Transparency, trust, and level of detail in user interface design for human autonomy teaming

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ABSTRACT

Effective collaboration between humans and autonomous agents can improve productivity and reduce risks of human operators in safety-critical situations, with autonomous agents working as complementary teammates and lowering physical and mental demands by providing assistance and recommendations in complicated scenarios. Ineffective collaboration would have drawbacks, such as risks of being out-of-the-loop when switching over controls, increased time and workload due to the additional needs for communication and situation assessment, unexpected outcomes due to overreliance, and disuse of autonomy due to uncertainty and low expectations. Disclosing the information about the agents for communication and collaboration is one approach to calibrate trust for appropriate reliance and overcome the drawbacks in human-autonomy teaming. When disclosing agent information, the level of detail (LOD) needs careful consideration because not only the availability of information but also the demand for information processing would change, resulting in unintended consequences on comprehension, workload, and task performance.

This dissertation investigates how visualization design at different LODs about autonomy influences transparency, trust, and, ultimately, the effectiveness of human autonomy teaming (HAT) in search and rescue missions. LOD indicates the amount of information aggregated or organized in communication for the human to perceive, comprehend, and respond, and could be manipulated by changing the granularity of information in a user interface. High LOD delivers less information so that users can identify overview and key information of autonomy, while low LOD delivers information in a more detailed manner. The objectives of this research were (1) to build a simulation platform for a representative HAT task affected by visualizations at different LODs about autonomy, (2) to establish the empirical relationship between LOD and transparency, given potential information overload with indiscriminate exposure, and (3) examine how to adapt LOD in visualization with respect to trust as users interact with autonomy over time. A web-based application was developed for wilderness SAR, which can support different visualizations of the lost-person model, UAV path-planner, and task assignment. Two empirical studies were conducted recruiting human participants to collaborate with autonomous agents, making decisions on search area assignment, unmanned aerial vehicle path planning, and object detection. The empirical data included objective measures of task performance and compliance, subjective ratings of transparency, trust, and workload, and qualitative interview data about the designs with students and search and rescue professionals.

The first study revealed that lowering LODs (i.e., more details) does not lead to a proportional increase in transparency (ratings), trust, workload, accuracy, and speed. Transparency increased with decreased LODs up to a point before the subsequent decline, providing empirical evidence for the transparency paradox phenomenon. Further, lowering LOD about autonomy can promote trust with diminishing returns and plateau even with lowering LOD further. This suggests that simply presenting some information about autonomy can build trust quickly, as the users may perceive any reasonable forms of disclosure as signs of benevolence or good etiquette that promote trust. Transparency appears more sensitive to LOD than trust, likely because trust is

conceptually less connected to the understanding of autonomy than transparency. In addition, the impacts of LODs were not uniform across the human performance measurements. The visualization with the lowest LOD yielded the highest decision accuracy but the worst in decision speed and intermediate levels of workload, transparency, and trust. LODs could induce the speed-accuracy trade-off. That is, as LOD decreases, more cognitive resources are needed to process the increased amount of information; thus, processing speed decreases accordingly.

The second study revealed patterns of overall and instantaneous trust with respect to visualization at different LODs. For static visualization, the lowest LOD resulted in higher transparency ratings than the middle and high LOD. The lowest LOD generated the highest overall trust amongst the static and adaptive LODs. For visualizations of all LODs, instantaneous trust increased and then stabilized after a series of interactions. However, the rate of change and plateau for trust varied with LODs and modes between static and adaptive. The lowest, middle, and adaptive LODs followed a sigmoid curve, while the high LOD followed a linear one. Among the static LODs, the lowest LOD exhibits the highest growth rate and plateau in trust. The middle LOD developed trust the slowest and reached the lowest plateau. The high LOD showed a linear growth rate until a level similar to that of the lowest LOD. Adaptive LOD earned the trust of the participants at a very similar speed and plateau as the lowest LOD. Taking these results together, more details about autonomy are effective for expediting the process of building trust, as long as the amount of information is carefully managed to prevent overloading participants' information processing. Further, varying quantities of information in adaptive mode could yield very similar growth and plateau in trust, helping humans to deal with either the minimum or maximum amount of information. This adaptive approach could prevent situations where comprehension is hindered due to insufficient information or where users are potentially overloaded by details. Adapting LODs to instantaneous trust presents a promising technique for managing information exchange that can promote the efficiency of communication for building trust.

The contribution of this research to literature is two-fold. The first study provides the first empirical evidence indicating that the impact of LODs on transparency and trust is not linear, which has not been explicitly demonstrated in prior studies about HAT. The impact of LOD on transparency is more sensitive than trust, calling for a more defined and consistent use of the term or concept - “transparency” and a deeper investigation into the relationships between trust and transparency. The second study presents the first examination of how static and dynamic LODs can influence the development of trust toward autonomy. The algorithm for adapting LOD for the adaptive visualization based on user trust is novel, and adaptive LODs in visualization could switch between detailed and abstract information to influence trust without always transmitting all the details about autonomy. Visualizations with different LODs in both static and adaptive modes present their own set of benefits and drawbacks, resulting in trade-offs concerning the speed of promoting trust and information quantity transmitted during communication. These findings indicate that LOD is an important factor for designing and analyzing visualization for transparency and trust in HAT.

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GENERAL AUDIENCE ABSTRACT

The collaboration between human and autonomous agents in search and rescue (SAR) missions aims to improve the success rate and speed of finding the lost person. In these missions, a human supervisor may coordinate with autonomous agents responsible for estimating lost person behavior, path planning, and unmanned aerial vehicles. The human SAR professional may rely on information from the autonomous agents to reinforce the search plan and make crucial decisions. Balancing the amount of information provided by the autonomous agents to the SAR professionals is critical, as insufficient information can hinder trust, leading to manual intervention, and excessive information can cause information overload, reducing efficiency. Both cases can result in human distrust of autonomy. Effective visualization of information can help study and improve the transmission of information between humans and autonomous agents. This approach can reduce unnecessary information in communication, thus conserving communication resources without sacrificing trust.

This dissertation investigates how visualization design at the proper aggregation of details about autonomy, also referred to as level of detail (LOD), influences perceived understanding of the autonomous agents (i.e., transparency), trust, and ultimately, the effectiveness of human autonomy teaming (HAT) for wilderness SAR. A simulation platform was built for proof-of-concept, and two studies were conducted recruiting human participants to use the platform for completing simulated SAR tasks supported by visualizations at different LODs about autonomy. Study 1 results showed that transparency ratings increased with more details about autonomy up to a point and then declined with the most details (i.e., lowest LOD). Trust, workload, and performance also did not linearly improve with more details about autonomy. The non-linear relationships of LODs with transparency, trust, workload, and performance, confirmed the phenomenon of the transparency paradox, which refers to the disclosure of excessive information about autonomy may hinder transparency and subsequent performance. Study 2 results also illustrated that when visualization with LOD adapted to instant trust, the speed of building trust and the plateau of trust on autonomy can achieve the same level as the visualization provided with the most details, which performed the best in building trust. This adaptive approach minimized the amount of information displayed relative to the visualization, constantly presenting the most information, potentially easing the burden of communication. Taken together, this research highlights that the amount of information about autonomy to display must be considered carefully for both research and practice. Further, this dissertation advances the visualization design by illustrating that visualization adapting LODs based on trust is effective at building trust in a manner that minimizes the amount of information presented to the user.

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List of Abbreviations

AI	Artificial intelligence
ANOVA	Analysis of variance
DPR	Duration per assignment round
GIS	Geographical information system
HAT	Human autonomy teaming
IPP	Initial planning point
LKP	Last known position
LOD	Level of detail
LPM	Lost person model
POA	Probability of area
SA	Situation awareness
SAR	Search and rescue
SAT	Situation awareness-based agent transparency
UAV	Unmanned aerial vehicle
UI	User interface
VR	Virtual reality

1. Introduction

Automation and autonomous technology can greatly improve the productivity of work in various domains such as manufacturing, autonomous driving, industrial control, aircraft, agriculture, etc. Machines are becoming autonomous and increasingly pervasive in both work and personal life recently. Forty years ago, there were virtually no autonomous vehicles on the road, and today, Waymo autonomous vehicles alone have driven more than 20 million miles on the road (Kris, 2021). According to the National Conference of State Legislatures (2020), as of 2019, twenty-nine U.S. states have passed laws permitting autonomous cars. Further, the autonomous vehicle industry is projected to be worth $23.33 billion worldwide (Globe Newswire, 2021). In healthcare, human errors affected approximately 1.3 million people and cost $42 billion annually (Simeon, 2017; Tariq et al., 2022). Autonomous technologies, robotics, and artificial intelligence (AI) are being investigated for dispensing medications, improving diagnostics, controlling hospital-acquired infections, and predicting risky transportation. Autonomous technologies are widely used in surgeries, surgical education and assessment, optimization of operating room management, clinical training, prescription dispensing, elder care, and disinfection (Attanasio et al., 2021; Haidegger, 2019; Moustris et al., 2011). Sheetz et al. (2020) analyzed the clinical registry data from Michigan between January 1, 2012, and June 30, 2018, for the trends in the use of robotic surgery. They found that robot-assisted procedures accounted for 15.1% of all general surgeries in 2018, up from 1.8% since 2012. The global market for surgical robotics market was valued at over $2.3 billion in 2020 and is projected to grow at the rate of 20% till 2028 (Grand View Research, 2021; Verified Market Research, 2020). From deploying contactless services from inventory monitoring and shopper tracking for cashierless checkout, autonomous retail stores are estimated to have a market of $11 billion in 2018 and are projected to reach over $23 billion in 2026 (Allied Market Research, 2019).

While autonomous technology is changing the way people interact in world, saving people from tedious and dangerous jobs, improving health with the help of AI, and facilitating better productivity and living experience, there are also observable setbacks and sometimes fatalities associated with design and deployment of autonomous technology in our daily lives. Autonomous vehicles can suffer failures uncommon to human drivers that have resulted in fatalities of drivers and pedestrians on the road. For example, the computer vision of Tesla's Model S autopilot failed to recognize a white tractor-trailer crossing the highway against a bright sky, resulting in a fatal crash into the trailer in 2016 (Danny & Dan, 2016). Even with software updates, in 2019, another Tesla Model S crashed into another vehicle because the engaged autopilot failed to detect obstacles, and the driver didn't slow the vehicle (Boudette, 2021). The first Uber self-driving car crashed and killed a pedestrian in 2018 when the driver was watching videos and thus failed to intervene accordingly (Rory, 2020). There are more crashes of autonomous vehicles being reported (California DMV, 2022; McCausland, 2019; Petrović et al., 2020). Although autonomous driving companies claim that their autonomous car is safer than manual control, nearly 43% of people in the U.S. do not feel safe in a driverless car (Kopestinsky, 2021). Both accident and acceptance rates highlight that the human remains the necessary partner in complex situations, and the failures in such a partnership often provide loss of productivity and even hazards to human lives.

In the medical domain, accidents and acceptance of autonomous technology is similarly problematic. Based on reviews of 10,624 reports, Alemzadeh (2016) found one big concern with robotic surgeries is technical complications such as, including unintended operation of instruments, system errors, and image problems. In robot-assisted surgeries, the unintended operation of the instrument is one of the crucial issues, which usually occurs without any explicit commands from the attending surgeons (Attia et al., 2018). Due to concerns about the unintended execution of operating procedures, manufacturers were reluctant to implement new autonomous features and opted to use the motion of the tools that are always under the direct control of the human surgeon instead (Haidegger, 2019). When the decision support algorithms conflict with human diagnosis, the surgeon or doctor may not be willing to admit to their error or misjudgment and reject the AI recommendation, or they may accept the AI diagnosis because of reasons other than professional concerns, such as the risks to withdraw the supposedly better decision conducted by the algorithms, inability to explain to the patient and obtain full consent, or deferred liability for the decision (O'Sullivan et al., 2020).

Autonomous agents refer to systems and machines that can perform actions and make decisions while learning and adapting to dynamic environments, such as robots and autonomous vehicles. Autonomous agents can perform complex tasks with minimum human involvement in known operational conditions; however, during events unanticipated by designers, the autonomous agents may perform actions that may not be comprehensible to human operators. The design to support effective partnerships between human and autonomous agents is relatively immature, as observed in various accidents and research. For example, Petrović et al. (2020) found that "rear-end" collisions happened more with autonomous vehicles than with conventional ones. The higher accident rate may be because autonomous vehicles reduce speed or stop for reasons that normal human drivers would not; consequently, human drivers in the following vehicle would not recognize the risk and stop in time. Drivers failing to take control back or losing situation awareness (SA) may also fail to avoid fatal crashes when autonomous agents make wrong decisions (Endsley, 2019). In robot-assisted surgeries, surgeons need sufficient information for telepresence of the surgical environment so that they have an intuitive awareness of the robot's working environment can be observed for safety (Meli et al., 2014).

With advances in hardware and software technologies, autonomous agents become more capable of performing complex tasks and are granted increasing authority to make decisions. However, autonomous agents or humans are not proficient in handling complex operations all on their own due to the demand on reasoning and computation under certain ethical responsibilities (J. Y. Chen & Barnes, 2014; Jobin et al., 2019; Johnson-Laird, 2010). Recent research use human-autonomy teaming (HAT) to describe human and autonomous agent working collaboratively to achieve a common goal (O'Neill et al., 2020). HAT is formulated as a critical concept in human factors engineering for effective partnerships between human and autonomous agents to maximize the safety and productivity of the complex system. Human response or intervention remains essential for efficiency, adaptability, usage, speed, and ability to handle unexpected cases in complex systems dictating overall outcomes (Freedy et al., 2007). My dissertation research aims to advance visualization design to improve human understanding of autonomous agents and thus their joint task performance. The next section reviews the state-of-the-art research on HAT and identifies critical issues that must be addressed by research in order to realize the promise of autonomous technology for enhancing safety and productivity.

1.1 Background

Research increasingly advocates that human and autonomous agents need to work as a team to accomplish tasks that take advantage of their respective unique abilities (Lyons et al., 2021; N. J. McNeese et al., 2018; Shively et al., 2018). That is, autonomous agents should not only be considered as tools but also as teammates who can share mental models, society affordance, and understanding with human teammates to achieve a common goal. The literature provides different definitions or conceptualizations of HAT (Table 1). Across the definitions reviewed in Table 1, the three main components in HAT are human, autonomous agents, and team design, with a common theme that humans and autonomous agents should work interdependently as teammates to achieve a common goal in complex and dynamic environments. Given the complex interactions across all the components in HAT, research has been delineating the characteristics of each component, the interactions between components, the response behaviors to the environments, and the ultimate impact on outcomes of HAT-supported missions.

Table 1. Table of HAT definitions (organized chronologically by publication year).

