# A Multi-Domain Robotic Teammate Framework: Next Generation Human-Machine Interface Guidelines to Support Trust and Mission Outcomes

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## ABSTRACT

The aim of this research is to inform how Human-Machine Teams (HMTs) engaged in multi-domain operations can build and maintain trust in synthetic teammates driven by complex Artificial Intelligence (AI) to improve mission outcomes. Warfighter performance will depend increasingly more on mission-specific tasks performed by unmanned vehicles with sophisticated AI to aid in team tasks and decision making. To be effective, these robotic teammates need to behave much like humans in terms of transparent decision-making and communications. Thus, it is imperative to understand (a) how robotic teammates should interact with humans as an intact, cohesive team, and (b) how these HMTs build and sustain trust. A multi-domain framework is introduced to describe how to optimize HMTs, based on three main components: measuring HMT trust in real time, building, calibrating and maintaining trust, and providing robust and adaptive interfaces that are context-sensitive and facilitate HMT interactions. Specifically, biometric sensors are used to glean psychophysiological data to train real-time Machine Learning (ML) trust classifiers. Level of trust then mediates HMT coordination via multimodal Man-Machine Interface (MMI) designed around HMT goals that promote shared situation awareness (SA). Shared SA is obtained by displaying pertinent team decisions and suggestions, and real time trust indices are used to moderate information presented on these shared displays. Trust is built and sustained over time by keeping a record of HMT interactions and mediating level of information presented based on that history. Theoretical findings are presented in terms of domain-specific guidelines necessary to (a) measure trust based on biometric sensor data, and (b) build and sustain trust via robust MMI interfaces. Finally, two applied use-cases, based on mature research, are presented in distinct domains—the air and undersea—to illustrate the application of these guidelines.

## ABOUT THE AUTHORS

**Sandro Scielzo** is an established innovator and multidisciplinary scientist at CAE USA, Defense & Security, in the areas of human systems engineering, human factors, and instructional system design. Dr. Scielzo received his PhD in Applied Experimental Human Factors and M.S. in Modeling & Simulation from the University of Central Florida in 2008 and 2005 respectively. His research has concentrated on the validation and implementation of next generation training solutions for military and commercial applications to accelerate learning, guarantee proficiency, transfer knowledge, and maintain skills in the operational environment. Over the course of his career, Dr. Scielzo oversaw a wide portfolio of DoD R&D applied research projects to enhance warfighter training and operational readiness.

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## INTRODUCTION

Artificial Intelligence (AI) use for developing synthetic autonomous agents capable of operating in hybrid human-machine teams is of paramount importance for the Department of Defense (DoD) to meet the demands of future warfare and maintain a technologic and strategic advantage over near-pear threats. In fact, the Pentagon recently prioritized the development of AI as a collaborative partner (Hinchliffe, 2019), and the Joint Artificial Intelligence Center (JAIC) underlined the necessity to gain a deeper understanding of how to optimize Human-Machine Teams (HMT) (Shanahan, 2019). To achieve this, an unprecedented increase in DoD Research & Development (R&D) budget not seen in 70 years aims to support both applied research and advanced technology development (Harrison, & Daniels, 2020). Providing focus to this ambitious research field, the DoD Communities of Interest (CoI) captured in great detail the scope and thrust areas the scientific and engineering community needs to support when developing and validating next generation HMT technologies (Reliance 21, 2018). In addition, the National Security Commission on Artificial Intelligence (NSCAI) introduced an integrated national strategy to "defend and compete in the coming era of AI-accelerated competition and conflict" (Schmidt, Work, Catz, Chien, Darby, Ford, ... & Moore, 2021, p. 8).

Achieving these goals to properly implement a defense strategy will require a close alignment between defense, industry, and academia. Failing to do so is a risk further compounded by aggressive DoD timetables mandating AI widespread integration by 2025 (Schmidt et al, 2021). The Human Factors literature is ripe with examples of poorly implemented technology requirements when stakeholders, users, and operators are not central to the design, development, and validation of new technologies. These technologies can lead to "human error," a term often associated with an operator being at fault, but many times reflects poorly implemented systems. And in the case of HMTs, which have very strong psychological and cultural components when looking at it under the lens of high-efficiency teams and team performance, a user-centric validation of HMT technologies is even more critical. In fact, Schmidt et al. assert that such misalignment can lead to AI systems that "routinely do not work as designed or are unpredictable in ways that can have significant negative consequences, then leaders will not adopt them, operators will not use them, Congress will not fund them, and the American people will not support them" (2021, p.10).

The aim of introducing a multi-domain robotic teammate framework is simply to support the development of next generation HMT solutions that foster a tight alignment between defense, industry, and academia. This is possible by providing a set of comprehensive general guidelines that not only capture the scientific literature but are presented in a manner that supports both system engineering and user-centered validation across military domains. The framework presented in this paper was not developed in a vacuum. In fact, it extracts knowledge from years of applied research and engagements with military labs and R&D agencies such as the Defense Advanced Research Projects Agency (DARPA) (Scielzo & Kocak, 2020). Thus, before presenting our framework, corresponding guidelines, and applied use-case examples, a review of HMT history is necessary, along with a discussion on a critical HMT component: trust between man and machine. This multifaceted psychological construct is at the heart of team dynamics, and consequently will impact all HMT interactions and outcomes.

### A Brief History of Human-Machine Teaming

The seminal work from Sheridan and Verplank, opened the field of Man-Machine Interface (MMI)—also known as Human-Machine Interface (HMI)—providing optimized models of performance based on human and robotic attributes across degrees of automation (Sheridan & Verplank, 1978). The focus then was on teleoperation, and the domain was underwater operations, which presents unique communication and coordination constraints to this day.

