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Situation Awareness–Based Agent Transparency

by Jessie Y. C. Chen, Katelyn Procci, Michael Boyce, Julia Wright, Andre Garcia, and Michael Barnes

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Situation Awareness–Based Agent Transparency

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14. ABSTRACT

We have provided a model and framework as a foundation for transparent interfaces via our Situation Awareness–based Agent Transparency (SAT) model. In this report we discuss the implications of agent transparency for operator trust and workload; we also review potential user interface designs (information visualization and displaying uncertainty information) to support agent transparency. Finally, we provide examples of transparent interface design efforts currently ongoing at the U.S. Army Research Laboratory's Human Research and Engineering Directorate under the Autonomy Research Pilot Initiative.

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1. Introduction

Autonomous agents have been increasingly used for military operations (e.g., casualty extraction, explosive detection and disposals, reconnaissance and surveillance, supply transportation, building clearing, and firefighting), search and rescue, transportation safety, space exploration, farming, and many other purposes yet to emerge (Barnes and Evans, 2010; Greenemeier, 2010; Jones and Schmidlin, 2011; "Morals and the Machine," 2012; Murphy and Burke, 2010; Osborn, 2011; Purdy, 2008; Singer, 2010). As these agents become more sophisticated and independent, it is critical for their human counterparts to understand their behaviors, the reasoning process behind those behaviors, and the expected outcomes to properly calibrate their trust in the systems and make appropriate decisions (de Visser et al., 2014; Lee and See, 2004). Indeed, past studies have shown that human operators sometimes question the accuracy and effectiveness of agents' actions due to the operators' difficulties understanding the state/status of the agent (Bitan and Meyer, 2007; Seppelt and Lee, 2007; Stanton et al., 2007) and the rationales behind the behaviors (Linegang et al., 2006). These limitations can be substantial impediments to overall system and task performance.

Lee and See (2004) identified three antecedents for trust development in the context of human-agent interaction: purpose, process, and performance. The purpose factor deals with the degree to which the agent-driven automation is being used according to the designer's intent. For example, an operator should understand his/her unmanned vehicle's current purpose, such as threat detection along a route. The process factor deals with the question of whether the algorithm of the automated system is appropriate for a given task. For example, in an unmanned vehicle, the underlying algorithm could be governing whether the system only monitors a given area or actually identifies threats within a certain distance, and the operator should understand the uses and limitations of the agent based on the integrity of its process. The performance factor deals with system reliability, predictability, and capability. For example, the operator should know that the unmanned vehicle tends to be unreliable in a certain terrain environment but can effectively communicate with the command center and accurately mark threats with a laser pointer. Lee (2012) proposed that to increase system transparency to the operator, the system's 3Ps (purpose, process, and performance), as well as the history of the 3Ps, should be visible to the operator. However, the presentation should be in a simplified form (e.g., integrated graphical displays) so the operator is not overwhelmed by the additional information he/she needs to process (Cook and Smallman, 2008; Neyedli et al., 2011; Tufte, 2001).

2. SAT Model

We propose a model of agent transparency to support operator situation awareness (SA) of the mission environment involving the agent, the SA-based Agent Transparency (SAT) (figure 1), based on the theory of SA (Endsley, 1995), the Beliefs, Desires, Intentions (BDI) Agent Framework (Rao and Georgeff, 1995), Lee's 3Ps described previously (Lee, 2012), and other relevant previous work (Chen and Barnes, 2012a, 2012b; Chen and Barnes, 2014; Cring and Lenfestey, 2009; Lyons and Havig, in press). According to Endsley (1995), SA is "a state of knowledge" of "the state of a dynamic environment" (p. 36). It has three levels, to include (1) perception of basic elements, (2) comprehension of those elements' meaning when taken as a whole, and (3) the ability to project the system's status in the near-term based on that comprehension. We have defined agent transparency as the descriptive quality of an interface pertaining to its abilities to afford an operator's comprehension about an intelligent agent's intent, performance, future plans, and reasoning process. From Endsley's model we borrowed the concept of identifying features of the environment necessary for global SA. Endsley's model refers to cognitive requirements for different levels of global SA whereas the SAT model refers to transparency requirements to understand the intelligent agent's task parameters, logic, and predicted outcomes.

- To support operator's **Level 1 SA** *(What's going on and what is the agent trying to achieve?)*
    - *Purpose*
        - *Desire* (Goal selection)
    - *Process*
        - *Intentions* (Planning/Execution)
        - Progress
    - *Performance*

- To support operator's **Level 2 SA** *(Why does the agent do it?)*
    - Reasoning process *(Belief)(Purpose)*
        - Environmental & other constraints *(Belief)*

- To support operator's **Level 3 SA** *(What should the operator expect to happen?)*
    - Projection to Future/End State
    - Potential limitations
        - Likelihood of error
        - History of performance

Figure 1. SA-based Agent Transparency model.

At the first level of the SAT model, the operator is provided with the basic information about the agent's current state and goals, intentions, and proposed actions. At the second level, the operator is provided information about the agent's reasoning process behind those actions and the

constraints/affordances that the agent considers when planning those actions. At the third level, the operator is provided with information regarding the agent's projection of the future state, such as predicted consequences, likelihood of success/failure, and any uncertainty associated with the aforementioned projections.