Cuevas et al. (2007) defined a "human–automation team as the dynamic, interdependent coupling between one or more human operators and one or more automated systems requiring collaboration and coordination to achieve successful task completion" (p. B64).
Chen and Barnes (2014) defined the roles, communications, and architecture for HAT that the role of an autonomous agent is "always the subordinate member, who can be given permission to act autonomously only under specified conditions". Communication includes sharing knowledge as coordination, working together as collaborating, and sharing a common knowledge framework. The underlying agent architecture should be compatible with human cognition. The agent should have characteristics of autonomy, environment observation through sensors, acting upon environments, and targeting on certain goals.
Schulte et al. (2016) described HAT as a system that humans work with highly automated cognitive agents that carried attributes like "autonomous" or "intelligent". HAT is much more capable in the situations where "workshare and interaction between the user and system is less stable" than traditional system engineering view.
McNeese et al. (2018) extended the human-human teamwork to HAT that in teamwork, multiple humans working interdependently to achieve a common goal, while with recent technology, "autonomous agents become intelligent enough to be considered a teammate, as opposed to a servant or a tool". Moreover, HAT includes essential teamwork functions of i) understanding the current task and taking on a unique role within the team, ii) communication, iii) team behaviors such as backup behaviors and providing feedback, iv) "good coordination or getting the right information to the appropriate teammate at the correct time".
Calhoun et al. (2018) described the HAT as "a human operator manages multiple heterogeneous unmanned vehicles by working together with an autonomy teammate that consists of several intelligent decision-aiding agents/services" (p. 321).
Demir et al. (2019) described HAT that "as computing systems continue to advance, there is a push to consider autonomous agents as team members. This role of autonomous agents as team members has started a paradigm shift from all-human teaming to HAT, the latter being teams composed of both humans and technology-based team members" (p. 150).
O'Neill et al. (2020) defined HAT as "interdependence in activity and outcomes involving one or more humans and one or more autonomous agents, wherein each human and autonomous agent is recognized as a unique team member occupying a distinct role on the team, and in which the members strive to achieve a common goal as a collective. The 'autonomy' aspect of human–autonomy teaming refers to the autonomous agent" (p. 8).
Lyons et al. (2021) defined the five essential elements of HAT: "i) the machine must have a high level of agency to act as a teammate, ii) the machine must be communicative, iii) the communication should convey information

that allows the human teammate to understand the intent of the machine, iv) the human and machine should share mental models of the team assets, team strengths/weaknesses, division of labor, and task context, v) a HAT is characterized by interdependence between the human and machine" (p. 8).

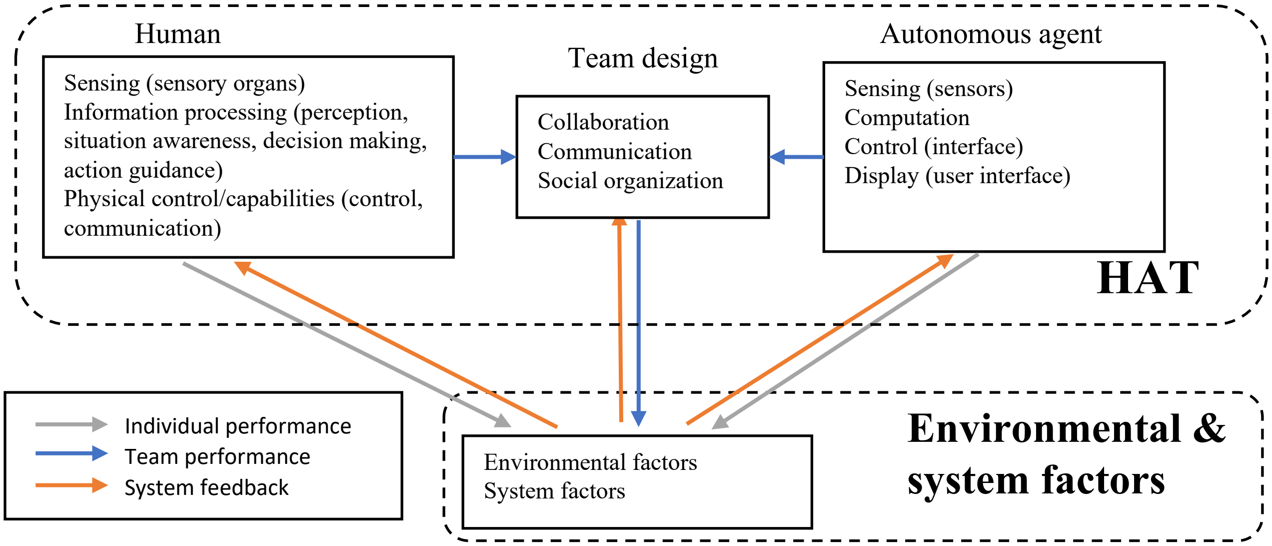


Figure 1. Key HAT components and their interactions. HAT is formed by components of human and autonomous agents that perform interdependently as a team to influence and be influenced by environment and system factors.

Figure 1 provides a conceptual illustration of the key HAT components and their interactions, highlighting how human and autonomous agents perform interdependently as a team to interact with the environment or the system. Humans and autonomous agents can act independently on the system or environment to operate the system or exert influences on the physical environment for desired outcomes (grey arrows of Figure 1). However, there are circumstances that the task requirements are beyond the capability of any individual agent, or the efficiency and accuracy could be dramatically improved by the cooperation and coordination between two or more agents in a pre-established social organizational structure. In these cases, knowledge, information, mental model, and physical states need to be exchanged and synchronized between the human and autonomous agents to interact with the environment and system jointly (blue arrows of Figure 1). Lastly, the environment and system can also influence both human and autonomous agents independently and together by imposing operational/design constraints and providing feedback/outcomes to their control actions (orange arrows of Figure 1).

To achieve the desired system performance, **human** needs to perform individual tasks and team activities by receiving and processing information through the embodied sensory organs, then interpreting and comprehending, and finally projecting future system states based on the information to make decisions (Endsley, 1995). Human capabilities have limitations on capabilities of sensory perception, cognition, and the musculoskeletal system. Human sensory perceptions have limitations on detecting range, precision, accuracy, working duration, and speed. For example, normal human naked eyes can detect visible light with wavelengths from 380 to 700 nanometers (NASA & SMD, 2010). Human cognition capabilities have limitations on the amount of information at a given time. Increasing the number of objects would decrease performance due to the memory load that adult humans can only retain about four items at the same time in mind (Buschman et al., 2011). The functions of the musculoskeletal system of the human body, including connective tissue, muscles, and joints, support and protect the body and organs to initiate and sustain bodily motion (Chaffin et al., 2006, p. 11).

Humans also need to perform actions to control the machinery or change the environment as well as to (physically) communicate/interact with teammates. Many human characteristics, such as demographics, personality, and experience affecting their decision-making and control actions, can influence interactions with teammates (Schelble et al., 2020; Thieme & Utne, 2017; Tokadlı & Dorneich, 2019). For example, based on the measure of the attitude towards using, perceived behavior, and intention to use, older drivers were found to be more likely to accept autonomous agents than younger drivers, and males were more likely to believe that they would need less mental and physical effort in an autonomous driving study (Rödel et al., 2014). Repeated exposures or familiarity tends to decrease the human intervention rate in the autonomous vehicle because the human would know what the car knows and how it would perform (Tenhundfeld et al., 2019). Individuals with positive prior experience with autonomous agents were more likely to rate the autonomous agents performing team tasks fairly and responsibly and more willing to continue interacting with autonomous agents than those with negative prior experience (Hafizoglu & Sen, 2018). People with high individualism, low power distance, and lower uncertainty avoidance tend to have a higher reliance and require less interaction time to build general trust than people with medium individualism, high power distance, and high uncertainty avoidance (Chien et al., 2016).

Autonomous agents play an important role in HAT with the necessary capabilities to perform individual tasks and team activities. Perception and decision-making are two main function blocks of autonomous agents when teaming with humans to perform tasks (Yeong et al., 2021). The perception of autonomous agents depends on sensors, which are the devices that detect stimuli or information in the environment or system (Fraden, 2004). Sensors could vary in stimulus types, range, sensitivity, material, detection means, and field of applications. Sensors, as a part of an autonomous system, need other devices and software for processing and actions. Autonomous agents are usually better at repetitive work than humans, who would eventually be fatigued. Modern technologies make autonomous agents more capable than humans from various perspectives, such as range of detection, precision, and data storage. AI, as part of autonomous agents, is generally more capable of supporting analytical decision-making, processing large datasets with speed, and reducing bias if the assumption or training data is correct (Jarrahi, 2018). However, humans have advantages in recognizing, associating, and interpreting data. Moreover, humans are more flexible with comprehensive capabilities, understand common-sense situations with intuitive decision-making abilities, and, as a resource, are easier to access. Thus, humans could be partially released from works that autonomous agents are good at and not be completely replaced under current technology (Robinette et al., 2016).

Autonomous agents and humans can be complementary when they work together efficiently. Autonomous agents have more computing ability, mobility, and physical power than humans, so they extend the capabilities of human's ability to explore the environments (Saltaren et al., 2007; Yoshida, 2009). Fewer humans are needed to execute the mission when autonomous agents work as a force multiplier in the team (Scharre, 2018). The fused sensory data of human and autonomous agents were found to improve the overall performance in visual-based object detection (Robinson et al., 2015). For example, AI enables decision-making and problem-solving, such as adaptive cruise control in semi-autonomous driving (Desjardins & Chaib-Draa, 2011) and lane keeping in autonomous driving (Z. Chen & Huang, 2017).

The complexity of autonomous agents demands that UI should promote usability, diminish cognitive overload, and facilitate effective interactions in HAT, where adaptive UI is one of the potential solutions. After reviewing various definitions, Rothrock et al. (2002) defined an adaptive UI as "an adaptive interface autonomously adapts its displays and available actions to current goals and abilities of the user by monitoring user status, the system task, and the current situation" (p. 50). Adaptive UI may help to present the autonomous agents of HAT according to the diversity of humans, such as the capability of observing and understanding the information, experiences, perceptual and cognitive skills, execution capabilities, abilities in particular domains, and demographic factors (Jameson, 2007). For example, participants were asked to perform tasks with an adaptive UI for the secondary task (like reading emails) during a driving simulation task (Lavie & Meyer, 2010). The adaptive UI was found to reduce performance time in familiar situations and increase performance time in unfamiliar situations.

Older drivers benefited more from the adaptive UI than younger drivers in familiar situations since the younger drivers were less negatively affected by the secondary task.

The nature of adaptive UI, such as content complexity, inconsistent interface, and control over time, may cause potential challenges, such as decreased predictability, lowered comprehensibility, privacy concerns, and usability problems (Jameson, 2007). Thus, performance may be decreased, as well as getting undesirable outcomes and lowered satisfaction. After comparing the adaptive Microsoft Word menu panes, Gajos et al. (2006) found that when spatial stability was consistent, the adaptive UI was strongly preferred and improved performance over the non-adaptive UI, whereas no improved performance or satisfaction was found in the adaptive UI that the location of items was moved. Hence, adaptive UI should be carefully designed for HAT.

The capabilities of the autonomous agents can affect teamwork, specifically with low-reliability automation that hinders performance too often (Desai et al., 2012; Hillesheim & Rusnock, 2016). High false alarms were found to be correlated with less human compliance and an increased possibility of failure in an unmanned aerial vehicle (UAV) control task (Dixon & Wickens, 2006). Consequently, as human get more involved with the autonomy control, human operators allocate more attention to the autonomy under high workload (Ruff et al., 2002).

Team design includes factors facilitating multiple members working together as a team to achieve a common task goal, independent of their individual abilities to perform tasks on their own. The team becomes essential when the complexity of the task exceeds the capacity of an individual. Mao et al. (2016) simulated a real-world crisis mapping scenario for people working collaboratively in teams of different sizes (i.e., 1, 2, 4, 8, 16, and 32) to identify relevant information, create reports, and verify information from a set of tweets. They found that performance (i.e., a balance of precision and recall rate) increased with time for all team sizes. As the team size increased, the meantime per person decreased, as well as the effort for classification, whereas the collaboration activities, the efforts on filtering information and chatting tended to increase. They further found that as the team size increased, the performance first increased fast, then slowly decreased.

Collaboration in HAT is usually based on shared activity, joint intention, common ground, and intended goals (Hoffman & Breazeal, 2004). Collaboration demand efforts of interacting with one another, expressing thoughts, monitoring others, attending to the same task at hand, establishing common ground, and joint decision-making, all of which could induce extra cognitive load and time (Dillenbourg & Betrancourt, 2006; Kolfschoten & Brazier, 2013). Effective teamwork is a crucial component in ensuring the delivery of high-quality patient care in medication, safety and efficient flight in aviation, and decision-making in military application scenarios (Leonard et al., 2004; Mckinney Jr et al., 2005; Pronovost et al., 2009).

Team design is often rooted in research on human teams that are characterized by seven essential factors: “team orientation, team leadership, monitoring, feedback, backup, coordination, and communication” (Dickinson & McIntyre, 1997). For HAT design, similar factors have been identified, including a shared goal and mental model, the relationship of each role, status monitoring, and how human and autonomous agents should collaborate in a task-related team activity (Lyons et al., 2021; N. J. McNeese et al., 2018). Jointly as a team, human and autonomous agents can collaborate effectively by playing out their strengths respectively through communication, coordination, and cooperation (Marquez et al., 2018). For example, a human can offload obligations and tasks to trustworthy autonomous teammates and adjust the task allocation based on the performance of autonomous agents through effective communication (De Visser et al., 2018).

Communication in HAT needs to be efficient bi-directional information sharing and mutual performance monitoring (Chadalavada et al., 2020). Inappropriate communications that deliver too much information in the wrong way can trigger abandonment or underutilization of autonomous agents due to too many interruptions. To build an effective team, humans need the ability to perform individual tasks while having a computational (rather than mental) model for understanding the information delivered by autonomous agents (Färber, 2016), be aware of responsibilities, sending and gathering information at the right time (Tokadlı & Dorneich, 2019), making decisions based on the recommendation of autonomous agents, and monitoring behaviors of autonomous agents (Calhoun et al., 2018; J. Y. Chen & Barnes, 2014; Feng et al., 2016). Autonomous agents need the capability to conduct their own parts of the task (Endsley, 2017), deliver the result to humans clearly (J. Y. Chen et al., 2014), carry out the human command, and, in some cases, monitor human behavior (N. J. McNeese et al., 2018; Nacpil et al., 2021). Moreover, the capabilities of autonomous agents affect how they should be treated in task allocation and communication (Grimm et al., 2018; Ranz et al., 2017).

The roles and responsibilities of human and autonomous agents in the team could be monitoring, providing authority, and backing up each other (Abbass, 2019). In highly coupled collaborative tasks of human and autonomous agents, the output of an individual can also be the input to others. In lightly coupled tasks, human and autonomous agents can backup each other. The roles of autonomous agents in HAT could be followers, partners, or leaders based on their potential contribution to the task, arrangement of work design, and organization (Tsai et al., 2022). The role of autonomous agents in the team can influence the outcome that the autonomous agents were more persuasive in peer roles than in the authority roles, and recommendations gained more acceptance with positive rewards over penalties (Saunderson & Nejat, 2021). For example, autonomous leaders can enhance productivity by adjusting the production pace of robot teammates to mitigate human stress, which can negatively affect human capabilities in performance (Messeri et al., 2021).

The **environment** that encapsulates the physical system and process imposes constraints on system operations and thus influences the agent behaviors and teaming process. Environmental characteristics may include geographic features, which are relatively static, or weather conditions, which are dynamic, that may shape how agents would reason or respond to a particular event (Hugo & Oxstrand, 2015).

In hazardous environments like tall structures and buildings, chemical industries, and power plants, inspection by human workers is usually risky and difficult, so the capability of robots in these contexts of monitoring, handling, and recovering is preferred (Chang et al., 2017; Luk et al., 2005). For example, gas leaking could be risky, especially for toxic gases, since they are usually invisible to the naked human eye. Autonomous agents-based gas monitoring plays an essential role in these circumstances in monitoring the leakage, as well as providing continuous evacuation measures for civil safety (Rossi et al., 2014; M. Xiong et al., 2016). Moreover, autonomous agents have the advantage of being expendable and could be used to assist human operators in some extreme circumstances, such as fire-extinguish (Taha & Marhoon, 2018), surveillance, and bomb detection (Thomas & Devi, 2017). However, in spite of all these merits, autonomous agents have limitations in various environments where humans are more capable.

Weather conditions could be huge environmental challenges, such as rain and high wind may cause sensor malfunction and imbalance of the sensory platform (von Bueren et al., 2015).