Their work produced the Sheridan-Verplank Scale, which describes levels of automation driving human-machine interactions. Less known is that even at these early stages of MMI research, the concept of trust was identified as a key aspect of teleoperations, defined in very forward looking terms as the belief that the machine "will behave as intended … [and to] identify or empathize with the responses of the teleoperator to various commands" (Sheridan & Verplank, 1978. p., 4-13).

From a human factors' perspective, trust between operators and machines manifests as trust in automation across levels of task control. A well-known taxonomy describes levels of automation across information processing and decision-making stages, from monitoring activities, to generation of information, to action selection and execution (Endsley and Kaber, 1999). These levels range from full manual control, with humans fully responsible for making decisions, to blended decision-making, with both humans and machines being responsible for making decisions, to full automation, where humans are fully removed from the decision-making loop. This taxonomy led to a better understanding of system requirements needed to promote task-specific and appropriate level of automation, aimed to minimize human error and maximize trust in automation.

**An Accelerated Paradigm Shift**

The current rapid technological and innovation pace—led by what is colloquially referred to as the AI revolution (e.g., Makridakis, 2017; Walsh, 2017)—have enabled a dramatic change in the manner in which we operate and perceive robotic or synthetic agents. These advances are quickly pushing the envelope on the complexity of tasks and level of decision-making automated systems or synthetic agents can make—a feat that, just recently, could only be performed by humans. Machines can now sense, decide and act in a manner analogous to the human information process. For example, a fully autonomous synthetic agent was capable of defeating an expert human pilot in a dogfight (Hitchens, 2020). As a result, the relationship between humans and machines is evolving from a traditional model where humans and machines perform dedicated tasks across different levels of automation, to a model promoting the relationship between humans and machines as teammates for the collective accomplishment of such tasks (Scielzo, Fiore, Jentsch, and Finkelstein, 2006). The result is a paradigm shift progressing from a human operated environment—where automation and machines are seen as subordinates and tools to support human operators—to a new paradigm where humans and AI-driven synthetic agents behave as equals and collaborate to meet mission objectives (Scielzo and Kocak, 2020). However, without a precise understanding of human-machine team dynamics, past mistakes, comprehensively documented by the human factors' literature, are destined to be repeated. And at the core of human-machine teaming is trust, shown to heavily mediate human-machine collaboration and coordination (Scielzo and Kocak, 2020). It is then imperative to have a clear understanding of such as multidimensional construct.

**TRUST IN THE AGE OF HUMAN-MACHINE TEAMS**

The starting point in defining human-machine trust is that it needs to be viewed under the same lens as trust between human operators; that is, a complex, multifaceted construct, which has been extensively defined across social science disciplines. At its essence, trust implies the willingness to be vulnerable or to depend on someone else (e.g., Mayer et al., 1995; McKnight et al., 1998), and to engage in cooperative behaviors to manage both risks and uncertainty related with trusting other teammates (e.g., Gambetta, 1988; Jones & George, 1998). It can be inferred that the level of trust largely depends on the extent to which team members meet each other's expectations; which will invariably change across time as shared experiences between teammates accumulate. The outcome is a complex and dynamic affective construct that mediates teammates behaviors, and, by extent, HMTs as well if synthetic agents or machines are to be seen as equal members of a team. However, what does it mean for a machine to be an equal member? At a minimum there is an implication that HMTs need to engage in the same communication, coordination and collaborative behaviors as those of traditional human teams. As a result, building and sustaining trust between man and machine becomes foundational to HMT operations.

**Building and Sustaining Trust**

The different collaborative teleoperation levels between operators and machines introduced by Sheridan and Verplank (1978) with the Sheridan-Verplank Scale, as well as the levels of automation taxonomy introduced by Endsley and Kaber (1999), underscore the significance of supporting appropriate man-machine trust to prevent misuse and disuse of automated systems (e.g., Wicks et al., 1999). Key concepts and processes promoting HMT trust can be extracted

from recent reviews on trust in automation and team trust (e.g., Costa, 2003; Hoff and Bashir, 2016; Lee and See, 2004). Trust calibration is one of these key processes by which optimal trust levels are built and maintained. Lack of proper calibration results in two outcomes: 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).

Trust calibration for HMTs is also affected by three key factors: dispositional trust, situational trust, and learned trust (e.g., Marsh and Dibben, 2013). Dispositional trust indicates an individual's tendency to trust machines based on individual differences such as age, gender, and personality, which are also influenced by societal and organizational cultural norms. Situational trust is affected by factors intrinsic to an operational environment, which manifests as external variability factors (e.g., automated system complexity, collaborative task difficulty) and internal variability factors (e.g., level of expertise, cognitive and attentional capacity). Lastly, learned trust—representing the temporal dimension of trust—is the result of operators' assessment of automated systems based on accumulated past experiences and an understanding of overall system capabilities. As a result, it is foundational to enable and calibrate trust between human and machines. Proper HMT trust calibration is key to support the development of a common understanding and shared perception between humans and machines, which, in turn, is favorable for supporting effective decision making (Overholt, & Kearns 2014).

Understanding the main factors driving HMT interactions provides a starting point for the development of technologies capable of mediating trust between humans and machines. Although the current focus is for ensuring humans develop a well-calibrated trust of their machine teammates, in a not so distant future AI-driven machines will be able to develop synthetic trust, allowing them to express level of confidence of the actions and behaviors of their human teammates. In fact, an emerging domain of interest promoted by the DoD CoI is investigating 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 additional complexity of such reality cannot easily be met if HMT interactions and opportunities for trust calibrations are not well understood and implemented.

