Enabling Advanced Air Mobility Operations through Appropriate Trust in Human-Autonomy Teaming: Foundational Research Approaches and Applications

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Emerging Advanced Air Mobility (AAM) operations will be enabled by increasingly autonomous systems, requiring technologies to take on more responsibilities and fundamentally altering traditional human-automation interaction paradigms. The growing reliance on higher levels of automation will necessitate research to identify capabilities and principles that facilitate humans and machines working and thinking better together, i.e., human-autonomy teaming (HAT). Trust is an inherent requirement in effective teams because when members work interdependently, those agents (human, automation) must be willing to accept a level of risk to rely upon each other to reach goals and contribute to team tasks. This work provides an initial approach to enabling AAM operations through appropriate trust within HAT. The main contributions of this approach resides in connecting the construct of trust to mental models. Using the outlined mental model approach, we propose novel HAT strategies, such as Adaptive Trust Calibration, and preview planned research activities derived from this approach. Additionally, we propose several practical applications that can currently be employed by AAM development communities.

I. Introduction

Advanced Air Mobility (AAM) represents an ecosystem of emerging aviation technologies and concepts that allow the transportation of people and goods to locations in both rural and urban environments, including those not traditionally served by current modes of air transportation [1]. Many of the proposed AAM concepts will be supported by increasingly autonomous systems, which will require technologies to take on more responsibilities and fundamentally alter traditional human-automation interaction paradigms. The growing reliance on higher levels of automation will necessitate research and development efforts that identify new and different ways in which humans and machines interact. Recognizing this need, NASA's Transformative Tools and Technologies – Revolutionary Aviation Mobility (T^3/RAM) Sub-project has identified Human-Autonomy Teaming (HAT) as a critical area of research required to enable safe and effective AAM operations. The notion of "teaming" between a human and machine should not focus on how machines can think or act like people, but instead on identifying capabilities and principles that facilitate humans and machines working and thinking better together [2]. Under T^3's Autonomous Systems (AS) Enduring Discipline Area of Research, the HAT Foundational Research Activity has been tasked with providing basic research that advances the field of HAT through theory-development and experimental validation in controlled laboratory studies. An initial focus of this research activity is investigating how humans calibrate their trust in increasingly autonomous systems, which was identified as a key HAT research challenge by the T^3/AS HAT Planning Team (see [2]). The purpose of the current work is to introduce the theoretical perspectives of trust adopted by the HAT Foundational Research Activity and then provide an overview of future research and practical applications. Although this activity is focused on foundational, basic scientific HAT development efforts, this work is geared heavily toward the advancement of AAM applications.

II. Advanced Air Mobility

The emergence of AAM has been driven largely by advances in electric and hybrid propulsion, energy storage, and increasingly autonomous software systems. AAM broadly includes both manned and unmanned aircraft of any

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size with any mission, provided that they leverage the transformative technologies of the AAM ecosystem [1]. Major applications within AAM will ultimately be determined by the technical, regulatory, and economic paths of least resistance, but the industry is moving forward with several key interests. These include, but are not limited to, the following AAM subsets: small Unmanned Aircraft Systems (sUAS), Urban Air Mobility (UAM), Thin-Haul Commuters, and Autonomous Cargo (i.e., large UAS). Currently, sUAS represent the most developed subset of AAM, but extensive resources are being invested to advance additional subsets to operational reality.

As these AAM subsets continue to evolve, stakeholders will be driven by economic forces to increase the level of automation and, thus, reduce the role of the pilot. For manned vehicle operations, this also includes relocating the pilot from onboard the aircraft to a ground-based location. This transition of duties correlates to a spectrum of pilot roles (see [3] for discussion on levels of pilot-in-command distancing), which fit into two distinguishing categories that correspond to the concepts of *Simplified Vehicle Operations (SVO)* and *Remote Vehicle Operations (RVO)*. Although there is limited research that addresses SVO (i.e., onboard pilots) as it applies to the AAM ecosystem (though see [4, 5]), the primary focus of the HAT Foundational Research Activity is RVO (i.e., remote operators).