Incorporating all three levels should allow an operator to gain understanding of an agent's reasoning process behind its actions and help the operator make informed decisions as to whether he or she should intervene. Additionally, the SAT model differs from Endsley's (1995) SA model in that not all three levels may be absolutely necessary to achieving transparency—they are simply different aspects. In Endsley's model, SA is the cumulative result of the levels while transparency may not be. For example, in a time-sensitive situation, the operator may only need to know the agent's proposed actions (level 1) and the projected outcome (level 3) to make a sufficiently informed decision. We will now discuss operator trust and workload in autonomous systems through the lens of the SAT model.

3. Implications for Operator Trust and Workload

Automation reliability strongly influences an operator's attitude toward the automation, which in turn affects their level of trust (Hancock et al., 2011; Lee and See, 2004; Parasuraman and Riley, 1997; Schaefer et al., in press). This then affects whether the operator will decide to use the automation, which is also known as the automation usage decision (AUD) (Beck, et al., 2007). Inappropriate levels of trust relative to the automation's reliability rate result in improper automation use. According to Parasuraman and Riley (1997), overtrusting automation results in automation misuse, in which an operator may become complacent and overrely on the automation. Automation overreliance is damaging to SA and results in accidents as operators may fail to monitor the system properly. This leads both to errors of omission (failing to notice a problem because the automation did not alert the operator) and commission (following the automation when there are indicators that it is incorrect). Lee and See (2004) refer to this as overtrust. Automation disuse stems from a lack of trust in the automation, most likely due to a high false alarm rate (Parasuraman and Riley, 1997). Proper automation use, then, is made possible as a result of awareness and understanding of the automation's reliability and other relevant factors (i.e., transparency) resulting in the development of an appropriate level of trust, which Lee and See (2004) refer to as calibrated trust. Including the appropriate level of information in the interface should increase agent transparency. This promotes the development of proper trust calibration, which results in an appropriate automation usage decision. Ultimately, this improves operator performance. This relationship illustrated in figure 2.
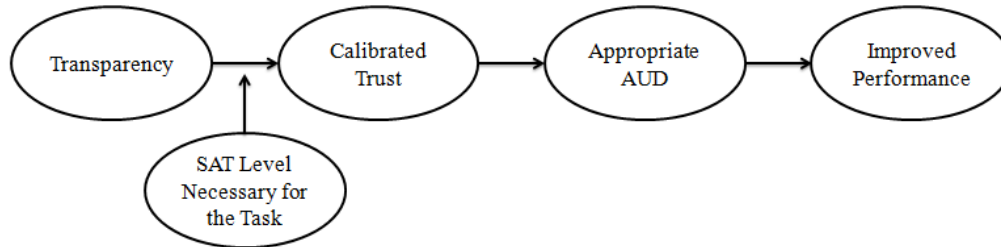
Figure 2. Relationship between transparency and performance.

The relationship between the automation's accuracy and the AUD can be analyzed in terms of Signal Detection Theory (SDT) (Green and Swets, 1966). A signal can be defined as every time the automation makes or executes its own suggestion and is accurate, and the operator either accepts that decision or does not opt to override the automation's execution strategy. When the automation is making a correct suggestion, accepting the automation's suggestion is akin to a hit. When the automation is wrong but the operator accepts the suggestion anyway, it is a false alarm. Failing to use the automation when it is correct would be a miss while not using the automation when it was wrong would be a correct rejection.

Another way to evaluate the AUD is to consider reliance and compliance. Meyer et al. (in press) define reliance and compliance as types of trust in terms of the response to a binary alert. Compliance is "the degree to which the binary cue, when it is present, causes the operator to act in accordance to the cue" (Meyer, et al., p. 1), while reliance is "the degree to which operators dare to avoid taking precautions when the binary indicator does not point to a signal." Essentially, compliance means taking action based on a cue while reliance is not doing anything in the absence of an alert.

In the AUD scenario, reliance occurs when the operator trusts the automation to alert them if there is a problem; otherwise they will not take any independent actions or override the automation's suggestions or actions. Compliance occurs when a decision must be made and the operator chooses to go along with the automation. We would like to think of reliance and compliance in a somewhat novel way, especially since not all instances of whether an operator will rely on an agent will be based on alerts. Reliance can be considered as the number of sources an operator uses to make a decision—to include the agent—while compliance is whether the operator chooses to adhere to the agent's suggestion or proposed plans. For example, if an operator only uses the agent to make decisions, rather than consulting outside sources such as intelligence reports, they have high reliance, but if they do not tend to carry out the agent's suggested course of action, they have low compliance. Conversely, when an operator uses multiple sources to make decisions it is considered low reliance, but if he/she complies with the agent's input without much modification when it is adopted it is considered high compliance. See table 1 for a representation of AUD in terms of usage, trust, SDT, and compliance. Only compliance is described because, in this context, automation usage implies relying on the automation to provide recommendations and then choosing to comply.

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Table 1. Automation usage decision matrix.

State of Automation	Operator AUD	Usage[a]	Trust[b]	SDT[c]	Compliance[d]
Accurate	Accepts	Proper use	Calibrated trust	Hit	Appropriate compliance
Accurate	Overrides, incorrectly adjusts	Disuse	Distrust	Miss	Inappropriate noncompliance
Inaccurate	Overrides, correctly adjusts	Proper disuse	Calibrated trust	Correct rejection	Appropriate noncompliance
Inaccurate	Accepts	Misuse	Overtrust	False alarm	Inappropriate compliance
Inaccurate	Overrides, incorrectly adjusts	Error	Error	Error	Erroneous noncompliance

[a]Parasuraman and Riley, 1997; [b]Lee and See, 2004; [c]Green and Swets, 1966; [d]adapted from Meyer et al., in press.

