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Visualization Techniques for Transparent Human–Agent Interface Designs

by Jackie Cha, Michael Barnes, and Jessie YC Chen

NOTICES

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14. ABSTRACT

The report outlines various visualization techniques as the basis for enabling intelligent agent (software) transparency. We discuss visualizations as vehicles to capture the dynamics of the system being portrayed to give a human operator insight into the agent's plans, logic, and expected outcomes (including uncertainties). Various techniques such as ecological interface designs, sensemaking, and storytelling are discussed with exemplars to indicate possible usages. General design principles are then explicated including principles for displaying uncertainty and are tied to a Situation-Awareness-based Agent Transparency (SAT) model. Techniques and their experimental results related to SAT projects are discussed to indicate the variety of SAT visualization solutions for diverse Department of Defense research programs.

15. SUBJECT TERMS

visualization, intelligent agents, Situation-Awareness-based Agent Transparency model, SAT model, human factors, displays

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1. Introduction

As autonomy and artificial intelligence (AI) are becoming an increasingly important part of future military systems, it is essential to stress the role of the human in these systems. AI and the use of intelligent software agent (IA) technology (software that performs specific tasks autonomously; Russell and Norvig [2009]) are only useful if they are understood in terms of their effect on the larger military picture. It is military doctrine that these systems must be supervised by human operators who are responsible for their results, in the sense that the risks and limitations involved are understood (Department of Defense [DOD] Directive 3000.09 [2012b]). For example, planning systems with IA components must be transparent to the human supervisor who is responsible for its consequences (Draper et al. 2018). US Army Research Laboratory (ARL)* scientists are investigating IA transparency concepts in various military paradigms (Chen and Barnes 2014; Mercado et al. 2016; Chen et al. 2018) that improve human–agent trust calibration by minimizing misuse (over-relying on agents) and disuse (under-relying on agents) (Parasuraman and Riley 1997; Lee and See 2004). The result of this experimentation was a generalized model, *Situation-Awareness (SA)-based Agent Transparency (SAT)*, which has aided in the development of transparency displays for various uses of IA in military systems (Chen et al. 2018; Pynadath et al. 2018).

However, enabling the software to display specific types of information is only part of effective interface design. Equally important is the use of visualization techniques to enhance an operator's ability to extract SAT information that is both intuitive and rapidly processed for complex military environments (Chen and Barnes 2014; Selkowitz et al. 2016; Stowers et al. 2016). Specific visualization requirements will depend on the depth of information and time constraints necessary to respond to mission parameters (Lee 2012). The following report evaluates visualization techniques and principles as building blocks to construct transparency interfaces that maximize the amount of critical information with the minimal processing overhead to map SAT information to complex military situations involving autonomous and human-controlled assets.

Visualization has two related meanings: to form a mental image or to create a representation of a complex process (Merriam Webster 2018). The former is an

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internal process whereas the latter is an external representation. The Department of the Army (1997) has defined visualization as the following:

> The process whereby the commander develops a clear understanding of his current state with relation to the enemy and environment, envisions a desired end state which represents mission accomplishments, and then subsequently visualizes the sequence of events that will move his forces from the current state to the end state.

During the battle of Vicksburg, General Grant, using only maps of the local terrain, was able to mentally examine the possible outcomes of various course of actions (COAs; Barnes [2003]). Also, scientist use visualization as a tool to image abstract processes in terms of concrete examples. Einstein used the example of a man walking on a moving train to explicate the concept of relative motion (Fowler 2007). It is this second meaning of visualization that is the focus of this report (Tsai et al. 2001). However, effective computer visualizations not only capture the dynamics of a process but also enable humans to create a mental model of the process.

The initial sections of the report review visualization paradigms developed by display designers to create intuitive portrayals of complex processes. Next, we discuss good-practice display design principles that are the result of research findings from a variety of human factors scientists. Finally, we review the findings of the two projects that were funded under the recently completed DOD Autonomy Research Pilot Initiative (ARPI) that investigated the effects of visualizations and transparency for autonomous systems. The purpose of the report is to create a menu of visualization concepts and lessons learned to form the basis of the design of a transparency interface for systems such as the Next Generation Combat Vehicle .

2. High-Level Visualization Techniques

Several visualization techniques have been established for interface design. These approaches propose guidelines and identify aspects of design that will be useful for operators in environments in a specific problem space (e.g., aircraft cockpit, nuclear control room). Rogers (2004) reviewed several theoretical approaches applied in human–computer interface (HCI): ecological approach, activity theory, external cognition, distributed cognition, and situated action. The author explains the development and application of these theories to HCI as well as alludes to hybrid and overarching approaches. This section reviews the principles commonly used in interface design and ecological interface design (EID), and elaborates on two hybrid approaches: sensemaking and narrative/storytelling.

2.1 Ecological Interface Design

EID is a design framework developed by Rasmussen and Vicente for complex human–system interfaces (Rasmussen and Vicente 1989; Vicente and Rasmussen 1992; Liu and Stasko 2010). It utilizes cognitive engineering principles to identify interface information content and structure to improve problem solving and decision making (Vicente 1996). Designs following EID principles should accommodate the limitations of human perception–action skills and should not add to the difficulty of tasks.

EID has been used in various disciplines to improve operator control such as aviation, military command and control (C2), and process control. Several studies have compared existing interfaces to redesigns using EID and found operator benefits such as increases in performance score and time (Lee et al. 2006; Jamieson 2007). Figure 1 shows a work-domain-based ecological interface for the petro-chemical industry that was developed by Jamieson (2007). Information was grouped into physical, functional, and task content. Increased operator performance scores and fault diagnosis were observed from those using the EID interface compared to those using the current process display. Bennett et al. (2008) developed Representation Aiding Portrayal of Tactical Operations Resources (RAPTOR), a military C2 interface for Army tactical operation (Fig. 2). Unit characteristics and vehicle properties (e.g., ammunition, types of weapons, speed of vehicles, and so on) are embedded on the interface to aid in quick decision making. Bennett (2017) further describes RAPTOR components.

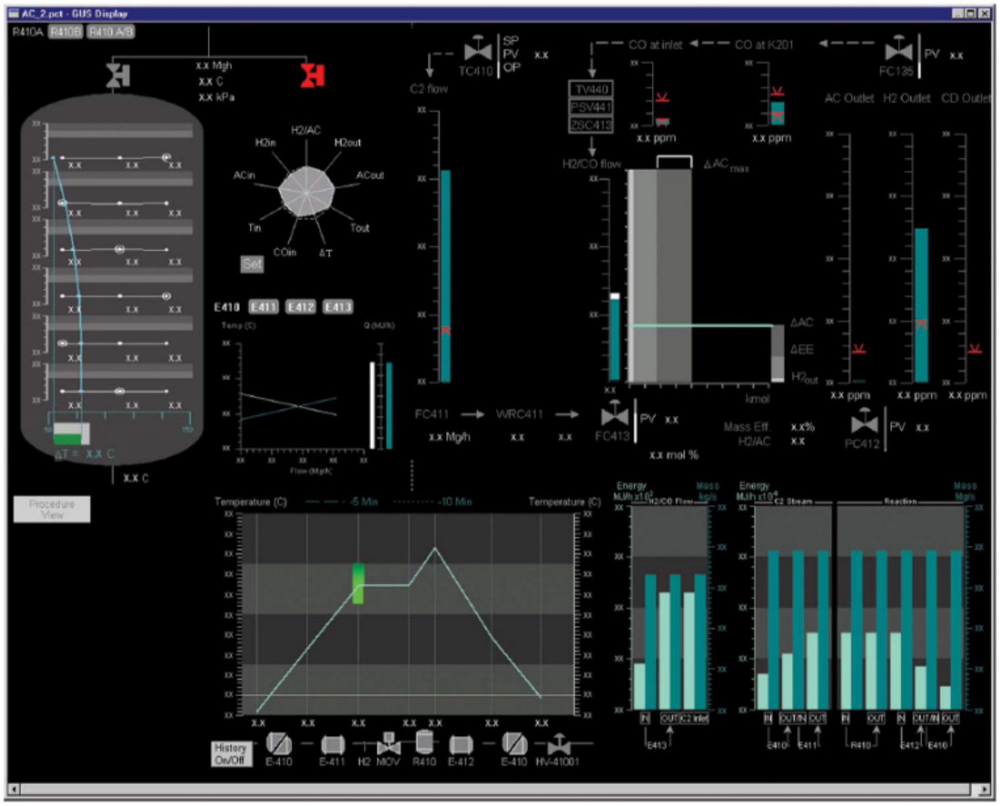

Fig. 1 Work-domain-based ecological interface (adapted from Jamieson [2007])

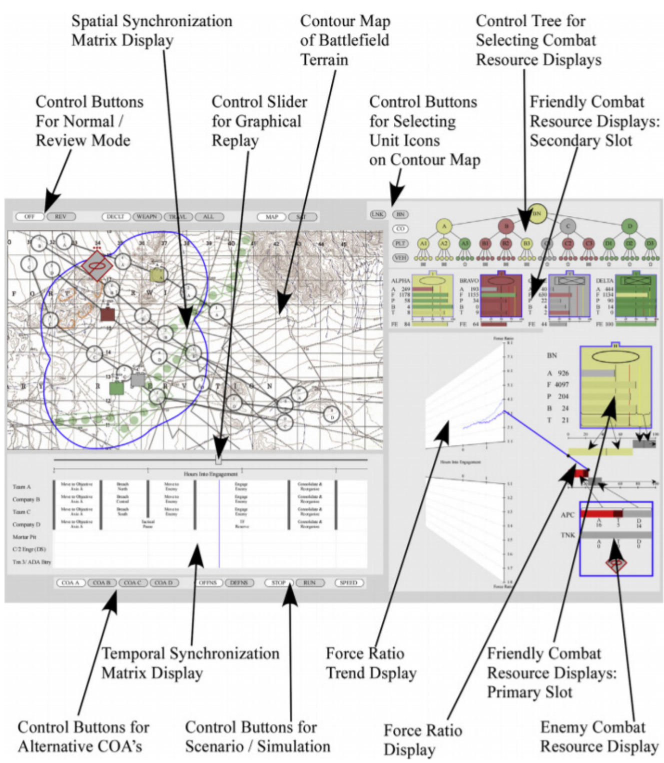

Fig. 2 RAPTOR, a military C2 interface (Bennett 2017)

2.2 Sensemaking

Sensemaking frameworks have been used to understand unfamiliar information visualization (Gordin et al. 1994; Ntuen et al. 2010). Sensemaking in visualization has been traditionally defined as "the collective application of individual 'intuition'—experience-based, subconsciously processed judgment and imagination—to identify changes in existing patterns or the emergence of new patterns" (Ntuen et al. 2010). There have been models in the domain of HCI and information visualization, such as the notional model of a sensemaking loop by Pirolli and Card (2005). This model describes intelligence analysis derived from a cognitive task analysis of searching external data courses and presenting the information to an audience.

Another model is the Klein et al. (2006) Data/Frame Theory. This model (Fig. 3) uses frames, or a person's internal mental structure of making sense of events. People use seven sensemaking events to refine an existing frame or create a better frame (i.e., re-frame). Moreover, Klein and colleagues expanded this model to the Flexecution model, which explores the paradigm for goal planning and re-planning (Klein 2007a, 2007b). The Flexecution model emphases the importance of adjusting and changing goals based on experiences obtained from executions (Fig. 4). The model shows the importance of goal planning and accommodating goal conflicts and changing priorities. These frameworks and models have been applied to information visualization.