The terrain constraints, like a high canopy in the area, may potentially block the view of the cameras (Mora et al., 2015). With HAT, complex tasks can be achieved more efficiently and safely. For example, in urban search and rescue, different types of cameras, such as optical, thermal, and hazardous material detectors, enabled autonomous agents to play a role in visual technical search tasks and search tasks only with limited ability of medical payloads, whereas an only human can handle the rescue part due to the complexity of operations and surrounding environment (Murphy, 2004).

In the meantime, the physical system imposes demands and constraints on the behavior of human and autonomous agents. The system demands include system purpose, functional capabilities (performance boundary), current system states (task-related requirements), and detailed design characteristics (inherent structure) (Rouse et al., 1992). The complexity and scale of system designs impose different cognitive and physical demands on human and autonomous agents (Vicente, 1999). Moreover, the constraints that influence HAT could be distance, delay, time limit, and task interdependency (Celmer et al., 2018; O'Neill et al., 2020). For example, humans are more likely to view autonomous agents as team members in tasks with high interdependence (Zhao & Henrichs, 2020).

The environment and systems are ultimately what the human and autonomous agents individually or jointly try to control for a desirable outcome at a certain level of efficiency, utilization, productivity, quality, and safety. Performance and actions in the system and environment are driven by the actions of human and autonomous agents. Humans perform actions on systems and deliver outcomes through either transforming raw materials into goods and services as products or maintaining the necessary organizational and psychological environment (Motowildo et al., 1997). The related contextual and task performance are influenced by the individual difference in cognitive abilities and personality variables on knowledge, skills, and work habits. McCrae & Costa (1996) presented a theoretical framework on the relationships between individual traits and performance in terms of five variables: basic tendencies (sensory-motor capacities, physical abilities, personality traits, etc.), characteristic adaptions (knowledge, skills, moral values, etc.), objective biography (performance), self-concept, and external influences. The features and capabilities of autonomous agents can affect the outcome of systems through intelligence, self-sensing, self-control, flexibility, connectivity, precision, and reaction time (Fragapane et al., 2022; Krebs et al., 2000; Qu et al., 2019; Rosen et al., 2015; Shariati et al., 2019).

Humans may take manual intervention more than necessary or refuse to work with autonomous agents due to concerns about the intent of use, collaboration efficiency, and rate of the takeover when facing potential failures. Humans may refuse to use autonomous agents due to failures (Gao et al., 2006). Manual interventions by human operators increased with the declined expectation of the performance of autonomous agents and decreased willingness to use them (Muir, 1994). These potential concerns can be solved through trust. Models of task allocation built based on trust can potentially promote overall performance and adjust workload (Dubois & Le Ny, 2020). The behavioral intention and willingness to rely on, accept and use autonomous agents can be promoted through trust (Choi & Ji, 2015; Freedy et al., 2007; Lee & Moray, 1994; Lee & See, 2004; Parasuraman et al., 2008). As one of the most important factors of effective team actions, trust is further discussed from the perspective of HAT in the next section.

1.2 Trust

For human teams or organizations at work, trust is widely investigated as a mechanism for improving employees' work efficiency (Mayer et al., 1995; Nyhan, 2000) and an essential part of facilitating team performance (Erdem & Ozen, 2003). Trust is recognized as a vital element in enhancing organizational productivity and fostering a stronger commitment between supervisors and workers (Nyhan, 2000). In HAT, trust is also essential for team collaboration so that proper actions can be taken in complex and uncertain situations (Lee & See, 2004). As a result, the strategies and activities will be influenced accordingly and ultimately affects the overall efficiency and workload of humans (Lewandowsky et al., 2000).

The literature presents multiple definitions of trust regarding humans and autonomous agents (Table 2). Trust for teammates is generally considered as the attitude of expectations of other parts of the team that can perform their roles and relies on their performance in the team missions.

Table 2. Definitions of trust.

Trust among humans refers to "the extent to which a person is confident in, and willing to act on the basis of, the words, actions, and decisions of another" **(McAllister, 1995, p. 25)**.
Mayer et al. (1995) defined trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (p. 712).
Emphasizing the emotional and attitudinal factors in interactions between human and autonomous agents, **Lee and See (2004)** defined trust as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (p. 51).
Salas et al. (2005) defined teammate trust or mutual trust, as "the shared belief that team members will perform their roles and protect the interests of their teammates" (p. 561).
In terms of human trust in automation, where automation includes machines, systems, and algorithms, trust was defined as "the reliance by an agent that actions prejudicial to their well-being will not be undertaken by influential others" **(Hancock, Billings, & Schaefer, 2011, p. 24).**
Hoff and Bashir (2015) defined dispositional trust as a representation of "an individual's overall tendency to trust automation, independent of context or a specific system" (p. 413).

Similar to the interpersonal and mutual trust, in HAT, trust is the subjective willingness of reliance on the other teammates playing their roles (McAllister, 1995; N. McNeese et al., 2019; Salas et al., 2005). The base of trust is the capabilities, performance, actions, and decisions that match the expectation (Mayer et al., 1995). Different from interpersonal trust, in HAT, the teammate is the autonomous agent, of which the behaviors are based on complicated mechanisms resulting in a performance with vulnerability and uncertainty (Lee & See, 2004). Hence, a definition of ***trust*** in HAT may be phrased as the subjective feeling of relying on autonomous agents based on the expectation that the capabilities and performance of autonomous agents can achieve a target to some extent under a level of uncertainty and vulnerability. A conceptual process of trust development between human and autonomous agents is shown in Figure 2.

Figure 2 shows a conceptual structure of trust development in HAT (adapted from Hancock et al. (2011)). Factors of trust influence trust in autonomous agents before, during, and after the HAT activities, thus facilitating trust evolution through providing baseline, explanation, and information from pervious experiences.

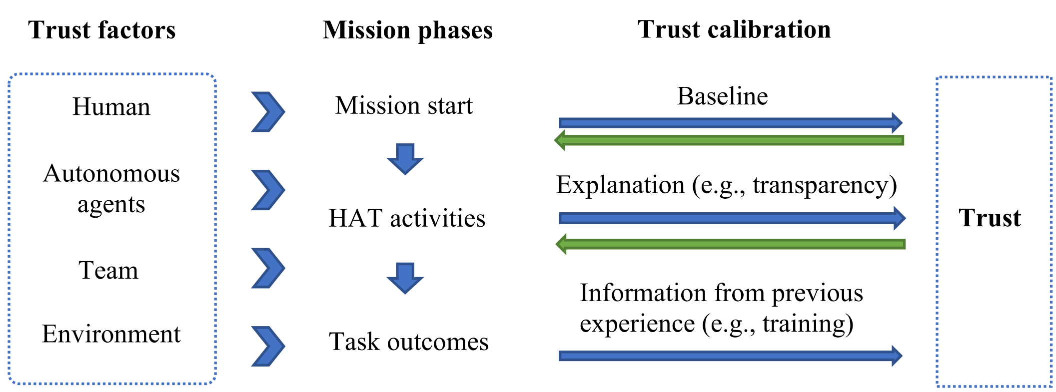


Figure 2. A conceptual structure of trust development in HAT.

Trust in HAT can be considered from the perspectives of interpersonal activities and activities between humans and autonomous. Hancock et al. (2011) examined trust in terms of human-robot interaction into human-related, robot-related, and environmental-related factors. Thus, the factors influencing trust during the three phases can be categorized into similar elements of the HAT structure, including humans, autonomous agents, team design, and environment. Hoff and Bashir (2015) further organized the factors of trust in automation into categories of dispositional, situational, and learned trust indicating that trust can be changed dynamically based on initial and learned knowledge of situations and experiences through interactions with automation. Hence, trust can evolve with the observation and understanding of the behavior, performance, and outcomes of autonomous agents over time. The baseline of trust is determined by factors before the mission starts and can affect the later HAT activities. Then trust can be calibrated during the task and, in turn, influence the activities and the outcomes, thus providing the experience for the future so that trust can be affected in a more extended learning period. The factors influencing trust across the whole period of HAT activities can be categorized from the perspectives of humans, autonomous agents, team design, and environment.

Human characteristics significantly influence trust-building. Schaefer et al. (2016) defined four groups of human-related factors in dispositional trust: 1) traits, such as demographics, personality, and trust propensity; 2) states, such as attentional control, stress, and fatigue; 3) cognitive factors, such as the ability to use and understand the automation, expectancy; and 4) emotional factors, such as attitude, comfort, confidence, and satisfaction with the automation. Similar findings that factor influencing trust were also studied. For example, stress and workload are essential for trust. Acute stress was associated with lower levels of trust in a social game task, as people tend to make risk-averse decisions under stress (Potts, 2017). Operators under fatigue showed excessive trust in autonomous agents in a simulated vehicle study in which fatigued drivers were more likely to rely on autonomous agents than non-fatigued drivers, even though the performance was not enhanced (Neubauer et al., 2011). Trust can also be influenced by affective factors, such as emotions and attitudes (Komiak & Benbasat, 2006). Navarro et al. (2021) found that experts have less trust than novices in autonomous agents performing aircraft piloting tasks.

Autonomous agents produce another essential impact on trust (Hancock, Billings, & Schaefer, 2011). Lee & See's (2004) characterizes the impact on trust in terms of performance, process, and purpose of autonomous agents. The performance reflects the ability of autonomous agents to achieve the operator's goals, including the current and historical operations. The performance of autonomous agents may include accuracy, competence, reliability, predictability, automation level, and ability. The process reflects the algorithms or mechanisms of how autonomous agents operate. The purpose reflects why the autonomous agents are developed and, thus, whether they are applied in accordance with the designer's intent.

The most investigated performance-based factor affecting trust is reliability. Reliability represents the overall trustworthiness of autonomous agents, which is the foundation of trust. Lower reliability resulted in lower trust in autonomous agents in process control tasks (Chavaillaz et al., 2016). In a simulated evacuation task in a virtual maze, humans lost trust when they accepted advice from autonomous agents in situations that resulted in bad outcomes (Robinette et al., 2017). Not only the level of reliability but also the consistency of reliability influence trust. High-reliability results in high trust, whereas early failures harm trust less than decreases in reliability following a phase of successful performance (Desai et al., 2012). Freedy et al. (2007) found that although the overall trust in low reliability is lower than in high reliability, the consistently failing performance of a low-reliability robot increased trust because human users can consistently anticipate the failures in a manner that matches real-world performance. That brings up another factor of predictability, which is another essential performance-based factor of trust (Madhavan & Wiegmann, 2007). Biros et al. (2004) found that as ratings of perceived predictability in system automation increased, ratings of trust also increased, and the subsequent use of the system increased. In simulated command control tasks, Daronnat et al. (2021) found that with the same high reliability, predictability had a positive effect on participants' trust.

The openness of process can influence trust in autonomous agents. Openness refers to the algorithm and operations governing the behaviors of the autonomous agents revealed and explained for humans to understand. It is usually achieved by simplifying the algorithms or presenting intermediate results in a manner that is understandable to human teammates (Lee & See, 2004). Only the desired information is helpful for improving trust. Information like the uncertainty of autonomous agents may reduce trust in autonomous driving ability (Helldin et al., 2013). Personalized feedback on autonomous agents' decision-making providing why-and-how information, such as the position of an object, unclear intentions of other vehicles, and traffic signs for safety marking, was found to improve trust in driving the autonomous vehicle (Wintersberger et al., 2020).

The purpose of the autonomous agents, fundamental design principles and the spectrum of potential applications should be properly communicated to the users to make sure the user's expectation of the behaviors of autonomous agents align with the designer's intended scope. Hoff & Bashir (2015) suggested that a lack of knowledge about the purpose or process of functions challenges users in calibrating their trust to the system's real-time reliability. Although there are limited empirical studies about how trust is influenced when using autonomous agents beyond its capabilities, Lee and See (2004) borrowed the motivation of lying in interpersonal trust into the context of autonomy and suggested that insufficient communication of design purpose to the users may negatively influence trust.

Team factors influence trust through communication and the roles of autonomous agents in the team. Communication is the exchanging of ideas and information, in which delivering information, modality, and strategies could potentially influence trust. The roles of autonomous agents being treated as teammates or tools in the task, or being leaders or partners in the team, has an impact on human trust in autonomous agents.

The information richness, modality, and strategies of communication are factors influencing trust. Information richness of communication was discovered to have a positive correlation with trust in an online marketing study that people had more trust when experiencing a virtual world rich in information than the traditional web-based environment to the extent of the features simulating face-to-face interaction (Chesney et al., 2017). Abe et al. (2002) found that failure to issue alarms seriously decreased trust in rear-end collision warning systems. However, too many false alerts generated by automated alarm systems may reduce trust and cause the disuse of autonomous agents (Parasuraman et al., 2008). Thus, the amount of information needs to be properly determined. Communication modality is another factor that affects trust. Qiu & Benbasat (2009) found that in online shopping environments, human voice improved users' perceptions of social presence and, in turn, facilitated more trust than a synthetic voice. Sanders et al. (2014) found that a constant level of information being communicated yielded more trust, whereas communication modalities of text, auditory, or graphics had little influence on trust in tasks in which humans and robots searched and marked targets' locations collaboratively. Communication strategies such as politeness, vulnerable expression, and styles can influence people's trust in autonomous agents. Spain & Madhavan (2009) found that people perceived the polite automated aid to be more trustworthy than the rude one that assisted people in detecting knives in a luggage-screening task. Rau et al. (2009) found that culturally familiar communication styles were associated with more trust.

The role of autonomous agents in the team can also influence trust. In a study of group trust among human teammates in an online strategy simulation game, Drescher et al. (2014) found that changes in shared leadership were positively related to the changes in group trust. After comparing people's reactions to decisions made by human and autonomous leaders in hypothetical work scenarios, Höddinghaus et al. (2021) found that the perceived trustworthiness of autonomous leaders was higher on integrity and transparency, whereas human leaders were perceived as more adaptable and more benevolent.

Environment factors need to be considered when adapting autonomous agents and the human operators to interact effectively for trust. Hoff and Bashir (2015) related situational trust to the external environmental factors that could directly influence trust and, thus, behavior toward autonomous agents. The risk, complexity, emergency, and environment of tasks dictate the uncertainty of autonomous agents functioning effectively and the demand on human information processing that would increase the likelihood of a mismatch between the expected and actual performance of autonomous agents. Salem et al. (2015) found that humans were more likely to comply with the recommendation leading to revocable than irrevocable harmful results. Perkins et al. (2010) evaluated the trust in suggestions of autonomous agents on route planning tasks with medium-risk conditions, such as common hazards of traffic jams and car accidents, and high-risk conditions, such as uncommon hazards of burning buildings and drive-by shootings. They discovered that as the potential risks and hazards escalated, the utilization of autonomous agents diminished, and trust in them decreased. Matthews et al. (2020) evaluated trust in a recommendation on threats using sensors in physical-based scenarios, such as analyzing radiation and sounds, and psychology-based scenarios, such as analyzing facial expressions and tone. They found that people were more likely to adopt recommendations from autonomous agents in physics-based scenarios than in psychological-based scenarios. Kim et al. (2015) found that college students felt less safe when working with the robot on a VR-based brick-laying task in shared areas than in separated areas.

An inappropriate level of trust can have negative consequences. A low level of trust can lead to the disuse or rejection of technology and high costs in efficiency and effectiveness (Hancock, Billings, Schaefer, et al., 2011; Parasuraman & Riley, 1997). In contrast, a high level of trust can lead to the opposite bias, including complacency and over-reliance on technology, thus causing the misuse of automation (Parasuraman & Manzey, 2010; Parasuraman & Riley, 1997). Safety issues and undesirable outcomes may happen when the process of autonomous agents is insufficiently monitored due to over complacency. This effect was especially pronounced for people who were only noticed but didn't actually face the failure (Bahner et al., 2008). High task workload can also exhibit an over-reliance on the autonomous agent, thus leading to sub-optimal decision makings in unreliable circumstances (Biros et al., 2004). Thus, there is a general consensus that trust needs to be calibrated at an appropriate level or otherwise result in misuse, disuse, and abuse of autonomous teammates (Parasuraman & Riley, 1997).

