An Approach and Three-Dimension Taxonomy for Adaptive User Interfaces

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ABSTRACT

Adaptive user interfaces change according to the needs of each user and context by conforming their appearance, interactions, and level of automation to the operator's cognitive state. Mental workload has been one of the most popular aspects of cognition to adapt, due to the potential to reduce stress and improve performance. Recent improvements in computing and physiological measurement have expanded possibilities for cognitive state measurement, and now include trust and situational awareness as potential candidates for interface adaptation. However, capturing and adapting three dimensions exponentially increases complexity, and makes it difficult to adapt specific dimensions without disrupting others. As a result most adaptive approaches focus on one primary trigger for adaptation. In contrast, this paper presents an integrated approach for conceptualizing the combined operator cognitive state, a set of priorities for adaptation, and a taxonomy for factors that can be adapted. The operator's cognitive state is uniquely conceptualized as a three-dimensional array —or tensor— with an ideal state of balanced workload, calibrated trust, and high situational awareness. This tensor permits demonstration of operator states that must be adapted first, and how adaptations interact with other states. A taxonomy of candidate adaptation factors is presented within this context, enabling designers to explore and implement this methodology within their own future work.

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INTRODUCTION

The Importance of Adaptive Interfaces

In the 1950s, the US Air Force attempted to create a cockpit that would fit their average pilot and maximize flight performance across aviators. After compiling pilots' dimensions, they discovered that not one of their sampled aviators aligned with the average dimensions (Hough, 2015) and thus universally fitted cockpit seating would hinder performance. In the intervening half-century, many tasks previously performed by these differently shaped pilots have been delegated to automation and swarms of drones. Through a combination of programmed tasking and AI, swarms are capable of performing multiple concurrent tasks such as reconnaissance, tracking, electronic warfare, or even search and destroy. While the swarm's "pilot" is no longer necessarily located in a cockpit or manually flying the drones, a human must monitor swarm tasks and make complex decisions in the service of everything from searching for lost hikers to kinetic strikes. The swarm command and control interface must be capable of controlling 30 or more assets and handling the exponential number of decisions produced by increasingly large swarms. The scale of interaction would quickly overwhelm an operator using an interface designed for the average operator and the average task. Operators may be too busy to perform some tasks at a given time, and some tasks may require their attention while others can be safely delegated to automation. The answer, as the Air Force discovered 70 years ago, is an adjustable platform to enable high levels of human performance.

Command and control interfaces are substantially more complex than manually adjustable cockpit seats. In addition to requiring adjustment along multiple dimensions, such interfaces cannot wait on human intervention, and must dynamically adjust themselves based on an understanding of the operator and the current tasks. Adaptive interfaces were conceptualized in the 1980s (Hancock & Chignell, 1988), and are increasingly crucial when controlling drone swarms. Fortunately, improvements in technology, sensors, and machine learning have made adaptive interfaces more feasible and capable than ever (Scerbo, 2007; Scerbo, 2018: Scerbo et al., 2003; Parasuraman et al., 1992). This paper seeks to outline the challenges faced by adaptive interfaces and present a solution in the form of a concept of operator cognitive states, a set of priorities for adaptation, and a taxonomy of interface behaviors and presentation methods that can be adapted.

Defining Adaptive Interfaces

Adaptive user interfaces change according to the needs of each user and context by conforming their appearance, interactions, and level of automation to the operator's cognitive state (Inagaki, 2003; Kaber et al., 2001). Mental workload has been one of the most popular aspects of cognition to adapt, due to the potential to reduce stress and improve performance (Parasuraman & Hancock, 2008; Prinzel et al., 2003). Recent improvements in computing and physiological measurement have expanded possibilities for cognitive state measurement beyond workload, and now include trust and situational awareness as potential candidates for interface adaptation. Maintaining an appropriate level of operator trust in the automation is essential for said automation to be appropriately and efficiently utilized (Moray, Inagaki, & Itoh, 2008; de Visser & Parasuraman, 2011; Miller, 2005), while situational awareness (SA) affects the operator's ability to correctly perform tasks and prevent errors (Kaber & Endsley, 2004; Kaber et al., 2006; Parasuraman, Cosenzo, & de Visser, 2009). These three constructs are essential for understanding and predicting team performance in complex systems (see Parasuraman, Sheridan, & Wickens, 2008 for a full review). The current manuscript hopes to advance the practice of adaptation based on a holistic approach to operator cognitive state: capturing and adapting all three states in one system. We acknowledge and emphasize that capturing and adapting three cognitive dimensions exponentially increases complexity, due to the dependencies and relationships between these constructs and the adaptations that seek to calibrate them. Any successful attempt to create adaptive interfaces for workload, situational awareness, and trust in automation requires concepts, priorities, and adaptation strategies that are cognizant of their impact along all three dimensions simultaneously. Accordingly, we present our approach in this manuscript.

