The Effect of Information Level on Human-Agent Interaction for Route Planning

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NOTICES

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14. ABSTRACT

This study investigated how differing levels of information affected decisions human operators made in a route-selection task. Experiment 1 examined how information about resource usage/requirements affected route-selection decisions for a remotely based supervisor guiding a dismounted Soldier unit through an urban environment. Experiment 2 included all the information from Experiment 1 but added a robotic asset and its resource usage/requirements information. Results suggest that a low level of information corresponds to a significantly lower decision time (DT) than its counterparts, and DT at all information levels increased with the addition of the robotic asset. Participants exhibited sensemaking by reducing DTs as the experiment progressed. In addition, as the amount of information increased, preference for specific information sources began to vary. In the condition with the greatest amount of information available, participants displayed no clear consensus as to preferred information source, with many indicating they preferred sources that were unsuitable for successful mission completion. Future research could investigate further into the complexity of appropriate display for user interfaces involving robotic assets.

15. SUBJECT TERMS

sensemaking, level of information, decision making, information display, route planning

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1. Introduction

This study seeks to investigate the effects of level of information (LOI) on human interaction with a route-planning agent in the context of dismounted infantry navigation. Previous research has shown that to facilitate effective human-agent teaming and fluid mixed-initiative decision making, the agent's user interface must facilitate optimal transparency by conveying the rationale behind its recommendations but must do so without burdening the human with an overwhelming amount of data (Lee and See 2004; Fallon et al. 2010; Lyons 2013).

Lessons learned from a US Navy intelligent autonomy program indicated that human operators sometimes questioned the accuracy and effectiveness of the output produced by intelligent systems, such as those generating automated plans, due to the operators' difficulties in understanding the rationale behind the output (Linegang et al. 2006). Lee and See (2004) recommended that when feasible, in order for the operator to develop appropriate trust and reliance, the automated systems must convey their capabilities and limitations to the operator. Lee (2012) proposed that to increase automation transparency to the operator, system designers should make the system's 3Ps (purpose, process, and performance), and the history of the 3Ps, 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 amount of information to process (Cook and Smallman 2008; Neyedli et al. 2011). In service to this goal, proper uses of information visualization techniques have been shown to help operators make sense of information and thereby enhance their situation awareness of the mission/tasking environments (Robertson et al. 2009).

1.1 Cartography and Route Planning

Cartographic researchers are currently in the process of working with psychologists to better understand how humans interpret map design. Lorenz et al. (2013) assessed indoor map design and user satisfaction. They explain that in the field of cartography, designers try to provide the correct context to allow for a mental representation and linkage between the user and the map. Providing an appropriate amount of visual information to create context can be accomplished by adding visual elements to increase transparency. Results from the Lorenz et al. (2013) study show that the helpfulness of a landmark's presence on a map depends on an association between the symbol and its meaning for the user. The same study also investigated the concept of route complexity in terms of quantity of landmarks; however, more landmarks did not increase performance. This result led the researchers to conclude that symbols and landmarks may overload the map display in a complex design, while an appropriate balance of symbols and landmarks could produce positive results.

Westerbeek and Maes (2013) examined the effect of visual clutter of information on map designs of New York City and how it affected the ability to use landmarks to navigate. They found that during interaction with cluttered maps, participants would more often miss essential information, instead using noncrucial information in their way finding. Ware (2012) describes this extra information as a visual distractor. Visual distractors interfere with the brain's preattentive processing, thereby increasing the time to find information (Treisman 1985). One of the key psychological functions of a graphic is to draw attention to the important elements in a design (Clark and Lyons 2010). By drawing attention to the important items in a display, divided attention is reduced. When exploring navigation of large sets of data, users' comprehension is best when they have to focus on a small area (Herman et al. 2000). Mosier et al. (2007), citing Wickens and Flach (1988), explain how an operator will focus on salient information under time pressure, but without salient information, the operator could become lost. The concept of determining what is important and what is not is also consistent with how Kilgore and Voshell (2014) built designs with explicit visual cues (such as icon size and opacity) to help operators recognize the key variables. Without essential information indicators, operators have difficulty building a complete understanding of the navigation information. Instead, simple, clear designs have been shown to support understanding (Lorenz et al. 2013).

1.2 Decision Making and Route Planning

Recent research by Van Tilburg and Igou (2014) demonstrated, through a series of wayfinding experiments, a construct known as action continuation. Once individuals have made a particular choice down a route, they tend to continue along similar pathways rather than selecting a different route. There are several strategies people use when selecting routes: the longest straight path (Bailenson et al. 2000); the choice with the least deviation to their original goal (Hochmair and Frank 2000); the hill-climbing strategy, where they break the route into a series of subgoals and select the easiest available choice (Robertson 2001, as cited in Van Tilberg and Igou 2014); or they may abstain from decision making altogether when the cost of developing strategy outweighs the benefits, also known as criterion failure (MacGregor et al. 2001).

Gigerenzer and Gaissmaier (2011) make the case that in the absence of imposed rules upon which to base their decisions, people often use simple heuristics. These heuristics can reflect competing goals, such as ignoring a piece of information to save a particular resource. Therefore, without some constraints to control how an individual searches or prioritizes information in a display, each person could make different decisions on what heuristics to apply.

Effective interface design uses the display to help the user understand his/her choices when making decisions, usually through visual cues or design elements. These visual cues combine in such a way as to assist the user in a process called "sensemaking". Sensemaking (Klein et al. 2006) is a deliberative process decision makers use to improve their understanding in uncertain and ambiguous situations. When users engage in sensemaking, they create a mental schema (or frame) as they begin to understand events and the connections between events, and their perspective is continuously updated by their experiences. In the case of this study, sensemaking provides a system to help operators transition from having no understanding of the events before them to developing relationships between the extant data to provide information for future decisions. Munya and Ntuen (2007) explain that in the context of a battlefield environment, sensemaking provides an opportunity to provide linkages (or as they put it, "connecting dots") to information that otherwise might be separated across domains. Sensemaking also has an adaptive quality in that it allows the user to learn as they go, potentially dealing with unexpected events that occur along the way. The mental model that the sensemaking helps to shape is also dynamic in nature, which explains the modification of understanding during the route navigation task (Munya and Ntuen 2007). For example, in a route-planning task, a user begins to build an understanding of what the different icons and status changes mean as they interact with the user interface. As they continue to learn, they can optimize their choices to achieve mission objectives.

1.3 User Interfaces and Information Visualization

A potential way to present information to users without increasing their workload is through information visualization. Information visualization takes existing performance data and translates it into a graphical format that can be more easily understood. Parsons et al. (1999) examined over 150 studies on warnings and risk perceptions, and their analysis provided a series of recommendations for effective design. Although not all of their recommendations apply to the paradigm of route planning, the following are relevant:

- Border usage: Increasing the weight of a border around an object can increase the urgency of a piece of information.
- Brevity: Keeping all information as simple and as clear as possible.
- Consequence information: Clarifying the consequences of each choice facilitates choosing among options.
- Visual design: Presenting information in terms of bulleted lists, easy to understand pictograms, and alternative label designs can influence the effectiveness of information (Parsons et al. 1999).

Complex environments are made simpler by appropriately matching the information presentation with the type of information processing required to successfully complete the task (Vessey 1991). For example, when comparing total values of noncategorical data between groups, the most effective graph is a clustered bar graph (Helfman and Goldberg 2007). However, some research has indicated that users prefer their information to be presented as short textual displays and graphical hints that appear when needed and then disappear afterwards (Jepson et al. 2009). This study investigates which of these methods is not only preferable but also more effective in successful completion of the route-planning task.

1.4 Trust and User Interfaces

The amount a user trusts an interface can directly affect their willingness to use it, their performance, and how they respond to unexpected scenarios (Lee and See 2004). The higher the level of autonomy of the system, the more important the system's LOI becomes in fostering trust in the human operator (Wang et al. 2009). Consequently, the presentation of information in an unfamiliar format reduces automation transparency (Kim and Hinds 2006). This study investigates how the appropriate LOI and the preferred manner in which the information is displayed affects performance and trust in the route-planning agent.

There are 2 major types of trust: dispositional and history-based (Merritt and Ilgen 2008). Dispositional trust is a stable construct describing someone's feelings about something before any actual encounter, in this instance, how one feels about working with a remote monitoring and communications system. Dispositional trust is generated by exposure to a variety of sources, primarily social influences such as media and literature, and can vary widely among individuals (Hancock et al. 2011). History-based trust is trust developed from direct interaction with a system. It is composed of 4 facets: competence, predictability, reliability, and faith (Master et al. 2005). As an individual's experience working with a particular system grows, they calibrate their trust in the system to an appropriate level that optimizes performance (Fallon et al. 2010). The effect of dispositional trust in automation on performance and of LOI on history-based trust will be explored in this study.