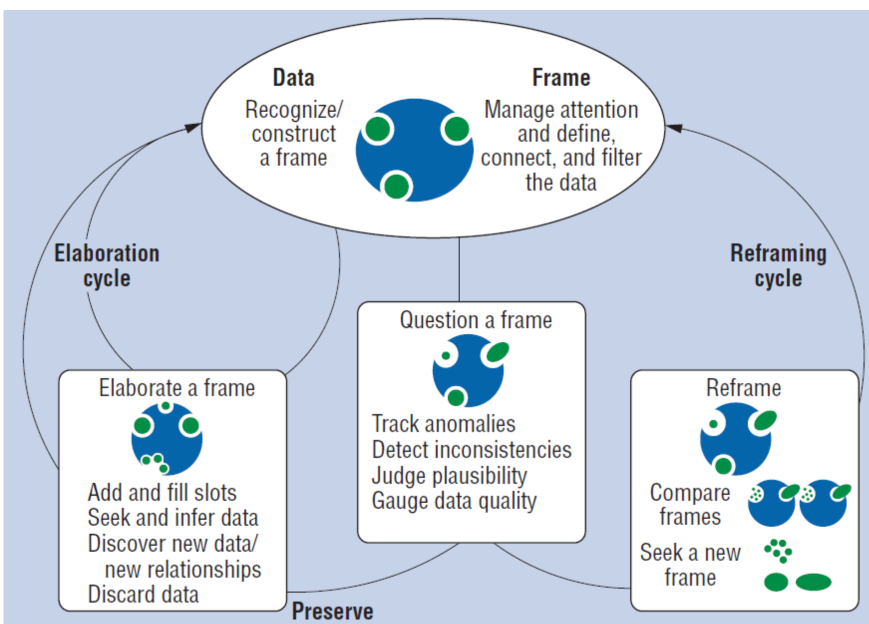

Fig. 3 Data/Frame Theory (Klein et al. 2006)

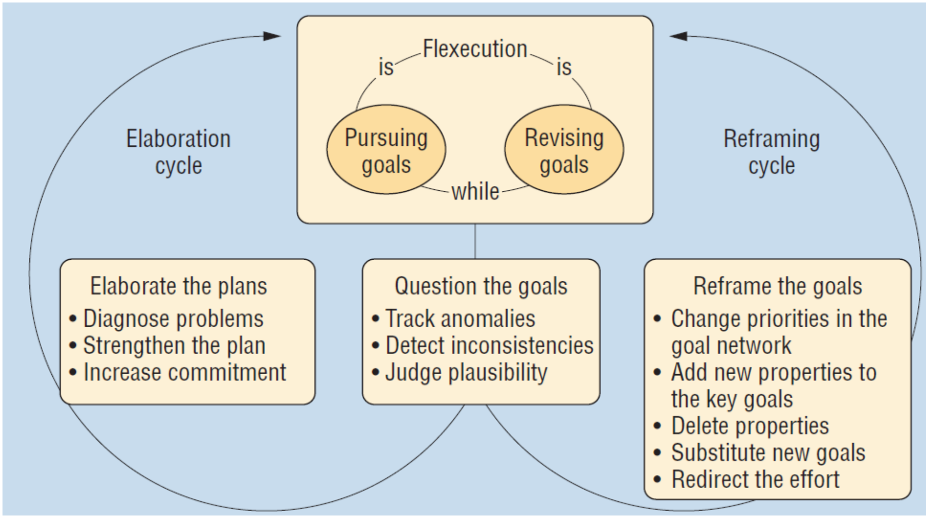

Fig. 4 Flexecution model (Klein 2007b)

Visualization models for sensemaking have also focused on information visualization. Liu and Stasko (2010) examined the relationship of mental models and external visualization. In their InfoVis model, external visualizations are internalized as mental models and this dynamic relationship can be used for external anchoring, information foraging, and cognitive offloading (Liu and Stasko 2010). Additionally, Lee et al. (2016) developed the Novices Information Visualization Sensemaking (NOVIS; Fig. 5) model, which uses five sensemaking actives to describe novices' sensemaking of interpreting an unfamiliar visualization, such as parallel-coordinate plots and treemaps. Results from this model can provide insight on how humans conduct sensemaking and cognitive activities, and could be expanded to understand visual literacy of novices.

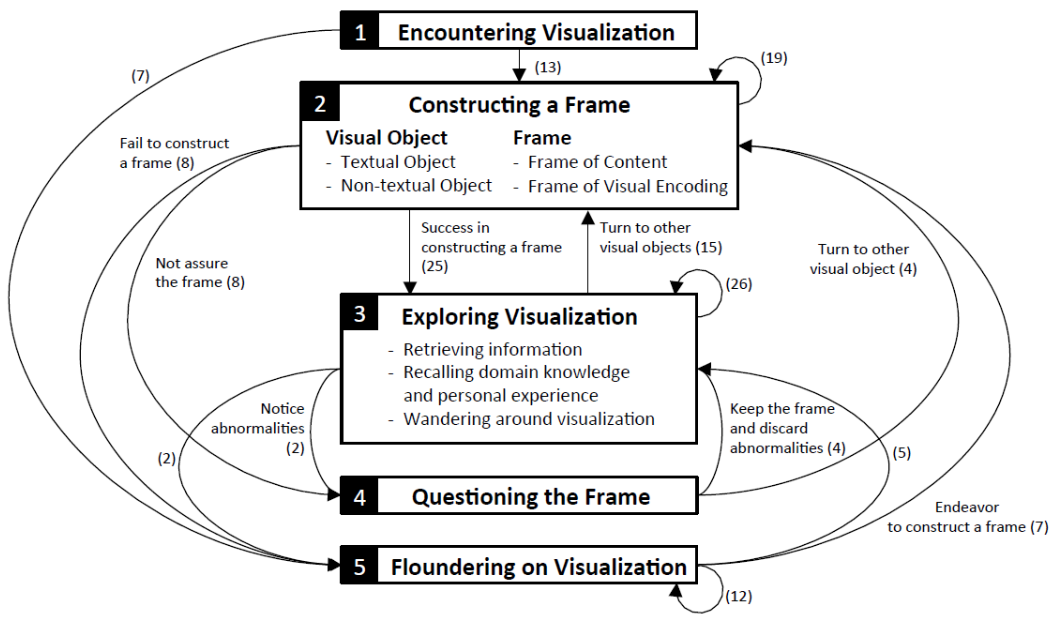

Fig. 5 NOVIS model (Lee et al. 2016)

Sensemaking models have been developed specifically for the military context. Sensemaking of visualizations in this domain is "the mental process of a commander achieving a clear understanding of the military force's current state with relation to the enemy and environment" (Ntuen et al. 2010). This framework has been implemented in visualization technology to improve recognition and understanding of information systems. For a military C2 decision-making context, Ntuen (2008) developed the Sensemaking Support System (S3). This visualization tool aims to increase collaborative sensemaking by sharing tacit knowledge, supporting a common operating picture, and allowing teams to visualize other team members' perspectives.

Results from an experiment conducted by Ntuen (2008) found that S3 model provides a groundwork for supporting operational visualization. Users were asked to rate the effectiveness of S3 on how it helped in sensemaking, SA, and situation understanding. It was found that the relationship of S3 perception rating to sensemaking cognitive measures was highly significant. A follow-up study applied S3 in the Aggie Visualization Architecture for Learning to Anticipate Novel Cognitive Human Task Environments (AVALANCHE) visualization interface to test visualization and sensemaking support, and it was found that groups that used the S3 aid improved in planning time, increased mean plan outcome accuracy, and reduced unnecessary information seeking.

2.3 Narrative/Storytelling

Storytelling has been a key form of communication for human civilization, and narrative visualization has been identified to aid information visualization (Segel and Heer 2010). This framework is centered around telling a story with data to increase the communication dimensions of information (Hullman and Diakopoulos 2011). Just as in fictional stories, narrative visualization builds the picture, animates the events, and ends with a conflict and ambiguity resolution (Gershon and Page 2001). This technique parallels storytelling by having narrative components such as genre and rhetoric.

Hullman and Diakopoulos (2011) summarized visualization rhetoric techniques of narrative visualizations (Table 1). These techniques focus on editorial layers to convey meaning on data, visual representation, textual annotation, and interactivity. These methods of rhetorical manipulation of information can be effective tools in information visualization.

Table 1 Narrative visualization techniques (from Hullman and Diakopoulos [2011])

Rhetoric	Components
Information access	• Determining data representation • Omission techniques to frame data
Provenance	• Citing and/or linking data sources, additional references • Annotating exceptions and corrections • Representing uncertainty
Mapping	• Manipulation of information presentation by data-to-visual transfer function—constraints that determine how information will be translated to visual feature • Obscuring to reduce noise
Linguistic-based	• Visual metaphor and metonymy • Typographic emphases (e.g., font bolding or italicizing) • Irony and rhetorical questions • Analogies using similarity and contrasts
Procedural	• Individualization • Expression of meaning through rule-based representations and interactive functions • Anchoring to shift user attention

In an example C2 situation by Gershon and Page (2001), a narration is played while supplemented with visuals to describe the scenario in which a friendly school with children trapped inside is surrounded by the enemy. The audience's attention is focused and information within the story is portrayed when features such as zooming and highlighting are used.

These visualization approaches are used in interface design to effectively relay information to users. These higher-level techniques review the many methods that can be taken to create a good design and aid in the performance of users. In addition to these techniques, visualization principles have been developed that can be applied to create an effective interface.

2.4 Visualization Principles

Visualization recommendations have been made in the field of cognitive psychology considering human visual information processing. Books have been written on recommendations of data visualization and presentation such as *The Visual Display of Quantitative Information* by Tufte (1983) and *Semiology of Graphs* by Bertin (1983). The authors of these books focus on how to format graphs and create effective designs considering memory-capacity limitations and long-term memory processing. For example, Tufte recommends maximizing the data/ink ratio by embedding as much information as possible. Perceptual grouping should follow the Gestalt Laws of Organization and explanations are incorporated in the texts. Kosslyn (1985) reviewed the aforementioned and three additional visualization works based on human information-processing properties and their recommendations. These texts are known to be seminal work in the visualization field and have been incorporated in the principles and guidelines for interface design.

Thirteen principles of display design were proposed by Wickens et al. (2014) (Table 2). These principles serve as best practices while designing an interface and have been utilized in many industries. For example, dos Santos et al. (2008) incorporated the principles to propose a new system interface design for a nuclear power plant control room display interface (Fig. 6). Features such as the redesign of graphic links to increase discriminability and the repositioning of navigation buttons to minimize information access cost were implemented to increase usability. Additionally, Cooper and Goodrich (2006) developed an interface to support navigation and control of unmanned aerial vehicles (UAVs; Fig. 7). The authors considered the interface's goal of supporting the primary task of the operator by minimizing information access cost and developing alternative views utilizing the principle of moving parts for the navigation assistance of the current state and commanded state of the UAV.