The goal of using transparent interfaces is to achieve both high rates of proper use when automation is accurate and high rates of proper disuse when it is not. Rates of disuse, misuse, and errors should be much lower if the interface is transparent. Knowledge of the system's unreliability will shape an operators trust in the agent (Lee and See, 2004). Overtrusting a system will increase the likelihood of automation misuse, and undertrusting a system will increase the likelihood of automation disuse (Parasuraman and Riley, 1997; Lee and See, 2004). It is important to be clear: it is not expected that trust will increase with transparency. For example, revealing more information should make a person trust the interface less if the operator understands it to be not reliable. Therefore, it is likely that high levels of agent transparency will result in appropriate trust calibration (e.g., low levels of trust when the automation is unreliable, high levels when it is perfectly reliable, and moderate levels when it is somewhat unreliable), which will then result in appropriate AUDs. We will now address how to support agent transparency through various user interface design.

4. Supporting Transparency Through User Interface Design

Automation transparency has been characterized by observability, directability, adaptability, and broadening (DePass et al., 2011; Scott et al., 2009; Truxler et al., 2012). Observability refers to a shared frame of reference for the automation and operator. Directability refers to allowing the operators to modify assumptions and guide problem solving via multiple mechanisms. Adaptability refers to supporting incremental commitment of resources and reserving degrees of freedom to accommodate changes. Broadening refers to enabling operators to compare multiple solutions in a "what if" mode. These four elements should be included in the user interface to promote transparency. Increasing the level of transparency, however, requires including more

information in an interface. This has implications for operator workload. As the level of information increases, operator workload should also increase as the operator will have to read and process more visual information than if less had been provided. This can be mitigated, in part, by offloading some complex computation by calculating projections of success—a part of level 3 SAT—for the operator. Still, Lee (2012) proposed that integrated displays of transparency information may further reduce workload.

4.1   Information Visualization

Transparency information in the form of both text and images can be integrated into an interface through what is known as information visualization, which has been defined as "the use of computer-supported, interactive, visual representations of abstract data in order to amplify cognition" (Card et al., 1999, p. 7), and its goal is to support user understanding of the presented information (Heer et al., 2010). Visualizations may be interpreted from a top-down perspective, also known as conceptually driven processing. An individual applies their previous knowledge, experiences, and motivations to how they interpret a given information visualization. Previous research in understanding the interpretation of instructions and symbols indicates that individuals who are familiar with the task of interpreting designs perform much more efficiently than those who are unfamiliar with such tasks (Tang et al., 2008). This is also found when examining task performance between novice users and experts (Charness, 1981). Charness noticed that the difference between novice chess players and experts was that experts were able to remember different search strategies and patterns, thereby relying more on predefined schema. A schema is an understanding of the general aspects of a given stimulus or situation (D'Andrade, 1995; Kellogg, 1995). It is through practice and experience that these schemata are developed, which results in the development of a situational mental model. These mental models help us to describe and predict the world around us (Rouse and Morris, 1986). Relying on preexisting schemata helps operators develop the mental model for the new data represented in the information visualization.

The Ecological Interface Design (EID) strategy minimizes workload by relying on top-down processing and existing schemata. EID is used to build interpretation affordances into interfaces, eschewing convention in favor of intuition so that information is quickly understood. It achieves this by using information visualization to "map such abstract properties—and their tightly coupled relationships across system components, processes, and operational goals—to readily perceived visual characteristics of interface display elements (e.g., the thickness, angular orientation, or color of a line; the size or transparency of an icon)" (Kilgore and Voshell, in press, p. 3). The effectiveness of EIDs for human-agent interaction has been investigated in several studies (Cummings and Bruni, 2010; Furukawa et al., 2004; Furukawa and Parasuraman, 2003; Kirlik, 1995; Seppelt and Lee, 2007; Vicente and Rasmussen, 1990; Vicente and Rasmussen, 1992; Vicente, 2002; Woods, 1991). In these studies, EIDs have been used to graphically portray the capabilities and limitations of the agent, intent of the agent, and quality of

plan revisions proposed by the agent. These studies consistently found that EIDs were effective in supporting operators' understanding of agents' behavior as well as predictions of agents' future behaviors and, thereby, promoting proper operator trust calibration.

Kosara et al. (2003) noted that one of the distinguishing points of information visualization is that it can convey the meaning of data without necessarily relying on an existing mental model. At the very fundamental, bottom-up level, Bertin (1983) attempted to create a classification structure for the various symbolic elements that result in responses from the visual system, which he denoted as marks. Healey et al. (1996) described mark combinations as preattentive cues, which are those items that can be cognitively processed prior to attending to a specific stimulus. A cue has characteristics that allow it to stand apart from the area around it (Heer et al., 2010; Treisman, 1985). Examples of preattentive cues that are relevant to this work are: number, length, closure, hue, size, and curvature. Kossyln (1989) developed recommendations for how to turn marks into chart data. Marks need to be individualized, unique, and distinguishable. There also should be a direct mapping between a mark and an interpretation of a piece of data. Even high-density data in combination with simple, clear graphics provide complete and understandable information (Guttormsen, 2012).