1.5 Current Study

In this study, the participant supervised 2 dismounted Soldier teams from a remote location. The participant directed one Soldier team as to which route they should take as they made their way from checkpoint to checkpoint through an urban environment. At each of these checkpoints (hereafter referred to as decision points [DPs]), the simulation paused, and the participant received information regarding the resource demands of several route choices. The LOI was varied across participants. After reviewing the available information, the participant selected the next route segment, and the simulation would resume. The participants' goal was to manage the available resources so that the Soldier team arrived at its final destination with at least the specified minimum amount of each resource.

In Experiment 1, the participant managed Soldier Energy Units (SEUs), with instructions they must have at least 5 SEUs remaining when they reached the final destination. In Experiment 2, a robotic asset was added to the Soldier team, so in addition to managing SEUs, participants also managed Robot Battery and Robot Fuel, with the requirement they must have at least 10 units of each when they reached the final destination.

Between DPs, the participant monitored the environment surrounding the second Soldier team as it progressed through the simulation, identifying threats defined as armed civilians by clicking on them with the mouse. The participants received no feedback on this task, and performance on this secondary task was not evaluated, as it was intended solely to keep the participant occupied between DPs.

1.5.1 Study Objective

This study manipulated the LOI the operator received to base decisions in a route-planning task. Participants were assigned 1 of 3 LOIs: Low LOI provided the operator with a map showing 3 route segments, color-coded to indicate difficulty (which implied resource usage); Medium LOI provided the same map as in Low, and displayed the resource usage requirements of each route segment both in a text box and in a bar graph below the map; High LOI included all the information in the Medium condition but also supplied another bar graph showing predicted resource usage information for the entire remaining route (mission completion). Therefore, the principal objectives of this study were to 1) determine how LOI supports operator performance and 2) determine how the addition of a robotic asset and managing the additional resources associated with such affects operator performance. In addition, which visual elements the operators relied upon (or found to be most useful) in their decision-making strategy were discussed.

1.5.2 Hypotheses

Based on the reviewed literature, the following hypotheses were developed:

- **<u>Objective 1:</u> How does LOI support operator performance?**
    - H1: As LOI increases, operator trust, as measured by posttest trust, will increase.
    - H2: As LOI increases, time spent at each DP will increase.
    - H3: As LOI increases, total decision time (DT) will also increase.
    - H4: Soldier energy usage will decrease as LOI increases due to the operator choosing more optimal routes when supplied more information.
- **<u>Objective 2:</u> How does having additional information from robotic asset change operator performance?**
    - H5: Soldier energy usage will be greater in Experiment 2 than in Experiment 1 due to the higher cognitive load associated with the additional resource management duties.
    - H6: Robot Battery and Robot Fuel usage will decrease as LOI increases due to the operator choosing more optimal routes when supplied with more information.
    - H7: Time spent at each DP will be greater in Experiment 2 than in Experiment 1.
    - H8: Total DT will be greater in Experiment 2 than in Experiment 1.
- **<u>Objective 3:</u> Across the 2 experiments, which visual elements do operators report relying upon most in their decision-making strategy?**
    - H9: As LOI increases, operators will rely upon information sources that better support their task objectives (i.e., text box and bar graphs).
    - H10: As LOI increases, operators that rely upon appropriate information sources (i.e., text box and bar graphs) will use less

resources than those that rely upon unsuitable information sources (i.e., colored map routes and resources gauges).

2. Method

2.1 Participants

A total of 120 participants were included for analysis in both experiments. Each experiment included 60 participants (20 per group, 3 groups). Experiment 1 included 23 female, 34 male, and 3 no gender reported participants (Min_{age} = 18, Max_{age} = 30, M_{age} = 21.20, and SD_{age} = 2.80), while Experiment 2 included 35 female, 24 male, 1 no gender reported participants (Min_{age} = 18, Max_{age} = 39, M_{age} = 21.58, and SD_{age} = 3.70). In Experiment 1, one participant had to be removed due to incomplete data, and another was added to equal out the conditions. Participants were recruited through the University of Central Florida's Institute for Simulation and Training's Sona System, a research participant management system. Participants received payment ($15/h) as compensation.

2.2 Apparatus

2.2.1 Hardware

The simulation was presented on a Dell personal computer with a 22-inch monitor, standard mouse, and keyboard. The system was an Intel i7 3820, with a GIGABYTE motherboard, NVidia GeForce graphics card with 2-GB random-access memory (RAM), running Windows 7. The system had 16 GB of RAM.

2.2.2 Simulator

The simulator for this study was a modified version of the Mixed Initiative Experimental Testbed (Barber et al. 2008). This distributed simulation environment was developed for investigating how automation affects human operator performance. The study interface was developed using the General Middle Eastern environment, and the target detection task was modelled after a similar task used in the RoboLeader studies (Chen et al. 2011; Chen and Barnes 2012; Wright et al. 2013). The user interface (Fig. 1) displayed a virtual environment, time, resource usage gauges, and information regarding route resource requirements (shown only when the simulation is paused at DPs).

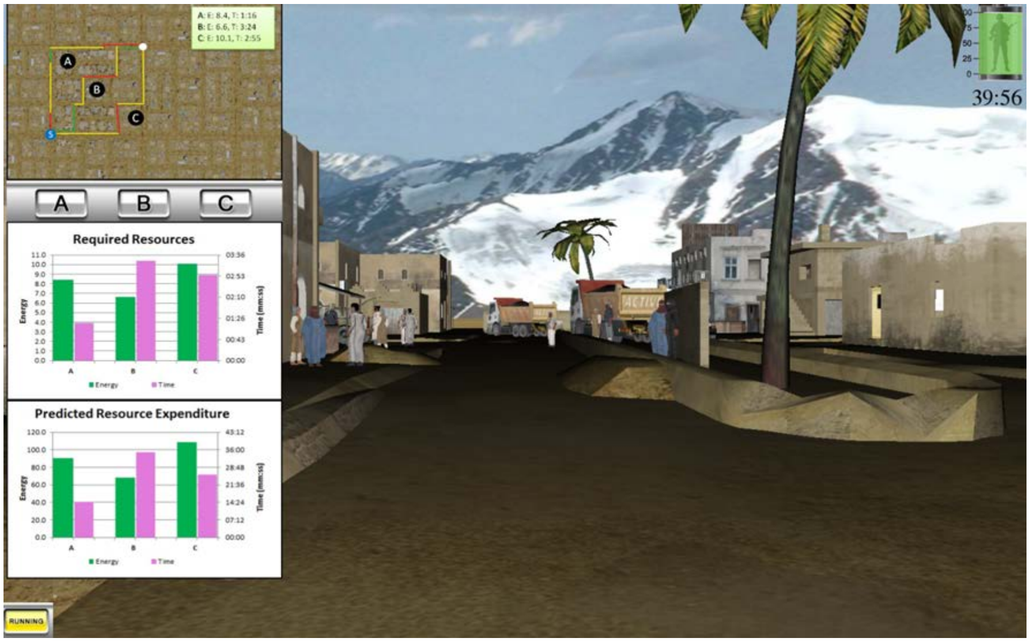

Fig. 1 Experiment 1 interface, displaying typical information presented at a DP for the high LOI condition

2.3 Surveys and Tests

Participants completed a demographics questionnaire at the beginning of the training session (Appendix A). Information on participants' age, gender, educational level, computer familiarity and usage, and gaming experience was collected. An Ishihara Color Vision Test (using 9 test plates) was administered via PowerPoint presentation. All participants had normal color vision.

A modified version of the "Trust Between People and Automation" survey (Jian et al. 2000) was used to assess participants' dispositional trust in automation (Appendix B). Operationalized as "Pretest Trust" for analysis, this measure was used to compare individual differences in performance based on preexisting attitudes regarding automation. Participants were categorized based on a quartile split of all scores. Experiment 1 revealed the following: (*Min* = 2.55, *Q2* = 4.75, *Q3* = 5.27, *Max* = 7.00, *M* = 5.25, and *Mdn* = 5.27); LowT (*N* = 15, score less than 4.75), MedT (*N* = 13, score greater than 4.75 but less than 5.27), or HighT (*N* = 32, score greater than 5.27). Experiment 2 revealed the following: (*Min* = 2.82, *Q2* = 4.55, *Q3* = 5.36, *Max* = 6.73, *M* = 5.18, and *Mdn* = 5.36); LowT (*N* = 16, score less than 4.55), MedT (*N* = 13, score greater than 4.55 but less than 5.36), or HighT (*N* = 31, score greater than 6.73).

Participants' perceived trust in the route-planning agent was evaluated using the Usability and Trust Survey from Chen and Barnes (2012) (Appendix C).

Operationalized as "Posttest Trust," scores from the Usability and Trust Survey were used to evaluate how differing levels and presentations of information affected their perception of usability and trust in the route-planning agent. Participants were categorized based on a quartile split of all scores. Experiment 1 showed the following: (*Min* = 2.42, *Q2* = 5.00, *Q3* = 5.63, *Max* = 7.00, *M* = 5.61, and *Mdn* = 5.63); LowT (*N* = 11, score less than 5.00), MedT (*N* = 19, score greater than 5.00 but less than 5.63), or HighT (*N* = 30, score greater than 5.63). Experiment 2 revealed the following: (*Min* = 3.58, *Q2* = 4.29, *Q3* = 5.46, *Max* = 6.83, *M* = 5.28, and *Mdn* = 5.46); LowT (*N* = 15, score less than 4.29), MedT (*N* = 15, score greater than 4.29 but less than 5.46), or HighT (*N* = 30, score greater than 5.46).