Table 2 Thirteen principles of display design (from Wickens et al. [2014])

Principle	Explanation
Make displays legible (or audible)	Optimize properties relating to issues such as contrast, visual angle, illumination, noise, masking, etc.
Avoid absolute judgement limits	Use discrete color changes instead of gradual
Top-down processing	Physical evidence must be presented to guarantee that something that is contrary to expectations is interpreted
Redundancy gain	Traffic light: position and due are redundant
Discriminability	Similarity causes confusion: use discriminable elements
Principle of pictorial realism	Display should look like (i.e., be a picture of) the variable that it represents
Principle of moving part	Moving element(s) of any display of dynamic information should move in a spatial pattern and direction that is compatible with the user's mental model of how the represented element actually moves in the physical system
Minimizing information access cost	Minimize the net cost of "moving" selective attention from one display location to another to access information by keeping frequently accessed sources in a location in which the cost of traveling between them is small
Proximity compatibility principle	Two or more sources of information are related to the same task and must be mentally integrated to complete the task (e.g., plant layout must be related to the warning indicator meanings). Good display design should provide the two sources with close display proximity so that their information access cost will be low. Close proximity can also be obtained by displaying them in a common color, by linking them together with lines or by configuring them in a pattern
Principle of multiple resources	Presenting visual and auditory information concurrently rather than presenting all information visually or auditorily
Replace memory with visual information	People ought not to be required to retain important information solely in working memory or retrieve it from long-term memory. Visual echo of a phone number, checklist.
Principle of predictive aiding	Proactive behavior is usually more effective than reactive, it stands to reason that displays that can explicitly predict what will happen are generally quite effective in supporting human performance. A predictive display removed a resource-demanding cognitive task and replaces it with a similar perceptual one.
Principle of consistency	Displays should be designed in a manner that is consistent with other displays that the user may be perceiving concurrently (e.g., a user alternating between two computer systems) or may have perceived in the recent past. Color coding should be consistent across a set of displays so that red always means the same thing. A set of different display panels should be consistently organized, thus reducing information access cost each time a new set is encountered.

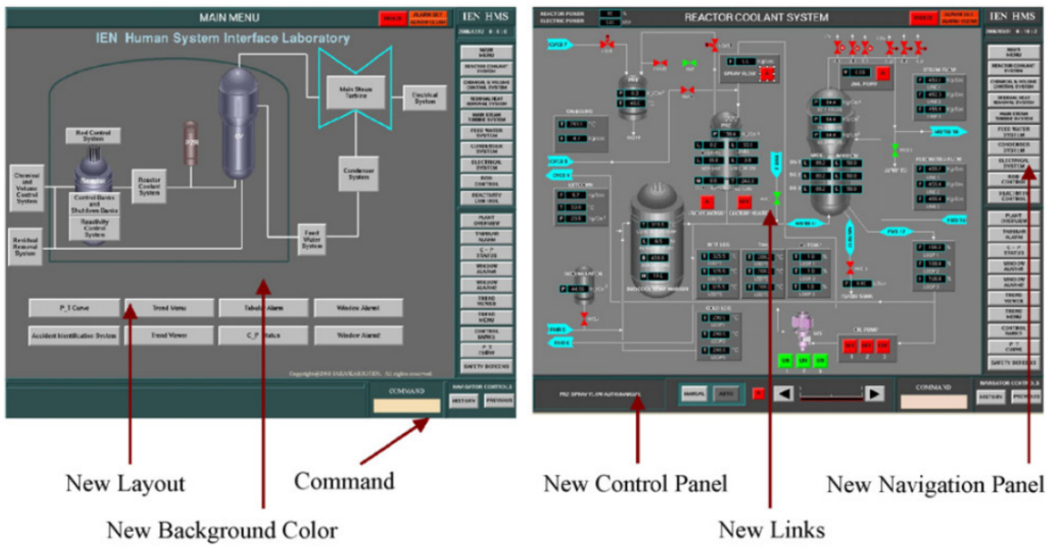

Fig. 6 **System interface for a nuclear power plant control room display interface (proposed by dos Santos et al. [2008])**

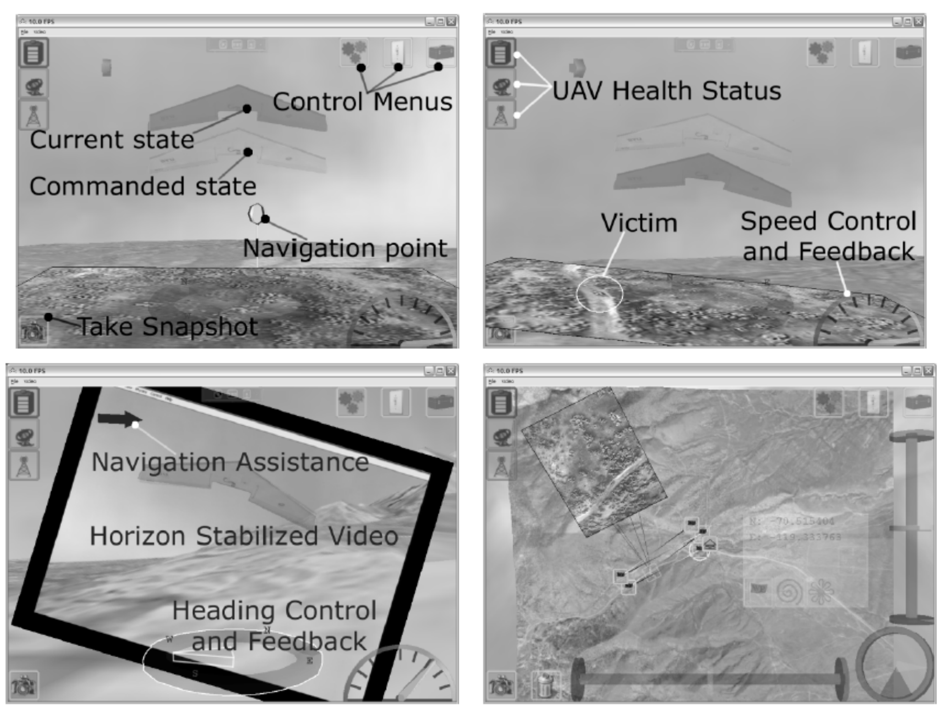

Fig. 7 **Interface to support navigation and control of UAVs (designed by Cooper and Goodrich [2006])**

Other design guidelines and texts exist such as those proposed by Hancock and Szalma (2003) and Endsley (2011). The former proposed guidelines for situations where operators are under time and task pressure. Recommendations relate to Wickens' principles such as designing to minimize information dispersal and the use of top-down processing design methods (Hancock and Szalma 2003). Literature has been written to aid in design such as *Designing for Situation Awareness: An Approach to User-Centered Design* by Endsley (2011). This work reviews SA-oriented design across domains and highlights the underlying principles through examples of how to support each SA level. Displays utilizing the principles will aid in increasing transparency of systems and improve the decision making of operators.

3. Visualization Applications to SAT

Visualizations extend the human's ability to understand complexity, whereas IAs extend the ability of humans to operate safely in complex environments. IAs are specialized software that perform specific functions with some degree of autonomy and can respond to changes in the agent's environment. Human–agent teams combine the software capabilities of the IA with the greater flexibility and metaknowledge of its human partner (Chen and Barnes 2014). However, the efficacy of the agent depends on the ability of the human to understand its output. IA transparency permits the human to know when to trust the agent's suggested COAs and when to intervene. Lee and See (2004) and Lee (2012) suggest that transparency depends on understanding the agent's COAs, purpose, process, and performance with the caveat that too much or the wrong type of information is counterproductive.

Chen and colleagues (Chen et al. 2014, 2018) developed a model of transparency based on the operator's SA (Endsley 2004, 2015) of the IA's plan, its reasoning, and its expected outcome. The SAT (Fig. 8) model posits three levels of information related to 1) *perception* of the agent's plan, 2) *comprehension* of the agent's logic, and 3) *projection* of the plan to predict likely outcomes (Chen et al. 2014). The model successfully predicted both SA and performance improvements as a function of increasing SAT levels and their visualizations for three different paradigms: RoboLeader, Intelligent Multi-UxV Planner with Adaptive Collaborative/Control Technologies (IMPACT), and Autonomous Squad Member (ASM; Mercado et al. 2015; Wright et al. 2016; Stowers et al. 2017). The results also showed the importance of uncertainty information for Level 3 on the IMPACT planning task (Stowers et al. 2017), but less so in the ASM small robot support paradigm (Selkowitz et al. 2017). One of the general conclusions is that that the static model represented by Fig. 1 needs to be expanded to include Lyons and colleagues' multidimensional model that stresses the importance of the effects of humans and teaming on the IA and not solely on the impact of agent transparency on human decisions (Lyons and Havig 2014; Lyons et al. 2017; Chen et al. 2018). The latter finding strongly implies the importance of bidirectional understanding and communications.

Situation Awareness-based Agent Transparency

Level 1: Goals & Actions

Agent's current status/actions/plans

- Purpose: Desire (Goal selection)
- Process: Intentions (Planning/Execution); Progress
- Performance
- Perception (Environment/Teammates)

Level 2: Reasoning

Agent's reasoning process

- Reasoning process (Belief/Purpose)
- Motivations
  - Environmental & other constraints/affordances

Level 3: Projections

Agent's projections/predictions; uncertainty

- Projection of future outcomes
- Uncertainty and potential limitations; Likelihood of success/failure
- History of Performance

Fig. 8 Original SAT model (adapted from Chen et al. [2014])

Increasing transparency of human–agent systems are critical for operations in many disciplines. The following section identify displays that are supported by each SAT level. As mentioned, the SAT model (Chen et al. 2018) assumes that the IA has a world model representing its basic plan (L1), the rationale for the plan (L2), and the plan's expected outcomes (L3).

3.1 SAT Level 1: Purpose, Desire (Goal Selection), Process, Intentions (Planning/Execution), Progress, and Performance

SAT L1 is supported by components of the interface that is displaying the current state of an IA or purpose. The current system state is displayed in the darker color as well as the UAV health status bar on the top left (Marusich et al. 2014). Figure 9 shows an interface developed for military C2 to test how information presentation affects decision-making performance. This display shows the status of platoons (returning in red or moving in yellow) to base and the task completion progress of capturing high-value targets (HVTs). The lines on the map show the planned path of the UAVs and the current status and progress of each platoon is identified on the modules above the map. In addition, spot reports communicate information about the units while intelligence updates present the location of the HVTs, which aid in operator planning and intermediate goal planning.

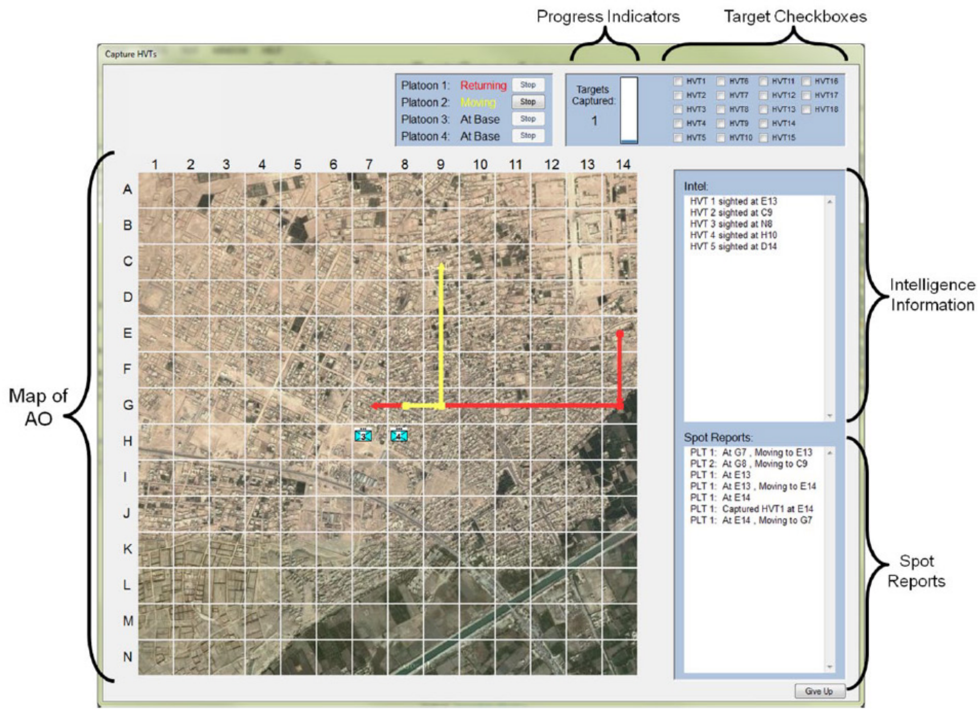

Fig. 9 UAV status and health state (Marusich et al. 2014)

Furthermore, the RAPTOR interface (Fig. 9) aids SAT L1 by allowing for user selection of display properties and easy access to control icons. The control buttons are along the display as well use intuitive indicators such as the control slider to control replay of display elements. The resource displays grouped on the right organizes the presented combat information and groups information for those referencing as friendly and enemy combat. The importance of the primary slot display, which communicates the overall information of the battalion, is emphasized and contrasts from the secondary display due to its larger size and contrasting yellow background.

