Effects of Agent Transparency on Human-Autonomy Teaming Effectiveness

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***Abstract*—Two human factors studies were conducted to assess the effectiveness of intelligent agents' user interfaces that were designed based on the Situation awareness-based Agent Transparency (SAT) model. Results show that agents' transparency (based on the SAT model) can benefit operator performance and support proper calibration of trust in the agents. Increasing levels of transparency enhanced operator's perceived trust in the agents, but only to a degree. When uncertainty was added to the interface, operator's trust did not further increase. Finally, the subjective workload data suggest that the benefits of increasing agent transparency do not have to be associated with higher levels of operator workload.**

Keywords - agent transparency; human-autonomy teaming; human-robot interaction; mixed-initiative; situation awareness; unmanned vehicles; military

I. Introduction

As intelligent agents (IAs) become more sophisticated, it is crucial to develop user interfaces (UI) that make the IA's intent, reasoning and predicted future states transparent to the human operator [1]-[6]. For example, Zhou et al. [6] showed that by revealing the internal states (i.e., real-time processes) of a machine learning-based IA, the system was perceived as more understandable rather than just a black box. Indeed, Lee and See [7] stressed the importance of conveying the IA's purpose, process, and performance (3 Ps) to the operator as a means to calibrate appropriate trust.

A. *Agent Transparency*

Chen et al. [1] leveraged Endsley's model of situation awareness (SA) [8][9] and developed the Situation awareness-based Agent Transparency (SAT) model, which mirrors the three levels (perception, comprehension, and projection) of Endsley's model (Figure 1). At the first SAT level (L1), the operator is provided with the basic information about the agent's current state and goals, intentions, and proposed actions (*perception* of the environment from the agent's perspective). At the second level (L2), the operator is provided with information about the agent's reasoning process behind those actions and the constraints/affordances that the agent considers when planning those actions (*comprehension*). At the third level (L3), the operator is provided with information regarding the agent's projection of future states, predicted consequences, likelihood of success/failure, and any uncertainty associated with the aforementioned projections (*projection*). Understanding the effects of uncertainty on the third level of SAT was considered of particular importance, because projection is predicated on many factors whose outcomes are never known precisely [1][2][10]-[12]. Prior research has shown that agents conveying uncertainty can improve the joint human-agent team performance and are also perceived as more trustworthy [2][13][14].

Situation awareness-based Agent Transparency

Level 1: *Agent's current status/actions/plans*
- Purpose: Desire (Goal selection)
- Process: Intentions (Planning/Execution); Progress
- Performance

Level 2: *Agent's reasoning process*
- Reasoning process (Belief/Purpose)
- Environmental & other constraints/affordances

Level 3: *Agent's projections/predictions; uncertainty*
- Projection of future outcomes
- Uncertainty and potential limitations; Likelihood of success/failure
- History of Performance

Figure 1. Situation awareness-based Agent Transparency (SAT) model.

B. *Implications for Machine Learning-Based Systems*

A recent keynote speech at the 2016 Intelligent User Interfaces Conference by Dr. Xavier Amatriain of Quora, who developed the recommender system for Netflix, highlighted the importance of system transparency to human-system interaction effectiveness [15]. Indeed, one of the top lessons offered by Dr. Amatriain based on his R&D efforts on machine learning (ML)-based systems was that system explanations to the users were often more effective than tweaking the algorithms. As systems become more intelligent and are capable of complex decision making, it becomes increasingly important for the human to understand the reasoning process behind the system's output in order to provide input when necessary. Transparency for a ML-based system poses a challenge, as explanations may not be easily generated; however, without proper transparency—at least high-level explanations—it may be difficult for the human to provide input (based on information that only the human has) to the system. Furthermore, predictability may be an issue for ML systems as they continue to evolve. Without proper transparency, the human may find it difficult to calibrate his/her trust in the system.

Current autonomy research programs, such as the U.S. DoD Autonomy Research Pilot Initiative (ARPI), have started to investigate some of the key human-agent teaming issues that have to be addressed in order for mixed-initiative teams to perform effectively in the real world, with all its complexities and unanticipated dynamics (DoD R&E Enterprise [16][17]). The current paper reviews major findings of two studies that systematically investigated the effects of levels of agent transparency on the effectiveness of human-agent teaming in various military human-agent interaction contexts. The first study, Autonomous Squad Member, deals with human interaction with a simulated robotic partner in a dismounted environment. The second study, IMPACT, describes human interaction with an intelligent agent to manage a team of heterogeneous robots. The user interfaces employed in the experiments were based on the SAT model; key findings from each study are summarized to illustrate the utility of agent transparency for effectiveness of human-agent team performance. Implications of current findings to ML-based systems will also be discussed. At SMC 2015, we presented results from the first year of the projects. In this paper, we will focus on major findings from the second year of both studies.