2.4 Measures and Variables

2.4.1 Independent Variables

The 3 LOIs for Experiment 1 were the following:

- Low LOI: The routes were color-coded red/yellow/green to denote relative energy and/or time usage requirements required to traverse that section of the route. Red indicates high energy, long time, or both high energy and long time; yellow indicates medium energy, medium time, or both medium energy and medium time; and green indicates low energy, short time, or both low energy and short time.
- Medium LOI: In addition to the LOI of the Low condition, text boxes containing the specific energy expenditure and time to complete for a segment were supplied. A bar graph was also presented below the map to facilitate comparing resource requirements across route selections.
- High LOI: In addition to the LOI of the Medium condition, a bar graph showing "predictive" information as to how specific route choices impact overall resource usage for mission completion was supplied (see Fig. 1 for High LOI display).

The 3 LOIs for Experiment 2 were the same as in Experiment 1; however, resource information for the robotic asset (Robot Battery and Robot Fuel) was added to all charts and graphs (see Fig. 2 for Experiment 2, High LOI display).

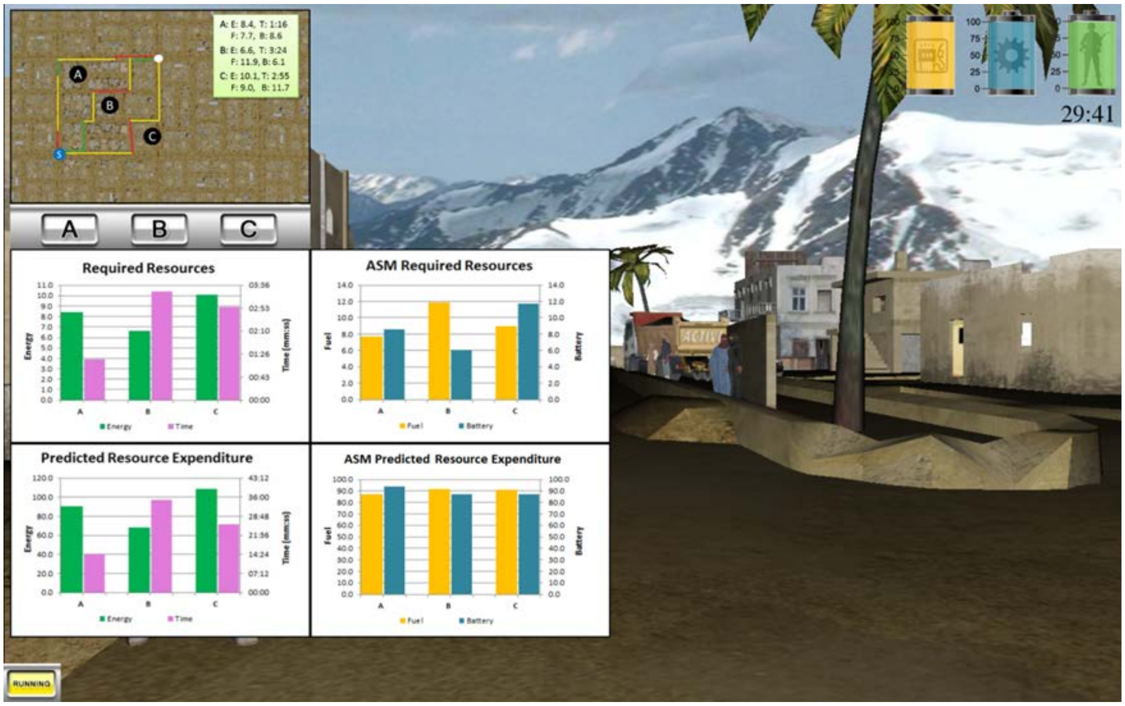

Fig. 2 Experiment 2 interface, displaying typical information presented at a DP for the high LOI condition. ASM, the robotic asset, stands for autonomous squad member

2.4.2 Dependent Variables

The following measures were collected in Experiments 1 and 2:

- Posttest Trust: evaluated using the Usability and Trust Surveys.
- Time spent at DPs: The amount of time (as measured by the system) the participant took to make route choice decisions. Both the time spent at each DP and total time at DPs were collected.
- Total SEUs used: The amount of energy the Soldier used to move along the route.

For Experiment 2, the following measures were added to accommodate for the addition of the robotic asset:

- Total Robot Battery used: This was measured as the amount of Robot Battery the robot used as it moved along the route.
- Total Robot Fuel used: This was measured as the amount of Robot Fuel the robot used as it moved along the route.

2.5 Procedure

Experiment 1

Upon arrival, the participants were instructed on the purpose of the study and signed the informed consent form. Participants then completed the demographics questionnaire, the “Trust Between People and Automation” survey, and a brief Ishihara Color Vision Test.

The participants were then randomly assigned to 1 of the 3 experimental groups and trained for their experimental task. The training was self-paced and delivered via PowerPoint slides. The slides explained the experimental scenario, the information they would receive, their goals for successful mission completion, and steps for completing various tasks. After completing the training slides, participants underwent a training scenario that mimicked the activities that would occur during the experiment. The training session lasted approximately 15 min, and all participants demonstrated adequate mastery of the system before proceeding with the study.

The experimental session lasted about 30 min. During the scenario, participants guided a dismounted Soldier through an urban environment through 10 DPs. The objective was to arrive at the final destination with at least 5 SEUs remaining in as little time as possible. At each DP, the simulation paused and the participant received information regarding the resource demands of 3 different routes that could be used to proceed to the next DP. Low LOI condition participants viewed a map showing the 3 routes, which were color-coded to indicate difficulty or resource requirements. Medium LOI participants viewed the color-coded map but also had a text box listing the energy and time requirements for each route and the same information displayed on a bar graph below the map. High LOI participants had all the information as the Medium condition but also had an additional bar graph depicting projected resource requirements if they continued to select routes that used up the same amounts of time and energy as the ones presently displayed on the map. Upon completion of the simulation, participants completed the Usability and Trust Survey. During debriefing, participants were asked about which sources of information they used in the route-planning task, then the experimenter answered any questions they had, and they were dismissed.

Experiment 2

Experiment 2 followed the same procedure as Experiment 1, except a robotic entity (i.e., autonomous squad member [ASM]) was added to the dismounted team, and the resource requirements for the robot entity (Robot Battery and Robot Fuel) were displayed in addition to the SEUs and Time in the text box and bar graphs.

Therefore, in making the route-selection decision at each DP, the participants had to consider additional information related to the robot.

3. Results

Between-subjects analysis of variance were used to evaluate the effect of LOI on the dependent variables, $\alpha = .05$. Linear regression was used to evaluate predictive relationships between variables. The Chi-Square Test for Independence was used to evaluate the relationship between pretest trust, posttest trust, and LOI, $\alpha = .05$. See Table 1 for means of performance measures across LOI for both experiments.

Table 1 Means and SD for performance measures across LOI[a]

Experiment	Measure	Low LOI		Med LOI		High LOI	
1	Total decision time (s)	85.26	(32.38)	103.28	(41.49)	103.28	(32.59)
	SEU used	77.18	(5.22)	79.69	(5.19)	77.37	(5.59)
2	Total decision time (s)	91.59	(50.94)	158.36	(71.77)	183.39	(73.90)
	Soldier energy used	81.93	(6.25)	82.43	(4.68)	82.52	(3.81)
	Robot Battery used	86.32	(4.48)	84.21	(4.07)	84.71	(2.95)
	Robot Fuel used	88.73	(5.11)	85.49	(3.80)	87.64	(3.49)

[a]Values shown are means. SD in parentheses.

3.1 Experiment 1

Study Objective 1: How does LOI support operator performance?

H1: As LOI increases, operator trust as measured by posttest trust, will increase.

Pretest trust was evaluated as a potential covariate for posttest trust and a predictor of task performance. Pretest trust was a significant predictor of posttest trust, χ^2 (4, 60) = 11.41, $p = 0.022$, and Cramer's $V = 0.308$, indicating there was no effect of experiment on posttest trust. Pretest trust was not a significant predictor of total DT, $F(2, 57) = 0.52$, and $p = 0.600$ (Fig. 3).

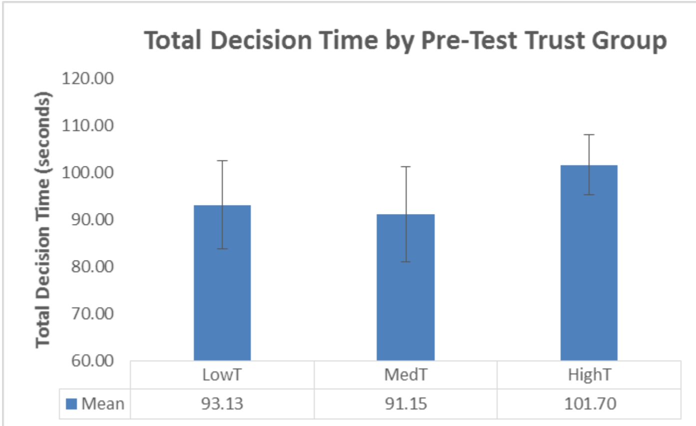

Fig. 3 Total decision time by pretest trust group membership. Bars denote standard error (SE).