BACKGROUND

Concept of Operator Cognitive State

The operator's cognitive state is conceptualized as a three-dimensional array, or tensor, with an ideal state of balanced workload, high situational awareness, and calibrated trust, as seen in Figure 1. This tensor permits demonstration of which operator states must be adapted first, and how each adaptation affects other states. A taxonomy of candidate adaptation factors is presented within this context, enabling future designers to explore and implement this methodology within their own future work.

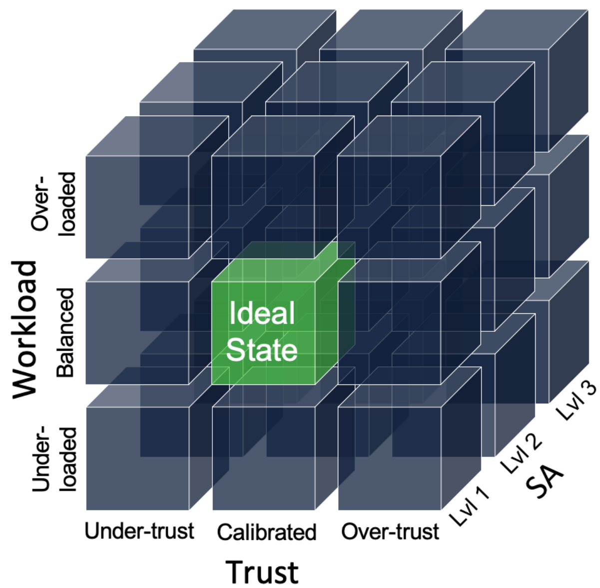

Figure 1. Three-dimensional tensor of operator states

Defining Cognitive States

Workload. The operator's cognitive workload is the level of mental resources required of a person at any time, where said resources are needed to process information, react to their situation, and make decisions (Parasuraman, Sheridan, & Wickens, 2008). Workload is the product of task load from the system as well as any external workload from secondary tasks or distractions. Workload is correlated with task difficulty and the number of concurrent tasks presented. The latter is particularly relevant within a swarm environment where multiple tasks are being performed simultaneously.

Workload has three states: balanced, under-loaded, and over-loaded. The alternative categorizations of boredom, optimal, and distress have been identified in some performance-oriented literature (e.g., Dehais et al., 2020). Workload should ideally exist in a balanced state, where the operator is engaged with the system yet neither overloaded nor stressed by their tasks. Overloaded operators have predictable performance deficits and must either ignore pressing tasks to reduce their workload or see reduced performance in the form of slow response times and incorrect responses (Bowling et al., 2015). Underloaded operators have limited engagement with the system and are therefore likely to experience mis-calibrated trust or decreased situational awareness over time.

Situational Awareness. Situational awareness (SA) is the perception of environmental information and events in time and space, the comprehension of their meaning, and the projection of their future status (Endsley, 1995). Situational awareness is crucial for effective decision-making, and insufficient SA is often implicated as the cause of accidents in aviation, air traffic control, and military command and control. The construct is often divided into three levels: Level 1 is simple perception of information; Level 2 is comprehension of the perceived information's meaning; and Level 3 is projection of the future states of comprehended information.

SA is a cumulative process where the operator builds awareness of the situation (Endsley, 1995) and the automation's role (Chen et al., 2018) by intaking information and synthesizing it, starting with no awareness —which we are labeling "Level 0" and culminating with projection of future states at Level 3. Level 3 is the desired level, as it helps to optimize decision-making. Operators must actively work to maintain their awareness. The situation evolves over time, and the ability to project future states decays as the projected future becomes the present and new information appears. These conditions mandate that the operator continually update their situational awareness to maintain the desired high level.