3.2 SAT Level 2: Reasoning Process (Belief/Purpose), Environmental, and Constraints/Affordances

Communication of SAT L2 components by an IA is critical to understanding its actions. Constraints in the environment may hinder the completion of a goal and may alter the actions of the IA. For example, a phone navigation application may suggest alternative routes if it has calculated that there is a constraint (e.g., a traffic accident) on the current path. Typically, the navigation will state that there has been a slowdown and suggest an alternative, faster route. This verbalization of the reasoning aids the driver's understanding of the change in route; however, the internal tradeoff of an IA is typically a black box analysis and only the results are told to the operator. This readjustment in the reasoning process should be communicated.

Tradeoffs are critical to consider for decision making. Tradeoffs are often visualized by the Pareto frontier in multi-objective optimization in economics and systems engineering. The frontier describes the set of the most optimum points where the allocation of resources (μ_1 and μ_2) cannot be relocated without negatively shifting the preference of at least one resource (Fig. 10). Mattson and Messac (2005) developed a GUI to visualize the frontier in an interface format where a user can visualize the relative goodness of three different concepts (Fig. 11). Sliders on the interface are moved between the best and worst for a specific design objective and results from the changes are updated. The GUI aids in informed decision making of applications such as finding the optimum weight/size ratios for package shipping costs.

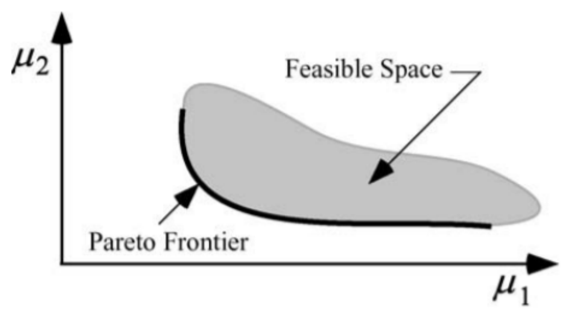

Fig. 10 Pareto frontier (from Mattson and Messac [2005])

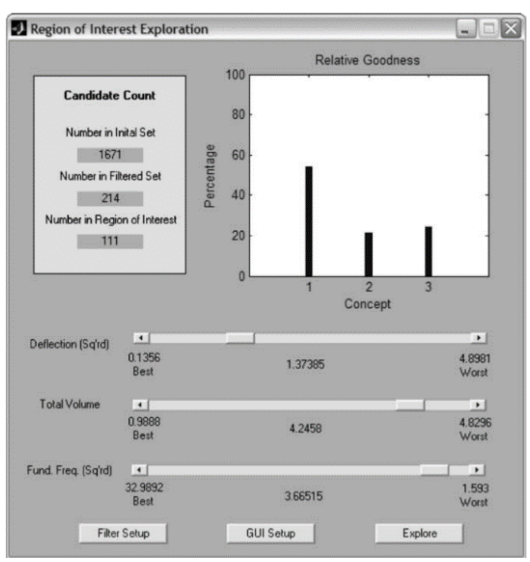

Fig. 11 Pareto frontier GUI (from Mattson and Messac [2005])

Different GUIs have been used for visualizing tradeoffs. Shaikh and Goodrich (2017) developed an interface that parallels a color palette. The interface, named the adverb palette, has several designs to visualize tradeoffs within a robot path-planning application. Each interface has two components: a map and command interface, which allows a user to balance different priorities or objectives, or "adverbs". For this application, the colors red, green, and blue signified the adverbs "Quickly", "Stealthily", and "Safely", respectively. Three initial interfaces were developed: palette (Fig. 12), sliders (Fig. 13), prism (Fig. 14), and waypoints (Fig. 15).

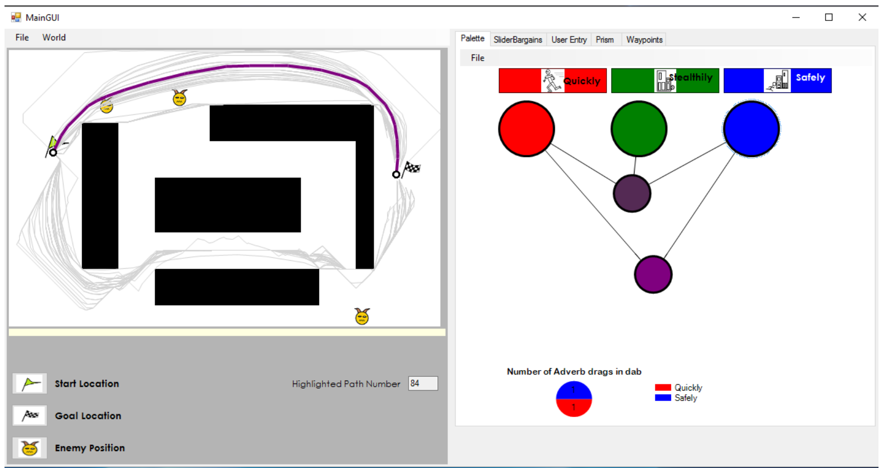

Fig. 12 Palette interface (Shaikh and Goodrich 2017)

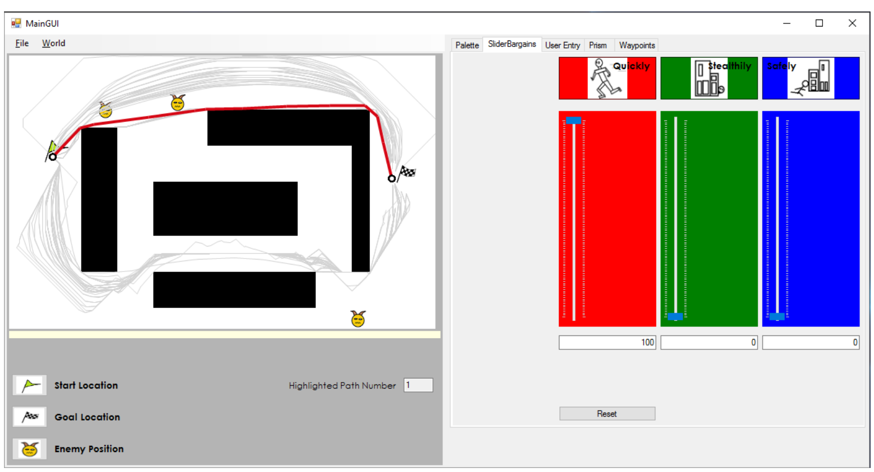

Fig. 13 Slider interface (Shaikh and Goodrich 2017)

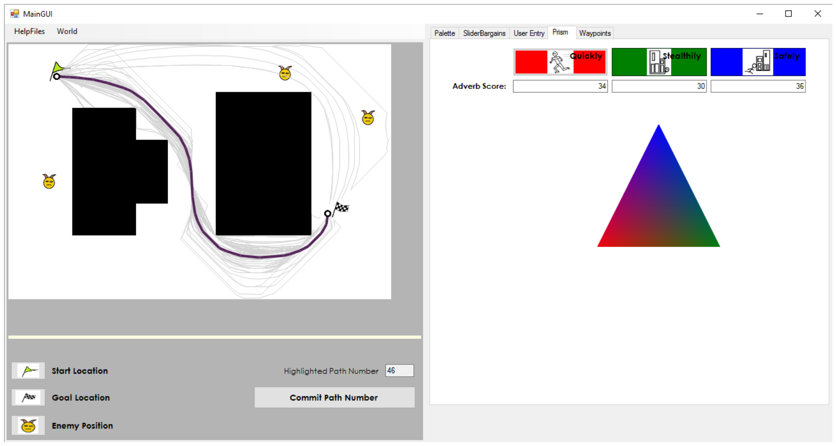

Fig. 14 Prism interface (Shaikh and Goodrich 2017)

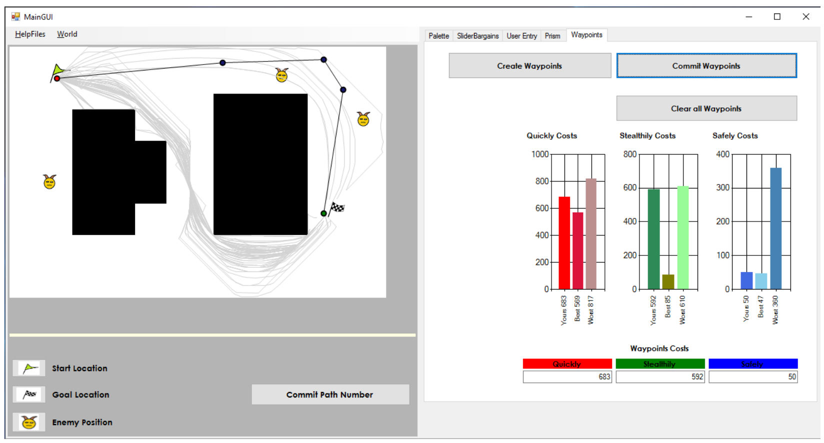

Fig. 15 Waypoint interface (Shaikh and Goodrich 2017)

Each interface is designed so that the user alters the controls to create tradeoffs of the different adverb. In the palette display, users drop the color of the adverb into the white space to create a "paint dab" that can be blended with other adverbs. This palette also summarizes the priorities in the pie graph. In the slider interface, the slider can be continuously shifted to see real-time updating tradeoffs. The interface maintains a maximum of 100 units and the sliders will automatically shift to maintain this maximum as the user alters one adverb. The prism interface is used by hovering over different areas of the prism. Each corresponding point is related to an associated path that considers proportional weights of the adverbs. Lastly, the wayfinding interface is different than the others in that the user will specify the path on the map and the interface will show how the user-created path compares to the best and worst possible options of the specific adverb. The authors conducted a user preference study and found that the palette interface was the most appealing and easiest to use. The waypoint interface was found to be the opposite.

Visualizing tradeoffs with affordances and constraints helps aid in the increase of transparency of an IA's reasoning. Traditionally, an affordance is an ecological property that describes the relationship between the environment and an agent (i.e., an affordance in the environment is what it offers for possible alternatives [St Amant 1999]). For example, affordances in user interface design are properties that allow for action execution such as icon selection. St Amant (1999) described execution affordances such as icon size, sticky icons, haptic feedback, capture effect, and area cursors. These guidelines are related to Wickens' (2014) principles described previously to improve GUIs.

3.3 SAT Level 3: Projection to Future/End State, Potential Limitations, History of Performance, Uncertainty, and Likelihood of Error

SAT L3 factors communicate to the operator the expected outcomes. This includes projections of the future or end states with the underlying potential limitations and history of performance. Potential limitations, uncertainty, and likelihood of error are especially critical to communicate in L3 and are discussed further in Section 3.4.