II. AUTONOMOUS SQUAD MEMBER

The objective of the Autonomous Squad Member (ASM) project is to investigate the effects of presenting information to support agent transparency in the user interface (UI) for an advanced autonomous robotic partner. The ASM provides information to support the operator's understanding of its current status/environment, the reasoning behind its decisions, and projections of future states including uncertainty information. The ASM agent uses a Goal Reasoning architecture [18] to direct its behavior, supporting its ability to act autonomously. The architecture is composed of several key artificial intelligence and machine learning capabilities including: automated planning (i.e., selecting actions for the robot to perform), explanation (i.e., inferring the causes of changes in the environment), plan recognition (i.e., determining the high level plans of teammates), and goal selection (i.e., dynamically changing its goals when necessary). Goal Reasoning-enabled autonomy increases the importance of agent transparency, which can support the human operator's understanding of the ASM's reasoning process and proper trust calibration [19]. The current study investigated the effects of agent transparency (based on the SAT model) on human operator's situation awareness of the agent, trust in the agent, and perceived workload. Specifically, we probed the operators on their SA of the ASM (in terms of their perception of ASM's current actions and plans, their comprehension of the reasoning behind these actions and plans, and their projections of future outcomes) in order to evaluate the effects of SAT level information provided to the participants.

A. Methodology

The study used a within-subjects design with level of agent transparency as the independent variable. There were four levels of agent transparency and the presentation order of these levels was counterbalanced. Level 1 included information about the ASM's current goal, location, environment, resources, and its human teammates' current goal. Level 1+2 included ASM's reasoning behind its current action, in addition to the Level 1 information. Level 1+2+3 presented Level 1+2 information, as well as information regarding the ASM's projected resource usage and time to reach its destination. Finally, Level 1+2+3+U included all information from the previous levels of information and added information regarding the ASM's uncertainty of its projection and environment (Figure 2).

Figure 2. ASM experimental user interface.

Sixty individuals, recruited from the general population, participated in this experiment. The average age of participants was 21 years (*sd* = 3.1). Prior to the experiment, the participants participated in an interactive training session to aid them in interpreting the information displayed on the ASM UI and their monitoring task. During the experiment, participants monitored the ASM and its accompanying human teammates as they completed four different routes in a virtual environment. During each route, the ASM displayed one of the four conditions of Agent Transparency. Along the route, the ASM and squad encountered obstacles, such as an IED or an ambush. The participant was instructed to monitor the information presented to them by the ASM. At random points in the experiment, the participant periodically answered questions assessing their SA of the information presented to them by the ASM. The SAGAT SA assessment method was used. During SA queries, the ASM UI was not visible and the participant had to rely on their SA to answer the questions correctly. SA questions included Level 1 queries concerning the ASM's actions, the squad's status, and the environment; Level 2 queries regarding the ASM's reasoning behind its actions; and Level 3 queries on projections of the ASM's resource usage. After monitoring the ASM and squad complete each route, the participant rated their trust in the ASM during that route [20] and their own perceived workload using the Trust in Automated Systems scale [20] and NASA-TLX respectively [21]. An example query from the Trust in Automated Systems scale is: "The system is deceptive" and the participant rates the system on a scale from 1-7(1 indicating 'not at all' and 7 indicating 'extremely'). Overall, monitoring the four ASM UI conditions and answering the queries (SA, trust, and workload) was completed in 80 minutes.

B. Results

Operator's SA of ASM. A repeated-measures ANOVA revealed that, for operators' Level 3 SA (*Projections* of future outcomes related to ASM), there was a main effect of Transparency display condition, $F(3,165) = 3.87$, $p < .05$, $\eta^2 = .07$ (Figure 3). Pairwise comparisons tests showed that operators were better able to make predictions of the future state of the ASM in the Level 1+2+3 condition than in the Level 1 and Level 1+2 conditions p*'s* $< .05$. For Level 2 SA (*Comprehension* of ASM's reasoning), there was a main effect of Transparency, $F(3,165) = 3.98$, $p < .01$, $\eta^2 = .07$. Pairwise comparisons tests showed that operators had a higher level of comprehension of the reasoning of the ASMs' actions in the Level 1+2+3 condition than in the Level 1+2 conditions, $p < .05$. There were no significant differences in Level 1 SA performance in any UI condition. These results suggest that the SAT-based UI with Level 1+2+3 information benefited the operator's predictions about the future state of the ASM (Level 3 SA) and reasoning (Level 2 SA). However, the additional uncertainty information available on the Level 1+2+3+U UI did not further benefit the operator's performance.