Chancey and Politowicz [3] define *RVO* as a concept of operations where “aircraft are remotely controlled by some combination of one or more humans piloting a single aircraft or operating/managing many aircraft, with varying degrees of automation support.” This definition covers a range of remote roles that vary from a single pilot controlling one aircraft remotely with full responsibility (similar to a military UAS remote pilot) to a team of remote operators managing a large number of aircraft (with a shift of responsibility to the automated aircraft). This team of operators represents the end goal for AAM operations, with an emphasis on maximizing the ratio of aircraft to operators. One of the key goals of the HAT Foundational Research Activity will be to address HAT in the context of RVO by focusing initial research on the role of trust in human-machine teams.

III. Human-Autonomy Teaming and Trust

Under RVO concepts, a significant increase in automation would be required to enable the range of proposed AAM operations. In many domains, automation is implemented extensively with the goals of reducing human workload, enhancing efficiency, and providing economic advantages [6, 7]. Increasingly autonomous systems promise to surpass current automation capabilities in furthering AAM goals, where the term “autonomous” represents a characteristic of automation to “independently assume functions typically assigned to human operators, with less human intervention overall and for longer periods of time” [8, p. 4]. Yet the emerging field of HAT suggests that many of the potential benefits of increasingly autonomous systems are more likely to materialize if human-technology pairings are structured as teams [2, 9]. Here, we adopt the definition of a team as “a distinguishable set of two or more *agents* who interact dynamically, interdependently, and adaptively toward a common and valued goal/objective/mission” [10, p. 7]. The progression from lower levels of automation to increasingly autonomous systems reveals an opportunity to expand human-automation interaction design strategies to also include more complex interpersonal teaming principles, such as trust. The field of HAT broadens the usefulness of trust as a theoretical construct to include human-technology collaboration approaches that were previously only applicable within interpersonal relationships.

Trust is “an attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability” [11, p. 51]. Without trust, team members tend to expend excessive time and effort crosschecking and inspecting each other, as opposed to collaborating toward an overall goal [12]. In the context of RVO, an operator that does not have sufficient trust in (potentially many) highly automated sUAS may feel compelled to monitor the raw data to continuously verify nominal operations. This creates a situation in which the operator is forced to divide attention among tasks, leading to increased workload and deterioration in performance indices [13, 14]. Trust is an inherent requirement in effective teams because when members work interdependently, those agents (human, automation) must be willing to accept a level of risk to rely upon each other to reach goals, contribute to team tasks, and cooperate without subversive intentions [12, p. 569]. Ideally, trust should match the automation’s capabilities (i.e., trustworthiness) to avoid the deleterious effects of disuse and misuse, a concept referred to as trust calibration [11]. To understand the psychological mechanisms that contribute to trust calibration, and subsequent human behaviors, the underling belief structures that form the bases of trust need to be considered. Researchers often describe interpersonal trust in terms of the beliefs (i.e., goal-oriented information) that support it [15, 16]. For example, Lee and See [11] propose three informational bases for human-automation trust: ***Performance*** describes a user’s understanding of *what* the automation does, corresponding to current and historical operation of the automation; ***Process*** describes a user’s understanding of *how* the automation operates, corresponding to the appropriates of the automation’s algorithms in achieving operator goals; ***Purpose*** describes a user’s understanding of *why* the automation was developed, and corresponds to how well the designer’s intent has been communicated to the operator. The robustness and stability of trust depend on how the human mentally represents these goal-oriented informational bases referencing the automation, and determines the appropriateness of intentions to use the automation and behavioral responses toward the automation (i.e., trust calibration; [11]).