Resource depletion is often the source of potential limitation in completing a goal in military C2 settings. Specifically, for route planning and wayfinding, energy levels of IAs often limit the amount of time in the field. In a supervisory control scenario of UAV swarms developed by Fuchs et al. (2014), the authors incorporated a battery state of charge component (Fig. 16). The figure on the left depicts area coverage of a UAV: the dark shade along the flight trajectory represents area already covered while light shaded indicates areas yet to be covered. Areas where the UAV cannot cover due to low battery level are not shaded. To compliment this, a red line is shown in the unshaded area to depict the depleted battery level (i.e., the UAV cannot reach the waypoint), while the yellow line represents the low battery level warning (i.e., the UAV can reach the waypoint but does not have enough energy to return to the ground station). Additionally, the state-of-charge indicator (Fig. 16) shows the energy levels of the UAVs. The height of the indicator ranges from 0%–100% energy and the green color represents a good energy level. In the figure, UAV 1 has enough energy reach waypoint 7 while UAV 2 does not, as shown by the red coloring below the 0% marker line. These visuals of energy management provide insight to the user of the potential limitations of completing a waypoint navigation task.

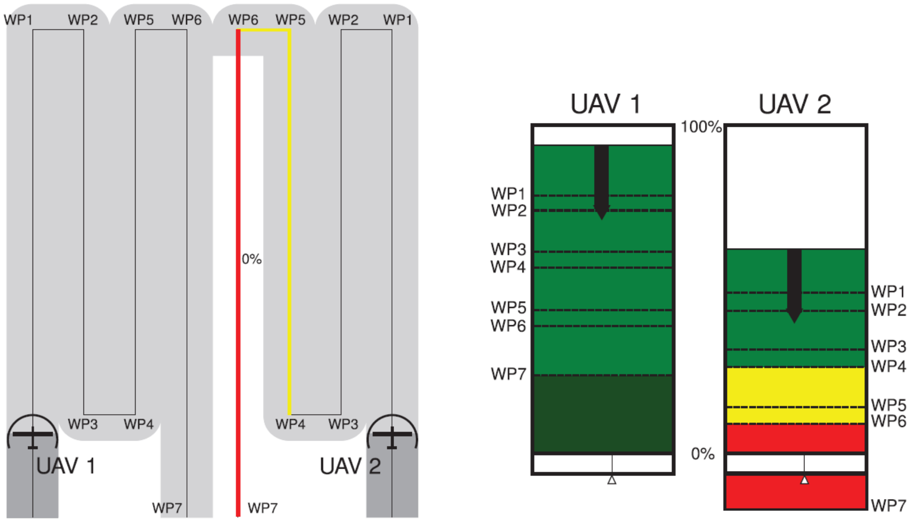

Fig. 16 Battery state of charge module (Fuchs et al. 2014)

Figure 17 shows an example of history of performance and predictive views from Piringer et al. (2012).

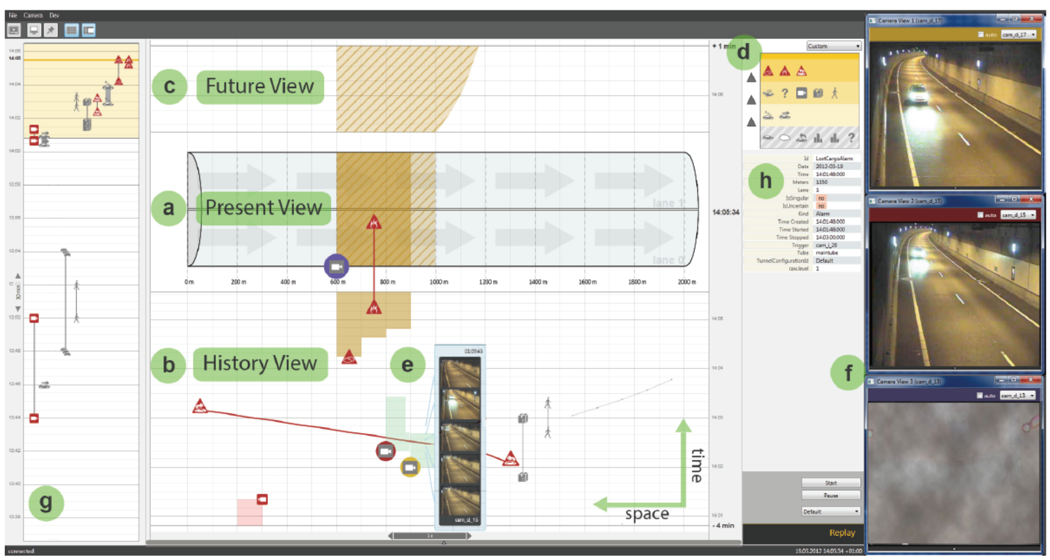

Figure 2: The AIVis client for visual tunnel surveillance: The Spatio-Temporal View consists of (a) a sketch of the present state, (b) a history of the past few minutes, and (c) predictions of future developments – in this example the expansion of smoke. (d) Situation-aware prioritization affects the visual representation of various types of incidents in the Spatio-Temporal View. (e) A video cursor enables an immediate access to live and historic video for any point in time and space within the tunnel. In this example, it also displays a temporal context as a filmstrip metaphor. (f) Additional windows for video playback employ color to visually refer to the source camera. (g) A Temporal Overview represents up to several hours and supports a navigation in time. (h) Details are provided on demand for selected incidents.

Fig. 17 Example history of performance and prediction views (from Fig. 2 in Piringer et al. 2012)

3.4 Uncertainty

Going beyond Endsley's (1995, 2015) original conception of SA; the SAT model posits that IA uncertainty should be represented as part of L3 as well. Uncertainty transparency has proven to be important because empirical evidence indicates that uncertainty information has a positive effect on performance. If operators know the IA constraints as well as its predicted outcomes, humans are better able to anticipate problems and adopt more flexible strategies (Bass et al. 2013; Helldin and Falkman 2011; Mercado et al. 2016; Stowers et al. 2017; Chen et al. 2018).

However, uncertainty is a difficult concept for humans to grasp. Instead of using normative methods to compute uncertainty, humans depend on simple heuristics based on well-established cognitive biases such as loss aversion, stereotypes, and the salience of unimportant cues (Kahneman 2003). In order to simplify the problem space, humans tend to under count the number of possible outcomes and assume equal probability when more complex distributions are appropriate (Johnson-Laird et al. 1999). Kahneman argues that humans are not irrational but rather they are time constrained; they make quick decisions that may be erroneous rather than derive normative solutions which (even if they were able to calculate them) would take too long to be practical (Kahneman and Klein 2009). As humans were evolving, speed–accuracy tradeoffs favored speed.

Visualizing uncertainty requires techniques that reflect normative prescriptions but are intuitive to humans (Spiegelhalter 2011). Using quantitative methods such as probabilities may not be appropriate by themselves; their values may be unknown, volatile, or easily misinterpreted. Humans are poor at interpreting extreme values—they tend to under weigh changes at the extreme ends of the scale (Gonzales and Wu 1999; Kahneman and Tversky 1979). For example, if probabilities are in the middle of the scale (p=0.55 and 0.50), then the odds they represent are fairly stable (1.22 to 1, compared to 1 to 1). At the end of the scale (p=0.99 and p=0.95), the odds (and associated risk) change dramatically (99 to 1 compared to 19 to 1). Also, what a probability represents can be unclear. For medical diagnosis, probabilities of a test result are often misinterpreted (false positives) because the probabilities of the test do not take into account the rarity of the disease (i.e., prior probability).

Even for moderate values, humans were no better at making decisions (and were sometimes worse) if given numerical probabilities than if given verbal descriptions (such as likely or somewhat likely) (Bisantz et al. 2011; Budescu and Wallsten 1990; Erev and Cohen 1990). Bisantz (2013) concluded that humans partition uncertainties into a discrete number of membership categories (either verbal or graphical) mirroring human limitations in processing continuous scales. Bisantz's results indicate that humans are particularly efficient at visualizing uncertainty as relationships using graphical techniques such as color-coding, shading, transparency, and so on. Also, graphical representations have processing advantages, heat maps portraying abstract or geographical relationships can be used to direct selective attention to high probabilities areas with minimum cognitive overhead (Treisman and Gelade 1980). More specific information (including uncertainty) can be encoded in glyphs or icons showing multi-attributes features of discrete elements of the tasking environment (Calhoun et al. 2017, Selkowitz et al. 2017; Stowers et al. 2017). Stowers et al.'s (2017) results indicated that coding outcomes as uncertain without assigning a value was useful especially if the reason for the uncertainty could be articulated (e.g., the condition of the road near the east gate is unknown). There are situations (e.g., severe time constraints) when coding uncertainty may not be that useful, but, in general, if the coding scheme is accurate and intuitive, uncertainty is an important dimension of the battlespace or any complex real-world environment.

Finger and Bisantz (2002) studied the graphical formats of uncertainty in decision making. The task was to identify if an icon represented a hostile (skull with crossbones) or friendly (dove). Uncertainty of the classification was represented in three ways: 1) degraded icons with probabilities, 2) nondegraded icons with probabilities, and 3) degraded icons only (Fig. 18). It was found that operators using displays with only degraded icons performed better in identifying an icon than those with probability supplements. This study showed that situational uncertainty can be portrayed through degraded images.

Display Type	Example Stimulus
Degraded Only*	
Degraded with Probability	
Probability Only	

Fig. 18 Uncertainty classification (from Finger and Bisantz [2002])

Additionally, using icons and glyphs to represent uncertainty have been studied extensively in representing geodata. MacEachren et al. have performed studies and reviews of this field and have defined nine types of uncertainty as shown in Table 3 (MacEachren et al. 2012; Kinkeldey et al. 2017). Others have explored uncertainty visualization on geographic systems for domains such as meteorology or coordination of emergency response during natural disasters. Pfautz et al. (2005)

explored the depiction of fire spread with uncertainty using graphical elements such as transparency or saturation. Other methods presented are using icon sizes, color, and hues to portray certainty.

Table 3 Components of information with uncertainty types (from MacEachren et al. [2012])

Category	Space	Time	Attributes
Accuracy/ error	coordinates., buildings	+/- 1 day	counts, magnitudes
Precision	1 degree	once per day	nearest 1000
Completeness	20% cloud cover	5 samples for 100	75% reporting
Consistency	from / for a place	5 say M; 2 say T	multiple classifiers
Lineage	# of input sources	# of steps	transforma- tions
Currency/ timing	age of maps	C = Tpresent - Tinfo	census data
Credibility	knowledge of place	reliability of model	U.S. analyst vs. informant
Subjectivity	local ←→ outsider	expert ←→ trainee	fact ←→ guess
Interrelatedness	source proximity	time proximity	same author

Riveiro et al. (2014a) developed a prototype interface for air traffic control threat identification (Fig. 19). Uncertainty associated with position is marked with red circles, while sensor data value uncertainty is represented by the thickness of the yellow line (Fig. 20). It was found that the uncertainty visualization aided improved performance: users using the uncertainty incorporated displays needed significantly fewer attempts to make a final identification than those who did not.