Top-down mental models combined with the preattentive cues from bottom-up processing shape how an individual assesses and understands his/her situation. In an automated agent's interface, well-designed information visualizations promote transparency and result in properly calibrated trust. Both top-down and bottom-up processing can help guide designers as to how particular visualizations should be designed, but the SAT model can be used to determine specifically what types of visualizations should be incorporated in an agent's interface to make it more transparent. The SAT model delineates several specific pieces of information that can be visualized to support each level of understanding. In the following, specific types of information that support each level of SAT are listed, and for each type of information, the relevant information visualization literature has been reviewed and examples provided.

4.2   Displaying Uncertainty Information

Prediction is an important criterion for understanding plans developed by intelligent agents. A disconnect between the intent of the operator and the predicted outcome should signal the operator to consider alternate plans. To further complicate matters, in complex environments, outcomes are rarely deterministic, and operators must assess the relative uncertainty of options as well as their expected outcomes. Decisionmaking in uncertainty is difficult, and there is strong evidence that humans use a variety of heuristics and rules of thumb to rapidly assess probabilities in real world situations that may lead to satisfactory solutions or in other cases to erroneous conclusions (Kahneman and Klein, 2009; Wickens and Hollands, 2000). A famous example is the so-called Monty Hall (of "Let's Make a Deal" television show) problem: the contestant picks which of three doors (1/3 probability each) has the prize behind it. When the contestant chooses a door, Monty (not so helpfully) opens one of the remaining two doors that does not have the

prize behind it and gives the contestant a chance to switch. Most often, contestants stay with the original choice assuming that the two remaining unopened doors are equally probable. In fact, contestants are better served by switching doors because the remaining unchosen door actually has a two-thirds probability of success—Monty always opened the non-prize door, thus there is still a two-thirds chance for the remaining unchosen door to have the prize behind it. Johnson-Laird et al. (1999) indicated that the Monty Hall example is not an isolated phenomenon; there are a number of "probability illusions" that deceive even well-educated participants. In general, they conclude that humans use an incorrect mental model of the processes generating the probabilities, tending to give less weight to possible negative outcomes (Johnson-Laird et al., 2004). The illusions are strong, and it is difficult to convince participants that the normative solutions are correct. Probability estimates are also influenced by stereotypes and human biases (Tversky and Kahneman, 1974), inability to enumerate possible outcomes (Rottenstreich and Tverky, 1997), overconfidence (Fischhoff et al., 1997), context of the information (Moldoveanu and Langer, 2002), and emotional responses to possible losses (Barnes et al., 2011).

Kahneman and Tversky's (1979) research on Prospect Theory demonstrated that supplying humans with veridical probabilities does not overcome cognitive biases. Prospect Theory posits two important human errors: (1) extreme probabilities in either direction are misinterpreted (see, also, Gonzalez and Wu, 1999) and (2) humans interpret probabilities in terms of their loss/gain values. The same information expressed in terms of a loss led to different decisions than its complement, probability of success. Decisions framed in terms of loses resulted in risk-seeking behaviors; that is, humans avoid taking a sure loss in the present rather than opting for a possible more severe loss in the future. Given the same decision framed in terms of success, humans are risk-averse and more likely to choose the sure thing rather than a riskier option with a higher payoff in the future. A current example is climate change; even with overwhelming evidence of change, humans are reluctant to make necessary reforms now (sure loss in terms of money) even though the consequences of waiting could be catastrophic (future loss).

Recent research indicates that loss aversion is a more general phenomenon than Prospect Theory because (1) loss aversion affects nonrisky decisions as well as risky ones, (2) neurophysiological recordings of loss information in the amygdala suggest emotional reactions to loss, and (3) there is evidence that processing is less effective for loss information (Barnes et al., 2011; Nygren, 1997; Shafir and Tversky, 1995). The misinterpretation of extreme probabilities is exacerbated by the scales used. For example, an increase of 0.95 to 0.99 appears slight but an increase of 19:1 odds to 99:1 odds indicates a five-fold increase even though they represent the exact same likelihood. There is evidence that presenting information in terms of frequencies instead of numerical probabilities improves Bayesian predictions (Gigerenzer and Hoffrage, 1995); however, other researchers have found that the cognitive illusions previously mentioned are not improved by frequency interpretations of uncertainty (Griffin and Buehler, 1999).

A number of experimenters found evidence that spatial representations and graphic displays of uncertainty improved decision accuracy, but not in all cases, and graphic displays did not ameliorate loss aversion affects (Barnes et al., 2011; Kirschenbaum and Arruda, 1994).

Interestingly, Israeli and American researchers found instances when probability assessment degraded performance compared with verbal cues for making normative choices related to bets about the outcome of basketball games (Erev et al., 1993). However, in a different context, Bass et al. (2013) found that graphical uncertainty information was an effective addition to aircraft status and predictive information for automated air traffic control. The additional information was presented in terms of noise information (mean and standard deviation as represented by color-coding and symbology) around key automation strategies (speed and heading as represented by projected path overlays) indicating the inherent uncertainty involved as limits. This was more effective than just presenting the automated system's scalar probability estimate or presenting the estimate and the logic underlying the estimate. However, Bass et al. (2013) also found that while providing information about environmental uncertainty through the use of colors and symbology is beneficial, adding projected path information to the display does not significantly increase accuracy. In this case, more information was not necessarily better. Although the literature is anything but clear as to the best way to represents uncertainty, a number of general principles were suggested:

- Numerical probabilities are confusing and alternative representations of uncertainty such as confidence limits or ranges should be considered (Bass et al., 2013; Erev et al., 1993; Gigerenzer and Hoffrage, 1995).

