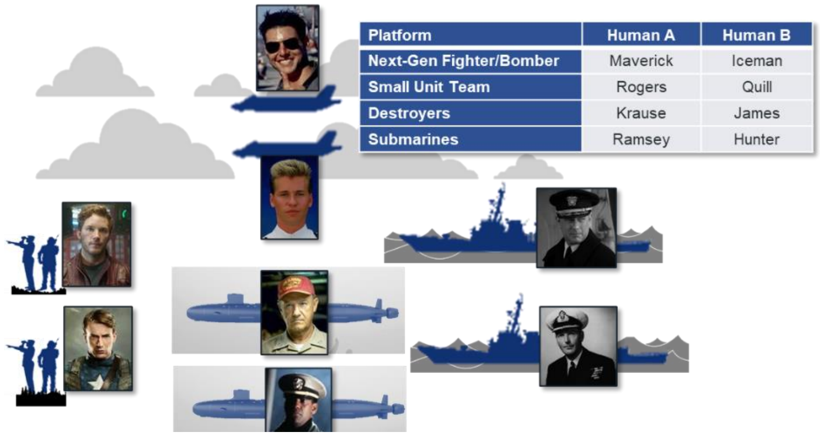


Figure 7. Maps of Kundu

Friendly units

US forces have an incredibly unique confluence of events which resulted in exact pairs of aircraft, teams, destroyers, and submarines that are 100% fully mission capable with identical weapons, fuel states, weapon loads, radars, and all other systems. The only difference is each is led, commanded, or flown by a different human (see Figure 8).



Platform	Human A	Human B
Next-Gen Fighter/Bomber	Maverick	Iceman
Small Unit Team	Rogers	Quill
Destroyers	Krause	James
Submarines	Ramsey	Hunter

Figure 8. Friendly Units

Enemy units

As illustrated in Figure 9, the enemy forces have a robust Integrated Air Defense Network and terrestrial offensive space weapons along the border poised to engage any airborne threats. They have also placed two transporter erector launchers (TELs) close the border to threaten land, sea, and space assets.

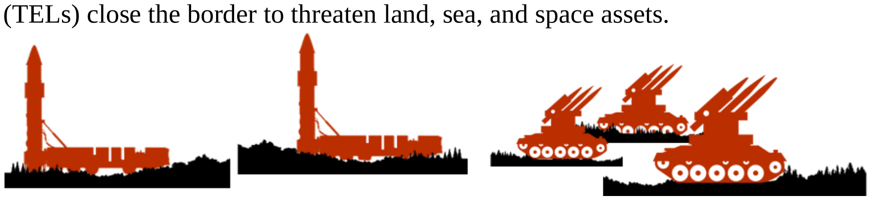


Figure 9. Enemy Units

Mission

The mission's main goal is to be prepared to engage any hostile act, prevent damage to friendly forces, and reduce the enemy's ability to continue an attack on Averna and US assets.