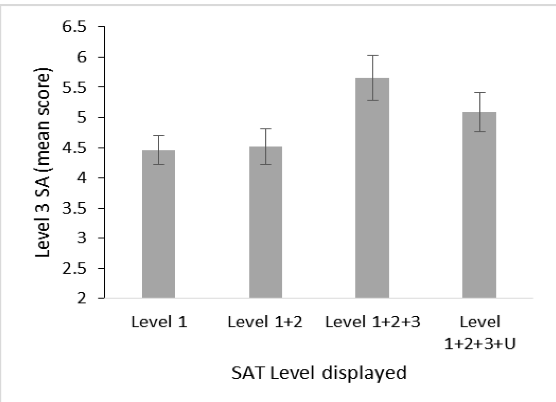

Figure 3. Operator's Level 3 SA of the ASM

Operator's Perceived Workload. There were no significant differences between transparency conditions on perceived workload. This finding suggests that including more information to support agent transparency can yield an increase in trust and SA without affecting workload.

Operator's Perceived Trust in ASM. Operators had the greatest subjective trust in the ASM in when it presented Level 1+2+3 information, $F(3, 165) = 5.87$, $p < .01$, $\eta^2 = .1$. Operators reported significantly greater subjective trust in the Level 1+2+3 condition than in the Level 1 and Level 1+2 conditions. While there was a slight decline in subjective trust between Level 1+2+3 and Level 1+2+3+U, this difference was not significant (Figure 4).

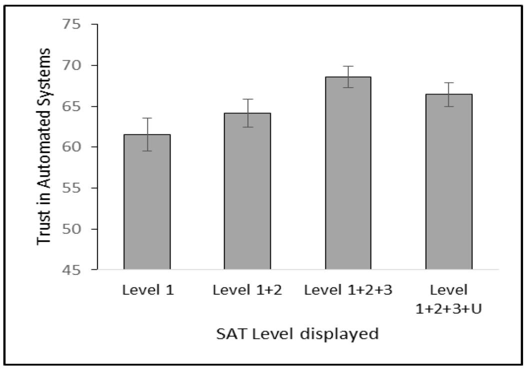

Figure 4. Trust in Automated Systems scores.

III. IMPACT

Successful operational employment of autonomous systems requires command and control agility. Indeed, agility in tactical decision-making, mission management, and control is one of the key attributes for enabling heterogeneous unmanned vehicle (UxV) teams to successfully manage the 'fog of war' with its inherent complex, ambiguous, and time-challenged conditions. Mission effectiveness relies on rapid identification and management of uncertainties that can disrupt an autonomous team's ability to complete complex operations. Increasingly, research and development efforts are focusing on developing intelligent agents (IAs) that can work with human operators on managing the UxV teams [19][22]. One of those efforts is the Intelligent Multi-UxV Planner with Adaptive Collaborative/Control Technologies (IMPACT) project, which is currently funded by the ARPI. IMPACT is investigating issues associated with flexible play-calling [23][24], global cooperative control and local adaptive/reactive capability, and bi-directional human-autonomy interaction in military mission contexts [17]. However, in order for the IA to collaborate with human operators, the IA must be able to communicate its current and future states and receive commands to alter them when necessary [19]. Furthermore, knowledge of the IA's state of uncertainty has proven to be a crucial factor in the ability of humans to interact with automated systems [1][2][10]-[12][25]. In particular, it is important for operators to understand not only the locus of the uncertainty, but also to understand its source [26].

A. Methodology

This experiment utilized a within-subjects design with agent transparency as the independent variable. A previous study using the same UI from IMPACT tested the utility of Level 1 transparency and found that it was most useful when combined with higher levels of transparency [2]. Thus, unlike the Autonomous Squad Member study (above), transparency was only tested at three higher levels: (a) Level 1+2: containing reasoning information, (b) Level 1+2+3: containing reasoning and projection information *without* uncertainty, and (c) Level 1+2+3+U containing reasoning and projection *with* uncertainty. The UI varied per condition by showing corresponding pieces of SAT-level information on the map, in text, and on a sliding bar scale (Figure 5). Fifty-three students from an American university were recruited for this experiment. The average age of participants was 21.7 years (*sd* = 3.6). Prior to beginning the experiment, participants completed several individual difference surveys, including an Implicit Association Test (IAT) to track any bias they may have against technology. They then received about 1 hour of training. The subsequent experiment was divided into 3 blocks of 8 missions, with conditions counter-balanced. Using the interface presented in Figure 5, participants were presented with two plans to complete each mission, and were instructed to choose just one of them to move forward. For each set of plans, the agent always recommended one plan over the other, but the human always made the final decision. Reliability of the agent was held constant such that it was right in 5 out of every 8 scenarios. Information regarding mission objectives and commander's instructions were given before each set of decision options were presented, while information regarding specific mission parameters and vehicle capabilities were given on the decision screen (Figure 5). Each experimental block (including corresponding surveys) took participants about 30 minutes to complete.