DT at DP was evaluated to see if it predicted posttest trust group. Linear regression indicated that DT at DP was not a significant predictor of posttest trust for the Low or the Medium LOI conditions; however, it was a significant predictor of posttest trust for the High LOI condition (Table 2).

Table 2 Regression results for DT at DP prediction of posttest trust

Condition	R^2	Adj. R^2	SE of the estimate	*B*	SE of *B*	B	t(18)	*p*
Low LOI	0.010	–0.045	1.138	0.003	0.008	0.101	0.432	0.671
Med LOI	0.036	–0.017	0.953	–0.004	0.005	–0.191	–0.824	0.421
High LOI	0.210	0.166	0.764	–0.012	0.005	–0.458	–2.187	0.042

Examining the High LOI condition results, it appears that DT at DP predicted high postest trust scores but not medium or low posttest trust scores (Fig. 4). Examining the regression lines for all trust groups, the High posttest trust group had $R^2 = 0.618$, while Medium $R^2 = 0.044$ and Low $R^2 = 0.035$ (Fig. 4). Overall, participants who scored high on posttest trust spent less time at each successive DP than those with medium or low posttest trust scores.

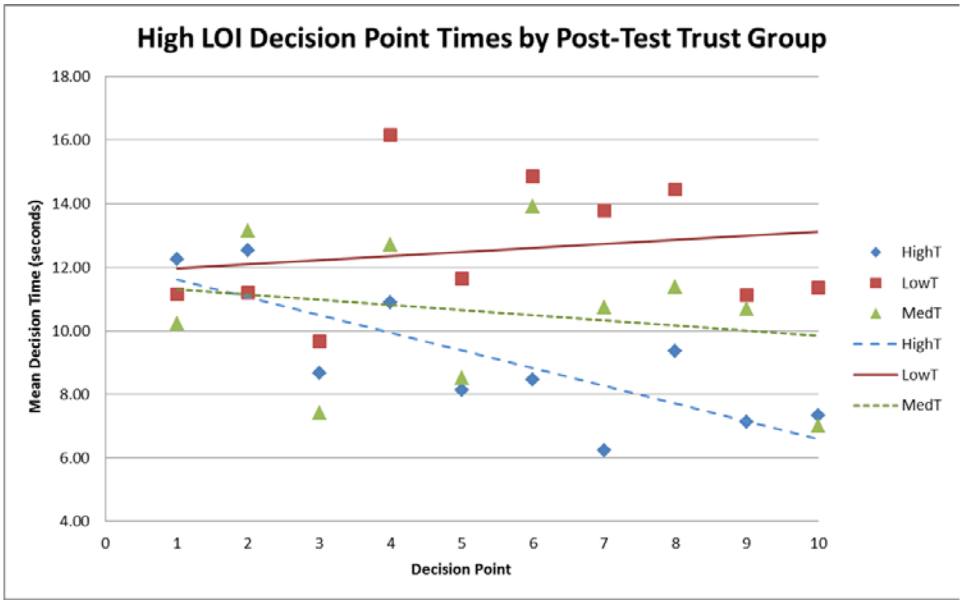

Fig. 4 **Experiment 1 shows regression results for time spent at DP predicting posttest trust group membership for the high LOI condition participants. Symbols denote mean DT at each DP for each trust group.**

H2: As LOI increases, time spent at each DP will increase.

There was a significant interaction between LOI and DP on time spent at the DPs, Wilk's $\Lambda = 0.576$, $F(18, 98) = 1.73$, $p = 0.046$, and $n_p^2 = 0.241$ (Fig. 5). Early in the simulation, DPs 1–4, participants in the Medium and High LOI conditions took longer to make a decision than those in the Low LOI condition. At DP 5, all participants took approximately the same amount of time to reach a decision. Although at DPs 6 and 7 the Low LOI participant's DTs increased slightly, their average time for DPs 6–10 continued to be lower than their Medium and High LOI counterparts, who appeared to still be developing a strategy, resulting in varied DTs.

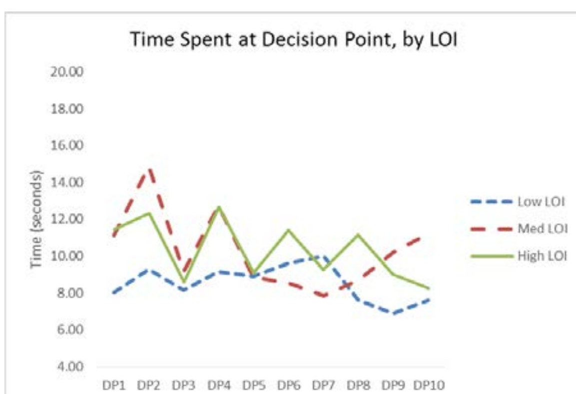

Fig. 5 **Experiment 1 showing time spent at each DP, sorted by LOI condition**

H3: As LOI increases, total DT will also increase.

There was no significant difference in total DT between the 3 LOI conditions, $F(2, 57) = 1.70$, $p = 0.193$, and $n_p^2 = 0.056$ (Fig. 6). Participants in the Low LOI condition ($M = 85.256$) spent less time overall making decisions than either the Medium LOI ($M = 103.276$, Cohen's $d = 0.484$, $p = 0.116$) or High LOI conditions ($M = 103.282$, Cohen's $d = 0.555$, and $p = 0.116$), but not significantly.

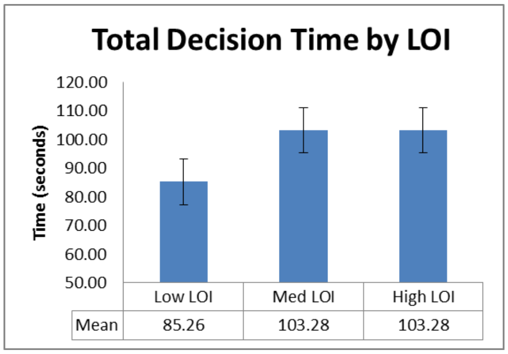

Fig. 6 Experiment 1 with total DT for each LOI condition. Bars denote SE.

H4: Soldier energy usage will decrease as LOI increases, due to the operator choosing more optimal routes when supplied more information.

All participants completed their mission with at least 5 SEUs remaining. Participants in the Medium LOI condition used more SEUs than those in either the Low or High LOI conditions, though not significantly, $F(2, 57) = 1.36$, $p = 0.264$, and $n_p^2 = 0.046$ (Fig. 7).

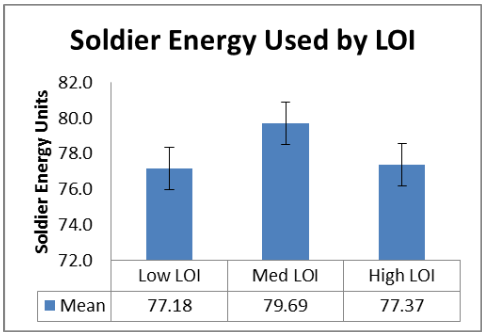

Fig. 7 Experiment 1 showing mean total SEUs used for each LOI condition. Bars denote SE.

3.2 Experiment 2

Study Objective 1: How does LOI support operator performance?

H1: As LOI increases, operator trust, as measured by posttest trust, will increase.

Pretest trust was evaluated as a potential covariate for posttest trust and a predictor of task performance. Pretest trust was a significant predictor of posttest trust, $\chi^2(4, 56) = 14.20$, $p = 0.007$, Cramer's $V = 0.344$, indicating there was no effect of experiment on posttest trust. Pretest trust was not a significant prediction of total DT, $F(2, 57) = 1.933$, and $p = 0.154$ (Fig. 8).

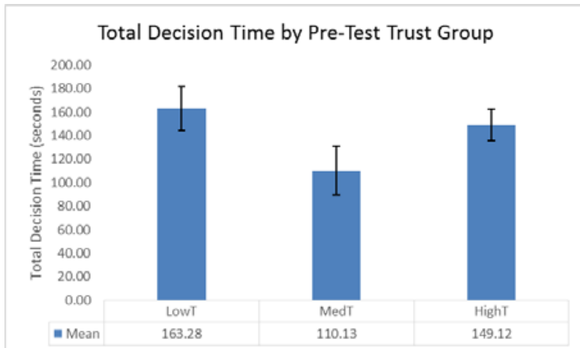

Fig. 8 **Experiment 2 shows total DT by pretest trust group membership. Bars denote SE.**

DT was evaluated to see if it predicted posttest trust group. DT per DP was not a significant predictor of posttest trust for any LOI condition (Table 3). There is no relationship between the amount of time spent at each DP and the posttest trust scores.