## Defining Human-Machine Team Interactions

HMT interactions—driven by the operator's internal predispositions, level of automation, and machine complexity—are largely mediated by MMIs and the constraints of the operational environments. The burden on MMIs has evolved from supporting simple teleoperated missions across various levels of automation, to promoting trust, situation awareness (SA) and shared situation awareness (SSA) between HMT teammates, as well as timely and effective communications (e.g., Scielzo and Kocak, 2020). Additionally, this next generation MMIs for HMTs have to support different levels of authority, control, and collaboration. In fact, these new MMI requirements are essential to promote future warfare outcomes and are a critical area of investigation for the DoD, delineated under the Autonomy CoI and spearheaded by the Human/Autonomous System Interaction and Collaboration (HASIC) group (see Bornstein, 2015). The intent is to promote a coherent research approach across military, industry and academic institutions. This is an important strategy as the wealth and disparate research on HMTs and MMIs lacks the focus necessary to answer technical challenges and hard problems necessary to develop effective HMT technologies that can positively translate into the operational environment. As a result, defining and categorizing HMT interactions into a testable framework is foundational to ensuring next generation MMIs will properly mediate HMTs and promote trust.

Key HMT interaction factors historically tied to trust can broadly fall into communication, collaboration, context awareness, and team performance categories. From a communication standpoint, recent research on MMI design to promote HMT trust have shown the importance of anthropomorphic design (e.g., Troshani et al., 2020; de Visser et al., 2012). Anthropomorphization of machines has traditionally been a double-edge sword, with results ranging from the grotesque—exemplified by the uncanny valley phenomenon whereby likeness to humans evokes strong feelings of unease—to very positive, with, for example, "natural" conversations between humans and digital assistants (popularized in industry with Alexa, Cortana, and Siri). Natural conversations with machines, enabled by conversational AI, is finding its way into military applications. Obvious benefits include speed and accuracy of information exchanged when interfacing with a synthetic agent (e.g., Jadeja and Varia, 2017), but recent research indicates it also fosters the development of a personalized relationship with such agent (e.g., Bellegarda, 2014), and ascribe mind and intentionality to them (De Graaf, and Malle, 2019), which is an aspect of dispositional trust, necessary to build and maintain HMT trust over time.

The next factors, HMT collaboration and context awareness, implies insights into team decision-making to facilitate allocation of individual and shared tasks. In human teams, collaboration, and the tools necessary to support such collaboration have been exhaustively researched and represent foundational attributes of trust. A unique line of research on SA and SSA provides a venue for quantifying team informational needs required for effective decision-making in support of team goals (e.g., Endsley, 2016; Endsley, and Jones, 2001). When translating this research to HMTs, additional requirements emerge, such as transparency requirements for machines to support collective decision-making (e.g., Madhavan et al., 2006). This requirement manifests as explainable AI (XAI), a concept implying the need for a second generation of AI system, allowing insights into their decision-making processes. As a result, XAI is a necessary requirement to promote HMT trust (e.g., Goebel, Chander, Holzinger, Lecue, Akata, Stumpf, Kieseberg, and Holzinger, 2018; Gunning, 2017).

Finally, team performance, and specifically HMT performance implies the need for real-time, objective performance measures to mediate information presentation and task allocation not only based on context and mission goals, but also on human psychophysiological states. For example, to properly mediate HMT trust, real-time measures of this construct need to be developed so that a trust index can be used to determine the level, frequency, and quantity of information presented via MMIs in support of trust calibration. Research from The National Aeronautics and Space Administration (NASA) on HMTs have produced real-time psychophysiological indicators of various mental states via unobtrusive biometric-based Machine Learning (ML) classifiers. Specifically, their technology enables the insertion of human states to support HMT prognostics by communicating the status of the human operator to an intelligent machine, including behavior, skill, physical, and mental states in order to promote trust (Harrivel, Stephens, Milletich, Heinich, Last, Napoli, ... & Pope, 2017). ML classifiers have also recently been developed to measure, in real-time, complex constructs such as SA in the aviation domain (Scielzo, S., Wilson, J., & Larson, E., 2020), as well as pilot eye scan accuracy, a process typically highly correlated with task performance (Wilson, Nair, Scielzo, and Larson, 2020). Consequently, to properly mediate HMT interactions and promote trust, a challenge will be to develop a testable HMT trust model that can be quantified in real time to support context sensitive adaptive MMIs.

**The Need for an HMT Multi-domain Framework**

Research on HMTs is complex, involves many interrelated engineering and social science disciplines, and, as a relatively new and emerging domain of inquiry, still lacks a solid bridge between researchers and developers across the military, academia and industry to support creating effective next generation HMT technologies capable of promoting trust and team performance. Compounding this issue are the unique constraints that each operational domain poses on HMT dynamics, from air to underwater operations. Consequently, grasping the interconnected nature of factors affecting HMT functioning is not an easy task. Existing HMT frameworks have extended traditional function allocation analyses on level of automation to HMTs, highlighting the importance of MMIs to support adaptive information demands across a number of factors such as joint performance, cognitive workload, shared knowledge of state, and interoperability (Madni, & Madni, 2018). Additionally, measurement frameworks identified metrics that are diagnostic of HMT efficiency, timing, and mission performance, and mapped those metrics to the human, to the machine, or both (Damacharla, Javaid, Gallimore, & Devabhaktuni, 2018). Finally, HMT requirements for system design are starting to emerge, illustrating the pressing need for guiding engineering efforts when developing HMT technologies (McDermott, Dominguez, Kasdaglis, Ryan, Trhan, & Nelson, 2018).