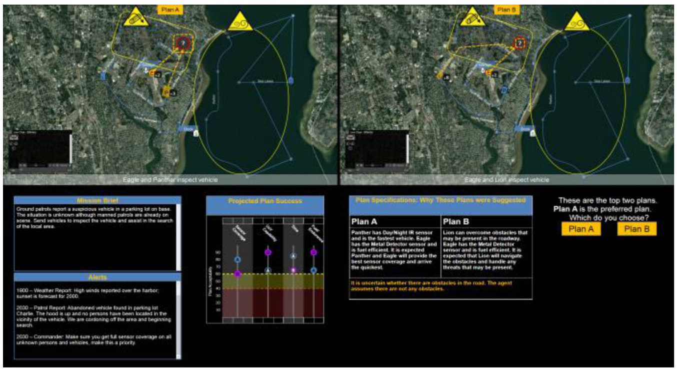

Figure 5. Transparency displays showing the advantages and disadvantages of the two experimental options from the IA's perspective (A or B). This display represents the L1+2+3+U condition.

After each block, participants completed surveys, including a measure of workload on an interval scale from 1 (low) to 10 (high) (NASA-TLX [20]), and a trust survey using a 7-point Likert scale (modified Trust in Automated Systems survey with two subscales [21][27]). Performance was measured throughout by tracking total correct responses, "proper use" (instances when the human agreed with the IA and answered correctly) and "correct rejections" (instances when the human disagreed with the IA and answered correctly). This performance measure was adapted from signal detection theory [28], but signal detection analyses were not completed.

B. Results

Operator Performance - Total Correct Response. A repeated-measures ANOVA showed significance, indicating an increase in operator performance (Total Correct Response, which combines Proper Use and Correct Rejections, see Figure 6) with transparency level, $F(2, 104) = 10.31$, $p < .001$, $\eta_p^2 = .17$. Pairwise comparisons showed a significant difference between Level 1+2 and Level 1+2+3 ($p < .05$), as well as between Level 1+2 and Level 1+2+3+U ($p < .001$). Total correct responses were highest in the Level 1+2+3+U SAT condition and lowest in the Level 1+2 SAT condition.

Operator Performance - Proper Use and Correct Rejections. To examine exactly what areas of performance were most impacted, a repeated-measures MANOVA of proper use and correct rejections was performed. A significant multivariate effect indicated an increase in performance with transparency across both sub-measures: $F(4, 206) = 6.05$, $p < .001$, $\eta_p^2 = .11$, *Wilk's* $\lambda = .8$. A univariate effect was found for proper use, $F(2, 104) = 10.66$, $p < .001$, $\eta_p^2 = .17$. Pairwise comparisons with Bonferroni correction indicated a significant difference between Level 1+2 and Level 1+2+3 ($p < .01$), as well as between Level 1+2 and Level 1+2+3+U ($p < .001$). As can be seen in Figure 6, both proper use and correction rejections were highest in the Level 1+2+3+U condition.

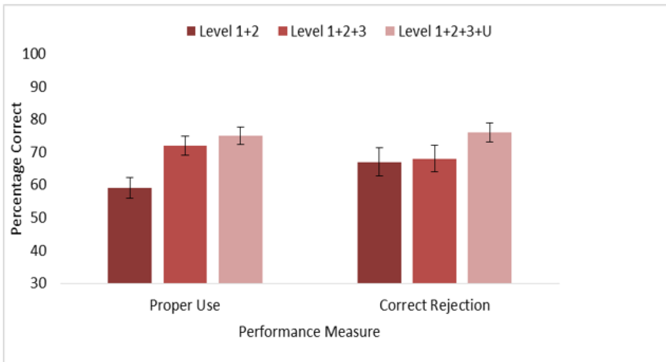

Figure 6. Percentage correct for both IA proper use and IA correct rejection rates for all three transparency levels.