Table 3 **Experiment 2: regression results for time at DP prediction of posttest trust**

Condition	R^2	Adj. R^2	SE of the estimate	B	SE of B	β	t(18)	p
Low LOI	0.077	0.025	0.892	–0.005	0.004	–0.277	–0.239	0.238
Med LOI	0.029	–0.025	1.054	0.002	0.003	0.171	0.737	0.471
High LOI	0.003	–0.052	1.085	–0.001	0.003	–0.056	–0.239	0.814

H2: As LOI increases, time spent at each DP will increase.

There was not a significant interaction between LOI and DP on time spent at the DPs, Wilks' $\Lambda = 0.616$, $F(18, 98) = 1.494$, $p = 0.108$, and $n_p^2 = 0.215$. There was a significant effect of LOI on the time spent at the DPs, Wilks' $\Lambda = 0.450$, $F(9, 49) = 6.660$, $p < 0.001$, and $n_p^2 = 0.550$ (Fig. 9). Participants in the Low LOI condition had shorter and more consistent DTs across all DPs than participants in either the Medium or High LOI conditions. There was no significant difference in average DTs across DPs between the Medium and High conditions. Early in the simulation, participants in the High LOI condition had the longest time at DPs 1 and 2 and then appeared to adopt a strategy similar to those in the Medium LOI condition for the remainder of the scenario. From DP 4 to the end, Medium and High LOI participants continuously reduced their time spent at each DP, until at DP 10 their times were very similar to those in the Low LOI condition.

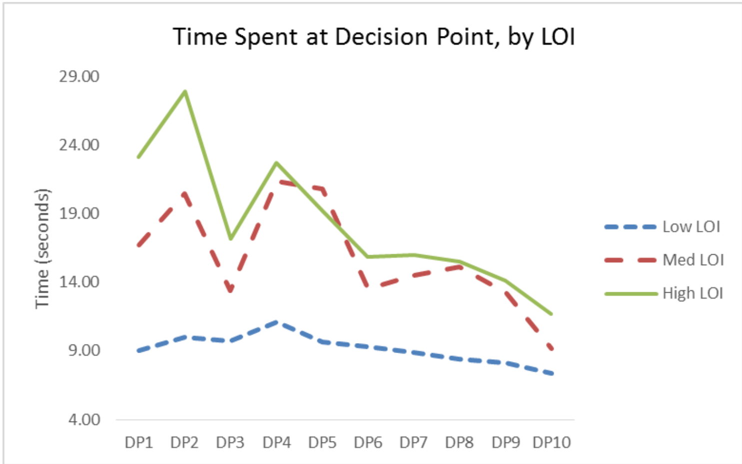

Fig. 9 Experiment 2 showing time spent at each DP for each LOI condition

H3: As LOI increases, total DT will also increase.

There was a significant difference in total DT between the 3 LOI conditions, $F(2, 57) = 10.228$, $p < 0.001$, and $n_p^2 = 0.264$ (Fig. 10). Participants in the Low LOI condition ($M = 91.595$) spent less time overall making decisions than either the Medium ($M = 158.364$, Cohen's $d = 1.073$, and $p = 0.002$) or High ($M = 183.385$, Cohen's $d = 1.446$, and $p < 0.001$) LOI participants. There was no significant difference in total DT between the Medium and High LOI conditions (Cohen's $d = 0.343$, and $p = 0.238$).

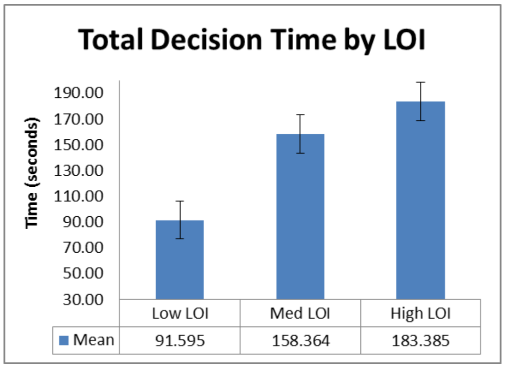

Fig. 10 Experiment 2 showing the total DT for each LOI condition. Bars denote SE.

H4: SEU usage will decrease as LOI increases, due to the operator choosing more optimal routes when supplied more information.

All participants completed their mission with at least 5 SEUs remaining. There was no significant difference in total SEU used between conditions, $F(2, 57) = 0.080$, $p = 0.924$, and $n_p^2 = 0.003$ (Fig. 11).

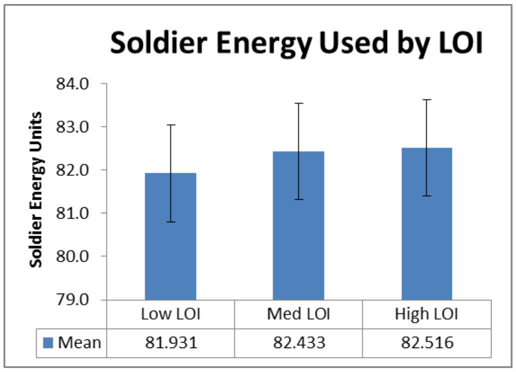

Fig. 11 Experiment 2 showing mean total SEU used for each LOI condition. Bars denote SE.

Study Objective 2: How does having additional information from robotic asset change operator performance?

H5: SEU usage will be greater in Experiment 2 than in Experiment 1, due to the higher cognitive load associated with the additional resource management duties.

There is a significant difference in total SEUs used between Experiment 1 and Experiment 2, $F(1, 118) = 20.010$, $p < 0.001$, $n_p^2 = 0.145$, and $R^2 = 0.138$ (Fig. 12). Overall, total SEU use was greater in Experiment 2 than in Experiment 1. While the actual difference between the 2 experiments is not great, both are well below the 95 SEU maximum allowed.

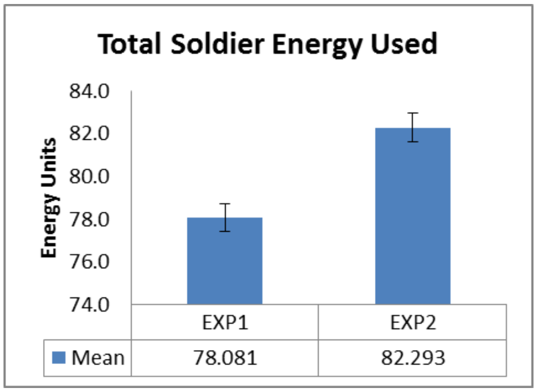

Fig. 12 Comparison of total SEUs used between Experiments 1 and 2. Bars denote SE.

H6: Robot Battery and Robot Fuel usage will decrease as LOI increases, due to the operator choosing more optimal routes when supplied with more information.

There was no significant difference in total Robot Battery used between conditions, $F(2, 57) = 1.608$, $p = 0.209$, and $n_p^2 = 0.053$ (Fig. 13). Robot Battery usage was highest in the Low LOI condition ($M = 86.315$ and SD = 4.477) than in either the Medium ($M = 84.206$, SD = 4.068, $p = 0.091$, and Cohen's $d = 0.493$) or High ($M = 84.710$, SD = 2.949, $p = 0.197$, and Cohen's $d = 0.380$) LOI conditions. However, not all participants completed their mission with at least 10 Robot Battery units remaining. Four participants in the Low LOI condition, 2 participants in the Medium LOI condition, and one participant in the High LOI condition finished their mission with less than 10 Robot Battery units. Removing these participants from the analysis had no effect on the outcome.

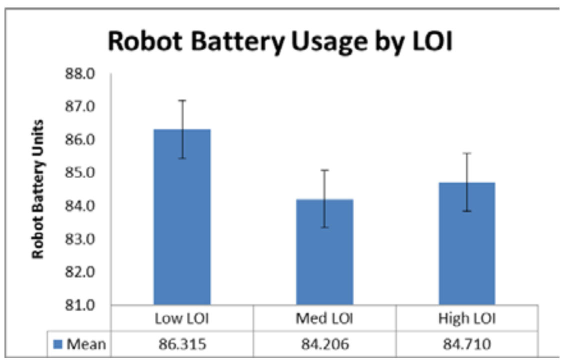

Fig. 13 Experiment 2 showing mean Robot Battery usage for each LOI condition. Bars denote SE.

There was a marginally significant difference in total Robot Fuel used between conditions, $F(2, 57) = 3.090$, $p = 0.053$, and $n_p^2 = 0.098$ (Fig. 14). Robot Fuel usage was higher in the Low LOI condition ($M = 88.725$ and SD = 5.114) than in either the Medium ($M = 85.488$, SD = 3.800, $p = 0.018$, and Cohen's $d = 0.719$) or High ($M = 87.645$, SD = 3.488, $p = 0.419$, and Cohen's $d = 0.247$) LOI conditions. Not all participants completed their mission with at least 10 Robot Fuel units remaining. Eight participants in the Low LOI condition, 3 participants in the Medium LOI condition, and 2 participants in the High LOI condition finished their mission with less than 10 Robot Fuel units. Removing these participants from the analysis had no effect on the outcome.