To date, a clear and present need exists for an HMT framework that maps requirements for developing real-time and objective trust metrics, methods for building, calibrating, and maintaining trust, and multimodal MMIs to support HMT interactions, while accounting for domain specific constraints. Additionally, few examples exist that extract actionable guidelines for developing HMT technologies, which are applied, as practical examples, to military use cases across contrasting domains. Our intent is to provide both, and, thus, support the development of next generation HMT solutions in a manner consistent with the desire for a strong alignment between defense, industry, and academia.
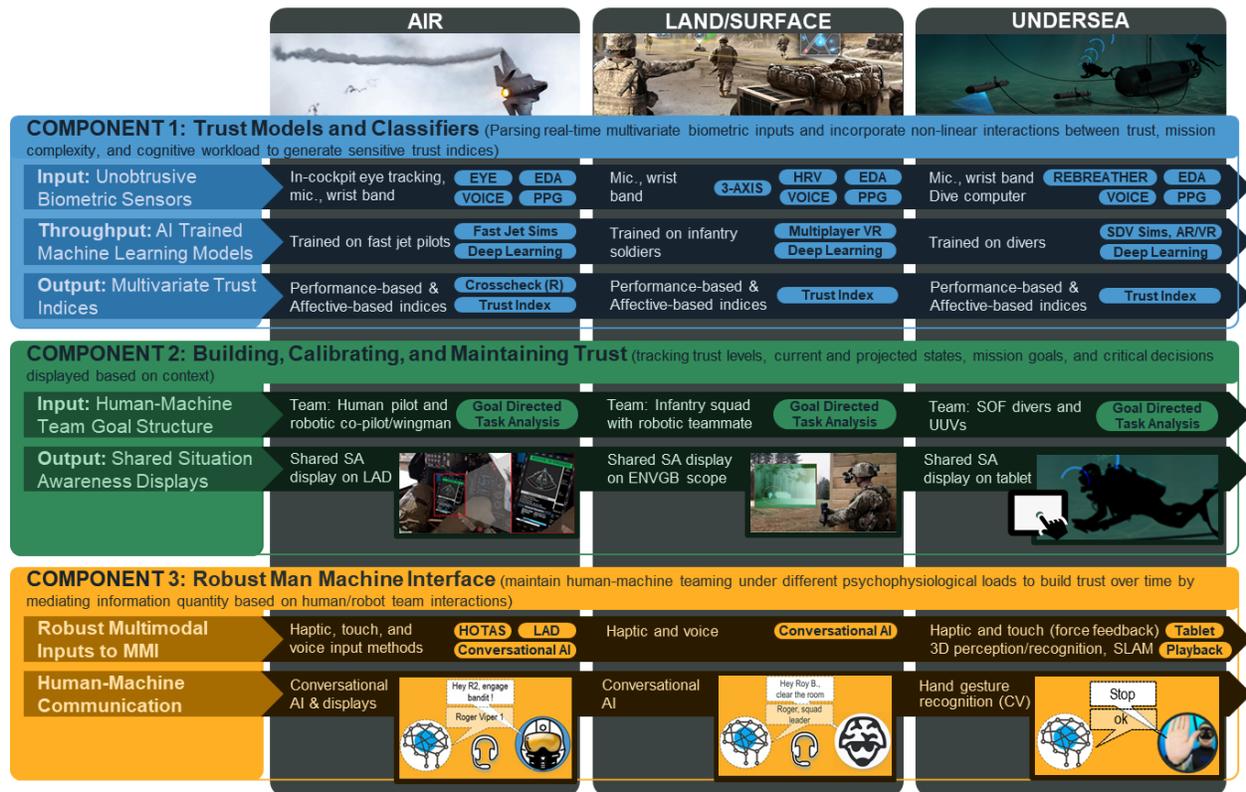
**IMPLEMENTING A MULTI-DOMAIN HMT FRAMEWORK TO SUPPORT NEXT GENERATION HUMAN-MACHINE INTERFACES**

The multi-domain HMT framework presented here represents the culmination of applied research efforts trying to answer DARPA hard problems across different domains. Scielzo and Kocak (2020) introduced high-level components of this framework as it applies to the development of trust between operators and autonomous underwater vehicles.

This paper expands the framework with additional domains and precise descriptions of the factors involved with the measurement and assessment of HMT trust, as well as promoting both communication and SSA via robust MMIs.

**Framework Overview**

The multi-domain HMT framework (Figure 1) provides the foundation for measuring trust in real time and properly calibrating and maintaining trust over time via domain-specific MMIs designed to promote coordination between humans and synthetic agents. This multi-domain framework focuses on three overarching components, and how they manifest across domains: (1) trust models and classifiers, guiding the development of domain and mission-specific real time and objective measures of HMT trust; (2) building, calibrating, and maintaining trust by quantifying HMT SSA to guide the development of next-generation HMT MMIs; and (3) a robust HMT interface, promoting communication and coordination between human and machines. Each of these components is reviewed in turn across the air, land/surface, and undersea domain, with diagrammatic processes applied to the air domain.