Trust. Trust in Automation (TiA) is the attitude that the automation will help achieve the operator's goals in an uncertain and risky situation (Lee & See, 2004). Trust has three states: calibrated and mis-calibrated by way of under-trust or over-trust. The ideal state is calibrated trust, when the operator trusts the automation in the situations and to the degree that it is reliable, only using it when it is correct. However, trust is often mis-calibrated due to low workload and infrequent use of the automation, or lack of SA leading to ignorance of the automation's role. As a result, the operator has an inappropriate concept of the automation's reliability on different tasks and in different contexts (Dzindolet et al., 1999). The use of automation to offload operator tasks often further contributes to decreased engagement, reduced SA, and thus mis-calibrated trust. Over-trusting the automation compared to its actual reliability results in misuse and causes errors, while under-trust results in disuse and increases the operator's workload as they reject reliable automation in favor of manual effort (Parasuraman & Riley, 1997; Freedy et al., 2007). Either scenario is unfavorable compared to the efficiency of calibrated trust and intervening only when the automation is unreliable.

Relationships Between Dimensions

Workload, SA, and trust are distinct constructs (Parasuraman et al, 2008) but they are related. As a result, changes to one state will invariably affect the others. This relationship is built into our conceptualization of operator state and must be considered when implementing adaptations.

Workload and SA. The relationship between SA and workload is complex due to the multi-faceted nature of Workload. We must consider task load and overall cognitive workload separately, where the latter is a combination of both task load from the swarm system and external workload from any secondary tasks or distractions. Task load as defined in this project is engagement with the system, including alerts, tasks, and interactions. Generally speaking, engagement requires building a cognitive model of the system— what the automation is doing and what is happening in the larger environment. Therefore, task load has a moderate positive correlation with higher levels of SA. Conversely, overall workload is defined in this project as workload from all sources, including task load from the system. However, this view is not strictly useful for estimating probabilities of SA, as it is unclear whether workload is due to engagement with the system (which would build SA) or due to external factors. Therefore, for our current purposes we must separately calculate workload from *outside* of the system: (Overall Workload – System Task Load = External Workload). External workload is often a distracting force on the operator, causing them to disengage with the system, and using cognitive resources that could be used to build or maintain SA. Notably, some information gleaned from outside of the system may be mission-relevant, used to build SA about the context or make better mission decisions.

Workload and Trust. Trust and workload are highly interrelated, as low trust leads the operator to disuse the automation and self-rely (causing more workload), while high trust causes misuse and overreliance on the automation (Parasuraman & Riley, 1997). In addition, operators who are overly burdened may excessively rely on the automation, manifesting behaviors that appear to be over-trust. Perceived risk also moderates the relationship between these two factors, as interactions with higher risk —a higher probability of something going wrong and the consequences being bad— prompt the operator to self-rely and increase their workload rather than trust the automation.

Trust and SA. The relationship between SA and trust is comparatively straight-forward. Calibrated trust is defined in this project as trusting the automation appropriately to its reliability level, when and where it should be trusted. Given that trust is based on a correct understanding of the automation's capabilities, it is correlated with the aspect of SA that is a correct understanding of the automation's actions within the environment (Chen et al., 2018). A greater understanding of the situation causes trust to become more appropriate and calibrated. However, this is not a dictate— trust can be influenced by many external factors and unlikely relationship states may exist.

RESULTS

Adaptation Priorities

Workload, Trust, and Situational Awareness are highly interrelated: no adaptive interface should seek to manipulate one state without acknowledging the role of the others. To give some examples of these intertwined relationships, high workload leads to over-reliance on automation, labeled "misuse" by Parasuraman and Riley (1997), while low workload can lead to disengagement and loss of situational awareness. Excessively low trust can lead the user to increase their workload by not trusting reliable automation, while trust that is too high can lead to inappropriate over-reliance on automation, and the resulting lack of engagement can reduce SA. Low situational awareness influences both workload and trust, by the requiring the operator to engage with the system to review poorly understood info or verify automation actions.

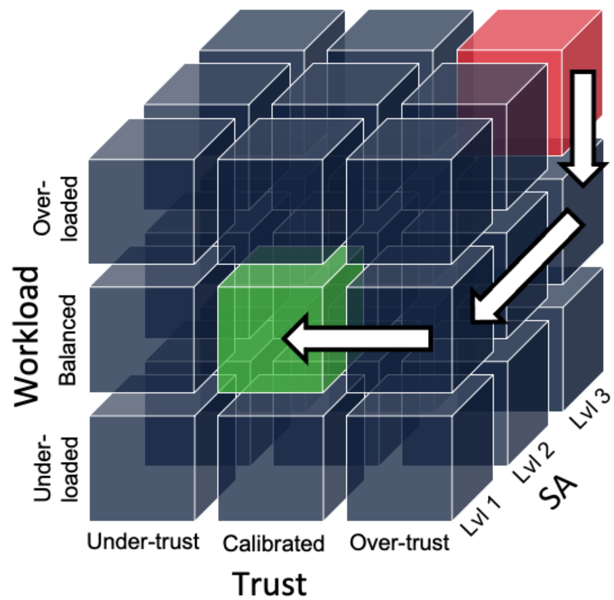

Figure 2. Fixing an incorrect operator state: prioritizing workload adaptations, followed by SA then trust for highest efficiency