Fig. 19 Threat identification prototype interface (from Riveiro et al. [2014a])

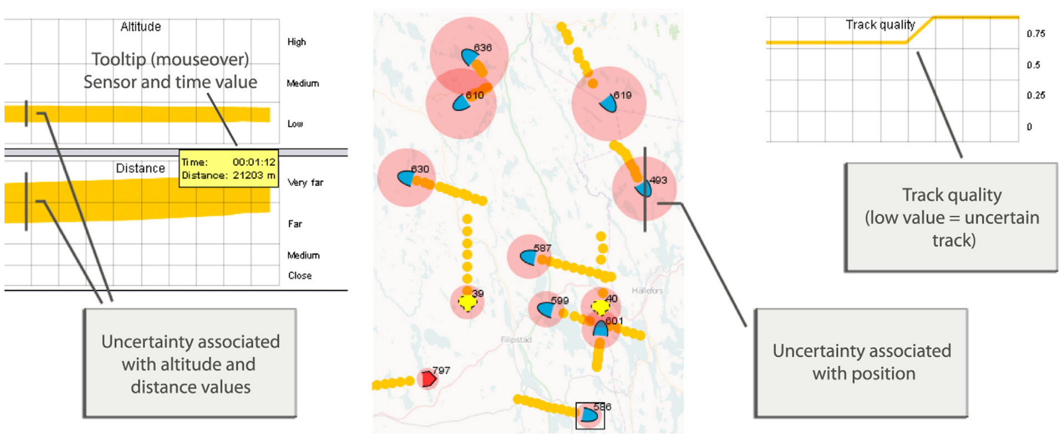

Fig. 20 Uncertainty associated with sensor value, position, and track quality (Riveiro et al. 2014a)

Likelihood or probability of error is associated uncertainty. In the previous navigation example, an application will often display the estimated time of arrival. This final number is calculated from an algorithm based on underlying assumptions of road conditions, speed limits, and so on. However, there is a likelihood of error that is often embedded within this system that is not visible to the user. For example, in air navigation, required time of arrival (RTA) error is often displayed. In work by Schmidt (2012), an interface was created to display error in RTA: a time box around the aircraft was colored blue if early and magenta if late (Fig. 21). The study explored using graphic or text information to communicate the temporal information and it was found that the use of graphic displays led to slightly higher performance. Moreover, Riveiro et al. (2014b) explored incorporating a system suggested identity of an object (e.g., friendly or hostile) and its likelihood value in their prototype (Fig. 22). Likelihood was displayed through graphical representation of probability and it was found that operators trusted the decision-aid system more than the system without likelihood estimates

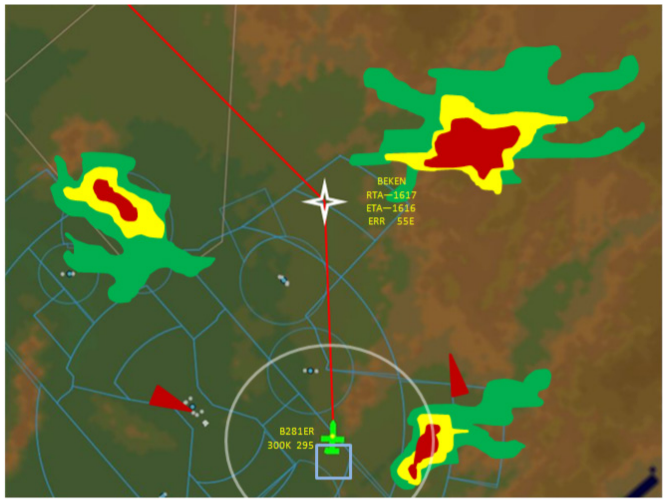

Fig. 21 RTA error display (in Schmidt [2012])

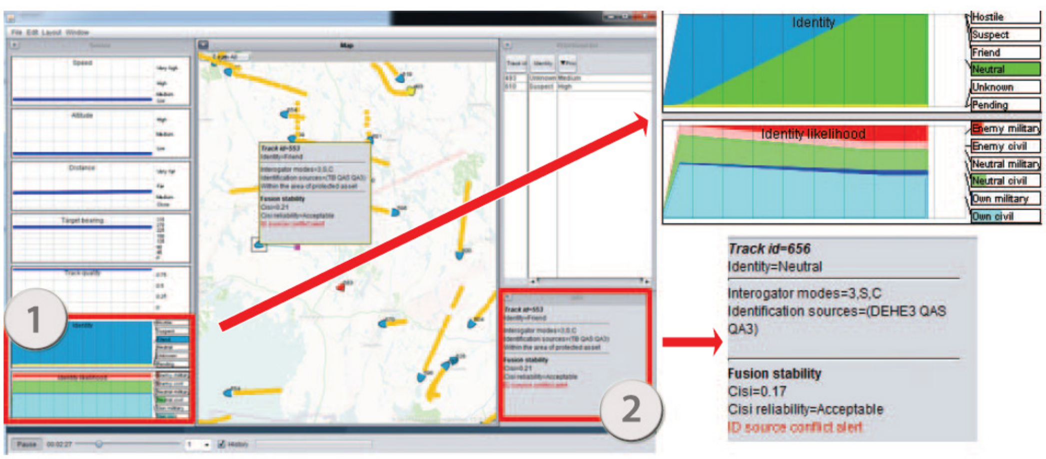

Fig. 22 Likelihood of identity suggested by the system (Riveiro et al. 2014b)

4. Applications to ASM/IMPACT

Chen and colleagues (2018) have conducted several experiments embedded in three diverse paradigms. We discuss the relationship of the SAT model to the reviewed experiments but focus on the variety of visualization concepts and their rationale.

This will enable us to compare various techniques and their utility under a variety of different conditions

A fairly obvious design principle is that the visualizations must reflect the ecological constraints of the mission environments in which they were designed to operate (Jamieson 2007). However, there is no perfect solution to any mission environment. All effective visualizations share the qualities of good display design: clarity, completeness, conciseness, and intuitiveness as well ecological validity (Tufte et al. 1998; Wickens et al. 2000; Barnes 2003). Two of the paradigms (IMPACT and ASM) were part of the ARPI (DOD 2012a) and as such represented IA prototypes created in Air Force, Navy, and Army laboratories that were informed by insights developed through collaborating with active duty personnel (Pettitt et al. 2017). However, because these experiments were conducted using university participants, it was necessary to simplify the interfaces to reflect the inexperience of the participants while capturing the gist of the ASM and IMPACT paradigms.

4.1 IMPACT

The IMPACT paradigm includes IAs, planning algorithms, and machine learning algorithms that can monitor the progress of ground, aerial, and sea unmanned vehicles (UVs) that are protecting a littoral military installation (Draper et al. 2018). The human operator has versatile planning options ranging from manual planning tools to having an IA function that can autonomously choose the best plan and optimal composition of UVs to conduct the plan (after receiving general mission guidance in the form of programmed *plays* (Calhoun et al. 2018). In two human-in-loop simulation experiments (Mercado et al. 2016; Stowers et al. 2016), the IA chooses plan A as the best solution and plan B as the alternative (slightly less *good* solution). During a 2-min planning trial, the operator is alerted to changes in the environment (not known to the IA) based on intelligence reports, sea state, weather reports, road conditions, and so on, which switched the best solution from A to B in 3/8ths of the trials. The independent variables were transparency conditions as per Fig. 1 for both experiments (EXP 1: L1, L1+2, L1+2+3 and EXP 2: L1+2, L1+2+3 and L1+2+3+U). Counterbalancing ensured that the mission alerts were seen equally often over transparency conditions during both experiments. The simulation interface for Mercado et al.'s (2016) experiment (Fig. 23) consisted of the right-hand display portraying the transparency condition for that trial by comparing option A and B's transparency information. The left-hand side showed miscellaneous mission information including alerts that were the same for both options.

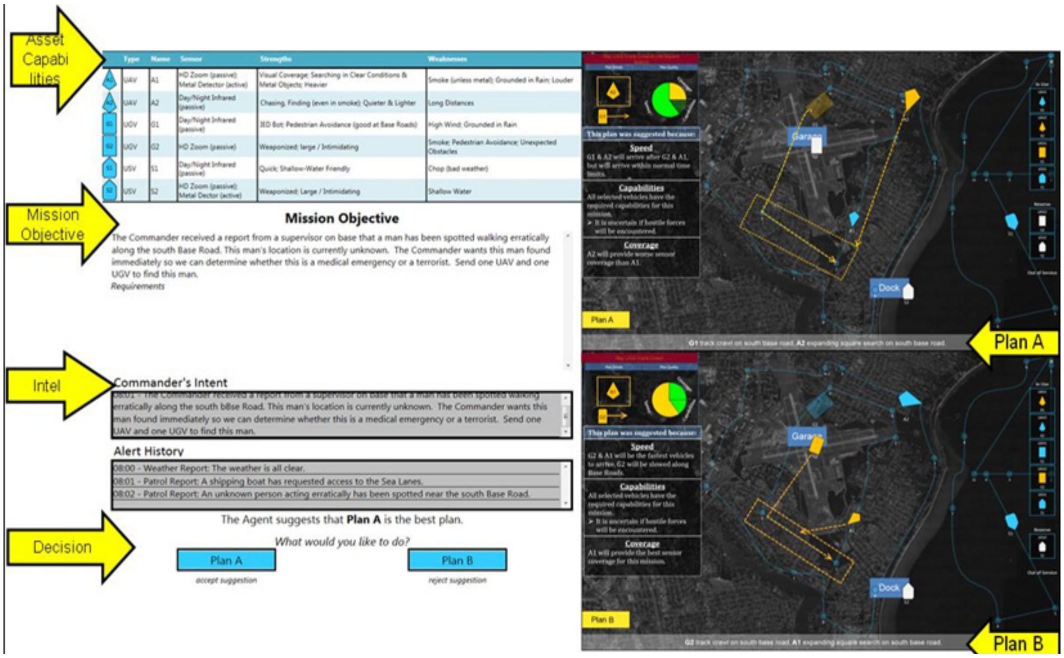

Fig. 23 Simulation information and visualization for plan A and B in Exp 1 (Mercado et al. 2016)

In both experiments, increasing transparency information improved performance. In experiment 1, L1+2+3 included uncertainty coding (translucence) concerning one of the end states (e.g., faster unmanned aerial systems not certain because of possible wind), which had a minimal effect on performance compared to adding only reasoning information (i.e., L1< L1+2 = L1+2+3) but surprisingly adding L3 improved subjective trust. The critical features for IA reasoning were coded on a sprocket (sectional areas of a pie chart showing the relative importance of sensor coverage, UV speed, and UV capability for planning). As Fig. 24 indicates, the pie charts were displayed vertically requiring the participant to compare the features serially. Also, it was noted after the experiment that participants made scant use of the map portion of the display, resulting in wasted space.