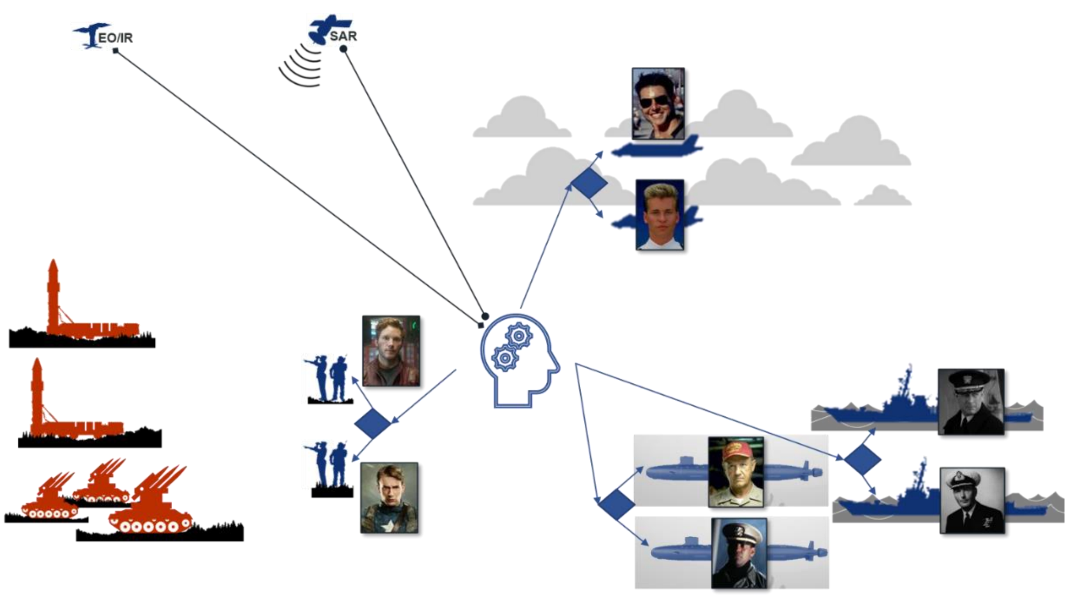


Figure 10. Kundu Situation and Agent Choices

Synthetic Trust in Action

Leaning into the portrayals from each of the fictional examples provided in Figures 8 and 10, the Mosaic warfare synthetic agent will be required to evaluate each of the choices provided to respond to the imminent threat posed by the anti-satellite missile launches. Maverick is known to be reckless and take chances when the opportunity presents itself. Iceman has a history of flying precisely by the book. Rogers follows instructions even at great risk to himself. Quill has shown that his emotional reactions can overwhelm the desire to stick to the plan. For each of these, and the other examples displayed, the overall trust that the Mosaic agent has in each of them, whether dispositional, situational, or learned, will influence the decision about which human to trust (see Table 2).

Table 2. Overall Synthetic Trust

Human A	Agent Trust	Human B	Agent Trust
Maverick	*Low*	Iceman	*High*
Rogers	*High*	Quill	*Low*
Krause	*High*	James	*Low*
Ramsey	*Low*	Hunter	*High*

Based on the history of each of these humans to follow specific taskings provided by authorities in power, as well as an assessment of their psychophysiological states along with real-time contextual information, the Mosaic agent assembles the pieces of the kill chain to form the team most trusted to ensure a positive mission outcome.

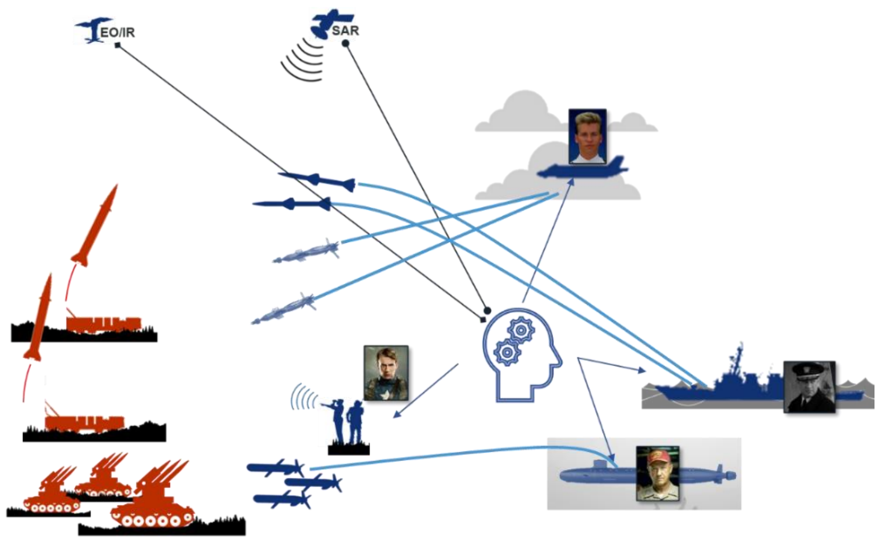


Figure 11. Agent Choices and Engagements

In this narrow use case, where each of the platforms and teams were identical in every way except for the human leading, commanding, or flying, the Mosaic warfare synthetic agent selected from the options those it decided were the best trusted to follow orders to accomplish the task. Each human followed the Mosaic agent's orders and, in this case, the missiles were shot down, the IADS system was reduced, and the TELs were destroyed.

CONCLUSION

This paper leveraged an existing multi-domain robotic teammate framework to explore and define the bilateral nature of HMT trust necessary to optimize mission outcomes in future warfare paradigms. First, we have underlined the importance of measuring human trust with synthetic agent teammates, and the importance of building and sustaining well-calibrated trust to promote HMT interactions necessary for successful mission outcomes. Second, we have applied methods and processes aimed at modeling, building, maintaining, and facilitating synthetic agent's trust, thereby providing a path to quantifying trust in humans for synthetic agents. Finally, we have provided a definition for synthetic trust, and introduced a taxonomy of synthetic agents by role and function. A result was identifying the need for a hierarchy of synthetic agents, with the introduction of a Mosaic warfare synthetic agent to evaluate synthetic trust in available human leaders, commanders, and pilots.

Theoretical findings were presented within an anti-satellite strike and response applied use case to further highlight the unilateral nature of synthetic trust in humans as a key enabler of mission success within Mosaic warfare. Future research needs to (a) support a more precise operationalization of agent trust in humans across trust factors, and (b) implement and test these trust factors in a controlled environment. The end goal is to provide a comprehensive framework to develop and train synthetic agents within a modeling and simulation environment that allow for human-in-the-loop testing, resulting in a set of precise requirements for Mosaic warfare synthetic agents utilizing synthetic trust with human teammates.

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