**Figure 1 – A Multi-Domain Robotic Teammate Framework**. *HMT framework that maps requirements for developing real-time and objective trust metrics, methods for building, calibrating, and maintaining trust, and multimodal MMIs to support HMT interactions, while accounting for domain specific constraints.*

**Component 1: A Real-Time Measurement Framework for Trust**

This first component comes out of the necessity to measure, in real time, operator's psychophysiological states that relate to the construct of trust directly and indirectly (e.g., Harrivel et al., 2017). The goal for an automated assessment of HMT trust is to use it both to inform machine-driven XAI—such as moderating the quantity and type of information exchanges in support of HMT decision-making—and to mediate the methods by which MMI information is displayed. This is possible thanks to advances in the use of unobtrusive biometric sensors to develop ML classifiers capable of assessing with high precision higher-order cognitive constructs and affective states (e.g., Scielzo et al., 2020; Wilson, Nair, Scielzo, and Larson, 2021; Wilson et al., 2020).

Component 1 adopts an input/throughput/output model, which is further depicted in Figure 2. Input to model begins with the identification of the operator and the type of biometric sensors compatible for the domain at hand. The type

of biometric sensors that can be gleaned and used to classify HMT trust depends on the domain at hand. In fact, while the air domain—using a fast jet use case—allows using multiple in-cockpit biometrics sensors, including eye-tracking, that particular biometric sensor is not applicable to the land domain—when looking at



**Figure 2. Component 1 Input, Throughput, Output model visualization**

dismounted infantry—and the undersea domain—with divers as a use case. Thus, the type of biometric sensors to be used are both domain and use-case dependent. When biometric sensor data is properly mapped to domain-specific operational demands, trust modeling can be generated via ML—this is the throughput phase of Component 1. The aim is to "parse real-time multivariate biometric inputs and incorporate non-linear interactions between trust, mission complexity, and cognitive workload to generate sensitive trust indices," represented by the output phase. These various HMT trust indices can be either performance-based or affective-based. An example shown here illustrates how an operator crosscheck ratio, which determines the ratio of the operator's visual gaze fixations between primary task MMI elements and machine controlled MMI elements, can be an effective trust index. Assessment of voice prosody (pitch, intensity) and other affective constructs (stress, frustration) are examples of affective-based trust indices. Developing domain-specific, highly diagnostic model of trust is thus central to Component 1.
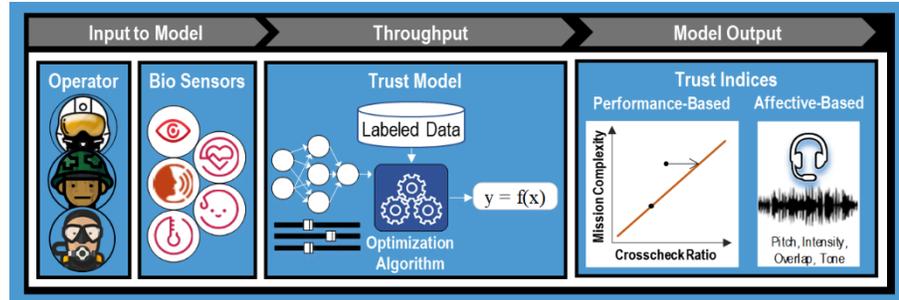
**Component 2: Building, Calibrating, and Maintaining Trust**

Measuring HMT trust in real time is necessary to support adaptive MMIs. However, to further build, calibrate, and maintain trust in HMTs, it is essential to capture HMTs' goals and decision points. The notion of shared SA, defined as "the degree to which team members possess the same SA on shared SA requirements" (Endsley &



**Figure 3. Component 2 mission goals driving adaptive shared SA displays**

Jones, 2001, p. 48), is essential to define shared informational requirements needed for HMTs to accomplish individual and shared tasks. Goal-Directed Task Analysis (GDTA) can be used to extract such requirements. This method has been successfully used across domains, from Army brigade officers (e.g., Bolstad et al., 2002) to maritime navigation (e.g., Sharma et al., 2019). Analyzing shared SA reveals HMT requirements that are both common and unique across team members. As a result, shared SA displays can be designed and made adaptive thanks to an HMT's goal structure, illustrated in Figure 3. When used in conjunction with real time trust indices, next generation MMIs can truly be made adaptive in a way that will promote both HMT trust and shared SA.
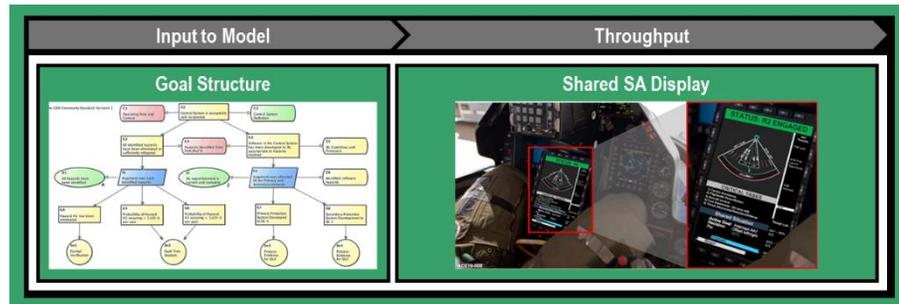
**Component 3: Implementation of Domain-Dependent Man-Machine Interfaces**

This final component, shown in Figure 4, underlines the importance of implementing robust multimodal inputs for MMIs tailored to vehicle, operational, and domain
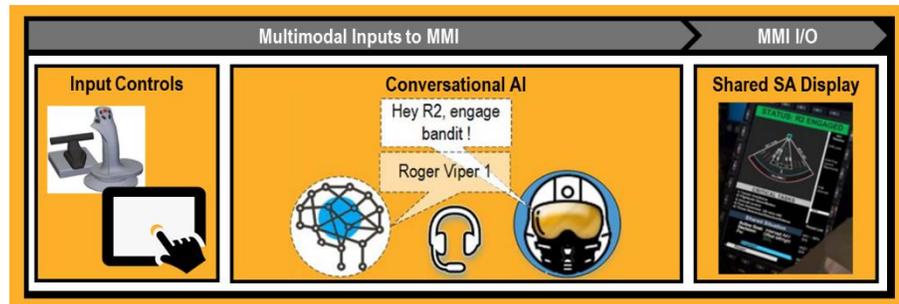