Calibration of trust refers to “the correspondence between a person’s trust in the automation and the automation’s capabilities” (Lee & See, 2004, p. 55). Calibration of trust parallels those of disuse and misuse in describing suitable reliance that lack of trust may cause disuse, whereas over-trust may cause misuse (Figure 3). Calibrated trust should match system capabilities, leading to appropriate use. When trust exceeds the capabilities of autonomous agents, autonomous agents would be used when they should not, which is also called misuse. In contrast, when the capability of autonomous agents exceeds the trust, underutilization of autonomous agents would occur, which is also called disuse. The calibrated level is the match between people's trust and the capability of autonomous agents (Parasuraman & Riley, 1997)

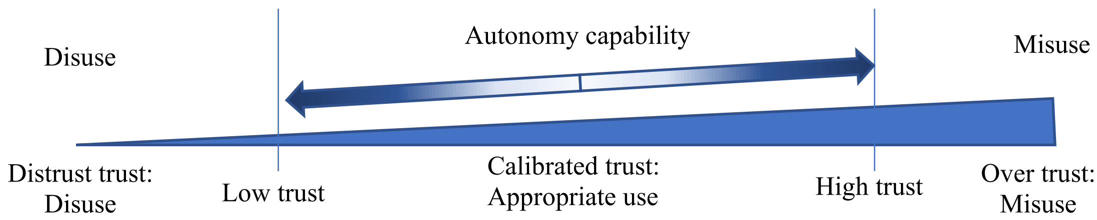


Figure 3. Trust calibration. Diagram is adapted from Lee & See (2004).

Poor calibration includes over trust and distrust. In over trust, trust exceeds the capabilities of autonomous agents leading to misuse, whereas, in distrust, the capabilities of autonomous agents exceed trust leading to disuse (Lee & See, 2004; Lyons, 2013). In addition, trust should be associated with a specific component or function of autonomous agents so that capability of autonomous agents could match human expectations, thus resulting in proper trust (Lee & See, 2004).

There are two approaches for calibrating trust: getting information from previous experience and sharing explanations of the current activities of autonomous agents (De Visser et al., 2020; Hancock, Billings, & Schaefer, 2011; Lee & See, 2004; Schaefer et al., 2016). Capability information of autonomous agents from previous experience through training can support accurate expectations of the capability of autonomous agents when getting familiar with autonomous agents. Muir and Moray (1996) found that novice operators' trust in autonomous agents with good performance increase with experience during training in process control tasks. Koustanaï et al. (2012) found that familiarization through training increased trust in autonomous agents during driving tasks. Johnson et al. (2021) evaluated trust calibration in a simulated remotely piloted aircraft operating training task. Participants in the condition of calibration training were informed before the task that mistakes and malfunctions of autonomous agents were expected because the system was still under development. They found teams with calibration training compared to the condition without pre notification would dampen expectations of human users in the autonomous agents resulting in more robust overall trust over time despite potential failures being introduced before the task.

Sharing awareness and reasons for the decisions and actions of autonomous agents can shape human expectations to match the capabilities of autonomous agents. Helldin et al. (2013) found that although showing the uncertainty of autonomous driving ability reduced driver trust, drivers were better prepared in situations that needed to switch controls. Koo et al. (2015) suggested that providing drivers with situational information explaining the reason for autonomous agents' reaction ahead showed more acceptance indicating more trust in semi-autonomous driving tasks. Lyons et al. (2017) found that decision support presenting the rationale for the recommendations attained higher user trust than one absent of explanations in an airport landing task. Zhang et al. (2020) found that showing information like confidence scores in AI-assisted decision-making could improve trust calibration for income prediction tasks. Kraus et al. (2020) found that delivering information about system shortcomings of autonomous driving capabilities can avoid the decline of trust during malfunctions and manual take over because information on the potential limitations lowered the performance expectation of autonomous agents during autonomous driving. Exposing functions and performance of autonomous agents can provide a basic understanding to human users and is good for establishing initial trust. Exposing mechanisms can help the reason for the processes. Exposing limitations or shortcomings could result in reduced trust but would ultimately avoid over trust and help to achieve better performance in the long run.

1.3 Transparency

Transparency can moderate trust by exposing the details of a system so that potential system malfunctions can be explained thus calibrating the trust of the capability of autonomous agents. Transparency of HAT could be considered as either “seeing through” or “seeing into” respectively (Ososky et al., 2014). From the perspective of “seeing through”, the design goal is striving for less content in UI for the humans to operate without noticing the UI. In other words, the UI should be invisible to the user. For the latter perspective of “seeing into”, the design for transparency strives to reveal more about what the autonomous agents are doing, how they work, and why they are working like that to the human users. The two perspectives adopt opposing design philosophies. In human factors research, the latter perspective is the dominant view that is adopted for further discussion in this document. Even within the perspective of “seeing into”, transparency has been given multiple definitions (Table 3).

Table 3. Definitions of transparency in HAT-related areas from seeing into perspective.

Sinha et al. (2002) defined “transparency in a recommender system as user understanding of why a particular recommendation was made” (p. 830).
Sørmo et al. (2005) used transparency to explain how the system reached a conclusion.
Kim and Hinds (2006) defined “transparency as the robot offering explanations of its actions” in human-robot interaction.
Lyons (2013) suggested that “transparency between the robot and the human was one mechanism to facilitate effective interactions between humans and their robotic teammates”, where transparency was divided into two categories of robot-to-human transparency focusing on sharing robot’s task, and robot-of-human transparency focusing on communicating robots’ awareness.
Chen et al. (2014) defined “agent transparency as an attribute of the human-robot interface that the descriptive quality of an interface about its abilities to afford an operator's comprehension about an intelligent agent's intent, performance, plans, and reasoning process” (p. 2).
Endsley (2017) used transparency as “the understandability and predictability” of the automated systems actions.(p. 7).
Weller (2019) formed transparency as “global interpretability or explanation for a general understanding of how an overall system works and local interpretability for an explanation of a particular prediction or decision” in the context of human interpretability of algorithmic systems.
Ananny and Crawford (2018) suggested that transparency is not only “a precise end state in which everything is clear and apparent” (p. 975), but also “a system of observing and knowing that promises a form of control”.
Skraaning and Jamieson (2021) referred automation transparency as “the design principle that the responsibilities, capabilities, goals, activities, and/or effects of automation should be directly observable in the human-system interface” (p. 380).

Transparency has commonly been decomposed into two subdimensions: visibility and interpretability in HAT with the considerations of the hardware capability and software intelligence of autonomous agents (Ananny & Crawford, 2018; Rader et al., 2018; Rieder & Hofmann, 2020; Rosenfeld & Richardson, 2019). *Visibility* refers to the degree of information disclosure in practice or the amount of information presented by autonomous agents and observed by humans (Ananny & Crawford, 2018; Rieder & Hofmann, 2020). *Interpretability* refers to the ability of designs to support humans in reasoning about how autonomous agents make decisions. The explanation is through the revealing of the mechanism of the rationale for decisions made by autonomous agents, or making humans understand the cause and effect through direct or secondary explanation. Some researchers differentiate between interpretability and explainability, in that interpretability is about observing a cause and effect (Rosenfeld & Richardson, 2019), whereas explainability is about explaining the internal mechanics directly in human terms (Tjoa & Guan, 2020). This document uses the two terms interchangeably to consider the ability of designs to support human understanding of the decisions made by autonomous agents. Hence, this document presents a narrower definition of ***transparency*** in HAT as transparency is the human subjective feelings and understanding of autonomy through visible and interpretable content about the status, functions, intent, behaviors, and mechanisms of autonomy.

In other studies, transparency was treated as a design characteristic or property that directly and indirectly affected trust in HAT-related studies. Transparency as a design characteristic, which generally provides more information and explanation of the autonomous agents, was found to recover or promote trust in HAT tasks when the autonomous agents were under the condition of high ability or spotted failed actions were explained (Brand et al., 2018;

Koo et al., 2015; Lyons et al., 2017; N. Wang et al., 2015). Skraaning and Jamieson (2021) setup and compared the display with traditional design principles and display with additional verbal and visual information about automation activities in full-scope nuclear power plant simulators with licensed operators. They found that trust in automation was promoted with additional information observable in all three experiments that the operators performed in component level as well as operated to achieve plant-wide goals. Transparency was also found to improve trust related factors, such as the acceptance of system recommendations (Cramer et al., 2008), performance like correct rejection and proper use (Stowers et al., 2020), and understanding of systems operation and correcting decisions (Kulesza et al., 2015). However, trust can be reduced when potential errors are exposed (Helldin et al., 2013; Kraus et al., 2020). Because trust is correctly increased and declined properly, the advantages and limitations of autonomous agents can be matched to human expectations, thus, malfunctions could be handled more properly, and takeover could be conducted when necessary. Thus, trust is not promoted by designed transparency through information and explanations but is calibrated for the proper use of autonomous agents. Models and processes have been developed to identify and categorize contents for achieving transparency in designs for HAT.

Lyons (2013) developed a transparency model in the context of supervisory control of multiple robots. The contents of achieving visibility and interpretability of transparency were categorized into two groups: robot-to-human and robot-of-human. The robot-to-human category focused on the different information that autonomous agents needed to share with the human in different scenarios. Four sub-models were introduced to cover the features of intention, task, decision-making reasoning, and environment constraints of autonomous agents. The robot-of-human category had two sub-models about teamwork and human status, focusing on the contents of robots communicating with a human. Researchers adopt and extend the model for identifying content for transparency (Debernard et al., 2016; Nesset et al., 2021). However, transparency was not measured as subjective feelings, instead, the type of content was used to directly indicate the level of transparency.

Chen et al. (2014) proposed a situation awareness-based agent transparency (SAT) model to determine what types of content should be displayed to facilitate the perception, comprehension, and projection of autonomous systems, thereby improving the visibility and interpretability of transparency of autonomous agents. The SAT model prescribes support for perception that autonomous agents would require information about the agent's purpose, intentions, progress, and performance (Level 1). Support for comprehension of autonomous agents would require information on constraints and reasoning processes behind those actions between alternatives (Level 2). Finally, projection about autonomous agents would provide requirement information on the future states and potential limitations (Level 3). Adopting the SAT model, Brand et al. (2018) showed that contents with more SAT levels (i.e., Level 1, 2, 3) presented to humans resulted in more trust as well as a higher workload in a simulated aviation mission in which a human operator teamed with the autonomous agent operating a helicopter and multiple unmanned aerial vehicles. Loft et al. (2021) found decision aids, including Level 1+2+3 SAT compared to Level 1+2 SAT, could improve decision time and reduce the manual verification of autonomous agents for humans deploying unmanned vehicles in simulated missions. However, transparency is treated as a design characteristic instead of a measurement.

Hepworth et al. (2020) suggested that the contents for supporting transparency for humans working with multiple autonomous agents should present agent state information, explanation and prediction, and bidirectional messages, respectively. Although no empirical examination was conducted about users' subjective feelings about transparency in this study, an architecture about trust and transparency was based on this reinforcing transparency as a key contributor towards situation awareness and effective trust.

The stage-based participatory design process was also used to promote transparency in the user interface design process. Eiband et al. (2018) built a stage-based participatory design process for transparent interfaces of intelligent systems. The design processes suggested answering what and how to explain autonomous agents based on existing UI guidelines. For example, interviews with domain experts were recommended to answer "what" the content should be for designing the interface, whereas focus groups and workshops were recommended for iterative prototyping to answer "how" the UI should look. A commercial intelligent fitness coach was developed, and several case studies were conducted for implementing explanations in AI interfaces based on this approach (Larasati et al., 2021). However, these studies focused on the practical perspective of users perceiving a prospective AI system with no empirical evaluation conducted to prove the effectiveness of the methods influencing trust.

These transparency models in the literature prescribe different types of content either from the perspective of robots and humans, SA, states, and bidirectional communication for multiple agents or from the stage-based design process suggesting the way of determining contents for specific problems. These models and studies treated transparency as a design characteristic instead of measurement, and a limited empirical study was conducted about subjective feelings of transparency. Besides the amount of information in each type of content that was not discussed, more details of how content should be considered for facilitating transparency need further discussion.

Despite the research efforts on content types and user interface designs, there are still challenges in promoting transparency of autonomous agents through user interface design or providing supportive information. In particular, presenting too much information may decrease usability (Stowers et al., 2016), potentially demanding more cognitive effort to process the information. When the information exceeds the operator's capability, information overload may be triggered (Moacdieh & Sarter, 2015), potentially harming trust in autonomous agents (Kizilcec, 2016). Moreover, displays with an excessive amount of information often lead to longer decision time (Stowers et al., 2020) and higher workloads (Bevan & Macleod, 1994; Helldin et al., 2014). A transparency paradox could happen when high "visibility" or a large amount of information may cause the important pieces of information to become inadvertently hidden among a large amount of information leading to opacity, which is also called transparency resistance (Stohl et al., 2016). It is not practical for autonomous agents to provide all available information for a human to perceive, analyze and operate to fit the requirements of time, accuracy, and quality (Westin et al., 2016). Therefore, the amount of information must be carefully controlled so that the human is not overwhelmed without any compromises to the overall performance. The discussions of the contents for transparency mostly talked about the types of contents.

Existing approaches for enhancing transparency face the information overload problem. In general, autonomy is considered transparent if its user interface follows certain design characteristics for transparency. However, piling up too many transparency design characteristics may cause information overload, i.e., the information exceeding the operator's capability (Moacdieh & Sarter, 2015). It is not practical for the user to perceive and comprehend all possible information from autonomy, which may cause the most important information to be buried in a large amount of less useful information and not perceived and comprehended by the user (Stohl et al., 2016). As a result, the information overload causes a transparency paradox or transparency resistance, which further influences users' trust in and respond to autonomy and thereby affecting their workload and performance. Even with the definition in this research, transparency is still about human subjective feelings and needs complicated measures that are tedious and error prone. To prevent information overload when designing user interfaces of autonomy, a metric is needed that can be measured more objectively.

1.4 Level of Detail

This dissertation introduces the concept of Level of Detail (LOD) to infer transparency. LOD indicates the amount of information aggregated or organized in communication for the human to perceive, comprehend, and respond. The design goal is that LOD should be objective and measurable so that transparency can be predicted and adjusted by measuring and controlling LOD. In the application scenario, LOD could be manipulated by changing the granularity of information in a user interface. High LOD delivers less information so that users can identify overview and key information of autonomy, such as important functions and outcomes. In contrast, low LOD delivers more information so that information on each aspect of autonomy, such as raw data, technical details, and mechanisms, can be delivered to users in a more detailed manner.

Research on transparency focuses extensively on what types of information about autonomy should be communicated to the users to promote transparency and trust. At the conceptual level, Lyons (2013) presented two categories: robot-to-human information about the autonomy's intention, reasoning in decision-making, and perceived environmental constraints to communicate to humans; and robot-of-human information about the labor distribution between humans and autonomy, and autonomy's perception of human status. However, the robot-to-human information category dominates human factors research. J. Y. Chen et al. (2014) developed the three-level, situation awareness-based agent transparency (SAT), arguing for designs that support the perception of autonomy's current state and goals, intentions, and proposed actions (i.e., Level 1), comprehension of autonomy's constraints and reasoning processes behind the actions (i.e., Level 2), and projection of autonomy's future state (i.e., Level 3). For multi-agent teams, Hepworth et al. (2020) advocated the presentation of state information, explanation and prediction, and bidirectional messages of the autonomous agents as an extension to the SAT model. Rader et al. (2018) suggested that the content for algorithmic transparency should capture four perspectives: (1) direct explanations of the inputs, outputs, reasons, and steps of a system producing outcomes; (2) justification, outcome, and explanation of the motivation of a system without describing how the system works; (3) revealing the existence of algorithmic decision-making; (4) the development and improved process of the system. These concepts for specifying types of information or details about autonomy to convey to the users dominate the empirical investigation on how to promote transparency of autonomy to the users.