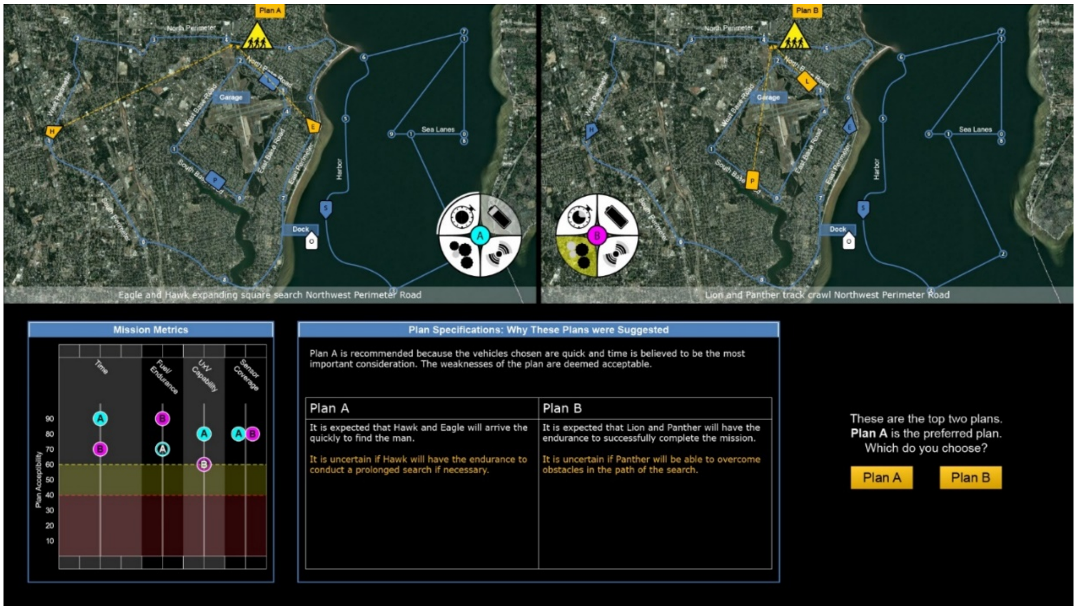

Fig. 24 IMPACT display

As Fig. 25 indicates, the visualization changes to the second experiment (Stowers et al. 2017) included 1) creating two conditions L1+2+3 and L1+2+3(U) to de-conflict prediction and uncertainty, 2) specifying the rationale for uncertainty in L1+2+3+U using yellow text, 3) coding the expected outcomes each mission objective (e.g., asset speed) by showing the relative heights of each of the plan options (A and B) on the same expected outcome bar graph, whereas the relative importance of each mission objective was shown by their ranking of left to right (Calhoun et al. 2018), and 4) adding additional information on the map to increase its salience. Specifically, there are three key modules or tiles in the display: a *Plan Maps* tile, a *Projected Plan Success* tile, and a *Plan Specifications* tile (Fig. 25).

Fig. 25 Improved transparency visualization for IMPACT experiment: direct comparison of plan options A and B (adapted from Calhoun et al. [2017]), a more concise format, and uncertainty information in the text box

4.1.1 Plan Maps

The interface presents two maps, one for each plan the IA suggests to the operator. SAT L1 information includes the IA's recommended plans and information about the UxV associated with these plans. SAT L2 information (reasoning) was displayed by the size of UxVs, with larger UxVs being faster. SAT L3 projection information was displayed as an icon attached to each UxV to depict the number of time units it was from its goal location. SAT L3 uncertainty information was displayed through changes in opacity of the UxVs themselves, where less opaque vehicles were considered to have uncertain capabilities or time projections.

4.1.2 Projected Plan Success

The plan comparison tool, based on a design developed by US Air Force researchers (Calhoun et al. 2018), adds additional SAT L2 and L3 information. This graphic shows the evaluation of both plans (A and B) on four different parameters: time, coverage, fuel endurance, and general capability. Circles representing each plan slide up and down scales corresponding to each parameter. Plan acceptability is rated on this sliding scale; the higher a circle is on the scale, the more acceptable the plan is for meeting that parameter. L2 information is conveyed through showing how heavily the IA is weighing each parameter as a representation of the IA's recommended plan and reasoning. This is done by ordering the parameters from left to right, with decreasing widths for less important ones. L3 projection information is conveyed by showing the projected plan success of each plan for all four parameters. Finally, SAT L3 uncertainty was represented with hollow circles instead of filled ones.

4.1.3 Plan Specifications

The Plan Specifications tile provides further information on the Plan Maps and Projected Plan Success tiles. For example, a detailed explanation of the reasoning process (constraints and/or affordances considered by the IA); projection statements to indicate the predicted outcomes of the plans; and uncertainty statements specifying 1) the IA was uncertain about certain aspects of the tasking environment and 2) the IA was making an assumption to deal with it were provided.

The main finding of the second experiment was improved performance for the uncertainty condition, L1+2+3(U). However, there was also improvement in the visualization techniques used including grouping similar functionality using the *perceptual compatible principle* (Wickens et al. 2000). Also uncertainty coding of a planning option was indicted by the white circle around options on the bar graph, which was located at the same visual level as the yellow text describing the cause of the uncertainty thus creating *visual momentum* between the icon and its descriptor (Hall et al. 2012). This suggests the importance of not only the type of SAT information displayed but also the importance of the visualization techniques depicting the information (Calhoun et al. 2018).

The IMPACT interface was redesigned to displayed uncertainty information through mission metrics, widget, and text (plan specifications). The presentation of uncertainty and prioritized factors of the mission were displayed through the three mediums, and the plan specifications provided the reasoning for the IA's recommended plan. Though this information provides transparency to the operator, the level of information may detrimentally affect the decision maker's performance.

4.2 ASM

While IMPACT's paradigm focused on deciding between plays using multiple IAs, the ASM paradigm focused on an operator monitoring an autonomous ground-based vehicle accompanying a squad of Soldiers (Boyce et al. 2015). The particulars of ASM were quite different, reflecting missions with severe time constraints. The ASM was a small autonomous robot (IA) whose mission was to improve an infantry squad's SA as well provide logistic support for the individual Soldiers. The ASM's visualizations were designed to be *status* at a *glance*, reflecting both the ever-present possibility of being under attack and the workload demands of the infantry squad. In the first human-in-loop simulation experiment (Boyce et al. 2015), the operator monitored one of three different interfaces showing the ASM moving along a series of waypoints to an end point; one interface only displays *Current Status*, another adds *Reasoning*, and a third also includes *Projection and Uncertainty*.

4.2.1 Current Status

In one condition, the operator monitored an interface that included the Current Status module, which operationalized the constraints of the robotic platform (e.g., sensor functionality, fuel constraints) and described their status as either good (displaying a green background), medium (displaying a yellow background), or poor (displaying a red background). This module is displayed in Fig. 26.

Fig. 26 ASM experiment 1 interface: current status module

4.2.2 Reasoning

In another condition, the operator monitored an interface that included the Current Status module and environmental constraints (i.e., enemy/supporting fire, rough/ easy terrain, and communication jammed/extended). These constraints were depicted using icons disseminated through the map, each surrounded by a ring to depict the area of effect and whether that field would hamper the ASM's resources (i.e., an icon surrounded by a red ring) or not (i.e., an icon surrounded by a green ring). Furthermore, each ring is interspersed with shapes, each of which correspond to the icon and the environmental constraint it represents. These rings are depicted in Fig. 27.

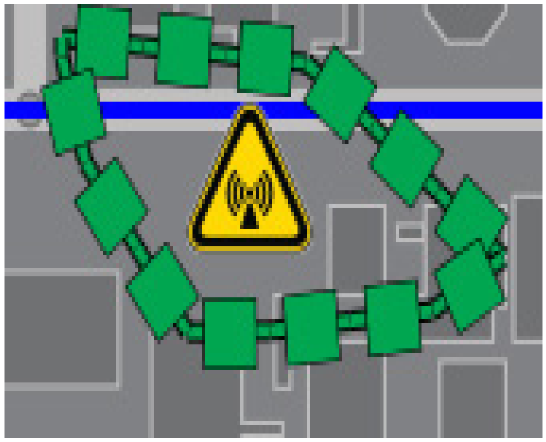

Fig. 27 ASM experiment 1 interface: environmental constraints that influence agent reasoning

4.2.3 Projection and Uncertainty

The last condition adds a Projected Status module at the top-right of the screen, similar to the Current Status module, except it describes the ASM's predicted resource loss. Like the Current Status module, it describes the constraints of the robotic platform, but projects that no resources are loss (displaying a green background), some resources may be lost in the future (displaying a yellow background), or many resources will be lost (displaying a red background). Furthermore, this module represents the ASM's uncertainty regarding the environmental constraint, with a semi-opaque background suggesting that resources may not be hampered or may only be somewhat hampered. Additionally, in this condition, any areas where the ASM is uncertain of the environmental constraints are represented by semi-opaque rings around the area. An example of all these modules displayed together is depicted in Fig. 28.

Fig. 28 ASM experiment 1 interface, including current status, reasoning, and projection/uncertainty

The first-year ASM study used a between-subjects design to explore the effect of varying levels of transparency (Level 1, Level 1+2, or Levels 1+2+3) on operator SA, trust, and perceived workload.

This experiment tested the effect of display design to convey environment and IA information in a simulation-based unmanned ground vehicle monitoring task. While there were no major differences in SA or workload, there were some findings with regard to trust. Participants who saw current status and reasoning information (L 1+2) had higher trust in the ASM than those who only saw current status (L 1) or current status, reasoning, and projected outcomes (L 1+2+3). This suggests that a providing a justification for its actions and resource loss made an agent more trustworthy, but that advantage was lost due to providing projecting outcomes and uncertainty information. Visualizations for projected outcomes and uncertainty were presented together, but people act in a variety of ways to mitigate uncertainty, so conflating the two may have obscured some fine differences between the two (Endsley and Jones 2016). The follow-up study sought to detangle these two factors to ascertain a finer understanding of the response to information supporting transparency in an agent interface.

Using information from the first-year study and the development of the agent architecture that the study simulated, the second year ASM study redesigned the interface. Figure 29 shows the possible information states for the subsequent ASM display. The icons were integrated using EID principles (Vincente and Rasmussen 1990; Bennett et al. 2008) generating scenes using intuitive icons depicting the ongoing mission including the current plan (L1: the how), motivators (L2: the why), projections (L3: the immediate future) and uncertainty coding (U). Compared to the IMPACT visualization; the scenario representation was simplified in order to create an easily understood pictorial narrative (Warner and Burnstein 1996; Barnes et al. 2006). Again, this reflected the difference in ecological requirements between IMPACT and ASM missions: extensive functionality required for base defense, immediate solutions required for squad support.

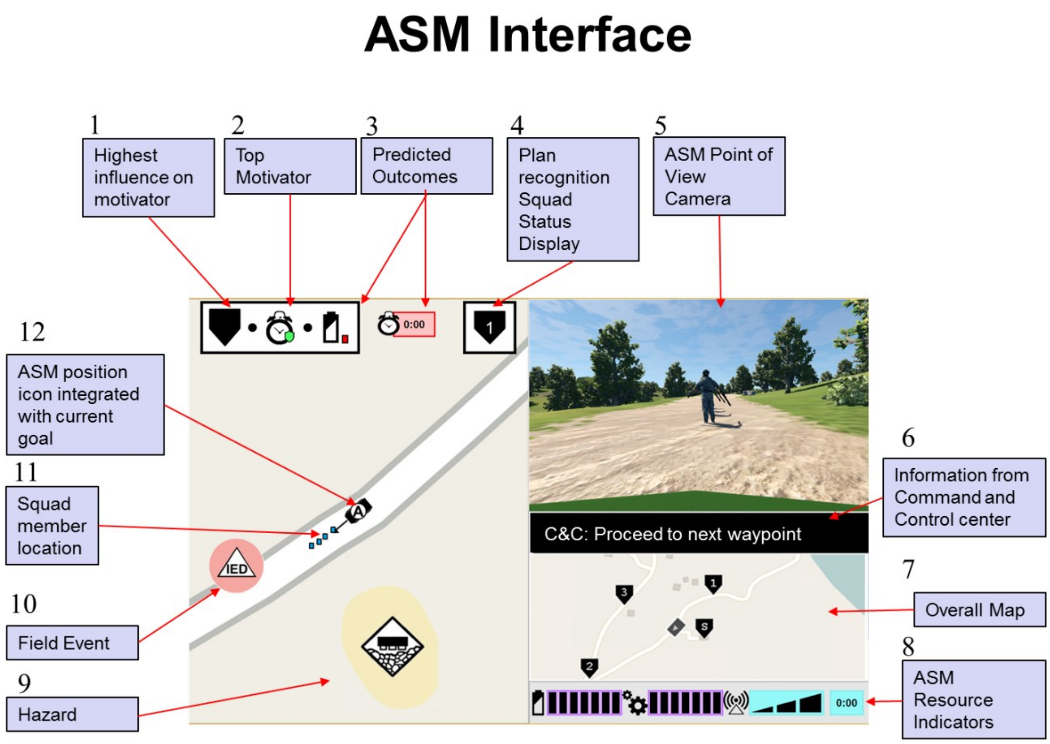

Fig. 29 Display for the ASM with annotations

The ASM interface used an "at-a-glance" module to promote transparency for each level of the SAT model. The red square aside the predicted outcomes icon is the amount of resources that will be consumed/lost. For L3 "predicted outcomes", uncertainty was displayed by non-opaque squares to represent the possibility of using the level of resource (e.g., with one opaque square and one non-opaque square next to a battery symbol, it represented that it is certain to lose one level of energy but there is the possibility of losing a second level). Although this module can be used to quickly interpret the status of the ASM, additional EID and usability principles can be applied for improvements.