- Graphical representations are easier for humans to process than numerical representations in order to gauge relative uncertainty values (Kirschenbaum and Arruda, 1994; Wickens and Hollands, 2000).

- In military situations, outcomes should be presented in terms of mission success instead of possibility of mission failure (Barnes et al., 2011; Nygren, 1997; Shafir and Tversky, 1995).

- Especially for extreme values and to counteract cognitive biases and illusions, users need specialized training to better understand the import of predictions and their uncertainty representations (Johnson-Laird et al., 1999; Wickens and Hollands, 2000)

4.3   User Interface Designs for Agent Transparency

4.3.1 Level 1 – Basic Information

The visualization of level 1 information includes the agent's purpose (the current goal), process (the agent's intent, planning process, and the agent's current progress), current performance, and status. This may include rudimentary details about the agent's planning process such as what routes it may wish to take. A common method of conveying basic planning information involves

a top-down view of a map with a route overlay. For example, in FLEX-IT, which is a prototype unmanned vehicle control interface, potential paths are displayed using a dashed line on top of a map of the operating environment (Calhoun et al., 2012). These dashed lines become solid once the plan has been confirmed by the operator.

4.3.2 Level 2 – Rationale

While level 1information describes the what, level 2 information conveys the why. The visualization of level 2 information is based on a constraint-driven reasoning process. This can be conveyed through a representation of resource limitations, constraints/affordances (environmental, situational, vehicular, etc.), feasibility, risk, trade-offs between alternatives, and history of past performance.

The use of lines overlaid on a map is often beneficial when considering spatial relationships and restrictions, such as no-fly zones and impassable terrain features, but is less useful for abstract constraint information related to the planning process (Kilgore and Voshell, in press). For example, for an interface supporting supervisory control of multiple unmanned vehicles, Kilgore and Voshell suggested representing time-to-target information across several different vehicles through icon size, where the vehicles that will arrive the fastest to the target location are the largest relative to the other icons in the set. Kilgore and Voshell also gave the example of where mission fit for the task can be represented by opacity (see figure 3). These interface elements allow the operator to select the appropriate assets and deploy them in a more timely fashion because the user can quickly identify which unmanned vehicles are appropriately equipped and can be most quickly be summoned without having to gather the various types of information from multiple sources and locations. An operator may understand at a glance why the agent suggested sending one vehicle over another that was closer to the target. Without the added information represented through icon opacity, the operator would not have understood that the obvious choice—the closest vehicle—did not have the capabilities needed for the task.
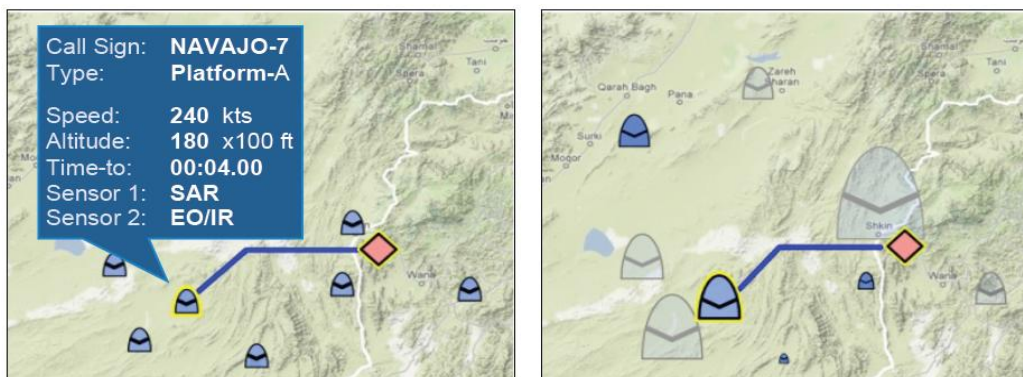

Figure 3. Time to target and capabilities can be represented through icon size and opacity.
(Reprinted with permission from Kilgore and Voshell [in press]).

Resource limitations affecting the agent's decisionmaking process can be visualized through an icon array. This will help an operator understand why certain assets were chosen by the agent. For fuel management, Kilgore and Voshell (in press) suggested using an icon array that represents the total fuel capabilities with different blocks and color-shading cues representing how different aspects of the plan impact fuel levels. In their example, the sum of all of the squares in the array represents the total amount of fuel capacity while different color sets of blocks represent the amount of fuel required for different plans in chronological order. Fuel reserves are represented by gray blocks and a bright red line dictates the directive-driven refuel line. When new plans are being considered, the fuel required may be represented within the array as a new set of highlighted blocks. If the fuel consumed by the new plan forces resource usage below the refuel line, this will be conveyed to the operator by turning the projected fuel blocks below that bright red line. This would allow operators to assess the impact of the agent's suggested plan in terms of resource usage.

4.3.3 Level 3 – Outcomes

The visualization of level 3 information focuses on the projection to future states (e.g., expected outcomes, probabilities of success with a confidence interval) as well as limitations (e.g., reliability, likelihood of error, history of past performance). Level 3 information is essential for improving human-agent teaming outcomes. In domains like autonomous-system management, the environmental context strongly affects the automation's accuracy. For example, Neyedli et al. (2009) found that a transparent interface that revealed automation reliability resulted in more appropriate reliance. Therefore, when appropriate, information about dynamic system confidence and the contextual nature of automation reliability should be conveyed to the operator (Atoyan et al., 2006; Dong and Hayes, 2012; McGuirl and Sarter, 2006; Seong and Bisantz, 2008). Cummings and Bruni (2010) suggested caution when using visualization tools for mixed-initiative multivariate planning tasks, especially when cost functions vary greatly in their sensitivity to changes in the variables of the plan. Operators' decisionmaking may be prone to errors when dealing with more-sensitive functions due to their difficulty in determining the true costs of different plan options. Proper uses of information visualization techniques can help operators make sense of information and thereby enhance their SA of their mission/tasking environments (Robertson et al., 2009).