Virtually all empirical studies used the term transparency as a label for autonomy or interface design rather than as a measurable impact on the user; however, it may be investigated how different types of information about autonomy influence trust, workload, and system performance.

Lyons et al. (2017) found that pilots showed more trust in an automated emergency landing planer providing diversion recommendations when presented with a probability of success and an explanation than the probability of success only and no information at all. In a simulated reconnaissance task of collecting information on potential dangers, Wang et al. (2015)

found that the presence of explanations for the decisions and actions taken by the autonomy improved user trust in low-ability autonomy. Nesset et al. (2021) also found that a robot requesting patients to follow basic instructions received greater trust when providing an explanation than otherwise.

Helldin et al. (2013) found that the presence of uncertainty information about the autonomy on the user interface increased trust ratings, albeit not significantly, and shortened the time significantly for drivers to take over the control of autonomous vehicles that could not handle the poor visibility in a driving simulation tasks. Helldin et al. (2014) followed up on their findings by providing uncertain information about autonomy with fighter pilots performing a simulated task classifying friendly versus enemy aircraft with the user interface of aircraft information only, aircraft information with a classification recommendation, or aircraft information with a classification recommendation and uncertainty values. The user interface containing the aircraft, recommendation, and uncertainty information (i.e., most information) induced the highest trust ratings but the longest classification time without any differences in classification accuracy. Thus, uncertainty information postulated to promote transparency did increase trust but resulted in a different effect on speed and performance depending on context.

Skraaning and Jamieson (2021) set up three experiments in full-scope nuclear power plant simulators with licensed operators and compared the displays designed by traditional principles by adding verbal and visual information about automation activities to promote transparency. They found conflicting results in different experiments and suggested that the benefits of transparency were hard to generalize to different operating contexts. In experiments one and two, the operators performed at the component level, whereas in experiment three, the operators engaged with the automatic systems to achieve plant-wide goals. They found that, compared with using traditional principles in displays, with additional information observable in displays, trust was higher in all three experiments. However, task performance, self-rated task performance, response time, workload, human-automation cooperation, and situation awareness in the first two experiments were better but worse in experiment three, where the automation overview display and detailed automation display were compared.

Many studies investigated the impact of the three SAT levels of information (J. Y. Chen et al., 2014) on trust, workload, and task performance. For example, Mercado et al. (2016) developed three displays to assess how information about autonomy helped select or reject the recommendation of a multi-robot management plan in a simulated defense task. The three displays corresponded to level 1 SAT, containing basic information on robot management plan information, level 2 containing the plan and reasoning information, and level 3 containing the plan, reasoning, and uncertainty information. The results showed that displays with the most information about autonomy yielded the best rejection rate and the highest increased trust on the subscale of making recommendations without any impact on workload and response time. Adopting virtually an identical set up to Mercado et al.'s study, Stowers et al. (2020) found that the display with all three SAT levels and uncertainty information (i.e., most information) increased trust ratings acceptance rate of correct recommendations compared to the display with just level 1 and 2 SAT information (i.e., least information), but at the expense of speed. Loft et al. (2021) revealed similar findings on trust, comparing two displays corresponding to level 1+2 and all SAT levels. After using the visualizations of recommendations for unmanned vehicles deploying in a simulation, participants, when provided with Level 1 + 2 level SAT display rated automation verification higher than when provided with all levels SAT display, but without the significant impact of trust, the accuracy of automation use, or workload. Though not explicitly based on the SAT model, Ma et al. (2021) found greater trust in an autonomous vehicle that provided feedback on what the vehicle was seeing and would do than in ones providing no feedback or only feedback on what the vehicle was seeing. The literature contains a few other studies comparing displays presenting different SAT level information with similar findings (Boyce et al., 2015; Brand et al., 2018; J. Y. Chen et al., 2016, 2018; Selkowitz et al., 2015). The empirical evidence from these studies supports that some amount of SAT level information is invaluable to user trust, though differences between displays at different SAT levels are not very consistent, indicating nuances to gaining trust (or even transparency) from presenting more information about autonomy.

Research is beginning to discuss the nuance impact of presenting more and more information about autonomy for promoting transparency. Stohl et al. (2016) presented the notion of transparency paradox or resistance, in which high visibility of the autonomy may actually decrease transparency and produce opacity. Specifically, poorly structured and excessive information about autonomy could overwhelm human cognitive and interpretive capabilities that ultimately make the information confusing and autonomy opaque. Inevitably, research not only needs to address the types of information but also the levels of detail about the autonomy that should be conveyed to the users to promote transparency.

As mentioned, there are virtually no empirical studies measuring transparency experienced by users with respect to the amount of information about autonomy. However, several studies have revealed that additional information for promoting transparency could harm trust. For example, Koo et al. (2015) found that, in situations where a simulated semi-autonomous car engaged in auto-breaking imminently to avoid an obstacle, the driver had more trust in autonomy when presented with information about “why” but less trust when presented with information on “how” the car was acting. Further, trust and driving performance were the worst when both why and how information was present. Göritzlehner et al. (2014) found that acceptance of autonomy’s advisory for resolving separation conflict between aircraft in low complexity scenarios was lower for the display highlighting the unsafe zone with than without heading and speed information. Wright et al. (2016) compared how trust changed with respect to displays without any information about autonomy, reasoning information about autonomy, or reasoning information with temporal information for a route selection task for a convoy of three vehicles in a simulated urban environment. Interestingly, the results revealed that trust was lowest for the display condition with reasoning information (i.e., an intermediate amount of information), even by comparison to the display without any information about autonomy. These findings suggest that additional types of information, and thus also a greater amount, do not guarantee an improvement in transparency or other important human performance constructs.

T. Chen et al. (2014) might have conducted the only study investigating the levels of details (LOD) about autonomy that would route unmanned aerial vehicles through hazardous areas requiring occasional operator engagement. Comparing displays with the highest LOD containing a general representation of the subsystem status, medium LOD containing functional information of subsystem with status, and the lowest LOD containing raw data on system components, T. Chen et al. found no effect on SA but the medium LOD display yielded the lowest workload. Transparency, trust, and system performance were not measured. Thus, this study also suggests that more information about autonomy cannot ensure performance benefits.

In summary, both theoretical and empirical research indicates that more types of information and LODs about autonomy in user interfaces and visualizations may not improve transparency as well as trust, workload, and system performance in a non-linear fashion. The available evidence suggests that transparency along with trust, workload, and performance would improve with more details about the autonomy up to a point before declining due to information overload. However, the literature does not seem to contain any studies that explicitly compare multiple LODs regarding transparency, trust, workload, and system performance to ascertain the hypothesized relationship.

1.5 Research Question

My dissertation research investigates how visualization design at different LODs about autonomy influences transparency, trust, and ultimately the effectiveness of HAT. Effective collaboration between humans and autonomous agents can benefit productivity and reduce risks of human operators in safety-critical situations, with autonomous agents working as the substitute and lowering physical and mental workload by providing assistance and recommendations in complicated scenarios. Ineffective collaboration may induce drawbacks, such as risks bought by the cognitive gap when switching over controls, increased time and workload due to the additional needs for communication and situation assessment, unexpected outcomes due to overreliance, and/or disuse of autonomy due to uncertainty and low expectations.

One way to overcome the drawbacks is to calibrate trust for appropriate reliance between humans and autonomous agents, thus reducing the cost of communication and disuse or misuse of autonomy. Moreover, calibrated trust also means accurate performance expectations of autonomy to avoid overreliance. This can be achieved by disclosing the details of elements in the collaboration through communication between agents. The LODs affect not only the availability of information but also the possibility of reasoning autonomous agents' decisions. Therefore, comprehension, workload, and efficiency of communication may be influenced and collectively impact transparency. Thus, the research question for this dissertation is:

How do the LODs and corresponding visualizations of autonomy influence transparency and trust in HAT?

To answer this central research question, there are three research objectives:

Objective 1: Create a representative testbed for the design and evaluation of LOD in visualization to facilitate HAT

The first objective is to build a simulation platform for a representative HAT task affected by visualizations at different LODs about autonomy. Specifically, this objective involves the development of a web-based application for search and rescue (SAR) in the wilderness, which can benefit from the deployment of UAVs to supplement the dwindling volunteers for those missions (refer to Chapter 2). This SAR web application supports different visualization of the lost-person model and UAV path-planner at different LODs for studying the impact on trust and performance empirically with human participants.

Objective 2: Identify optimal LOD for transparency, trust, and performance

The second objective is to resolve whether the lower LOD leads to higher transparency, given the potential information overload. As more details are delivered, users are more likely to understand the underlying mechanisms and reasons for behaviors and performance of the autonomy, but information processing demand may also increase. Fewer details in the visualization sometimes provide an overview of action and performance of the autonomy to facilitate collaboration. Less information may be intrinsically associated with less transparency, but key information buried in a large amount of information may actually lead to cognitive clutter and thus lower (perceived) transparency. Hence, this research objective examines how visualization at different LODs about autonomy could have different impact on users with respect to transparency and based on an empirical study recruiting human-participants to complete SAR scenarios simulated in the Objective 1 testbed.

Objective 3: Adapt LOD with respect to trust

The third objective is to examine how to adapt LOD in visualization with respect to trust as users interact with autonomy over time. As the users interact with the autonomous agent over time, their understanding, familiarity, and trust often improve. Improved understanding and familiarity could mean that users can process more information about autonomy without any additional mental demands. From one perspective, LODs should increase to continue improving transparency and thus calibrated trust. From another perspective, LODs should decrease to mimic implicit communication between humans, alleviating the workload for other tasks and minimizing "clumsy automation" that impact trust. In other words, this research objective examines how static and adaptive UI designs with increased or decreased LODs would be better in elevating the speed of building trust and plateau of trust as users interact with autonomy over time.

1.6 Overview

The remainder of the dissertation describes three research objectives in separate chapters, followed by a detailed discussion of their contributions. Chapter 2 presents the SAR web application that is used as an experimental platform for the empirical research of this dissertation. Chapter 3 presents the study on the impact of visualization designs at different LODs on transparency of a lost person model for guiding the allocation of search teams to specific search areas. Chapter 4 presents the study on how to adapt LOD in visualization with respect to trust as users interact with autonomy over time. The last chapter discusses the contributions of the three objectives collectively.

2. Web Application

Humans and autonomous agents establish efficient HAT activities that need transparency and trust. As mentioned, LOD may be an important effect on transparency. An experimental platform for evaluating the effect of LOD on transparency and trust needs to be implemented. Specifically, SAR missions in the wilderness could be a practical scenario where humans and autonomous agents work collaboratively as a team to achieve the same target. This chapter focuses on the platform for supporting HAT activities in which visualization of different LOD. The rest of the chapter describes the overview of SAR, lost person modeling, the web application scope, and a detailed description of the key components.

2.1 Search and Rescue Mission

SAR missions are time-critical, sometimes situated in high-risk environments, including dangerous terrain and extreme weather. Based on the report of the National Crime Information Center (2017), about 650, 000 people went missing, and approximately 100,000 of them resulted in a SAR mission in 2016. Typically, if a missing person is not found within the first 51 hours of a SAR mission, the chances of being located and survival decline significantly (Adams et al., 2007).

A typical wilderness SAR mission includes three stages: investigation, containment, and search (Phillips et al., 2014). The investigation stage involves gathering resources, including volunteers and background information. The background information includes a lost person profile documenting their personal characteristics (e.g., children vs. adults) as well as the point last seen (location where a witness last saw the lost person), last known point (LKP, location where a verifiable clue was found), and initial planning point (IPP, a reference point that does not change during the mission). The investigation informs the selection of search areas and strategies.

After the investigation, the containment stage begins with executing the procedure to prevent the search area from expanding exponentially. Thus, containment involves estimating the largest boundary the lost person can reach and sending searchers to locations that can easily spot and confine the lost person. Depending on the available SAR resources (e.g., people, dogs, helicopters), strategies are selected to match the specifics and progress of the mission. In the early stage of the search, wilderness SAR teams would adopt search strategies based on the lost-person profile, such as attraction and hasty search techniques. The attraction techniques involve search teams making sounds by blowing whistles, calling the lost person's name, or using a light source to attract the lost person (e.g., hikers, adults, or children with consciousness and some mobility). The hasty search techniques involve search teams surveying along linear features or specific locations where the lost person might be following or heading (Conover et al., 2018).

If those strategies fail, the mission turns to the area search techniques that involve search teams carefully surveying segments surrounding the IPP. If the lost person is not found in the early stage of the search, the rest search would be very time-consuming, such as grid search, which is the last resort that searchers move slowly and deliberately through an area in a straight line (Kentucky Emergency Management, 2020). The search stage begins with planning and sending out teams of professionals and volunteers to survey various segments of the search area to find the lost person based on a mission plan developed from the investigation. Because the search resources are usually limited, the number of teams usually cannot afford to cover the whole area simultaneously. Thus, the potential area is segmented and assigned to the teams in order. Figure 4 shows the flow of search tasks in a typical search of a SAR mission.

Making a search plan includes exploring information about the environment, segmenting the area, estimating the probability of area (POA), prioritizing the search order, and assigning teams. Teams are assigned to different segments and communicate any findings (e.g., clues) to the planning officer(s) to update the plan until the lost person is found or the mission terminates (Koester, 2008; Phillips et al., 2014). The bold box shows the process that could potentially benefit from this research. The flow starts with making a search plan. After launching the search, check if the target is found. If not found, then analyze the feedback of field search teams to update the search plan and continue the next round. The whole search would stop if the target is found, or time is out.

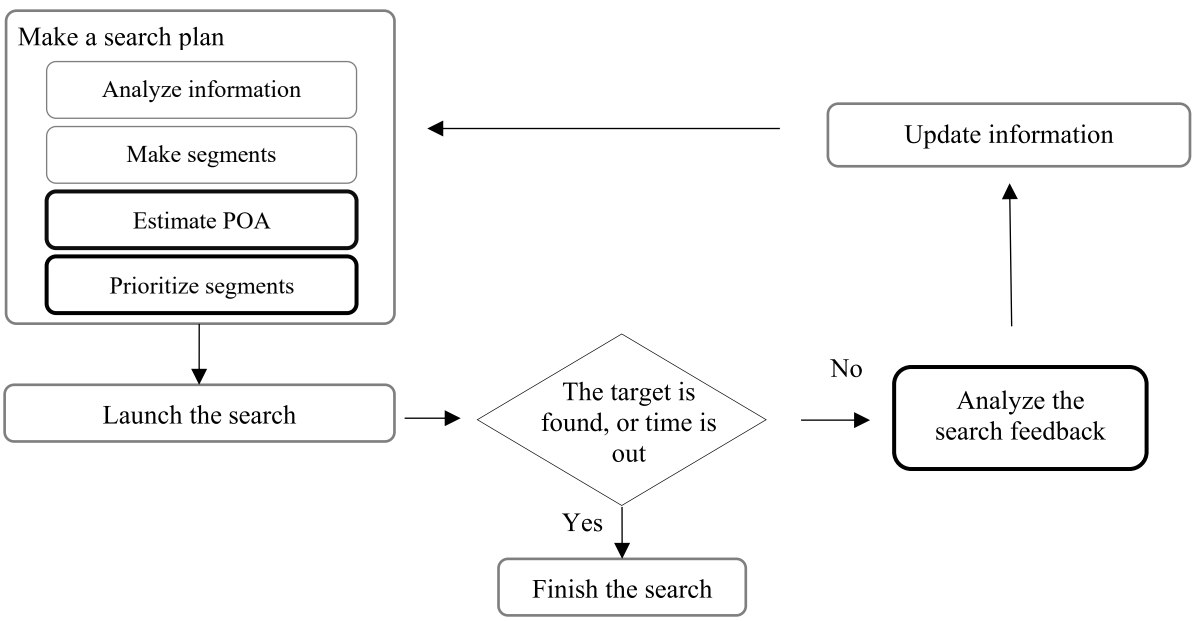


Figure 4. The flow of a search mission during SAR.