One approach to describing the belief structures of Performance, Process, and Purpose, are to conceptualize these as the user's mental models of the automation. Mental models are the mental representations of system processes humans use to reason, infer, and make predictions about the technologies they interact with [17, 18, 19, 20]. We propose that appropriate mental models for what the automation is doing (Performance), how it is doing it (Process), or why it was developed (Purpose) will lead to well-calibrated trust in the automation. One method to facilitate the development and maintenance of appropriate mental models is to design and train for automation transparency, which is "…the communication of system-centered factors and human-centered factors that promote shared awareness and shared intent within a human-machine team" [21, p. 41]. Lyons et al. propose several transparency design models that correspond well with the belief structures that support trust [21]. Specifically, the ***Task Model*** describes the information available to the human that can be used to analyze the actions of the automation (cf. Performance), the ***Analytical Model*** describes information available to the human that can be used to analyze how the automation is making decisions (cf. Process), and the ***Intentional Model*** describes the information available to the human that can be used to place the actions and decisions of the automation in the appropriate strategic context (cf. Purpose). Although researchers often focus on the user mental model (e.g., pilot, operator, passenger, customer), these transparency models are better conceptualized as a translation of the designer's mental model of the technology in the form of the automation's "system image" (i.e., the physical system, user interface, training, instructional material). From the perspective outlined in the current work, a transparent system image is a design and training method that translates the designer's mental model of the automation into the operator's mental model of the automation, with the specific purpose of calibrating trust to match technical capabilities (i.e., trustworthiness). Specifically, the closer the user's mental model of the automation is aligned with the designer's mental model, the more appropriate trust should be in that automation (i.e., well calibrated). To enable effective HAT in AAM operations, the HAT Foundational Research Activity has created a theoretical framework outlining this perspective. The novel contribution of this work resides in connecting the construct of trust to mental models and showing how this method could be used to enable emerging HAT concepts (e.g., see Adaptive Trust Calibration in Section IV). Yet to begin validating concepts within this framework, empirical evidence will be required in several key areas. Section IV provides a preview of the research envisioned under this activity and Section V reviews the practical applications that may be derived from the proposed research.

IV. Future HAT Trust Research and Approaches

Many of the AAM concepts discussed in Section II are being geared toward the types of automation that will emerge in the coming years and decades. Fortunately, at the time of this writing, these approximate periods offer a buffer to allow the research and development community to test and evaluate System Image concepts that align the Design Model (i.e., designer's mental model of the automation) with User Models (i.e., user mental models of the automation) to support appropriate trust in AAM operations. The Iterative Design model in Figure 1 illustrates a process that is similar to the concept of bridging the gulf of evaluation (i.e., the mismatch between a system's representation and what an operator expects, which is joined by "moving" the system closer to the user) [22]. This approach lends itself to iterative experimentation that attempts to establish the effects of the match (or mismatch) between the Design Model and User Model on trust and behavioral responses toward the automation. Yet mental models are not directly observable, and instead are generally inferred from user performance metrics or verbal think aloud protocol (see [23] for comparisons of techniques). One option for operationalizing mental models is with Pathfinder Network Analysis. Based on graph theory, Pathfinder is a statistical technique that represents knowledge structures in graphical form [24], and has been used extensively in human-computer interaction studies to represent and quantify mental models (see [25]). Moreover, quantitative comparisons between individual networks can be made using the C statistic (ranging from 0 [not related] to 1 [strongly related]), which is a measure of shared links for matching nodes. Specifically, the Pathfinder method provides the ability to quantify the degree to which a representative Design Model matches a User Model. A parallel multiple-mediation analysis could be used to analyze specific pathways (see Figure 2). Chancey and Politowicz [3] used a similar statistical technique to establish the relationship between UAM concept of operation factors on public acceptance through individual factors of trust (i.e., Performance, Process, Purpose; see also [26]). This approach could be used as a framework to pursue iterative experimental studies that begin validating the concepts outlined in this document.