Brust-Renck et al. (2013) described multiple different ways risk can be represented depending on the context. Similar to EID, their method of visualization was based on fuzzy-trace theory, in which communicating the gist of the message rather than the exact numbers is beneficial for communicating risks to patients in the medical domain. For example, shaded maps can be used to represent level of risk across a geospatial area; pairs of bar graphs can represent the relative differences between two magnitudes and show incremental benefit (Brust-Renck et al., 2013).

Rather than traditional, number-based representations of automation reliability, Rovira et al. (in press) explored the utility of graphical representations. The contextual information of interest included "asset travel time, asset exposure to threats and weather, and target coverage" (Rovira et al., p. 3). Reliability for each contextual factor was influenced by aspects such as sensory quality as affected by environmental conditions and age of information (e.g., older information degrades reliability). Rather than providing a numerical value for each regarding reliability of that contextual information, colors were used where green indicated a fully reliable source, yellow indicated a semi-reliable source, and red indicated deteriorated reliability. Rovira et al.'s study required that participants rely on both the contextual information and information provided by a scheduler display. They found that, in high task demand conditions, those using the contextual automated decision aid had less of a performance decrement than those who used the automated decision aid without it. They believed that these results suggested that, in the cases in which perfect automation reliability is unachievable, providing contextual information regarding the automation algorithm's reliability improved decisionmaking.

A unique approach to displaying multiple types of risk information in one unique icon is a Dynamic ICON (DICON) (deVisser et al., 2014). De Visser et al. created a decision support system that uses multiple panels, colors, positions, and the various combinations of these variables in their DICON design. These panels represent various stages of perceived trustworthiness and actual trustworthiness to inform the user of actual calibrated trust. The DICON packed five levels of trust evidence into one design to provide one simple "at a glance" representation of uncertainty and trust. These five levels include the current support and known risk, current best assumption and net risk, disagreement about risk, incompleteness of information about risk, and quality of evidence. Colors were used to represent various levels of trust from green (trust), black (miscalibration), and red (resolution). This approach has two potential drawbacks. First, there are too many potential combinations of variables to remember and retrieve quickly from memory, thus requiring a steep learning curve. Second, two or more configurations may be nearly identical except for one small change in one of the variables, lending itself to confusion or an incorrect assessment of the DICON.

This section focused on how transparency can be incorporated into interfaces by considering the different levels of the SAT Model. The following sections present applied examples of transparency display design in human-robot interaction contexts. The studies are part of projects under the Department of Defense Autonomy Research Pilot Initiative.

5.   Example: Autonomous Squad Member

As technology continues to develop in support of military operations, there is a research push toward investigation of unmanned systems and the relationship of human-agent teams (Barnes and Evans, 2010). There are several efforts throughout the armed forces, such as the U.S. Army's Robotics Collaborative Technology Alliance (U.S. Army Research Laboratory, 2011) and the U.S. Office of Naval Research's Maneuver Thrust Program (2013), that are aimed at human-agent collaboration. The Autonomous Squad Member (ASM) project aims to increase agent participation in dismounted soldier reconnaissance efforts by placing emphasis on a complex scenario where an agent suddenly has to assess the situation (i.e., a firefight has broken out), reason, and act accordingly. The concept of supporting complex dynamic missions is consistent with the Unmanned Ground Systems Roadmap, which highlighted the need for autonomous systems in combat logistic patrols, support for dismounts, and reconnaissance (Robotic Systems Joint Program Office, 2012).

The research approach of the ASM project begins with semantic understanding, which takes the perceptual data in the environment and develops it into an organized format that the agent can use to comprehend and anticipate the world around it. Following this, the agent needs to weigh the environmental and vehicular constraints and convey that to the operator. These constraints are generated from a goal reasoning framework called Goal Driven Autonomy (GDA), which takes the actions of an agent needed to navigate and generates a series of states (where it is currently and where it wants to go), actions (the various activities that can be used to progress toward the goal state), and events that occur in the environment and the system needs to adjust to (Aha et al., 2011). The events generated by GDA are then passed to the transparency module, where the ASM project implements the tenants of the SAT. By examining each level individually, informational content can be created to support the right amount of information at the appropriate time.

5.1   SAT Level 1

In level 1, the ASM is trying to convey what is going on currently and what it is trying to achieve by accomplishing its goals (i.e., task decomposition). In this state, the ASM is receiving information from the operator, interpreting its meaning, and developing a series of actions to reach the end goal state, as well as accomplishing any goals that occur while reaching the end goal. The information requirements of task decomposition also coincide with Endsley's (1995) model for stage 1 SA, as it is the need to understand a list of proposed actions that the user intends to accomplish. Task decomposition content also matches with Lee's (2012) 3Ps: (1) for purpose, it identifies the goals and objectives that need to be accomplished, (2) for process, the

ASM demonstrates planning by laying out the desired objectives and execution by confirming that these plans are feasible given its technical capabilities, and (3) the ASM will be assessing its performance in understanding the operator's instructions.