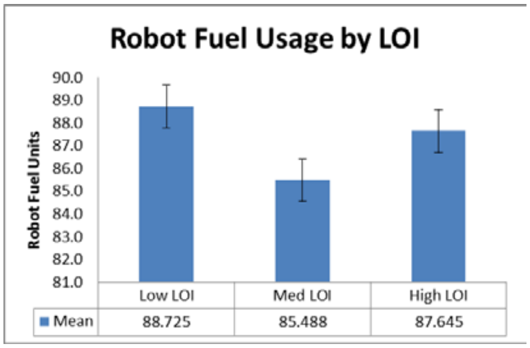

Fig. 14 Experiment 2 showing mean Robot Fuel usage for each LOI condition. Bars denote SE.

In Experiment 2, mission LOI condition and successful mission completion correlated significantly, $\chi^2(2) = 10.050$, $p = 0.002$, and Cramer's $V = 0.409$. More participants failed to complete their mission with the required minimum resources in the Low LOI condition than in either the Medium or High LOI conditions (Fig. 15).

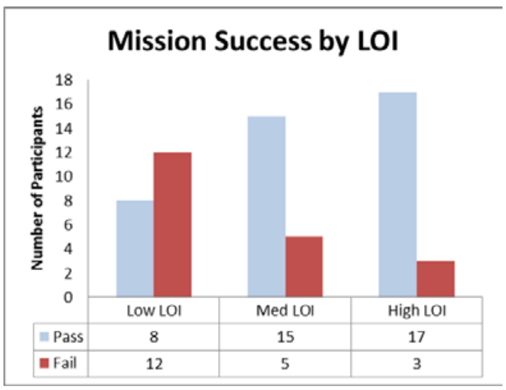

Fig. 15 Experiment 2 showing participant success/fail by LOI condition

H7: Time spent at each DP will be greater in Experiment 2 than in Experiment 1.

There is a significant difference in DT at each DP between Experiment 1 and Experiment 2 (Table 4) except for the final DP, DP 10. Time to make a decision was significantly longer in Experiment 2 than in Experiment 1. This difference was greater in the beginning of the experiment, with the difference becoming smaller at later DPs, eventually having no significant difference at DP 10 (Fig. 16).

Table 4 Comparison at each DP between Experiments 1 and 2

DP	F	Sig.	n_p^2	*Adj* R^2	Cohen's *d*
DP1	7.441	0.007	0.059	0.051	0.498
DP2	13.444	0.000	0.102	0.095	0.669
DP3	14.682	0.000	0.111	0.103	0.700
DP4	16.640	0.000	0.124	0.116	0.745
DP5	18.957	0.000	0.138	0.131	0.795
DP6	6.597	0.011	0.053	0.045	0.490
DP7	9.450	0.003	0.074	0.066	0.561
DP8	10.135	0.002	0.079	0.071	0.581
DP9	4.591	0.034	0.037	0.029	0.391
DP10	0.054	0.817	0.000	–0.008	0.042

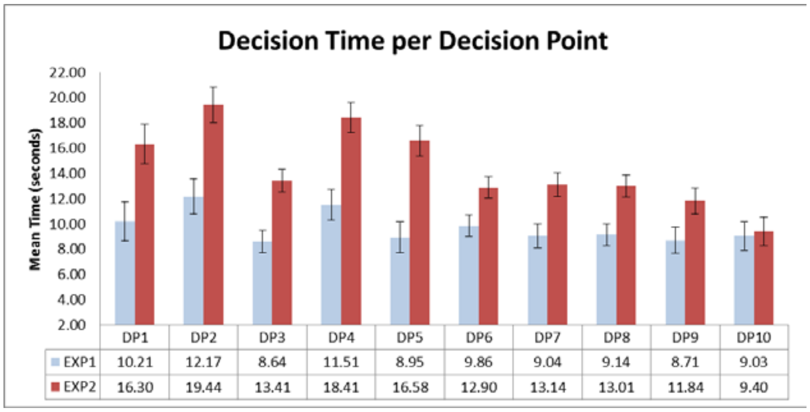

Fig. 16 Comparison of time spent at each DP between Experiments 1 and 2. Bars denote SE.

H8: Total DT will be greater in Experiment 2 than in Experiment 1.

There is a significant difference in total DT between Experiment 1 and Experiment 2, $F(1, 118) = 18.841$, $p < 0.001$, $n_p^2 = 0.138$, and $R^2 = 0.130$ (Fig. 17). Overall, time to make a decision was significantly longer in Experiment 2 than in Experiment 1.

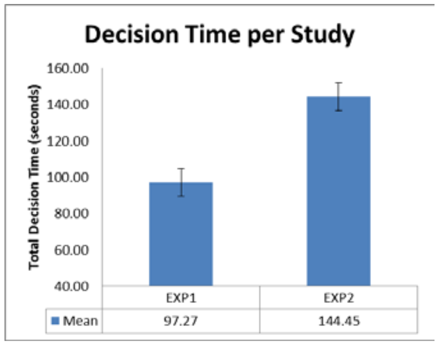

Fig. 17 Comparison of total DT between Experiments 1 and 2. Bars denote SE.

There is a significant difference in DT per LOI condition between Experiment 1 and Experiment 2 in the Medium, $F(1, 38) = 8.831$, $p = 0.005$, and $n_p^2 = 0.189$, and High, $F(1, 38) = 19.671$, $p < 0.001$, and $n_p^2 = 0.341$, LOI conditions but not in the Low LOI condition, $F(1, 38) = 0.221$, $p = 0.641$, and $n_p^2 = 0.006$ (Fig. 18). Time to make a decision increased as the LOI increased more in Experiment 2 than in Experiment 1.

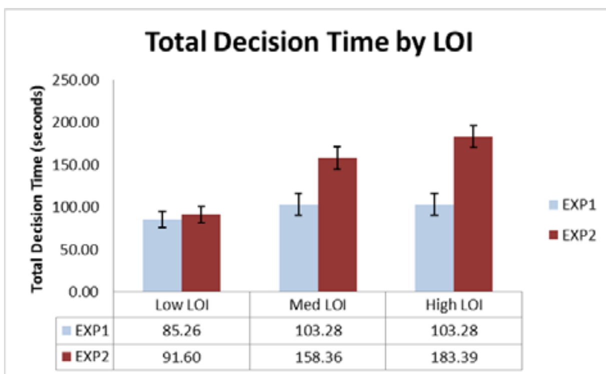

Fig. 18 Comparison of total DT between Experiments 1 and 2, sorted by LOI condition. Bars denote SE.

Study Objective 3: Across the 2 experiments, which visual elements do operators report relying upon most in their decision-making strategy?

H9: As LOI increases, operators will rely upon information sources that better support their task objectives (i.e., text box and bar graphs).

This question is aimed at understanding the information attention strategies of each of the operators and focuses on the medium and high levels of information for both Experiment 1 and Experiment 2 (Fig. 19). Examining Experiment 1, it appeared that most operators relied on the resource (bar) graphs (55% in medium and 45% in high), instead of other sources of information. However, as the LOI increased, some participants shifted back to the map route color.

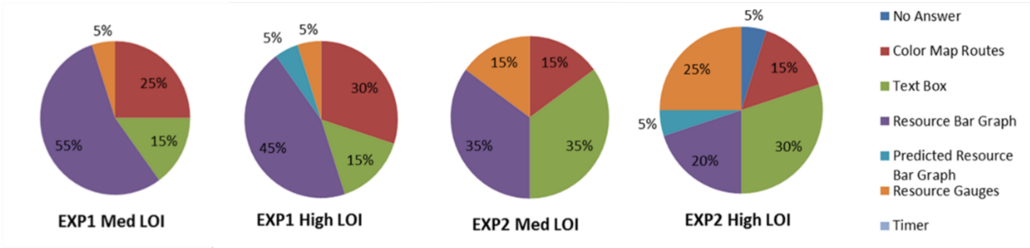

Fig. 19 Operator preferred information sources in medium and high LOI conditions for Experiments 1 and 2

The distribution of preferred information sources in Experiment 2 differed from Experiment 1. In the Medium LOI condition, the resource graph and the map information boxes were preferred and utilized equally, while the map route colors and resource gauges were used less often. In the high condition, the distribution changed once again with the increase in information; reliance on the resource graphs dropped while resource gauge usage increased.

As the LOI increases, a preferred strategy as to what source of information to use for task completion seems to disappear. In Experiment 1 Medium condition, the resource graphs were the preferred information source, with the map route colors being the second most preferred. However, in Experiment 1 High condition, fewer participants chose the resource graphs as their preferred source, with more relying upon the map route colors or the predictive information. Then considering Experiment 2 Medium condition (which is arguably the next highest LOI after Experiment 1 High condition), even fewer report the resource graphs or the map route colors as the preferred information source, instead relying upon the map info box or even the resource gauges to base their decisions. In the highest LOI condition (Experiment 2 High), there appear to be 4 equally preferred information resources, indicating that there is a limit to how much information can be clearly conveyed in each of the different methods. The majority of participants in either experiment did not consider the predicted resource usage information useful; however, this could have been a result of inadequate training as to how to utilize that particular resource.