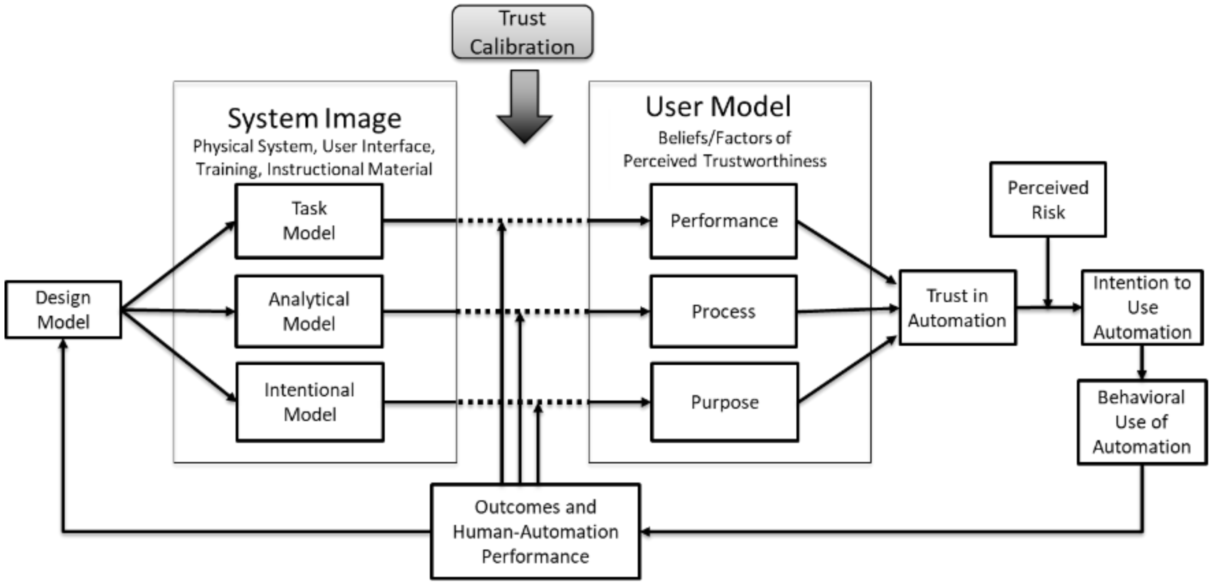

Figure 1. Model for Iterative Design in HAT paradigms.

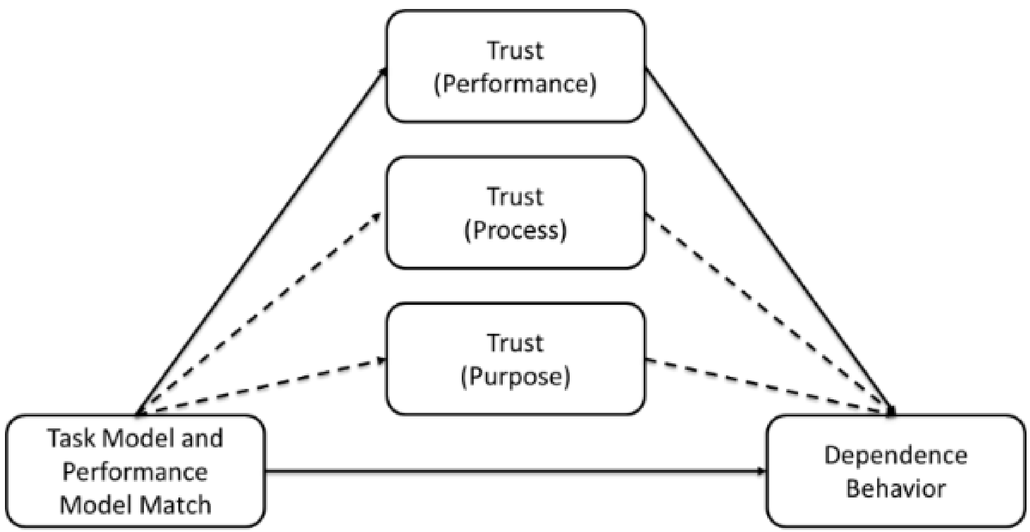

Figure 2. Parallel multiple mediation model for the effects of Design and User mental model match on dependence behaviors through factors of trust. Note: The example model indicates that the Performance basis of trust should provide the strongest mediating effect on dependence behaviors because it is based on the degree of similarity between the Task Model and Performance Model.