The first step of making a search plan is to analyze the information from the previous investigation, including geographical, personal, point last seen, LKP, weather, etc. Then, the area is segmented by terrain and salient terrain features. Estimated information is then calculated based on the existing information and cited from historical statistics, such as the lost person model (LPM), probability of detection, and lost time.

The second step is to make segments, which are usually made based on landmarks, size, and linear features on the map.

The third step that contributes to the optimization of team assignments is integrating the lost person behavior model (LPM) into the decision-making process. The aim is to provide an estimation of the possibilities allocation of the subject and compute POAs.

The final step before launching the search is to prepare a team assignment to prioritize the segments based on the probability map showing the area with the likelihood of the lost person being located so that the search efforts can be allocated to minimize search time.

During the search, the search manager needs to update the plan based on the feedback from search teams, such as updating the map and managing the completed search. If new clues are found, the estimation of the subject's motion and the location of the lost person can be adjusted accordingly (Stone, 1981). The whole search would stop if the target is found, or time is out.

Area search is usually very time-consuming, and a trained area search team requires about 3.5 hours to cover one mile. As the search area expands geometrically from the initial search point, covering many areas requires a huge workload and sometimes high risk with terrain and weather on the searchers. Along with the declining number of well-trained volunteers for SAR (Brown, 2020), the need to reduce search time to find the lost person is increasing through better technology adoption or decision-making.

2.2 Unmanned Aerial Vehicles for SAR

SAR would benefit from deploying Unmanned Aerial Vehicles (UAVs) piloted remotely to augment human efforts in searching for lost persons in the wilderness. UAVs have the potential to reduce the risk of traveling to dangerous or difficult-to-access terrains for target search or supply dispatch and improve search coverage in terms of speed, a field of view, and sensor information (Jiang et al., 2022; Karaca et al., 2018; Xiao et al., 2017). However, the current operation of a UAV involves at least a pilot and a sensor operator (Goodrich et al., 2007), presenting a high demand for human resources that would significantly constrain the number of UAVs deployable in a SAR mission.

To reduce the demand for human resources in operating UAVs, (autonomous) path planning has received substantial research attention (Tisdale et al., 2009; L. Yang et al., 2014). Silvagni et al. (2017) setup and field tested a system to demonstrate how UAVs can be instrumented and programmed to survey for signals from heat and avalanche beacons in a lawn-mower (i.e., GRID) flight pattern after specifying the location of the affected area. Avalanche SAR is less demanding on a path planning algorithm because the search perimeter is relatively well-defined, and the victims would not be moving. For many other wilderness SAR missions, the lost person could be moving, and the search perimeter would be ill-defined. In these cases, the lost person's behaviors would be invaluable for selecting the strategies and segments to search for (Koester, 2008).

Only a few studies consider the lost person behavior in UAV path planning (Cangan et al., 2020; Heintzman et al., 2021; Lin & Goodrich, 2009). Goodrich et al. (2007) were the first to argue for considerations of lost person behaviors in UAV path planning for wilderness SAR and proposed a random walk model in which the lost person moves in a random direction with speed constrained by the environmental and prior state for estimating probabilities of the lost person in a location. Later, Lin and Goodrich (2009) formulated a UAV path planning algorithm that uses a lost person probability distribution map from any model as an input parameter along with other constraints, such as time, starting point, and flying altitude. However, Lin et al. never seemed to have integrated their lost-person model and path planner explicitly.

Building on these past efforts, our research team developed UAV path planning frameworks that plan UAV paths to reduce uncertainty or risk of missing detection with explicit integration of a lost person model based on Monte Carlo simulation of movements constrained by the environment and human-searcher model moving in a lawn-mower pattern Cangan et al. (2020). Heintzman et al. (2021) tested the framework with a more sophisticated lost-person model, which accounted for more movement dynamics and environmental conditions. In a simulation study, they found that the risk of not finding the lost person was reduced compared to the conditions of human searchers conducting searches with UAVs following lawn-moving trajectories and manually operated UAVs tracking human searchers from above to stay within visual range.

Existing path planning algorithms tend to focus on search within a segment, which is only one sub-unit of the area search. In practice, a SAR mission involves surveying many segments, which must be allocated to the available search teams (Hill, 2012). Given limited resources, path planning must prioritize searching for the segments that possess higher probabilities of containing the target. Further, some factors or variables are situated or highly mission-specific (e.g., extreme weather, unanticipated terrain change) that are not factored into the algorithm. Thus, there are always some risks that a path planning algorithm misestimates the probability of the target located in the segment and thus recommends a suboptimum sequence of segments for search. Hence, professionals must also engage in this decision-making process during the mission to adapt the path-planning recommendations as necessary. The process of prioritizing also needs the estimation of the lost person's location. Hence, lost person estimation is essential for successfully locating the lost person and shortening the search time.

2.3 Lost Person Modeling

Lost person modeling (LPM) computes the probability of a lost person for a given location and probability of area (POA). POA stands for the likelihood that a subject is located within a specific search area. LPM estimates POA based on the probable movements given the behavioral profile of the lost persons and environmental conditions such as distance, weather, and elevation (Koester, 2008; Mansfield et al., 2020). After dividing the search area into segments, POA is estimated for each segment and used to prioritize the segments for the search given resource constraints (Hill, 2012). Thus, LPM is the enabling technology that can support humans and autonomy in planning the mission on what segments to search.

The literature presents three LPM methods for calculating the probability map of the search area. Most commonly used and accounting for different profiles of the lost-person (e.g., adults vs. children), the distance ring model computes radii from IPP for 25%, 50%, 75%, and 95% chance of finding the lost person (Syrotuck, 2000). The distance ring model represents the four POA as concentric circles or rings extending from the IPP (Figure 5 (a)). The size of each ring (i.e., the geographical area of each quantile) is adjusted according to 30 different statistical distance tables. These statistical tables were built on data from more than 145,000 searches worldwide and categorized with respect to lost persons' activity and strategies or demographic information (Koester, 2008). Each lost person category has a distinct distance that the lost person would move within each probability level of the ring model. The ring model can be adapted to calculate POA for more specific mission scenarios by overlapping the estimated POA quantiles derived from multiple tables. The ring model is widely used given its basis on a large dataset, intuitiveness, and ease of adaptation. In practice, the planning officer applies these statistic tables to contain the search effort, create probability maps, estimate POAs, and prioritize segments for search (Hill, 2012).

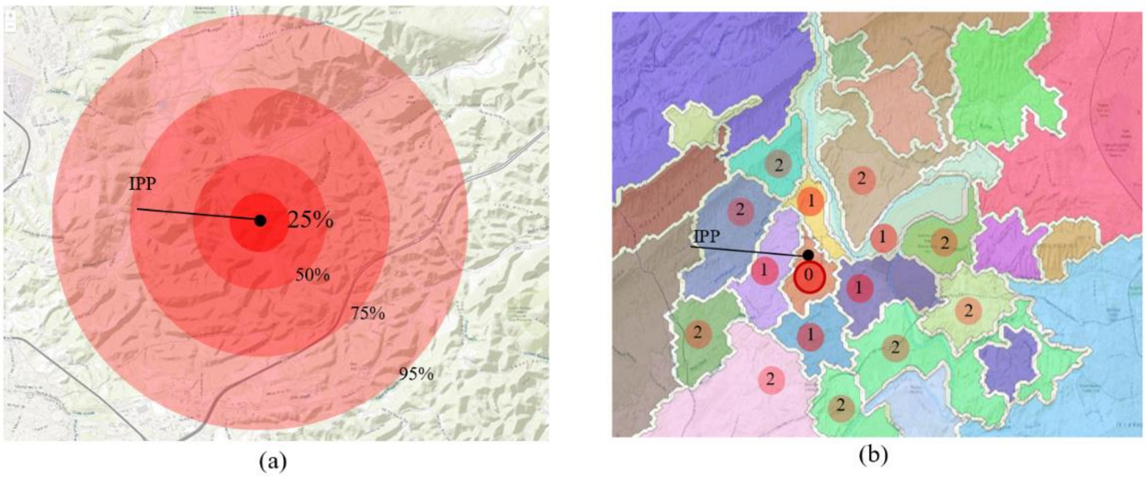


Figure 5. Example of models of lost person behaviors. (a) A ring model, in general. (b) A watershed model.

One limitation of the ring model is the lack of consideration for the terrain. To address this limitation, Doke (2012) developed the watershed model that divides the search area into segments based on ridge lines. Figure 5 (b) presents a sample output of a watershed model. The area is first divided into small segments based on ridgelines and then incrementally indexed from IPP (as zero) to outside boundaries (1,2,3…). Sava et al. (2016) compared the effectiveness of using the ring, watershed, and both models for searching for the lost person in the area. They discovered that using both models yielded the best probability of finding the lost person, while just using the watershed model was the worst. The limitation of ring and watershed models is the lack of consideration for temporal dynamics of lost-person behaviors. In other words, the estimated probability map by the ring and watershed models does not change concerning the duration from when the person is reported lost.

Adopting the Monte Carlo simulation of moving particles based on behavioral heuristics and environmental elements (Kratzke et al., 2010; Lin & Goodrich, 2010), our research team

(2019) developed an agent-based model that accounts for temporal dynamics in estimating the location of the lost person in the wilderness. This modeling method uses the lost-person profile and environmental parameters, as captured by Koester (2008), as inputs to define the parameters of agent and lost-person behaviors. Agent-based modeling simulates possible and likely lost-person movement trajectories by randomly selecting movement behaviors from the distribution of known lost-person reorientation strategies for the given terrain. The probability map can then be estimated based on the distribution of lost-person locations for all simulated trajectories at a given time (Hashimoto & Abaid, 2019). SAR planning officers can benefit from more geographically and temporally precise POA estimates provided by agent-based LPM that explicitly incorporate movements with respect to specific terrain features and the time when LKP was reported. In contrast, ring and watershed modeling assume the lost person stopped moving at the beginning of the mission. Furthermore, agent-based LPM can re-compute the lost person's location (with or without additional simulation runs) for the clues discovered by search teams during the mission. The improved geographic and temporal precision of the agent-based LPM not only could improve human and autonomy in deciding what areas to prioritize for search but also support how UAVs should perform the search (i.e., path planning that can affect the speed and altitude for a more careful survey) according to the potential risk of missing clues or the lost-person in the wilderness (Heintzman et al., 2021).

Despite all the advances in LPM, domain expertise remains necessary to interpret and adapt the estimated POAs because model results may contain substantial uncertainties for several reasons. The historical data for developing LPMs varies across lost person profiles, such as more cases for adults than children. LPM currently cannot account for many specifics or idiosyncrasies of individual missions, such as the target destinations of the lost person as indicated by their family and friends. Similarly, LPM relies on distributions and sometimes only statistical averages from past cases that do not consider the nuances in the geographic, weather, and health conditions. For these reasons, SAR experts are indispensable in the field and must know how to interpret model results concerning the mission details to make the best use of LPMs.

Proper use of LPM can lead the search to move in the correct direction and potentially speed up the search process that the model provides the optimized search order that area segments could be searched from the highest to the lowest probability. At the same time, the pursuit of improving geographic and temporal precision increases the complexity of LPM. This complexity, in turn, imposes a demand on user trust to utilize LPMs for decision-making and, subsequently, for directing UAVs autonomously.

However, potential misuse or disuse of the LPM will slow down the searching process or even cause fatal results due to some practical problems. Not all the variables are guaranteed to be covered and updated as the input parameters of LPM, especially in the field search scenario, such as extremely bad weather or a new trial. The data that built the LPM are from historical data, and when adapting to the actual case, every individual is different. The manager needs to regulate the current model results, which have some uncertainty, by adding their own experience to make an adjusted decision. When making strategic and tactical recommendations in a field case, the search expert's input is indispensable, and knowing how to interpret observations and statistics concerning LPM is essential to make efficient adjustments in the practice. A user interface is needed to enable human inputs, bridge communication, and facilitate the SAR mission.

2.4 Web-based Application Design

A web-based application prototype is being developed to integrate this research into the SAR mission so that the SAR professionals can efficiently facilitate their missions. The application is connected to a geographical information system (GIS), specifically ArcGIS (ESRI, 2022), to gather high-quality maps with many different layers of information (e.g., linear feature layers such as rivers and roads) and built on JavaScript to provide custom user interface features. The interface from search management and health-supporting perspective in wilderness SAR missions should include information about search resources, allocating strategies, tactics, area division, search theory, probability of area, lost person model, etc. In addition, geographical information, such as linear features, landmarks, transportation information, label, altitude, contour map, terrain, wood density, and river, is provided for potential assistance in decision-making. This web application supported automatic segmentation of the search area around IPP, visualizations of the agent-based LPM (Hashimoto & Abaid, 2019), task management, and search progress monitoring. With some customization, this SAR web application prototype can be used by SAR professionals and experimental researchers on any computer with stable internet access.

2.4.1 Area Segmentation

Every mission involves assigning teams of professionals and volunteers to search the surroundings of the Last Known Position (LKP), where the lost person was, or suspected to be, last seen. The mission command assumes this responsibility by dividing the surrounding of the LKP, known as the search area, into "search segments" according to historical statistical guidelines (Koester, 2008) with respect to the available information on the lost person. After dividing the search area, the mission command assigns each search team to a segment according to the POA, the likelihood that a lost person resides in a given region. The current practice of dividing the search area into segments involves a SAR professional manually drawing the segments on a paper map or in a SAR software program (e.g., Caltopo (CalTopo, n.d.)) while following the aforementioned historical statistical guidelines with respect to the subject's type, LKP, Point Last Seen, lost duration, etc.

The web application automates the segmentation of search areas based on the statistical guidelines to alleviate workload so that SAR professionals can focus on critical human-centric activities (e.g., gathering additional information from friends or relatives of the lost-person). To automatically divide the search area into segments, the web application employs a Voronoi partitioning algorithm (Lévy & Liu, 2010) with three mainly key steps:

• Step 1: Computer number of segments. The human specifies or inputs the start location, the search area (i.e., the length and width of the searching area), the size of a search segment (typically set to $U_{area} = 40$ acres for a search team to cover within four hours). These inputs permit computation of the total number of the searching segments for the mission.

• Step 2: Generate the center point of each segment. Given the number of segments, an array of concentric circles, denoted by $C = \{c_1, c_2, c_3, \ldots, c_n\}$, sharing the same center point as the searching area (Figure 6). R is the radius of the first circle (i.e., $r_{c_1} = R$). Radius of each circle in the array is set to $r_{c_n} = n \times R$. The largest circle is inscribed within the search area (i.e., $n \times R \leq (Length, Width)$). Hence, for a given searching area with known length and width, the number n of circles can be calculated. Then, K segment central points are evenly distributed in the middle of each annulus (i.e., for the ring between the first and second circle ($r_{c_1} = R, r_{c_2} = 2R$), the middle of the annulus is a circle of radius $1.5 \times R$). For each annulus between the n circle and the $n+1$ circle, the size of the annulus is $\pi \times \left[\left((n+1) \times R\right)^2 - (n \times R)^2\right]$, and set K as the amount of search segments of size Uarea in the annulus, i.e.,

$K_n = \frac{\pi \times \left[\left((n+1) \times R \right)^2 - (n \times R)^2 \right]}{U_{area}}$. Finally, the center points of the segments are stretched to fit the searching region.