The "at-a-glance" dashboard display usability can be increased by displaying the status of goals and motivation, and allowing users to access underlying logic. The representation of the current motivation does not allow for the interpretations of the purpose or the weight of different goals: users cannot see the reasoning process and prioritization that the system made. If this information can be displayed upon user request, there will be better transparency and understanding of the agent's actions. Additionally, usability heuristics could be implemented. Using the guidelines of helping users recognize and diagnose errors as well as increasing flexibility and efficiency of use can allow users to better interact with the ASM interface (Nielsen 2006).

Using the updated ASM interface, the second year experiment investigated four transparency conditions, similar to the IMPACT paradigm (Selkowitz et al. 2016, 2017). The independent variable in the experiment was be level of SAT model information displayed (L1, L1+L2, L1+L2+L3, L1+L2+L3+U). The lowest transparency condition, L1, depicted the current goal using the "at-a-glance" module (Fig. 30). The next condition, L1+L2, depicted the current goal and top motivator in the "at-a-glance" module. The following condition, L1+L2+L3 depicted the current goal, the top motivator, and the projected outcome in the "at-a-glance" module. Finally, L1+L2+L3+U depicted the current goal, the top motivator, the projected outcome, and the uncertainty of those projected outcomes in the "at-a-glance" module; this condition also represented area uncertainty around events by surrounding them with either opaque or non-opaque fields. This approach singled out uncertainty for examination allowing researchers to determine if displaying "uncertainty information" and different levels of the "transparency information" (based on the SAT model) would affect operator trust in the agent, workload, and SA. During the experiment, participants monitored the progress of an autonomous robotic agent and its simulated human squad members through a simulated environment.

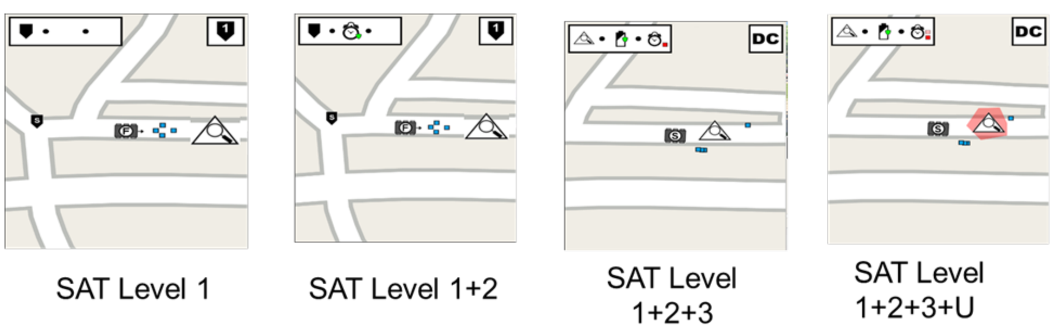

Fig. 30 A comparison of the four interfaces presented to participants in the second-year ASM study (Selkowitz et al. 2017)

Unlike the first-year ASM study, a within-subjects design was employed to compare the four transparency conditions; the study found that "transparency information" influenced SA and trust in the robot, but did not seem to influence workload (Fig. 31). Specifically, when participants worked with a display supporting L1+L2+L3, they showed higher SA than when they worked with a display supporting L1 or L1+L2. Similar differences in SA were not found when participants worked with a display that supported L1+L2+L3+U. Trust followed a similar arc. Working with a L1+L2+L3 interface resulted in significantly higher trust in the ASM than working with a L1 or L1+L2 interface, but working with a L1+L2+L3+U interface did not. The "transparency information" displayed in the interface did not seem to affect participants' subjective workload, which corresponds with findings from the IMPACT suite of studies (Mercado et al. 2015, 2016). These findings suggest that the addition of uncertainty information in an interface may allow participants to calibrate their trust in the ASM—which is important when it comes to appropriate reliance—without unnecessarily adding to workload (Lee and See 2004; Chen and Barnes 2014). The addition of uncertainty information to the interface seemed to result in a loss of the gains from displaying information pertaining to SAT L1, L2, and L3. The implications of these findings suggest that conveying uncertainty can have mixed responses, and thus should be used carefully and in very specific situations where trust and appropriate reliance are vital to the success of the mission.

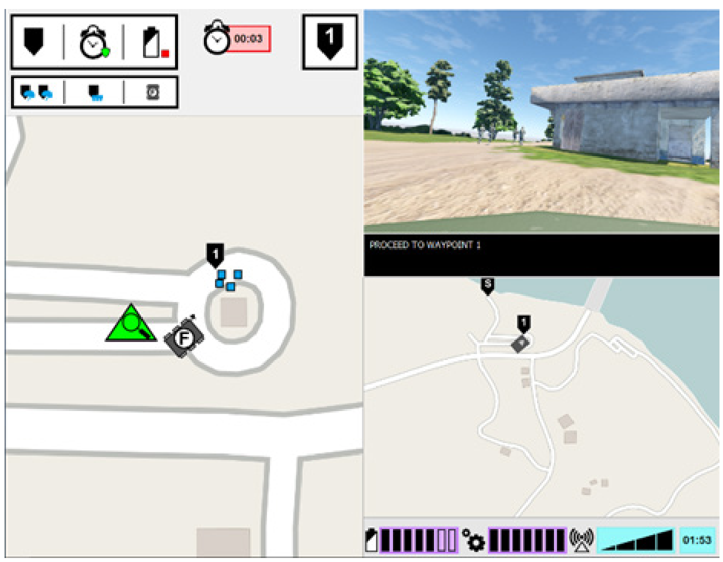

Fig. 31 Display for ASM year-3 study. "In-depth" transparency information was added, showing the robot's underlying logic for its goal, reasoning, and projected outcomes, respectively (Wright et al. [in progress]).

The third-year ASM study explored how agent transparency interacted with agent reliability to influence operator behavior and attributions of the robot (Wright et al. in progress). In the high-transparency scenarios, the robot would also explain the underlying logic behind its goal, reasoning, and projected outcomes by adding a secondary "at-a-glance" display below the original, in which displayed the underlying logic for each factor (goal, reasoning, projected outcome). The underlying logic factors could be related to either what the robot perceived in the environment (e.g., squad lying down, detecting loud noises) or an internal factor (e.g., energy consumption, preserving mechanical integrity). In the unreliable conditions, the robot would occasionally misinterpret the squad's behavior for a similar action (e.g., the squad gets on the ground to crawl under an obstacle, but the robot misinterprets this as a response to incoming fire, that is, hitting the deck). The robot would then respond to the wrong situation (e.g., instead of going around the obstacle the robot would begin evasive actions).

In this within-subjects design, the transparency of the robot nor the reliability affected participant performance, workload, SAT L1, or SAT L2 scores. While these findings agree with earlier results that indicate increased transparency does not increase perceived workload, in this instance, the task required very low effort, which most likely contributed to the lack of differences in task performance, workload, and SA. However, the reliability of the agent had a negative impact on the participant's trust in the agent, their perceptions of the agent and, interestingly, their confidence in their own ability to assess the robot's reliability. Agent's perceived errors had a profound and lasting effect on the human teammates' perception of the agent's reliability, causing the human to rate the agent as less reliable even when it did not commit any errors. This effect appeared to diminish as the agent continued to display reliable behavior. Agent error also resulted in participants' reduced confidence in their assessment of the agent's reliability, regardless of the agent's continued error-free behavior, and this effect was persistent over time. These findings could have important implications for continued use of automated systems when the user is aware of system errors.

5. Summary and Conclusion

Various visualization techniques were reviewed. Successful techniques depend on re-creating the external reality of the environment in ways amenable to the human's mental representation of the processes involved such as sensemaking and narrative formats. Narration, for example, has been the principal means of imparting information since the time of pre-literate societies. Whereas certain display guidelines such as the 13 principles discussed by Wickens et al. (2010) should be considered for every visualization design, there is great deal of latitude concerning a specific design. The general requirement is that it reflect the constraints of the operator in the intended environment. For example, in the ASM environment, not only was the SAT narrative format successful but its simplicity of form was essential because of the importance of status-at-a-glance information. Because of the importance of making rapid decisions for the ASM operator, uncertainty information was not particularly valuable. In the IMPACT planning environment, by contrast, details of the ecological interface were important for transparency and the inclusion of uncertainty information alerted the operator to the agent's processing limitations.

6. Additional Resources

The following are good resources on this topic:

- DOT/FAA/AM-01/17. Human factors design guidelines for multifunction displays. https://www.faa.gov/data_research/research/med_humanfacs/oamtechreports/2000s/media/0117.pdf.
- DOT/FAA/TC-07/11. Human factors criteria for displays: a human factors design standard update of chapter 5. http://hf.tc.faa.gov/hfds/download-hfds/hfds_pdfs/dot_faa_tc_07_11.pdf.
- Using color in information display graphics. NASA; n.d. https://colorusage.arc.nasa.gov/.
- ANSI/AAMI HE75:2009/(R)2013. Human factors engineering—design of medical devices. Arlington (VA): Association for the Advancement of Medical Instrumentation; 2013.
- ISO/IEC. 9241. Ergonomics of human system interaction. https://www.iso.org/standard/52075.html.
- O'Hara JM. Advanced human–system interface design review guideline. General evaluation model, technical development, and guideline description. Washington (DC): Nuclear Regulatory Commission (US); 1994. Report No.: NUREG/CR--5908-Vol. 1; BNL-NUREG--52333-Vol. 1.
- Bowser SE, Adams SM. Emerging human–computer interface (HCI) design guidelines for graphical user interface (GUI). Richland (WA): Pacific Northwest Lab; 1993. Report No.: PNL-SA--22009; CONF-9310100—7.

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List of Symbols, Abbreviations, and Acronyms

AI	artificial intelligence
ARL	Army Research Laboratory
ARPI	Autonomy Research Pilot Initiative
ASM	Autonomous Squad Member
AVALANCHE	Aggie Visualization Architecture for Learning to Anticipate Novel Cognitive Human Task Environments
C2	command and control
COA	course of action
DOD	Department of Defense
EID	ecological interface design
EXP	experiment
GUI	graphical user interface
HCI	human–computer interface
HVT	high-value target
IA	intelligent agents
IMPACT	Intelligent Multi-UxV Planner with Adaptive Collaborative/ Control Technologies
L1	IA has a world model representing its basic plan: the how
L2	IA has a world model as the rationale for the plan: the why
L3	IA has a world model for the plan's expected outcomes: the immediate future
NOVIS	Novices Information Visualization Sensemaking
RAPTOR	Representation Aiding Portrayal of Tactical Operations Resources
RTA	required time of arrival
S3	Sensemaking Support System
SA	situation awareness

SAT	Situation-Awareness-based Agent Transparency
U	uncertainty coding
UAV	unmanned aerial vehicle
UV	unmanned vehicle

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