The concept of HAT implies that a human and automated system coordinate dynamically, interdependently, and adaptively toward a common goal (cf. [10, p. 7]). Increasingly autonomous systems may be better "equipped" to enter into this type of collaboration with a human partner than systems at lower levels of automation. To this point, increasingly autonomous systems have been described as possessing the ability to be "generative and [to] learn, evolve and permanently change their functional capacities as a result of the input of operational and contextual information" [27, p. 284]. Trust will play an important role in mediating the relationship between the human and increasingly autonomous systems, and true teaming may be difficult to achieve if the system is unable to dynamically adapt to facilitate collaboration. To accomplish this, we introduce the concept of *Adaptive Trust Calibration*, and propose an initial descriptive model that may be used to operationalize this concept (Figure 3).

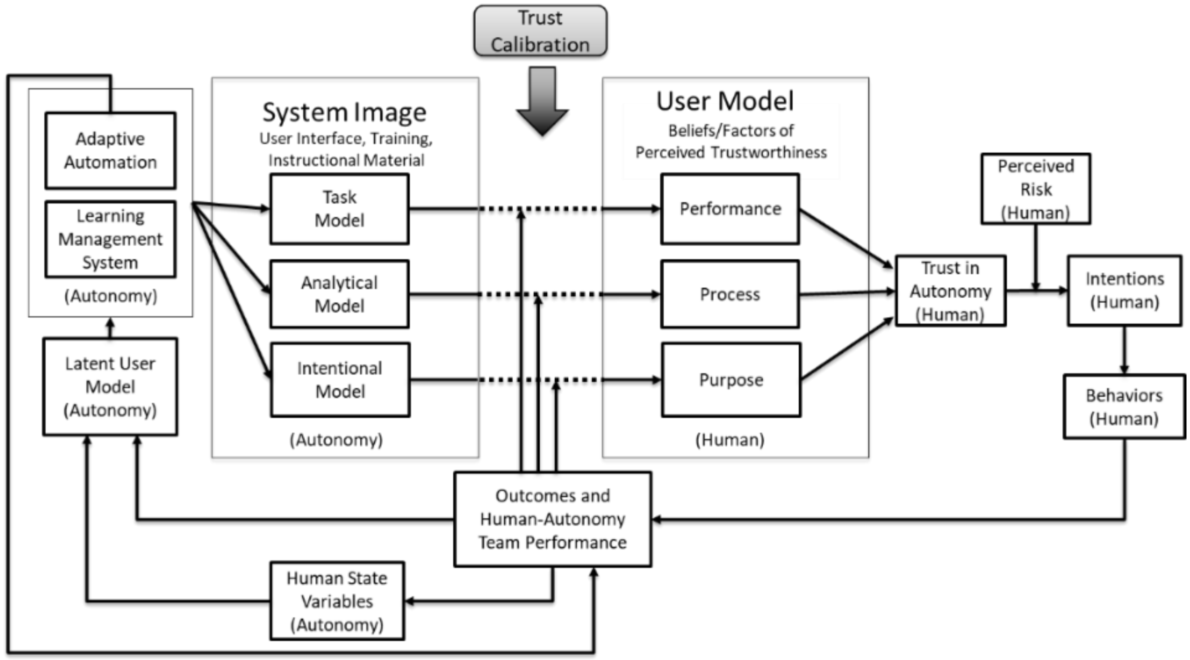

Figure 3. Model for Adaptive Trust Calibration in HAT Paradigm. Note: Added feedback loop through Human State Variables, Latent User Model, Adaptive Automation, and Learning Management System.