H10: As LOI increases, operators who rely upon appropriate information sources (i.e., text box and bar graphs) will use less resources than those who rely upon unsuitable information sources (i.e., colored map routes and resources gauges).

In Experiment 1 Medium LOI, there was a significant difference in SEU usage by information source, $F(1, 18) = 5.483$, $p = 0.031$, and $n_p^2 = 0.233$. Operators who used the text box and resource bar graph had higher SEU usage ($M = 81.29$ and SD = 5.02) than those who used the colored routes or gauges ($M = 75.95$, SD = 3.59, and Cohen's $d = 1.224$). In the High LOI, operators who used the text box and resource bar graph had lower SEU usage ($M = 75.91$ and SD = 4.71) than those that used the colored routes or gauges (M = 79.56, SD = 6.38, and Cohen's d = 0.651); however, this did not reach significance, $F(1, 18) = 2.169$, $p = 0.158$, and $n_p^2 = 0.108$.

In Experiment 2 there was no significant difference in SEU usage by information source in either the Medium LOI, $F(1, 18) = 0.200$, $p = 0.660$,and $n_p^2 = 0.011$, or High LOI, $F(1, 18) = 0.011$, $p = 0.919$, and $n_p^2 = 0.001$, conditions. There was no significant difference in Robot Battery usage by information source in either the Medium LOI, $F(1, 18) = 0.485$, $p = 0.495$, and $n_p^2 = 0.026$, or High LOI, $F(1, 18) = 0.349$, $p = 0.562$, and $n_p^2= 0.019$, conditions. There was no significant difference in Robot Fuel usage by information source in either the Medium LOI, $F(1, 18) = 0.019$, $p = 0.891$, $n_p^2 = 0.001$, or High LOI, $F(1, 18) = 0.026$, $p = 0.875$, and $n_p^2 = 0.001$, conditions.

One-third of the participants in Experiment 2 failed to complete their mission successfully (i.e., with at least 10 Robot Battery and 10 Robot Fuel remaining). There was a significant difference in information source preference between participants who successfully completed their mission and those who did not, $X^2 (5, N = 60) = 12.56$, $p = 0.028$, and Cramer's $V = 0.458$. Often participants who failed to meet mission objectives relied upon information sources that were not suitable for their task (Fig. 20). The addition of projected information appeared to impact their performance disproportionately, as evidenced by their total DT in the High LOI condition (Fig. 21).

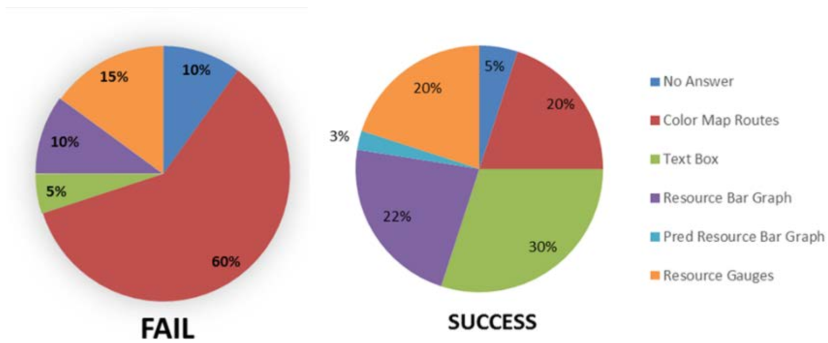

Fig. 20 Comparison of operator preferred information source between participants who failed to meet mission objectives in Experiment 2 and those who were successful

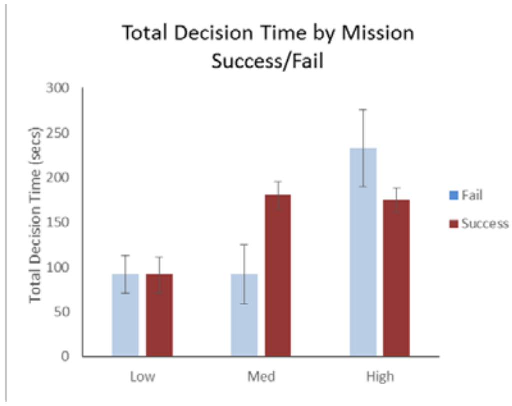

Fig. 21 Total DT for Experiment 2, sorted by success/fail and LOI condition. Participants who failed to meet mission objectives had equal or shorter decision times in Low and Medium LOIs, but the inclusion of the predictive information in high LOI resulted in total DT greater than those who succeeded.

4. Discussion

The goals of this study were to determine whether and how differing LOIs of a route-planning agent impacted a human operator's decision making on a route-selection task, whether the addition of a robotic asset reduced performance, and whether LOI affected human trust of the agent. In all experimental conditions, the task was to make a tradeoff decision among 3 route options, each with unique constraints. The LOI varied across experimental conditions, with each participant exposed to only one LOI.

In both experiments, participant's pretest trust scores were correlated with their posttest trust scores but were not predictive of DTs. For the most part, DTs did not predict posttest trust scores, except in Experiment 1 High LOI where DTs at each DP were predictive of high posttest trust scores. Participants in this group steadily decreased the time spent at each DP (Fig. 4), indicating that those who continuously learned and adapted their strategy for handling the large amount of information ultimately trusted their decisions and the information they received more than those who did not. This same pattern was not evident in Experiment 2 High LOI group, which may be an indication that there can be so much information that the participant cannot make sense of what information is important and what is not (Westerbeek and Maes 2013).

Participants in the Low LOI condition had shorter DTs than those in Medium or High LOI conditions, and DTs in the Low LOI were similar in both experiments. An effect of LOI on DTs becomes apparent in the Medium and High LOI conditions, particularly for DPs 1–5. In Experiment 1, DTs for DPs 1–5 were similar between Medium and High conditions; however, for DPs 6–10, DTs varied widely between the 2 conditions. Participants in the High and Medium conditions seemed to find a point where they felt confident in their ability to complete their mission successfully, after which they appeared to explore alternate strategies, resulting in varied DTs at each DP for the remainder of the experiment. This trend suggests that without constraints to influence their decisions, participants will vary their strategy based on other means besides direct experience (Gigerenzer and Gaissmaier 2011).

Experiment 2 provided these additional constraints by adding a robotic asset. Participants in the High LOI condition started with the longest DTs at DPs 1 and 2, most likely due to the additional information presented in the predictive resource usage graphic. They seem to have decided to disregard this additional information as part of their strategy development, as illustrated by their DTs being similar to those in the Medium condition from DP 3 onward. After DP 4, DTs for Medium and High LOI conditions become consistently shorter, evidence of strategy development and practice, with their times finally approaching DTs similar to those of the Low LOI condition in DP 10. This trend appears to be an indication of sensemaking in progress; operators are modifying their mental model of the agent as they gain understanding as to how to successfully complete their mission (Klein et al. 2006). Comparing DTs across the 2 experiments, participants in Experiment 2 took significantly longer than those in Experiment 1, in both terms of total DT and individual DT, and this difference becomes more pronounced as the LOI increases (Fig. 16). This increased time supports the concept that without clear indication of essential information, users have greater difficulty when trying to build understanding (Westerbeek and Maes 2013). Lorenz et al. (2013) noted that in more complex displays, screen elements (in our case maps, graphs, and gauges) might overload the operator, causing an inability to meet appropriate performance goals. However, the data indicate that most participants in the Medium and High LOI conditions had better resource management than their Low LOI counterparts, even though they took more time at each DP, suggesting that taking more time may not necessarily mean an “overload” of information.

All participants in both experiments successfully met their performance goal of completing the task with at least 5 SEUs remaining; however, 20 participants in Experiment 2 failed to meet the robotic asset goals of completing the mission with at least 10 Robot Battery units and 10 Robot Fuel units remaining. The majority of participants (N = 12) who failed to meet mission objectives were in the Low LOI condition, indicating that there is a minimum amount of information, or a preferred information presentation, required to successfully balance multiple resources. Overall, participants in the Medium and High LOI conditions managed the robotic assets more effectively than those in the Low LOI condition, demonstrating the importance of access to appropriate information for the task.

Even though the Soldier movement goal, “complete with at least 5 Soldier Energy Units,” was more difficult to achieve than the robotic asset goals, all participants successfully achieved this goal. Even though no specific instructions were provided that ranked the goals in order of importance, all participants seemed to have independently ranked this goal as more important to achieve than the others. Reviewing the average SEU used in both Experiments 1 and 2, regardless of condition, SEU used never approach the maximum 95 allowed, instead averaging about 80 SEUs across both experiments. Access to higher LOI did not have a significant impact on SEU, indicating this resource usage was not a result of LOI or information presentation. Prioritizing this goal, even when evident that the SEU goal would be achieved with room to spare, may have contributed to failure on the other goals. This finding could have important ramifications for designing effective human-agent teams, as operators favoring human-based goals at the expense of agent-based goals, even when there is no danger of failure on the human-based goals, could ultimately lead to mission failure.