Another example where SAT level 1 is used is during Task Sequence Identification (TSI), in which the ASM provides the Soldier with a current status of task completion in terms of mission goals. This can occur concurrently with other activities of the squad, such as moving to the next reconnaissance point. During the TSI, the operator assesses whether the ASM is acting in accordance to intent for the ASM. If this is true, the function of the operator is purely monitoring. However, if there are discrepancies, they can be identified quickly and efficiently. It will also serve as a benchmark for the route selection/mission plan that the ASM developed.

5.2 SAT Level 2

Using SAT level 2, the user interface needs to show the reasoning process of the ASM as well as explain the constraints that exist for the environment. In essence, the ASM needs to reason about its process of reasoning. This is also known as the ASM's metacognition, the concept of which represents a person's understanding of what thought processes are going on within oneself (Flavell, 1976). In this context, metacognition refers to where the ASM provides input as to what types of information it is missing in order for the ASM to perform at its optimal level in a given state. For example, if the ASM wanted to traverse an area, it would need to first determine where the potential areas are to protect it from enemy fire. If, due to the nature of the terrain or the stream of information received, it did not have that information, it would need to notify the operator.

One way to notify is to incorporate simple graphical designs called pictograms, simple drawings used to convey a specific action or activity that an end user must take. Dowse et al. (2010) found that visuals that were simple, had a clear focus, and reflected familiar life experiences were successful at conveying information. The authors argued that pictograms should be used only to clarify a process or convey a complete message. Therefore, the development of graphical elements to support is being explored from both a separate representations for variables as well as integrated visualizations.

In the current research, the ASM user interface expresses environmental and vehicular information through one of three types of information: needs, hazards, and affordances. Each one of these types of information has a different icon style that is overlaid onto a Google Earth view of potential navigation routes. For example, a blue icon with a cell tower signifies that the ASM is in need of more information about signal strength. It may be the case that the ASM needs continued connectivity to continue functioning and wants confirmation from the operator that the signal will be present.

The hazard icon warns the operator that if the ASM travels to a particular area, there is a possible stressor on the ASM state. The ASM may get overheated if it travels across an area due to rough terrain. An affordance is the opposite of a hazard, so that it helps improve the performance of the

ASM. A green eye icon indicates that there are no restrictions to the line of sight for the ASM. This is important since one of the primary methods of information gathering for the ASM is visual stimuli.

5.3   SAT Level 3

SAT level 3 is leveraged when the ASM begins to help the operator to understand what might happen given potential limitations. The ASM assists the operator by providing a visual display demonstrating the existing data trends so far, an analysis of resource expenditure rates, and an understanding based on what is known about the remainder of the mission. The ASM must analyze all the data it has collected up to this point and use that data to make predictions. It can also use previous scenario outcomes to increase its understanding if that knowledge is available. By consistently increasing the size of its reference model (i.e., learning from behavior) it can produce more informed results.

Lomas and Chevalier (2012) developed a projection system where a robotic entity was able to respond to questions asked to it in terms of understandable reasoning/projections of future state. Even though the projections were rooted in mathematical models, it was important to provide users with focused answers to facilitate better communication as to not just what the information was but why the entity believed it to be so. It is not sufficient to provide only information to the user; why this information is valuable and how this will change the final outcome is also of important. It is this that helps raise the SAT model beyond traditional user-centered design (a tool for someone to use) versus an intelligent agent to collaborate with.

In the development of level 3, there is a focus on two primary aspects: projection and uncertainty. For the projection image design, the work of Smallman and Cook (2013) served as the foundation. This work incorporates the idea of a trendicon, which is an integrated variable that represents more than one quantity using basic perceptual principles; for example, using triangles to show increasing and decreasing quantities and color to code overall system state/health. With regard to uncertainty visualization, several principles are developed from the work of MacEachren et al. (2012). These include more opacity to represent uncertainty, increased distance from center to represent uncertainty, smaller size to represent uncertainty, and icon disorganization to represent uncertainty. Through the combination of these two factors, the goal is to help the operator understand how confident the agent is related to information about its future state.

6. Example: Intelligent Multi-UxV Planner With Adaptive Collaborative /Control Technologies

Future capabilities of unmanned systems include reducing the ratio of operators to vehicles. Rather than manually controlling unmanned vehicles, this will require a single operator to assume a supervisory role over multiple heterogeneous unmanned vehicles (UxVs). Successful implementation of such a strategy involves increased agility, workload management, and optimized human-automation teaming. This may be achieved through advanced automation capabilities involving cooperative control planning algorithms (CCAs), machine learning (ML), and advanced intelligent agents (IAs). The goal of the Intelligent Multi-UxV Planner with Adaptive Collaborative/Control Technologies (IMPACT) project is to develop a prototype interface for supervisory control of UxVs that incorporates these systems.

Given increasing amounts of supervisory control supported by IMPACT, workload is inherently inflated. To address this, an effective adaptable interface through which operator-automation teams interact should use the human delegation approach (Calhoun et al., 2012). The human delegation approach incorporates natural language instructions (e.g., simple, spoken commands) provided by the supervisor to subordinates based on shared mental models (Calhoun et al., 2012). The human delegation approach minimizes workload as it is an easy to use, quick, and natural mode of interaction for the operator. IMPACT facilitates the human delegation approach in human-autonomy interaction by incorporating a Playbook system (Calhoun et al., 2012).