• Step 3: Apply Voronoi partitioning to generate each segment polygon.

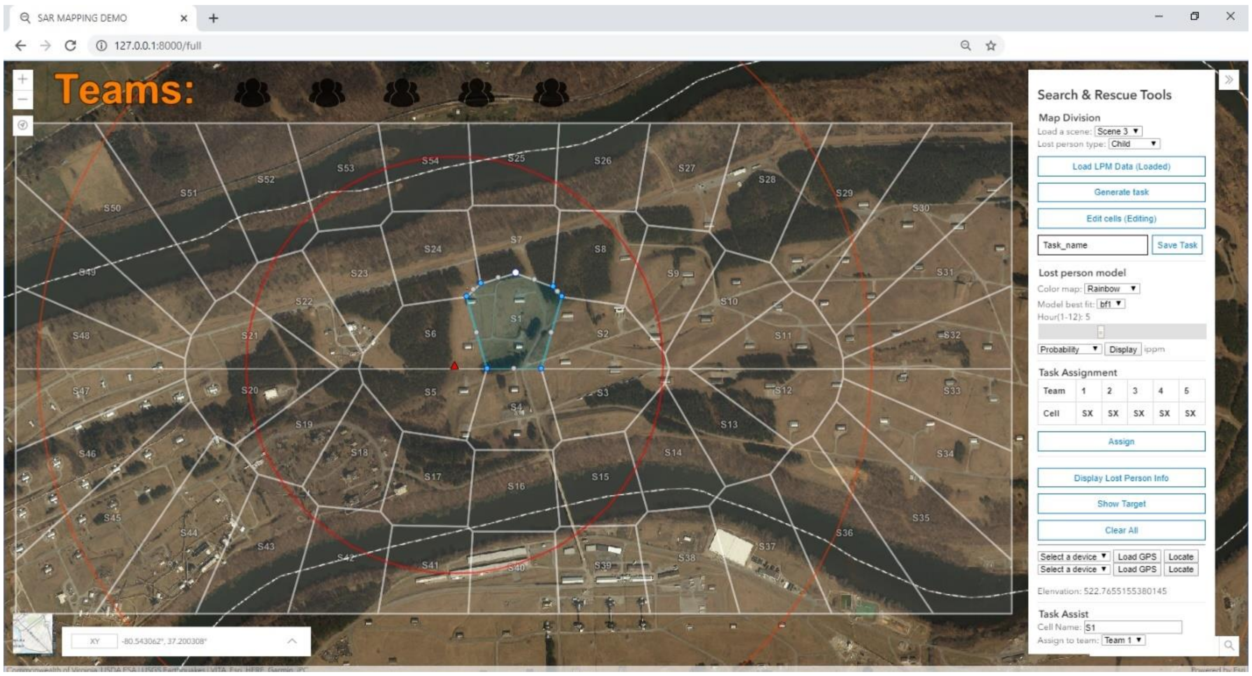


Figure 6. The web user interface.

The user interface of the web application displays a full search area in satellite image view that contains the Initial Planning Point (IPP) marked as a red triangle and the 25%, 50%, 75% POA rings marked in red circles (Figure 6). The web interface for 2D segment editing includes the main view and a side bar. The main view provides functions for displaying and editing information about the searching area, segments, team assignment, and basic map manipulation. The side bar is for task management-related functions, which include the manipulation of lost person model display, task management, team assignment, path planning, UAV monitoring, and assistant tools.

The white polygons denote the search segments for assigning to the search teams. To accommodate unique characteristics of each search mission (e.g., volunteer skills, geography) that cannot be anticipated with the algorithm, the web application provides control inputs for the users to alter each search segment by dragging and dropping the vertices of the polygon. The web application aims to alleviate mission command from the workload of dividing search area into segments while retaining the flexibility to customize segments as necessary.

2.4.2 Lost Person Behavior

LPM used in wilderness SAR is generally created as probability maps and creates a web app using ArcGIS to prepare for SAR incidents (Vezina & Dohery, n.d.). In practice, GIS planning tools are used to integrate and visualize basic LPM, such as CALTopo (*SARTopo*, n.d.), IGT4SAR (Ferguson, 2013/2020), etc. The visualization in these tools is pretty straightforward; for example, a ring distance model is usually drawn as four concentric circles centered by IPP marked with percentages or filled with gradient color. Doherty (2014) used a probability region model with the watershed segments filled with different colors based on the likelihood of containing the subject.

Researchers used different visualization strategies, such as symbols, points, heat maps, weighted maps, and trajectories, to present LPM to assist in planning, decision-making, and data analysis before, during, and after SAR missions. Stoddard & Pelot (2020) plotted raw data of incidents of SAR cases as colored circles on the map and provided a detailed summary of the incident by hovering the mouse over the symbol. Siljander et al. (2015) modeled and visualized the response time of a colored gradient map in maritime SAR planning. Guitouni & Masri (2014) used a simple 2D contour map to present the distribution of the possible location of the lost target and then present the result in the information fusion process on the map with target areas marked by circles. Guoxiang & Maofeng (2010) visualized search patterns in lines with arrows overlaid on the user interface. W. Xiong et al. (2020) presents the predicted path of drifting objects in trajectories to assist marine SAR activities. Environment parameters like sea current and wind are presented in arrows and marks. Points present the output particles of the Monte Carlo simulation. Details of models are revealed but may also induce excessive-high compression of data onto the same visualization. Cheng et al. (2016) used symbols and gradient paths with time marked in different colors to present incidents crossing a period. However, a lack of research can reveal how transparency is improved or deteriorated in visualization design, especially in the context of the lost person model.

The web application prototype further supports mission command with visualizations of the lost-person behavioral model to aid the assignment of search segments to individual search teams, which include multiple searchers and, in the future, UAVs. As mentioned, the lost-person behavioral model estimates the POA for every location inside the search area for a given time. The web application can currently visualize the POA values with a single marker for the likelihood of the lost-person location (Figure 7) and a series of markers for a trajectory of the lost person over a period of time (Figure 8), a heat map for a region (Figure 9), and a weighted map (Figure 10).

Each visualization can provide unique advantages in supporting mission command to prioritize the segments for search team assignment. A single marker of the highest likelihood of the lost person's location might help focus the attention of the mission commander. The series of markers illustrating the likely path being traversed by the lost person might help the commander to assignment of search segments over time. Finally, a heatmap presenting POA distribution over the entire search area helps the commander to understand the relative importance of the segments. These visualizations should enable the mission command to utilize the lost person behavior model intuitively for prioritizing search segments effectively, thereby improving the chances of finding the lost person faster.

Figure 7. Concentric rings of varying sizes and colors used to represent different probability levels.

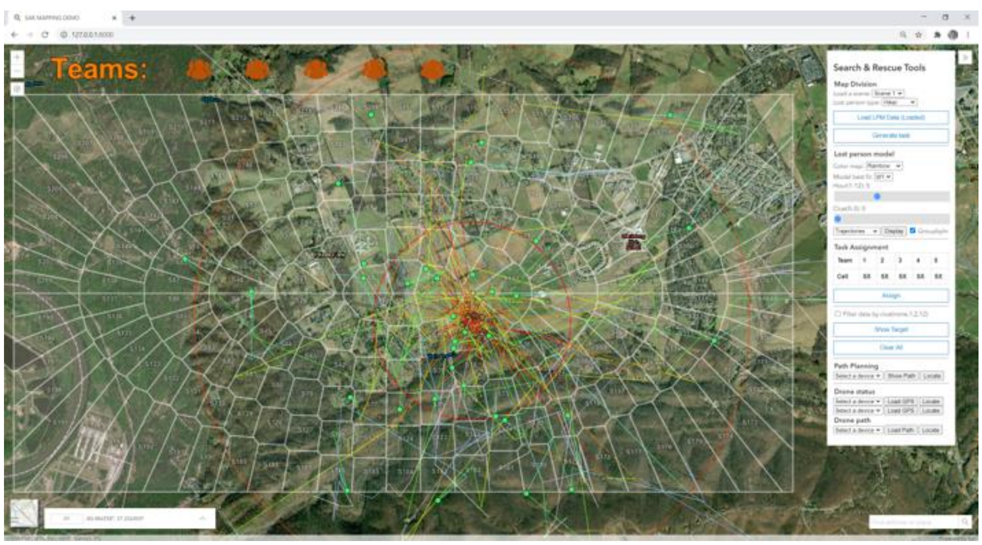


Figure 8. Within a given time interval, the lost person's location is estimated, sampled, and linked to trajectories.

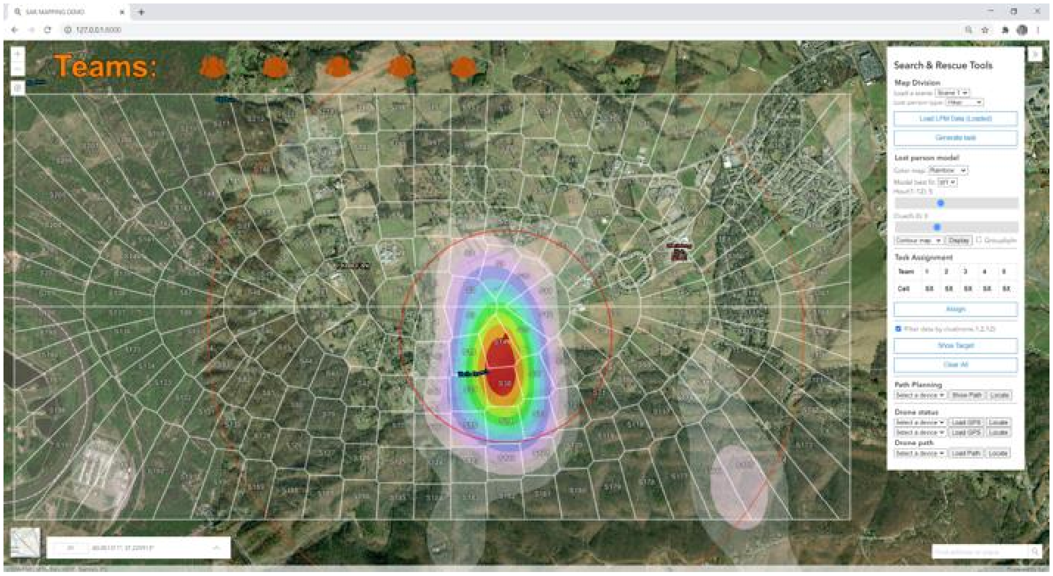


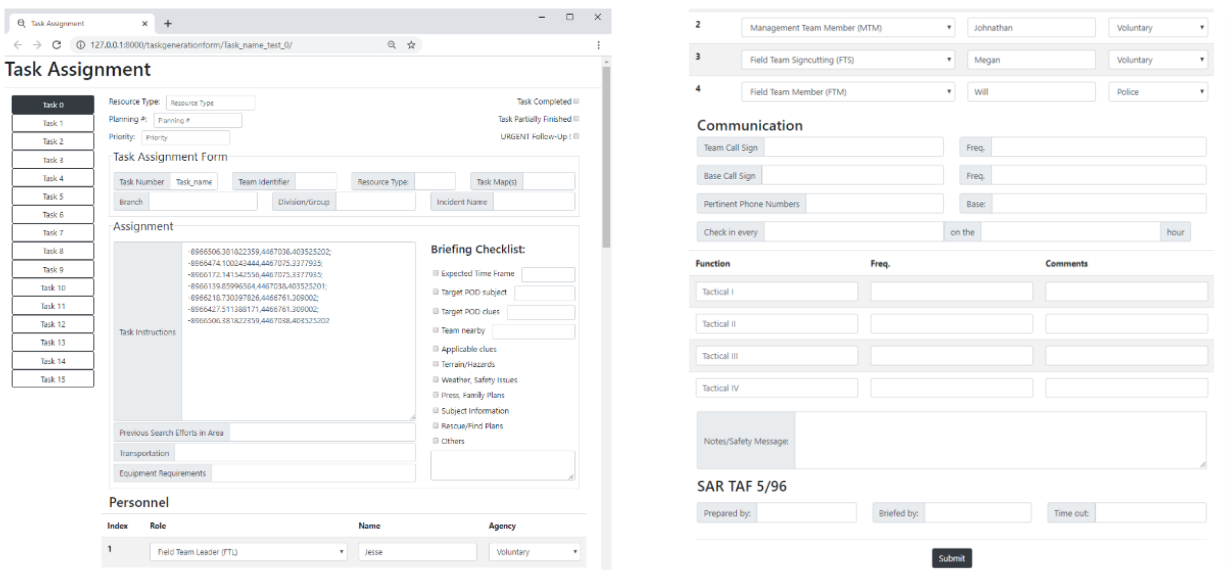
Figure 9. A heat map of the lost person model. The color scale can be changed based on user preference. In a rainbow color scale, the red area has the most probability.

Figure 10. The probability of the area is calculated and presented as the color with different bright.

2.4.3 Task Management

The web application also supports mission command in assigning search tasks for each team. To make an assignment, the user can drag and drop each black search team icon on the top of the user interface onto a search segment. After finishing allocating every team to a segment, the user can automatically generate a task assignment form, which is designed based on the

Commonwealth of Virginia Department of Emergency Management (Figure 11). The digital form for each search segment automatically contains available or previously inputted task information, including the coordinates of vertices for each segment, task type, IPP, base, etc. Further, each field remains editable for users to add and modify information. The task assignment functionality should further alleviate the task assignment workload for the mission command to spend time on other tasks.



(a) (b)

Figure 11. The task assignment form.

2.4.4 Search Progress Management

The web application is being developed for processing and displaying the UAV data (e.g., location, waypoints, images, etc.) (Figure 12). Thus, the web application enables SAR professionals to assign UAVs for searching segments and observing sensor data (Figure 13), as well as visualize lost-person behavior and generate task assignment for human teams. Furthermore, detailed path planning information is displayed to support the human supervisory and identification process, which is essential for the efficiency and accuracy of the search mission (Figure 14, Figure 15).

Figure 12. The path planning module in the SAR user interface. The module includes three sections on the right panel: a path planning section, a drone status section, and a historical path section. In the main view, the planned path of the two drones is presented by the yellow line and green line with index numbers independently.