As the LOI increased, a preferred strategy as to what source of information to use for task completion seemed to disappear. In Experiment1 Medium LOI condition, participants had a clear preference for using resource graphs as a primary source of information, but as the LOI increased to High, and then increased again in Experiment 2, this preferred strategy disappeared, until finally in Experiment 2 High LOI we see no clearly preferred resource but rather 4 equally used sources. Again, without clear understanding as to which information is the most useful, participants found it more difficult to build understanding and thus one clear strategy never emerged (Westerbeek and Maes 2013). This finding supports the idea that it is important to keep information presentation as clear and simple as possible (Parsons et al. 1999).

Although this research had findings for LOI and decision-making, the research also had some limitations:

- Inclusion of workload measurements may have assisted in understanding when or if the user was struggling with too much information to consider while making decisions.
- Inclusion of individual difference factors may have shed light on differential effects of performance and information visualization methods that would help in the design of more universally useful interfaces.

5. Conclusion

In the current study, we investigated whether differing LOIs in a route-planning agent affected an operator's decision making on the route-selection task, the impact of adding robotic resources to the team, and the impact of trust on operator performance through 2 experiments. Overall, increasing LOI increased DT for participants and decreased the likelihood of failure to complete the mission within predefined parameters; however, differential effects of sensemaking, DT, and reported trust are apparent. Participants in Medium and High LOIs in both experiments continued to improve DTs throughout the scenario, as they appeared to revise and adapt their strategy, improving to the point of having nearly the same DT as the Low LOI participants at DP 10 in Experiment 2. This learning effect was more apparent in Experiment 2, where the additional resource management requirements appeared to have imposed constraints that helped the participants focus. Participants in Experiment 1 High LOI who demonstrated continued learning throughout the scenario reported higher trust in the system than those who adopted a strategy early and did not alter it. Thus, DT on the route-planning task depended not only on the amount of information an individual had to consider, but how effective they were at learning and adapting as well (Klein et al. 2006).

All participants successfully met their performance goal of completing their mission with at least 5 SEUs remaining. However, 20 participants in Experiment 2 failed to meet the robotic asset goals of completing their mission with at least 10 Robot Battery and 10 Robot Fuel remaining. The majority of participants (N = 12) who failed to meet mission objectives were in the Low LOI condition, which indicates there is either a minimum amount of information or an optimal information presentation required to balance multiple resources successfully. Overall, participants in the Medium and High LOI conditions managed the robotic assets more effectively than those in the Low LOI condition, demonstrating the importance of access to appropriate information for the task. Even though no specific instructions were provided that ranked the mission objectives in order of importance, participants seemed to have independently ranked the human-centric goal of completing with at least 5 remaining SEUs as more important to achieve than the robot-centric goal. Prioritizing the human-centric SEU goal over the robot-centric goal, even when it is evident that the SEU goal would be achieved with room to spare, may have contributed to the failure on the robot-centric goals. This finding could have important ramifications for designing effective human-agent teams, as operators favoring human-centric goals at the expense of agent-centric goals, even when there is no danger of failure on the human-centric goals, could ultimately lead to mission failure.

Examining reported information resource preferences in Experiment 1, as information increased, strategies changed slightly but overall remained similar; however, as the amount of information continued to increase in Experiment 2, preferences began to differ as each participant struggled to meet their objectives. In Experiment 1 there was a clear preference for using the bar graphs to make route decisions over route color-coding and text information, which agrees with matching information and usage to appropriate presentation (Vessey 1991). In Experiment 1, when the LOI increased from Medium to High, some participants returned to the baseline condition (route color-coding). As LOI continued to increase (Experiment 2 Medium LOI), more participants abandoned the bar graphs for other information presentations, and in the highest LOI (Experiment 2 High), there is no longer one preferred information source, instead splitting into 4 (roughly) equally preferred sources. Interestingly, as the information increased, usage of graphs was reduced in favor of simpler displays, such as gauges and text boxes. As the amount of information increases, participants struggled to make sense of what was important, reverting to simpler methods, and illustrating the importance of defining essential information in complex displays (Westerbeek and Maes 2013).

Future research could focus on presentation of information and how to properly display robotic asset constraints/resources and conveying that to an operator. This line of research would require a clear definition of essential information, with the capability to adapt given changing goals and priorities. We are currently in the process of developing multiple studies on the conveyance of information in human-agent teams, which should assist in further defining the problem space. The key contribution of this work demonstrates that there is a limit on information processing for human-agent teams and that LOI can both positively and negatively impact completion of mission goals.

6. References

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Appendix A. Demographic Questionnaire

This appendix appears in its original form, without editorial change.

Participant # _______ Age _____ Major ______________ Date ___________ Gender ___

1. What is the <u>highest</u> level of education you have had?
Less than 4 yrs of college ____ Completed 4 yrs of college ____ Other ____

2. When did you use computers in your education? (*<u>Circle all that apply</u>*)
Grade School Jr. High High School Technical School College Did Not Use

3. Where do you currently use a computer? (*<u>Circle all that apply</u>*)
Home Work Library Other________ Do Not Use

4. For each of the following questions, <u>circle</u> the response that best describes you.

How often do you:

Use a mouse?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use a joystick?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use a touch screen?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use icon-based programs/software?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use programs/software with pull-down menus?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use graphics/drawing features in software packages?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use E-mail?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Operate a radio controlled vehicle (car, boat, or plane)?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Play computer/video games?	Daily, Weekly, Monthly, Once every few months, Rarely, Never

5. Which type(s) of computer/video games do you most often play if you play at least once every few months?

6. Which of the following best describes your expertise with computer? (check √ one)
   _____ Novice
   _____ Good with one type of software package (such as word processing or slides)
   _____ Good with several software packages
   _____ Can program in one language and use several software packages
   _____ Can program in several languages and use several software packages

7. Are you in your good/ comfortable state of health physically? YES NO
   If NO, please briefly explain:

8. How many hours of sleep did you get last night? ______ hours

9. Do you have normal color vision? YES NO

10. Do you have military service? YES NO If Yes, how long __________

Appendix B. Pretest Trust Survey

This appendix appears in its original form, without editorial change.

Automation Survey

Automation refers to a system that reduces the need for human work. According to Lee and See (2004), “Automation is technology that actively selects data, transforms information, makes decisions, or controls processes.” Below is a statement evaluating your feelings about automation. Please circle the number that best describes your feeling or impression.

1 = not at all; 7 = extremely

1. Automation is deceptive.
1 2 3 4 5 6 7

2. Automation systems behave in an underhanded manner.
1 2 3 4 5 6 7

3. I am suspicious of the intent, action, or outputs of automation.
1 2 3 4 5 6 7

4. I am wary of automation.
1 2 3 4 5 6 7

5. The actions of automated systems will have harmful or injurious outcomes.
1 2 3 4 5 6 7

6. I am confident in automation.
1 2 3 4 5 6 7

7. Automated systems provide security.
1 2 3 4 5 6 7

8. Automated systems have integrity.
1 2 3 4 5 6 7

9. Automated systems are dependable.
1 2 3 4 5 6 7

9. Automated systems are reliable.
1 2 3 4 5 6 7

10. I can trust automated systems.
1 2 3 4 5 6 7

The Trust Survey is based on the questionnaire of Human-Computer Trust from Jian et al. (1998)

Appendix C. Posttest Trust Survey

This appendix appears in its original form, without editorial change.

1. **The Route Planning Agent is deceptive.**
   Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
   1 2 3 4 5 6 7
2. **The Route Planning Agent behaves in an underhanded manner.**
   Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
   1 2 3 4 5 6 7
3. **I am suspicious of the Route Planning Agent's intent, action or outputs.**
   Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
   1 2 3 4 5 6 7
4. **I am wary of the Route Planning Agent.**
   Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
   1 2 3 4 5 6 7
5. **The Route Planning Agent's actions will have a harmful or injurious**
   Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
   1 2 3 4 5 6 7
   outcome.
6. **I am confident in the Route Planning Agent.**
   Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
   1 2 3 4 5 6 7
7. **The Route Planning Agent provides security.**
   Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
   1 2 3 4 5 6 7
8. **The Route Planning Agent has integrity.**
   Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
   1 2 3 4 5 6 7
9. **The Route Planning Agent is dependable.**
   Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
   1 2 3 4 5 6 7
10. **The Route Planning Agent is reliable.**
    Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
    1 2 3 4 5 6 7
11. **I can trust the Route Planning Agent.**
    Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
    1 2 3 4 5 6 7
12. **I am familiar with the Route Planning Agent.**
    Strongly DISAGREE |----|----|----|----|----|----| Strongly AGREE N/A
    1 2 3 4 5 6 7

List of Symbols, Abbreviations, and Acronyms

ASM	autonomous squad member
DP	decision point
DT	decision time
LOI	level of information
RAM	random-access memory
SE	standard error
SEU	Soldier Energy Unit

1 (PDF)	DEFENSE TECHNICAL INFORMATION CTR DTIC OCA
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