Playbook was developed by Miller et al. (2005) and encompasses a set of templates for common, preplanned yet easily modifiable maneuvers, known as plays, from a shared database that can be quickly activated ("called") using short commands that are often verbal (Miller et al., 2005; Calhoun et al., 2012). In IMPACT, the system may suggest a play or the operator may call one. Once a play has been called, the CCA, ML, and IA work together to develop a plan. When making decisions about whether to use the plan generated by the autonomy, the operator needs to understand the decisionmaking process executed by these advanced, interconnected systems (Rovira et al., in press). Increased transparency will help operators better understand the capabilities of the system, thus contributing to more-informed, better decisionmaking, which then results in higher rates of proper automation use based on properly calibrated trust, culminating in overall improved performance (Parasuraman and Riley, 1997; Lee and See, 2004; Beck et al., 2007; Rovira et al., in press). The SAT model can be used to provide guidance as to what sort of information should be visualized in the IMPACT interface to support the operator's understanding of how the different autonomous systems generated a given plan.

6.1 SAT Level 1

Recall that level 1 information pertains to basic details about the plan, such as goals, intent, and planning. For IMPACT, pertinent level 1 information includes the current system status, the assets' health, the current goal of the play, the assets' role in the current plan, and basic route planning information. For example, system status information may include the relevant maps for the operational area, sensor feed information, weather reports, alerts, and threat conditions (Kilgore and Voshell, in press). When an automated system is making decisions and is transparent, accurate system status information must be present so that operators can check the factors related to the plan development to the known system state to confirm whether the automation is accurate (Rovira et al., in press). For example, to visualize threat condition, a shaded map, as suggested by Brust-Renck et al. (2013), can be used as an overlay on top of the overhead map or in a separate window solely for conveying threat information when pertinent.

As another example, vehicle health information should include information pertaining to available fuel, current speed, altitude, and current time on station (Kilgore and Voshell, in press). One strategy for conveying this information to the operator is representational analysis, where different variables and representations are identified, based on the task hierarchy, and placed into context, i.e., displayed relative to data limits or ranges (Zhang and Norman, 1994). Examples include using a tachometer with a red area for maximum revolutions per minute for speed or remaining fuel out of total fuel capacity (Kilgore and Voshell, in press).

6.2 SAT Level 2

Level 2 information represents the rationale behind the currently selected plan. In IMPACT, this takes the form of delivering information about constraints/affordances within the context of the plan, specifically regarding asset capabilities, available resources, and environmental constraints/affordances.

Regarding asset capabilities, information should be present about the vehicle's speed, agility, rate of fuel consumption, range based on fuel, sensor capabilities, autonomous behavior capabilities, communications latencies, and expected communications drop-out incidence (Kilgore and Voshell, in press). Rather than solely using a drill-down menu to display specific values, which increase operator workload as they need to be held in memory as the menu will disappear once the operator moves off of it, capabilities in reference to the plan can be visually displayed in terms of suitability through relative icon size where the larger asset icons indicate better fit for achieving the current plan based on asset-specific capabilities (Kilgore and Voshell, in press).

In the event of dropped communications between the operator and the asset, the system must visualize where the communications were lost (a large red X on the vehicle route, perhaps with a small label that states "comms lost" and lists the time), where the asset was going (a dashed line with a similar red X on the destination), where it was programmed to go when communications

were lost (a new dashed line with an arrow to indicate that this is the new route), and where it will reroute to once communications are restored (a solid circle to represent the new destination connected to the new dashed line) (Kilgore and Voshell, in press).

Available resources, such as fuel, should be visualized within the context of the plan. This will help an operator understand why certain assets were chosen by the automated systems. For fuel management, Kilgore and Voshell (in press) suggested using an icon array that represents the total fuel capabilities, with different blocks and color-shading cues to represent how different aspects of the plan impact fuel levels.

6.3 SAT Level 3

Level 3 information provides the operator an understanding of the expected outcomes. In IMPACT, this includes time to complete objectives, limitations, and probability of success for achieving the play's goals.

A timeline view with each asset on its own line with a sized-based representation of the time required for completing given plans and subtasks within plans could be used to represent the amount of time to complete objectives. Such a display would also allow for a visual confirmation of asset availability in the context of all plans and allow an operator to determine whether the chosen plan fits the needs of mission parameters.

The limitations and reliability of the automated system must be made apparent to the operator so that he/she can make an informed judgment as whether to accept the automation's suggestion (e.g., if the last weather report is very old, it may no longer be accurate and render some plan options outdated). As Rovira et al. (in press) suggested, this can be achieved by a color-coded list of reliability for the different factors' the system uses to generate its plans (i.e., the factors constraining the automation's decision discussed in level 2). If given a variety of plan options, understanding the reliability of the factors influencing the automation's decision helps the operator project the likelihood of mission success. Confidence data can also be tied to the icons on the map, such as where wide margins around projected paths indicate execution uncertainty (de Visser et al., 2014).

7. Summary

In this report, we have provided a model and framework as a foundation for transparent interfaces via our SAT model. We have also provided examples of transparent interfaces that are consistent with SAT model principles as well as applied examples. It is suggested that the research community focus future efforts on empirical comparisons of effective transparent interface designs to compile guidelines for designers of future autonomous systems. The effects

of display transparency should also be investigated in multiple domains to assess whether results are context-specific. The additional information provided by transparent displays may also introduce additional workload to the user, so investigations as to the effects of transparent displays on workload should also be performed.

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