**Figure 4. Component 3 multimodal input AI-driven HMT interactions**

constraints. In addition, to support HMT interactions and decision making it is imperative to incorporate emerging AI capabilities such as conversational AI and XAI introduced earlier. Conversational AI allows for rapid and effective exchange of information, and, over time, the synthetic agent's responses can be tailored based communications history to increase trust. Finally, XAI is pivotal for transparent decision-making, which is essential to build HMT trust. In fact, XAI ensures AI transparency across the Observe, Orient, Decide, and Act (OODA) decision making continuum (e.g., Angerman, 2004) and allows the human operator to remain in the loop and support team decisions.

## GUIDELINES FOR NEXT GENERATION MAN-MACHINE INTERFACES

This section introduces high-level guidelines designed to extract critical factors from the HMT framework. Failing to address these guidelines will likely result in inefficient HMT interactions, poor trust between human operators and synthetic agents, and will negatively impact mission outcomes. Table 1 lists the guidelines by framework component.

**Table 1. High-level guidelines by HMT component with rationale**

| HMT Component | Guideline | Rationale |
|---|---|---|
| Component 1 <br><br> *"A Real-Time Measurement Framework for Trust"* | Determine which unobtrusive biometric sensors are applicable to your domain and specific use case | Biometric sensors allow for real time input on operator physiology |
| | Develop AI-trained machine learning models of HMT trust to support next generation adaptive MMIs | Machine Learning (ML) classifiers have shown to accurately assess psychophysiological states |
| | Develop trust indices germane to your domain across performance and affective dimensions | There are indirect ways to assess HMT trust in real time with high diagnostic power |
| Component 2 <br><br> *"Building, Calibrating, and Maintaining Trust"* | Develop human-machine team goal structures to determine HMT requirements that are common and unique across team members | Quantifying the relational nature of HMT goals and decision structure allows to maintain a common operational picture |
| | Use goal structure to drive adaptive design requirements for shared SA displays | HMT goal structure can drive the development of adaptive shared SA requirements |
| Component 3 <br><br> *"Implementation of Domain-Dependent Man-Machine Interfaces"* | Implement robust multimodal inputs for MMIs tailored to vehicle, operational, and domain constraints | Environmental stressors require multiple redundant input methods to sustain HMT interactions |
| | Adopt natural team communication with conversational AI | Verbal communications, when possible, can improve speed and accuracy of information exchanges |
| | Keep a record of HMT interactions to mediate level of information presented based on that history | Trust is built over time allowing for implicit communications to strengthen HMT bonds |
| | Ensure Transparency AI (XAI) to allow for robust team decision-making | Agent transparency enables the human operator to understand what the synthetic agent is doing and why |

## TWO APPLIED USE CASES

Two use cases are provided as examples of applying the HMT guidelines presented in the previous section: fast jet air combat, and an undersea Special Operation Forces (SOF). The first use case is being heavily researched to better understand HMT trust when pilots operate as mission commander, while a synthetic agent serves as a fully capable pilot to take over flying for the human pilot (e.g., Javorsek, 2020). The underwater use case is a high-stakes domain where direct interaction and cooperation is needed between special forces and their unmanned underwater vehicles (UUVs) for beach reconnaissance, obstacle clearance, and flank security missions (see Scielzo and Kocak, 2020).

### Air Domain: Fast Jet Air Combat

DARPA has been championing the concept of a robotic teammate to support warfighters across a variety of programs, while being keenly aware of the negative impact a poorly calibrated trust between the operator and the synthetic agent

would have. Without trust in the AI synthetic agent, a pilot's mission command tasks would suffer. This example illustrates the process of defining HMT display requirements that promote shared SA.

To determine context-driven information presentation on shared SA displays, a Goal-Directed Task Analysis (GDTA) is performed to define all information requirements and corresponding MMI functional requirements. GDTAs are a specific form of cognitive task analysis that focuses on mission or job specific goals, subgoals, critical decisions (to achieve goals), and information requirements (for effective decision-making) at all three levels of SA (i.e., perception, comprehension, and projection). Figure 5 introduces these relationships, which is central to the design MMIs. A preliminary GDTA targeting air-to-air engagement aided by a synthetic agent pilot was conducted with an F-16 Instructor Pilot. The outcome was the identification of information



**Figure 5. Goal Structure**

requirements that have to be displayed to ensure a global understanding of how the synthetic agent is performing its tasks. Figure 6 shows a notional graphical representation of the F-16 Central Display Unit (CDU), showing a prototypical SSA display. High-level informational requirements shown on the CDU are presented in Table 2.

**Table 2. AI Agent MMI Display Key Features**

| Display Feature | Description |
|---|---|
| 1. AI agent status with on/off function | Color coded AI status with ability to rapidly turn it on or off |
| 2. Dynamic Weapons Engagement Zone (WEZ) | A dynamic WEZ showing critical bandit information |
| 3. Target engagement live timeline | A vertical active timeline with key events (e.g., intercept, lock) |
| 4. Dynamic threat list | List of all the threats in the area of operation |
| 5. Critical tasks status | Status on all AI flying critical tasks (e.g., terrain avoidance) |
| 6. Shared situation status | Status showing the AI agent active goal and critical decision |
| 7. Human-machine chat | Chat view of the human-machine conversational AI exchanges |



**Figure 6. SSA display providing the Pilot with critical time and context sensitive information**

**Undersea Domain: Special Operations Forces**

Navy SEALs are undoubtedly one of the highest performing teams in the world. *Trust* in each team member is vital to their success, by far outweighing individual performance skills (Sinek, 2019). During a mission, when time is of the essence, trust increases speed; while lack of trust slows everything down. Elevated stress and pressure of the mission can expose and amplify areas of distrust. If there is no trust, there is no team.