Considering these relationships, our system uses the adaptation priority shown in Figure 2. First, the system focuses on moving workload to a balanced and sustainable level. An overworked operator cannot intake any more information to calibrate their trust nor increase their SA. Second, the automation seeks to increase operator SA to the ability to project future system states (level 3). This effort requires some increased workload as more information is pushed to the operator. The SA adaptation also aids trust calibration, as increased SA helps operator understand whether the automation's actions are appropriate in context. Third and finally, the system seeks to calibrate trust. More information is added in the form of transparency about the automation's reliability and decision making. Figure 2 illustrates how the prioritization helps a specific operator move from a state of overload, low SA, and over-trust to the ideal state of balanced workload, calibrated trust, and high SA. This structure makes the adaptation process more efficient and effective. Each adaptation will have varying degrees of effect on their respective states, called the "impulse" of the adaptation. For instance, increasing automation will have a strong negative impulse on workload, while increasing the level of transparency in some interactions will have a weak positive impulse on workload. Each adaptation will also cause varying degrees of disruption to the workflow. The prioritized adaptations should therefore be those that cause the strongest impulse in the desired direction, while causing the least amount of disruption.

Taxonomy of Adaptations

The following section describes the adaptations of workload, trust in automation, and SA that were enacted in our system. Adaptations are shown in Tables 1-3. Each adaptation is listed with the degree of impulse and disruptiveness as instantiated within our specific system. Some adaptations affected the overall workflow and presentation of all tasks and are thus labeled "global." Others affect only behavior and content within specific interactions and are thus "local." Not every adaptation is feasible for every possible interaction, and designers may be constrained by the necessary workflow. The order in which adaptations were enacted is based on the aforementioned priorities. More adaptations and increasingly disruptive adaptations are turned on as the operator stray further from the ideal state.

Workload adaptation. Workload adaptations are triggered by specific workload states, where the states are the algorithmic product of overall workload and system task load. The desired state is balanced workload, a manageable level of cognitive effort that the operator can sustain for a long period of time with acceptable performance. High workload should be reduced to minimize stress and error potential, while low workload may be increased in service of maintaining SA or calibrating trust. Workload adaptation is achieved through two high-level mechanisms: level of automation, and task presentation.

As the operator becomes busier, the level of automation can increase. Sheridan and Verplanck define 10 levels of automation to describe the range of potential automation, progressing from no assistance at Level 1 to completely autonomous at level 10 (Sheridan & Verplanck, 1978). These levels ordinally increase automation, with Level 3 offering a narrow set of recommendations, Level 5 recommending a single choice, and Level 7 executing the selection automatically and informing the operator. Adaptive automation is a well-established solution using these levels to avoiding surpassing the aforementioned “red line” at which human performance necessarily decreases (Grier et al., 2008). The handoff of tasks from the human to the automation has itself been automated, using methods such as neuro-physiological measurement to capture cognitive workload and delegate tasks accordingly (Aricò et al., 2016).

Task presentation may be changed to reduce operator workload. Tasks may be shifted in time, without removing them from manual control. Delaying non-crucial tasks in favor of prioritizing more important interactions allows the operator to focus and reduce distractions. Similar tasks may also be grouped together so that the operator can process similar tasks quickly rather than incurring the cognitive cost inherent in task switching. These two approaches, along with various permutations, may be seen in Table 1. This table displays our high-level approaches to adapting workload, primarily focused on decreasing workload that is too high. Each type of adaptation is customized for different contexts, and increasingly strong and disruptive approaches —such as Delaying Tasks or Level of Automation (Level 5)— are implemented as workload becomes increasingly high. In some rare circumstances, adaptations may attempt to increase workload for the purpose of increasing the operator’s engagement with the system. However, this is only performed in service of improving the operator’s trust and SA state.