Operator's Perceived Workload. In order to examine operator workload, we conducted a repeated-measures ANOVA on the total NASA-TLX scores, as well as a repeated measures MANOVA on the 6 unweighted subscales of the NASA-TLX. The effect of total workload was not significant, $F(2, 104) = .86$, $p = 43$, $\eta_p^2 = .02$. The effect of the subscales was also not significant, $F(12, 198) = .87$, $p = .58$, $\eta_p^2 = .05$, *Wilk's* $\lambda = .9$.

Operator's Perceived Trust in the IA. Individual differences in IAT scores were covaried with participant trust scores in order to account for pre-existing biases that may affect trust. Trust was thus examined using a repeated-measures MANCOVA across the two subscales of our modified trust survey. A significant multivariate effect was found, $F(4, 202) = 2.61$, $p < .05$, $\eta_p^2 = .05$, *Wilk's* $\lambda = .9$. Additionally, significant main effects of both subscales were found: (a) for integrating and diplaying information – $F(2, 102) = 3.48$, $p < .05$, $\eta_p^2 = .06$, and (b) for suggested decisions – $F(2, 102) = 4.08$, $p < .05$, $\eta_p^2 = .07$. Pairwise comparisons with Bonferroni correction indicated a significant difference between Level 1+2 and Level 1+2+3 in *suggesting decisions* ($p < .05$; Figure 7).

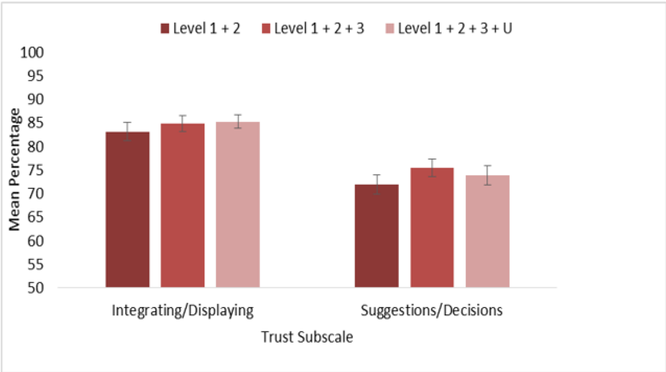

Figure 7. Trust in integrating and displaying information, as well as suggesting decisions, for all three transparency levels.

IV. CONCLUSIONS

We briefly reviewed two studies on the effects of agent transparency on operator performance, perceived workload, and trust in the agents. The user interface designs were based on the Situation awareness-based Agent Transparency (SAT) model, and the level of transparency was systematically manipulated in both experiments. The results show that agents' transparency (based on the SAT model) can benefit operator performance and support proper calibration of trust in the agents (particularly in the case of IMPACT, knowing when to reject the agent's recommendation). However, when uncertainty information was added to the user interface, operator's performance did not always improve (as shown in the ASM study). More specifically, the IMPACT study showed that participants' decision-making benefitted from increasing levels of transparency; however, the ASM results showed that the participants' SA of the agent peaked at Level 1+2+3 and the addition of uncertainty information did not further enhance their SA. In terms of operator trust in the agent, the two studies showed remarkably similar patterns – increasing levels of transparency enhanced operator trust, but only to a degree. When uncertainty was added to the interface, operator's trust did not increase further. One exception to this pattern is the "integrating and displaying information" aspect of operator trust in the IMPACT study (Figure 7), which did not show a negative effect of the uncertainty information. This pattern is consistent with what is reported by Mercado and colleagues [2]. Future research should investigate when and how uncertainty information affects operator's perceived trust in the agent. For example, effects of the following can be investigated: agent capabilities and task types (e.g., the four stages of automation [27]), mission environments and requirements, and individual differences. Finally, the subjective workload data for both studies are consistent, and the results suggest that the benefits of increasing agent transparency do not have to be associated with higher levels of operator workload.

The results of these two studies have implications for ML-based systems, particularly in high-stakes military settings. User input to guide the learning process is not only beneficial, but also critical in some situations (e.g., when the systems do not have access to all the information they need). Results of the current studies suggest that systems that are transparent about their intent, logic, and possible outcomes support the most effective human-agent team performance. However, system uncertainty information, no doubt beneficial in some cases, presents a mixed picture and does not always benefit the operator's task performance and engender trust. ML-based systems, with their inherent nature of uncertainty, can benefit from research efforts on human-system interface development, particularly on explanation generation and information visualization techniques. Furthermore, a prudent next step in this research is to consider not only how ML-based systems can be more transparent, but also the role of operators in helping machines learn the information they are missing or might be uncertain about.

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