Although the model in Figure 3 possesses the same underlying theoretical principles outlined in Section III, and in Figure 1, there are important differences that allow for the “adaptive” aspect of the model to function as a closed-loop process (i.e., closing the loop does not require iterative experiments to align the User Model and Design Model). Specifically, the Adaptive Trust Calibration model assumes that the increasingly autonomous system is consistently sampling, storing, and analyzing information about the human operator and the overall performance of the human-automation team. *Human State Variables* provide a baseline to establish the current state of the human (e.g., fatigue, workload, attentional tunneling), given the cognitive and physiological metrics available to the system (see [28], for overview of biocybernetic adaptation strategies in a closed-loop system). Both the Human State Variables and overall HAT performance metrics inform the *Latent User Model,* which is formed by the system as a dynamic analog to the Design Model discussed in the previous section. Here, the system constructs a hypothesized User Model in an attempt to anticipate potential trust mis/discalibration between the System Image and the actual User Model. Lattice Theory may offer a method to formalize the Latent User Model. Moray [18, 19] proposed the use of lattice notation as a mathematical modeling technique to represent homomorphic models that share similar qualities to the theoretical descriptions of mental models. Graphically, lattices form interconnected nodes (e.g., knowledge about a system) that are partially ordered sets to show how elements relate to each other [19] (compare to Pathfinder method above). Moreover, adapting causal classifications originally introduced by Aristotle, Moray [19] proposes that the ordering of nodes can be considered as causal links. Those classifications align well with the informational bases of trust outlined in the current work:

- *Efficient Causes* (related to *Performance*) refer to actions that bring about change. For example, clicking on a displayed drone causes the interface to give me additional control options for that drone. Selecting a destination causes that selected drone to go to that location.
- *Material Causes* (related to *Process*) refer to the underlying processes. For example, if fog reduces visibility to less than 1 mile at the peninsula, then that will cause the vertiports (i.e., takeoff and landing areas for the UAM concept) to be out of service in that location.
- *Final Causes* (related to *Purpose*) refer to the end purpose for which the event happens. For example, the package arrived at my doorstep by drone because I wanted it within the hour.

To construct the lattice, however, the system requires a method to sample pertinent information from the user and organize it into a coherent model. The Conant Method of Extended Dependency Analysis may provide a means to construct user mental models of increasingly autonomous systems via operator control strategies (see [19, 29, 30, 31] for descriptions of this method). Beyond interactions and control strategies, eye tracking techniques may offer additional information to create robust intentional strategy models to complement this method.

Once the autonomous system has created the Latent User Model, if the system hypothesizes a misaligned mental model that would lead to inappropriate (mis/discalibrated) trust, then it has two methods to alter the system image. First, *adaptive automation* strategies could be employed to dynamically reconfigure or add/remove informational elements in the displays (see [32, 33, 34] for reviews). Additionally, the system could also attempt to reorient or alert, using various modalities, the user to important environmental or display elements. This information, tailored via communication strategies, enables the user to have the most relevant information possible, thereby increasing the user's understanding of the decisions and actions made by the automation. Second, a *Learning Management System* (LMS; e.g., Blackboard®[1]) could prepare and tailor training material that explicitly attempts to realign the User Model, or Artificial Intelligence scheduling algorithms that choose training courses and even schedule learning events for students, as used in the United States Air Force [35]. Both approaches could be used to update the System Image and support Adaptive Trust Calibration.

V. Practical Applications

The two proposed approaches (i.e., Iterative Design and Adaptive Trust Calibration) for calibrating user trust described in Section IV can be applied broadly within the AAM ecosystem. Although the primary focus of the HAT Foundational Research Activity is RVO (i.e., remote operators), in this section we address the practical applications of this research for potential users within AAM. To understand the specific application of these approaches, we first define the users and their corresponding interactions with AAM operations. Generally, users can be grouped as: onboard pilot, remote operator, passenger (onboard), and customer (remote). An onboard pilot in the context of AAM corresponds to the SVO concept, which implies that the user will primarily interact with simplified flight deck systems onboard the vehicle. A remote operator in the AAM ecosystem corresponds to the RVO concept, which implies that the user will primarily interact with a ground control station (GCS) to control the vehicle remotely. Passengers and customers will interact with various systems throughout the transit experience (e.g., personal travel, package delivery), including smartphone applications and informational displays onboard the vehicle. Additionally, these users will be subject to passive interactions with the AAM ecosystem as members of the general public. To discuss the practical applications associated with these users and interactions, we focus on the following categories of interfaces:

- Flight deck systems for onboard pilots (SVO);
- Ground control station (GCS) for remote operators (RVO);
- Passenger/customer experience (in the context of AAM); and
- Public acceptance (in the context of AAM).

The *Model for Iterative Design* (Figure 1) can be an effective tool for developers and designers to evaluate users' mental models based on the informational bases of human-automation trust. A simplified approach to applying this method during user testing (e.g., A/B testing) is to collect user feedback using a trust questionnaire that measures *Performance*, *Process*, and *Purpose* (see [26, 36] for examples), compare the results across users and designs (e.g., small *n*, quasi-experimental studies), and then use those results to inform modifications to the user interface (UI) or user experience (UX). Although this approach will not produce a definitive trust estimate across all potential users, it gives designers a cost effective method for identifying design issues that could lead to inappropriate trust in systems. Politowicz, Chancey, and Glaab [37] used this method to evaluate the design of a representative commercial-off-the-shelf (COTS) GCS and several increasingly autonomous systems onboard remote sUAS vehicles. Alternatively, this method can be applied using more controlled experiments, providing a means to compare fundamental principles associated with trust in human-automation interaction paradigms (e.g., [26]). Chancey and Politowicz [3] used this method to evaluate public acceptance for UAM operations, showing how this approach can be applied more broadly

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[1] The use of trademarks or names of manufacturers in this report is for accurate reporting and does not constitute an official endorsement, either expressed or implied, of such products or manufacturers by the National Aeronautics and Space Administration.

than to just software systems. The HAT Foundational Research Activity has adopted a research model that intends to conduct studies that are both highly representative of AAM applications (yet experimentally uncontrolled) and studies using tasks that are abstract enough to derive general HAT principles (experimentally controlled, yet less representative of AAM operations; see [38] for description of this approach to human factors research). Because the Iterative Design method is intended for the design phase of development (i.e., prior to verification and validation of systems), it can generally be applied to all four interface categories listed above.

The *Model for Adaptive Trust Calibration* (Figure 3) is intended to be used as a tool for real-time evaluation and calibration of user trust. This implies direct integration with software systems, so the model will require extensive development, testing, and operational validation prior to consideration for safety-critical systems in AAM operations (i.e., flight deck systems for onboard pilots, GCS for remote operators). This model, however, can be applied to passenger/customer interfaces without risk to safety. For example, the model could be deployed as a technology that integrates directly with passenger displays onboard a UAM vehicle (i.e., air-taxi) and evaluates passengers' trust based on real-time eye tracking data. If the model determines that passenger trust is inappropriately calibrated, the system could respond by adjusting the UI and communicate intent, with the goal of increasing their understanding of the vehicle's action. These timely interventions can be highly effective if the adaptive trust calibration technology is developed with empirical data and extensive testing. However, a deficient system could introduce additional problems, as misinterpretation of the user state has the potential to compound trust calibration issues.

VI. Conclusions

In this paper we have outlined an approach to enabling AAM operations through trust in HAT. The main contribution of this approach resides in connecting the construct of trust to mental models. Using the outlined mental model approach, novel HAT strategies such as Adaptive Trust Calibration could be researched for use in increasingly autonomous systems within AAM operations and beyond. Additionally, we have proposed several practical applications that can currently be employed by AAM development communities. This paper, however, represents only an initial proposal for future studies, and research will be required to validate the ideas presented in this paper. The HAT Foundational Research Activity intends to pursue these avenues under the AS Enduring Discipline Area of Research within NASA's T^3/RAM Sub-project.

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