Table 1. Workload adaptations

Adaptation Type	Direction of Impulse on Workload	Description	Impulse	Disruptive - ness	Global/ Local
Abstraction	Decreasing	Decrease detail about interactions where applicable and safely possible.	Weak	Med.	Local
Cluster Tasks	Decreasing	Cluster alerts/interactions that are similar in nature, or related to a similar entity. May be combined with Delay Tasks for greater effect.	Moder.	Med.	Global
Delay Tasks	Decreasing	Delay low-priority tasks, and display when the user's workload has dropped to an ideal level. May be combined with Cluster Tasks for greater effect.	Moder.	Med.	Global
Duration of Interactions	Decreasing	Low priority/low risk information feeds are automatically closed and resolved if the operator has reviewed them and has shifted focus to another primary task.	Weak	High	Local
Increase Detail	Increasing	Increase detail about the sensor feeds, providing the highest level granularity and specificity. Used only if engagement is extremely low.	Weak	Med.	Local
Increase Level of Automation (Level 4)	Decreasing	Automation recommendations are automatically prioritized and visually focused, yet not selected by default.	Moder.	Low	Local
Increase Level of Automation (Level 5)	Decreasing	Automation recommendations are auto-filled or selected in the interface. The user may change this selection if desired. Increasingly high priority and high risk interactions are handled by the automation as workload increases.	Strong	Med.	Local
Lower Level of Automation	Increasing	Automation does not make recommendations, and only alert user if the decision they make is different from what the ATR would select. Used only if engagement is too low.	Moder.	Low	Local
Offloading	Decreasing	Automation will automatically determine the level of investigation and sensors needed at each point of the mission. The user may change these decisions.	Strong	Low	Global
Prioritize Tasks	Decreasing	High priority interactions are put in focus, with all other tasks minimized until the most important tasks are completed.	Strong	High	Global
Push/pull	Decreasing	High priority tasks (as determined by automation) are pushed to users, but lower priority tasks must be pulled by the user. Lower priority tasks may be pushed after all other tasks are completed.	Weak	Med.	Global

Situational awareness adaptations. Situational awareness adaptations are triggered when the system estimates that the operator has unacceptably low SA. When the operator is both perceiving and comprehending the situation (Level 2), but is not projecting (Level 3), the system may enact some adaptations to help them better understand the implications of team decisions (e.g., showing the future course of events given the current course of action). However, these adaptations will only occur if the operator has sufficiently low workload. If the operator's workload is very low, and they are not comprehending or perhaps not even perceiving their environment, further adaptations are enacted. These adaptations change the appearance of the interface to direct their attention to mission critical information and provide more details about ongoing actions. Greater levels of automation risk decreasing situational awareness (SA), where SA is the operator's perception and comprehension of their situation, along with their ability to project future events and consequences (Endsley, 1995). As level of automation increases, the operator performs less information collection and decision-making, and their SA decreases as a result (Endsley & Kaber, 1999; Riley, Kaber & Draper, 2004) This often results in decreased performance as the operator is less able to detect and prevent errors produced by imperfect automation. In short, achieving higher levels of automation (Sheridan & Verplank, 1978) risks the operator being out-of-the-loop resulting in poor performance and safety (Kaber & Endsley, 1997; Stanton, Chambers & Piggott, 2001). To achieve the highest possible performance, the operator should maintain high situational awareness so that they can rely on the automation while being able to takeover when required. Our adaptation methods shown in Table 2 help the operator achieve high SA while also maintaining the ability to use automation in the IHMI. These adaptations provide mission-critical information where and when it is needed, and focus the operators attention when they are distracted and SA is unacceptably low. The Alternative and Projection adaptations, in particular, help the operator achieve higher levels of SA through visual aids that help them understand the future consequences of their team's actions.

Table 2. Situational awareness adaptations

Adaptation Name	Description	Impulse	Disruptive-ness	Global/ Local
Alternatives	Visualize alternative choices on screen for comparison and analysis.	Moder.	High	Local
Increase Detail	Increase detail on all tasks, including paths, the map, and information about potential threats.	Moder.	Med.	Global
Highlighting	Higher urgency/risk events and alerts more salient via color, audio, etc.	Weak	Med.	Global
Prioritize	Re-sort information within the task to prioritize high priority/urgency information. All information is still shown.	Moder.	High	Local
Projection	Show future consequences of the current task.	Strong	High	Local

Trust adaptations. Trust adaptations are triggered by trust states that are incongruent with the reliability of the system, resulting in mis-calibrated trust. The solution to mis-calibrated trust is transparency, explicitly informing the user of the capabilities and limitations of the system. While some transparency should always be provided to operators, too much information can increase workload and disrupt workflow without necessarily increasing performance. Thus, adaptations to increase transparency are strategically applied when trust is mis-calibrated and the disruption serves a greater purpose. Our approaches to calibrating trust to the appropriate level are shown in Table 3. Five high-level strategies are shown, each of which seeks to increase or decrease the operator's trust via these transparency strategies. If the operator trusts the automation too much, these adaptations will bring their attention to the automation's limitations and provide estimates of its confidence and reliability, communicating that the system is less capable than the operator believes. If the operator trusts too little, then the adaptation approach will communicate the automation's capabilities and communicate high confidence.