In this use case—illustrated in Figure 7 with pertinent HMT components overlaid—two unmanned underwater vehicles (UUVs) deployed from a SEAL Delivery Vehicle (SDV) are used by Special Operations Forces (SOF) to conduct forward-deployed reconnaissance ("scout") and flank security missions ("security"), respectively. Just as trust is vital between human team members, establishing and supporting trust with robotic teammates is also essential. In this application, instead of relying solely on the vehicle's autonomous AI capabilities, a high-bandwidth fiber optic tether offers a means to transmit sensory data from the vehicles and send human input to the vehicles for shared decision-making during missions. The vehicles are controlled by an AI Ontogenesis Engine (OE) (Smith and Henning, 2020) that captures, generates and analyzes temporal and contextual knowledge and maintains the same over time. The OE is able to recognize new knowledge, determine when the knowledge needs to be changed, and determine when the knowledge becomes obsolete. Knowledge generation of the OE is integrated with an OODA loop framework to improve contextual awareness in multiple dimensions (e.g., time, location, geospatial and haptic) and modify system behaviors to produce a desired result. A simplified flow diagram of the OE is shown in Figure 8.
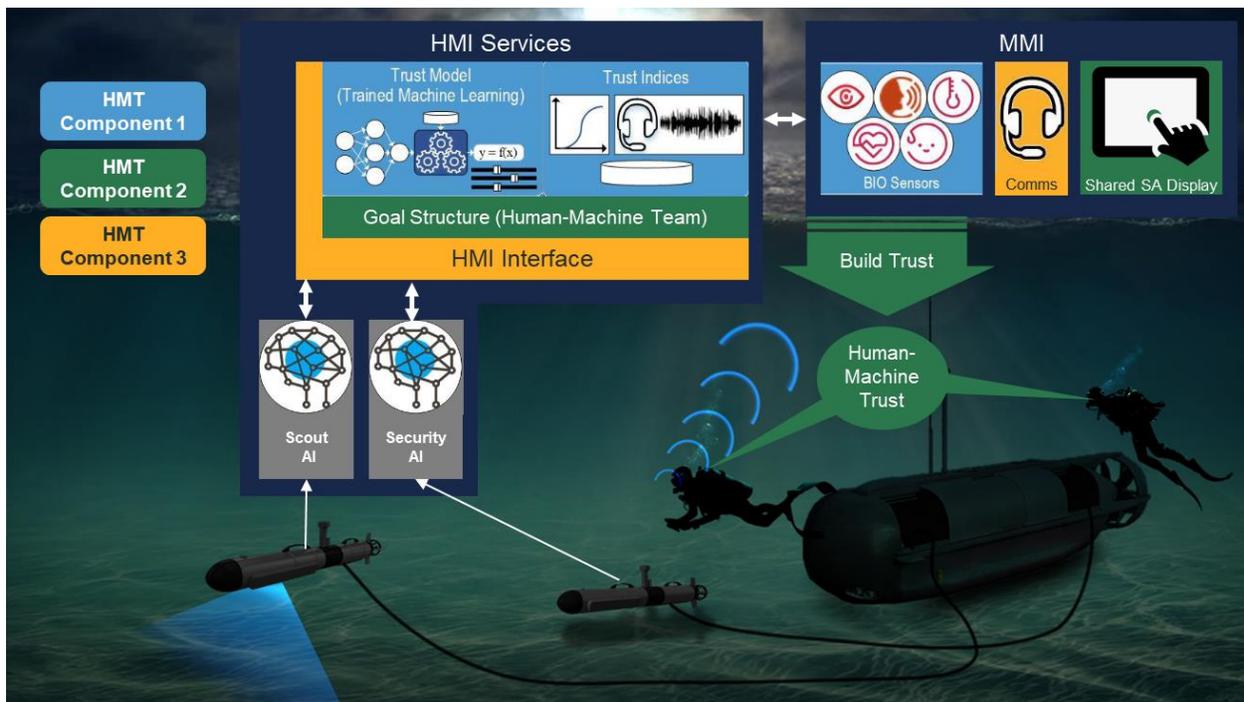


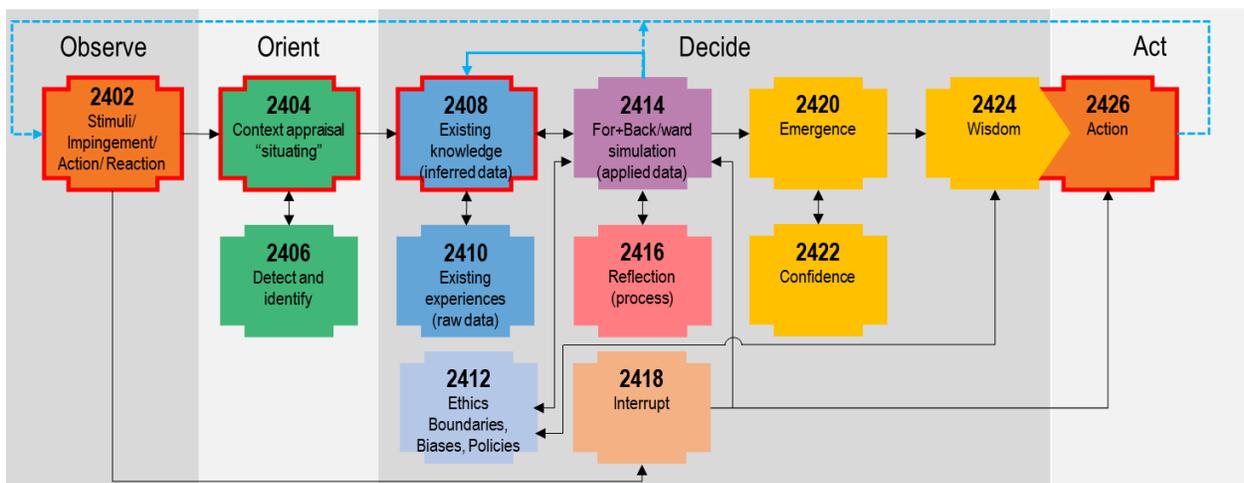**Figure 7. Underwater SOF HMT team with HMT framework component overlaid**