Table 3. Trust adaptations

Adaptation Type	Description	Impulse	Disruptive-ness	Global/ Local
Capabilities/ Limitations	List capabilities/limitations of automation on task.	Moder.	Med.	Local
Confidence	Show confidence of automation in each recommendation.	Strong	Low	Local
Highlighting	Highlight the route/area characteristics that were used to make each automation recommendation.	Moder.	Med.	Local
Level of Automation Transparency	Show and emphasize what tasks the automation currently has taken over, and the level of automation involved on each task.	Moder.	Med.	Global
Reliability	Show and highlight reliability of automation on the current task, with context.	Strong	Low	Local

CONCLUSION

Controlling complex automation such as swarms of drones is an extremely complicated task which strains the capabilities of trained operators. Previous attempts to adapt automation interfaces based on workload to reduce stress and improve performance have been effective, but often fail to consider trust in said automation or situational awareness. The current paper posits that calibrating these three dimensions are essential for improving performance with complex automation, while acknowledging the inherent complexity and interactions. We have proposed a taxonomy of adaptations and a prioritization for their application that resolves a portion of this complexity.

To give an example, consider a swarm identifying a potential enemy threat using Automatic Target Recognition (ATR). The swarm operator is overloaded with too many tasks, under-trusting the automation, and has a level of SA consistent with Level 2, Understanding. This operator is highly stressed by their Taskload, with low performance on any given task. Any additional incoming tasks are unlikely to be processed appropriately. Their inappropriately low trust in the automation contributes to this overload, as they manually perform tasks that the automation could competently complete. Finally, their SA is lower than ideal, as they do not have sufficient time to devote to understanding each task and projecting forward to predict future states and consequences. Our proposed taxonomy would start by adapting workload. First, we would increase the Level of Automation to level 4 or level 5 (Sheridan, 1973), which in this instance would occur by providing the ATR's recommendation of the target type, or selecting the recommendation, respectively. This action gives the operator a short-cut but allows them to alter the decision before completing the task. Second, we would Cluster and Delay Tasks as feasible. The operator may be burdened with system tasks that are not as high priority as identifying threats, such as addressing battery power alerts, or map updates. These alerts may be delayed for short periods of time until the urgent ATR task is complete, then presented in clusters: all battery alerts in sequence, and all map alerts in another sequence. This method avoids the workload increase that comes from task-switching and interruptions (Grier et al. 2008; Squire et al., 2006; Wickens et al., 2013). After enacting adaptations that would decrease workload to appropriate levels, and thus enables operators to improve their SA by properly processing current tasks, our prioritization focuses on SA. First, we would increase the level of detail on the current task, showing more data about the potential threat. Second, we would provide information about alternatives, including support for alternative hypotheses about the threat's identity. Third and finally, interface elements that relate to the current ATR task would be highlighted compared to lower priority tasks. This action may be achieved by making the current task more salient or making other tasks less salient. These three efforts focus the operator's attention on the ATR task and provide as much situational information as can be meaningfully processed. However, each adaptation may increase workload, which further emphasizes the need to address workload before SA. When both have been sufficiently addressed, our prioritization approach recommends addressing the operator's inappropriately low trust. The aforementioned SA adaptation effort gives the operator greater insight into the situation's ground truth, which is enhanced further by transparency. First, the interface displays a confidence value for the ATR's target identification recommendation, as well as data on its reliability for this task. Second, the automation details any special capabilities or limitations that apply to the current task in context, such as a tendency to mis-identify threats during rain. Third and finally, the display highlights the data that the automation used to produce its recommendation, such as a specific frame of a video clip, or the recognition of a specific weapon on the threat. This set of adaptations provide transparency into the automation's methodology and whether its recommendation is trustworthy.

We posit that the proposed adaptation taxonomy and approach maps to the needs of each user and task to a greater degree than most current adaptive interface methodologies. Further validation and verification are needed, yet we believe that the proposed integrated approach will prove both effective and efficient. Designers are encouraged to explore and expand this methodology within their own future work.

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