**Figure 8**. **HITL-enabled Ontogenesis Engine components (red outline) across the OODA loop**

To illustrate how this works, consider a scenario where the flank security UUV sets up a "trip wire" to look for vessels entering a harbor while the scout UUV is inside the harbor conducting a bathymetric survey towards shore. The SEAL divers are at the SDV stationed inside the harbor, between the two vehicles, monitoring input data from both vehicles. Table 3 steps through the OODA loop and OE blocks to demonstrate the decision process and human-machine interaction (HITL) on the security UUV as an unidentified boat approaches the harbor.

**Table 3. HMT decision making across the OODA loop**

| Step (OE Block) | Description | HITL |
|---|---|---|
| 1 (2402) | The Flank UUV observes a boat approaching the harbor in a trip wire zone. The UUV is equipped with cameras, sonar, and a microphone. In this example, a sound was detected underwater (impingement). The database (2402) matches the sound to a specific motor and infers that this is a "fishing boat". This assumes a similar motor was stored in the database, so it is recognizable. | Yes, the human can evaluate the sensory input |
| 2a (2404) | Context appraisal is performed: is this a threat or not? "Fishing boat" could be a cover. Orient to this context of behavior; e.g. consider speed, direction, fish/depth sounder, and any change in these parameters. Check with 2406 to see if there is agreement and then set the expectation/threat level. | Yes, the human can confirm or change the result |
| 2b (2406) | Detect and identify the impingement. Yes, this is a large horsepower outboard motor (e.g. recreational). A depth sounder is also detected, and the boat is traveling within channel speed, etc. | No |
| 3a (2408) | Consider existing knowledge given this is a fishing boat. What can we decide to do based on historical data? Check with 2410. | Yes, the human can confirm or change the result |
| 3b (2410) | Existing experiences (raw data): Boat behavior matches – charted course and speed are as expected. Report back OK. | No |
| 4a (2414) | Forward/Backward simulation determines all possible behaviors in response to the impingement. The full set is built here. What are the possible set of actions we can do in response to the given behavior? In this case: do nothing, alert divers to standby, or abort the mission. Check with 2416. Given 2416 simulation set and "do nothing" outcome, go to 2420. (Note: post-mission analysis can occur here.) | No |
| 4b (2416) | Reflection; probability of success; have we seen this before? Given the risk, importance, SA, etc., what are we willing to accept as an outcome (e.g. damage, discovery, etc.)? Also consider risks; in this case, do the divers have enough air to prolong the mission to wait? The outcome: pass simulation set back to 2414. This will be used in the emergence engine (2420). | No |
| 5a (2420) | Emergence does a pairwise comparison using the simulation data set to get the highest probability solution. The action here is to hold steady to mission parameters. | No |
| 5b (2422) | Determine confidence of 2420 action and perform a final check. For example, can we hold steady for the duration? | No |
| 6 (2424) | Wisdom checks with 2412 and checks for an interrupt (2418). If there is no interrupt, then wisdom passes off to 2426. | No |
| 7 (2426) | Action is to hold steady on the bottom | Yes, human can confirm, abandon or redirect |
| 8 (Blue line) | Loop back to step (1) and repeat this until the fishing boat passes into the harbor. | No |

**CONCLUSION**

This paper provided some historical background on the ongoing paradigm shift from a traditional teleoperated environment where automation exists to support human operators' needs and goals, to a new paradigm where both humans and AI-driven synthetic agents are seen as equal and dynamically collaborate to achieve mission goals. This shift is accelerating rapidly; however, without a clear understanding of the factors that are key to drive effective HMT interactions, the pressing need to develop next generation adaptive MMIs to support future warfare will likely suffer.

Trust is key when trying to understand HMT dynamics, and it has been throughout the history of automation. However, with HMTs dealing with highly sophisticated AIs, trust is even more critical, and is the foundation for our multi-domain framework, designed to draw attention to critical factors impacting the design of MMIs that are conducive to the level of interactivity required between man and machines. Thus, the multi-domain HMT framework presented here aims to provide a foundation upon which next generation adaptive MMIs can be developed.

This is precisely why high-level guidelines, extracted from the HMT framework were provided. And because guidelines can often remain abstract, two applied examples in air and undersea domain detailed how some of these guidelines were applied. However, this multi-domain HMT framework alone is not sufficient. HMTs and corresponding design for effective MMIs that adapt based on context and human operator psychophysiological states is still an emerging field. It behooves the military, industry, and academia to collectively push the research envelope and ensure the development of rigorously empirically tested MMI standards, capable of synergizing complex human-machine interactions.

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