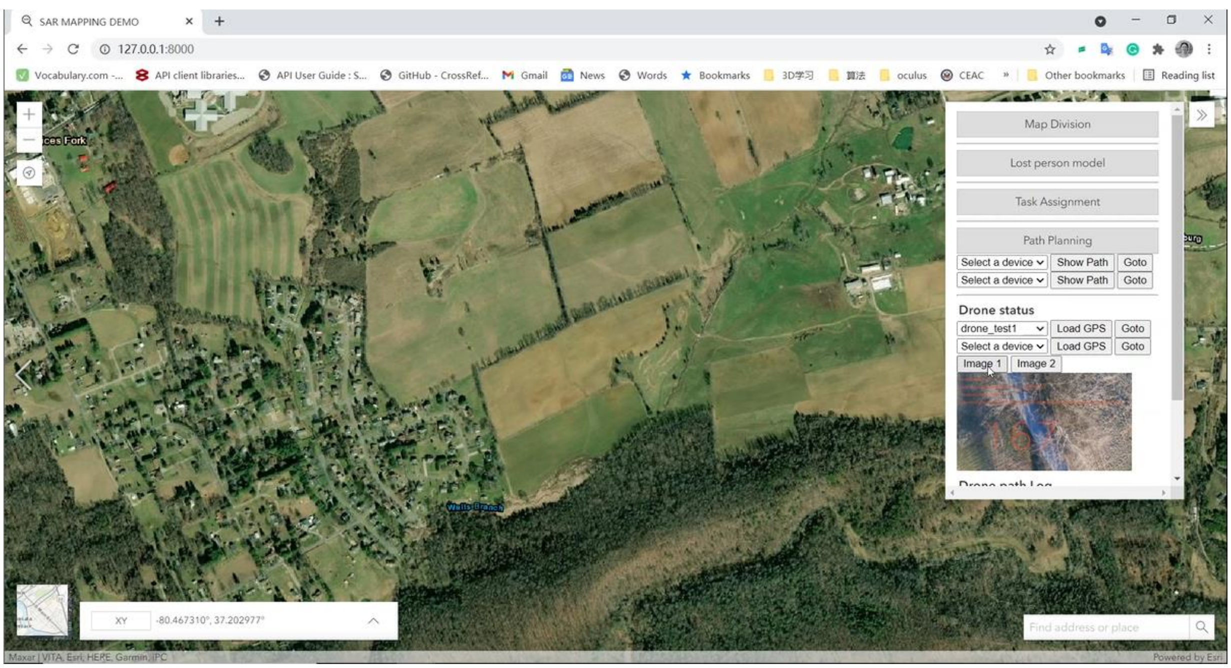


Figure 13. The section on data status includes information on the real-time and historical waypoint and the image captured from mounted sensors, in this case, an optical camera.

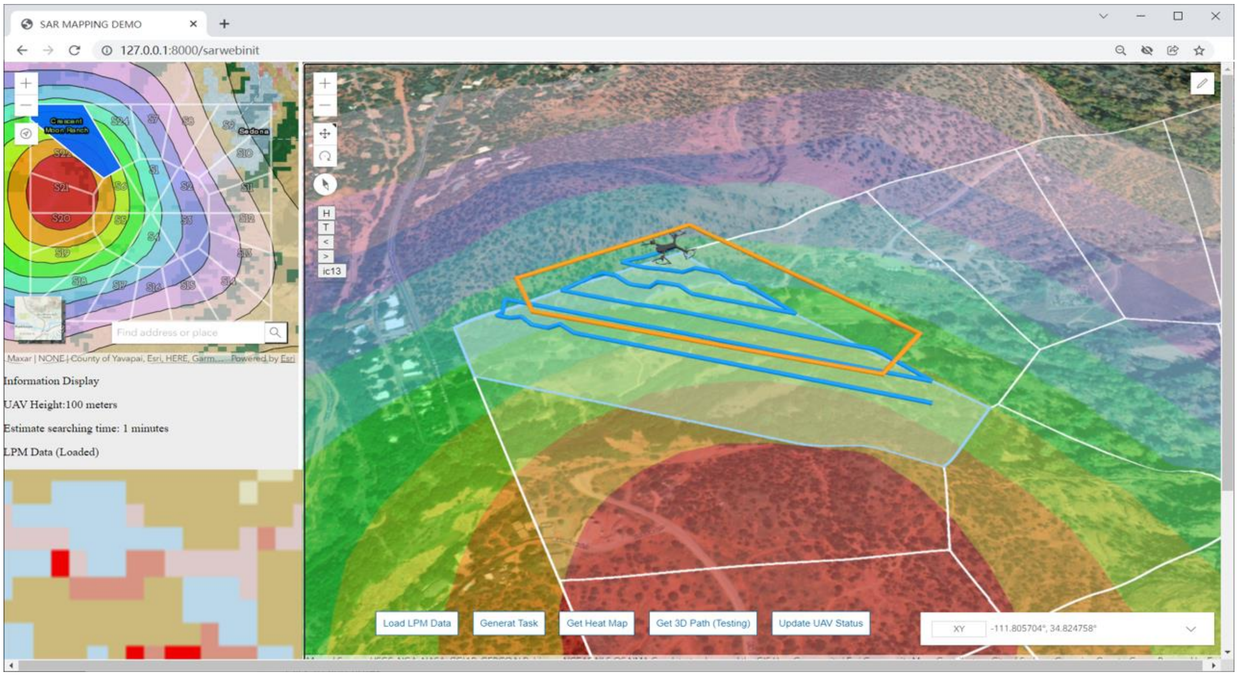


Figure 14. The 3D path planning and real-time feedback from UAVs for human UAV teaming in a field search. The left top panel shows the lost person model and segmented area. Parameters of the UAV, team member, terrain, LPM, and the task is displayed on the left bottom panel. The right panel shows the main view of the path and the interactions of the map.

Figure 15. Pictures from the UAVs are displayed for further human identification during the human-UAV collaborative search task.

3. Transparency and LOD

3.1 Introduction

Search and rescue (SAR) missions in the wilderness are time-critical, sometimes situated in high-risk environments. Typically, if a missing person is not found within the first 51 hours of a SAR mission, the chances of being located and survival decline significantly (Adams et al., 2007). As an important step of a SAR mission, an area search is conducted by the search professionals and volunteers surveying the area to find the lost person and all useful clues. Area search is usually very time-consuming because available resources and search teams can only afford to cover a limited area at any time. Along with the declining number of well-trained volunteers for SAR (Brown, 2020), the need to reduce search time to find the lost person is increasing through better decision-making or technology adoption.

SAR would benefit from deploying Unmanned Aerial Vehicles (UAVs) that UAVs have the potential to reduce the risk of traveling to dangerous or difficult-to-access terrains for target search or supply dispatch and improve search coverage in terms of speed, the field of view, and sensor information (Thiels et al., 2015; Xiao et al., 2017; Karaca et al., 2018; Jiang et al., 2022). With autonomous path planning, the human resources (i.e., UAV pilots and sensor operators) can be further relieved (Goodrich et al., 2007; Silvagni et al., 2017; Tisdale et al., 2009; L. Yang et al., 2014).

In order to enhance the efficiency of the search path, lost person behaviors are considered in using UAV path planning for SAR (Cangan et al., 2020; Heintzman et al., 2021; Lin & Goodrich, 2009). Lost person behavior can be estimated through lost person modeling (LPM). LPM is calculated based on the probable movements given the behavioral profile of the lost persons and environmental conditions (Koester, 2008; Mansfield et al., 2020). After dividing the search area into segments, the probability of area (POA) is estimated for each segment and used to prioritize the segments for the search given resource constraints (Hill, 2012). Thus, LPM is the enabling technology that can support humans and autonomy in planning the mission on what segments to search.

The LPM includes models that use the summarized statistics of real-world case data to create probability maps, such as the distance-ring model (Koester, 2008; Syrotuck, 2000) and watershed model (Doke (2012), Sava et al. (2016)), and model lost person dynamics based on behavioral heuristics and environmental elements (Kratzke et al., 2010; Lin & Goodrich, 2010). Our research team (2019) developed an agent-based model that simulates possible and likely lost-person movement trajectories by randomly selecting movement behaviors from the distribution of known lost-person reorientation strategies for the given terrain. SAR planning officers can benefit from more geographically precise POA estimates that explicitly incorporate movements with respect to specific terrain features. Furthermore, agent-based LPM can re-compute the lost person's location for the clues discovered during the mission, thus not only could improve what areas to prioritize for search but also supporting how UAVs should perform the search according to the potential risk of missing clues or the lost-person in the wilderness (Heintzman et al., 2021).

Despite all the advances in LPM, domain expertise remains necessary to interpret and adapt the estimated POAs because model results may contain substantial uncertainties for several reasons. The historical data for developing LPMs varies across lost person profiles, such as more cases for adults than children. LPM currently cannot account for many specifics or idiosyncrasies of individual missions, such as the target destinations of the lost person as indicated by their family and friends. Similarly, LPM relies on distributions and sometimes only statistical averages from past cases that do not consider the nuances in the geographic, weather, and health conditions. For these reasons, SAR experts are indispensable in the field and must know how to interpret model results concerning the mission details to make the best use of LPMs.

This study presents a study from our research program that seeks to redefine wilderness SAR by enabling teams of human searchers and multiple UAVs to collaborate toward improving search outcomes and reducing human effort (Williams et al., 2020). Figure 16 depicts the new concept of operations for wilderness SAR. In this new concept of operations, the planning officers interact with the lost-person model to direct professionals and UAVs to different search segments. Once search segments are assigned, the UAVs autonomously plan their search paths within their segments and transmit relevant sensor information for either edge (i.e., backpack) or cloud computing. The processed sensor information would be distributed to SAR team members via the user interface for updating decision-making. This study focuses on transparency of the lost-person model, which is central to the joint decision-making between humans and autonomy in what segments to search. That is, in light of the idiosyncrasies in every mission, human interpretation of the probabilities computed by the lost person model would be necessary to optimize the prioritization of segments to search and, thus, reduce the time to find the lost person. Information from investigation teams was sent to the backpack computer to analyze and compute recommendations. Geographic information, lost person estimation, segments of area, and plan recommendations can be dynamically computed with the backpack computer, which is especially useful when the internet is inaccessible in the wilderness. The information is then sent to the planning officer through the user interface. The planning and operations officer then makes decisions considering the investigation team’s results and field information and sends the final assignment plan back to the backpack. The search teams formed by UAVs and humans are then sent to the field to deploy the search task. Then information collected from the search is updated in the backpack for the following rounds of planning and searching.

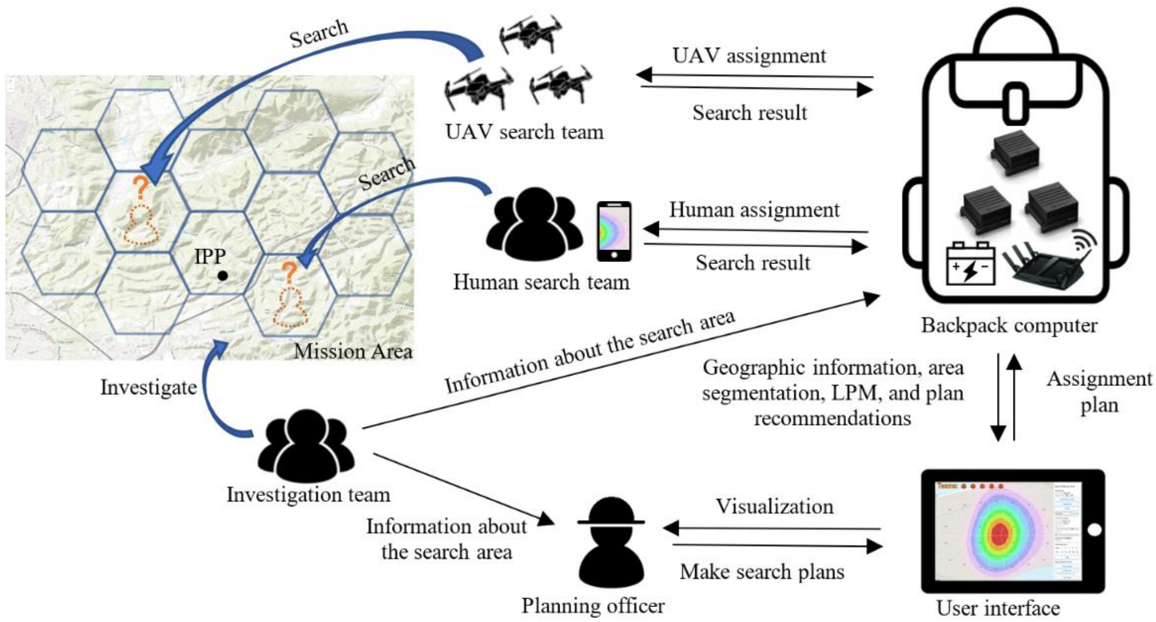


Figure 16. A human-UAV system for a SAR mission.

The pursuit of improving geographic and temporal precision increases the complexity of LPM. This complexity, in turn, imposes a demand on user trust to utilize LPMs for decision-making and, subsequently, for directing UAVs autonomously. Trust may be defined as “the reliance by an agent that actions prejudicial to their well-being will not be undertaken by influential others” (Hancock, Billings, & Schaefer, 2011, p. 24). In complex situations with uncertainty, trust is an essential factor in the acceptance and rate of usage of autonomy, which impact the effectiveness of the system concerning safety and profitability (Lee & See, 2004; Parasuraman & Riley, 1997).

Lack of trust can lead humans to engage in unnecessary tasks and prevent autonomy from providing all the potential safety, capacity, and efficiency benefits. In contrast, as trust increased, the subsequent use of autonomy increased (Biros et al., 2004). When trust exceeds the capabilities of the computational model or autonomy, the users may over-rely on or misuse technology. Neither distrust nor over trust is ideal (Bahner et al., 2008; Hancock, Billings, Schaefer, et al., 2011; Parasuraman et al., 2008; Parasuraman & Manzey, 2010; Parasuraman & Riley, 1997). The SAR planning officer(s) should calibrate their trust to the capabilities of the LPMs for deciding on what search segments to prioritize and, subsequently how to search individual segments. Calibration of trust in LPMs can be facilitated by automation or model transparency, which generally refers to the relationship of information about the autonomy to improve system understanding to help with calibrating trust and thus promoting appropriate reliance (Lyons, 2013).

The literature sometimes attributes transparency as design features or characteristics, such as providing an explanation for a decision or action of the autonomy, and sometimes as (measurable) impacts on the users, such as understanding or subjective experience of the autonomous system, and sometimes as a combination of the two. For example, autonomy was considered to have transparency for providing explanations of its actions during human interaction (T. Kim & Hinds, 2006). In this case, transparency is a design feature irrespective of the impact on the user. On the contrary, Sinha and Swearingen (2002) considered transparency as the user's understanding of why a decision was made. In other words, transparency, similar to trust, is defined by the impact on the user rather presence or absence of some design features.

Other definitions or uses of the term – transparency - may be deemed ambiguous between interface design of autonomy versus the impact on users. For example, J. Y. Chen et al. (2014, p. 2) defined transparency as "the descriptive quality of an interface about its abilities to afford an operator's comprehension about an intelligent agent's intent, performance, plans, and reasoning process." For this definition, transparency may be considered in terms of the features on the user interfaces or in terms of user comprehension of autonomy. Transparency is also commonly defined in terms of "the understandability and predictability" of the automated system actions (Endsley, 2017, p. 7), or interpretability or explanation for an understanding of how a system works as well as a particular prediction or decision is made (Weller, 2019). These definitions do not clearly delineate between autonomy/interface design and user experience. That is, is autonomy transparent because of a feature (e.g., the presence of an explanation) or user comprehension (e.g., resulting knowledge about autonomy)? The discussion on the definition of transparency is beyond the scope of this study; however, for clarity and consistency, this study defines transparency as the human subjective feelings and understanding of autonomy through visible and interpretable content about the status, functions, intent, behaviors, and mechanisms of autonomy. In other words, this study considers transparency as some measurable user experience as a result of some design characteristics.

This study presents an empirical study investigating how the visualization of the agent-based LPM at different LODs impacts transparency, trust, performance, and workload. In the context of the agent-based LPM, the LODs are defined by the spatial resolution of how the probability estimates for the locations of the lost person are aggregated and visualized in the user interface. The study results speak to the research question on how different LODs would influence transparency and, ultimately trust, workload, and performance.

3.2 Method

3.2.1 Participants

Twenty-five students (M=10, F=15) were recruited from a major university in southwest Virginia. The average age was 24.90 (SD=5). Seven participants were undergraduates, and eighteen were graduate students.

3.2.2 Experimental platform

The SAR web application prototype was developed as the experimental platform for this study (Williams et al., 2020). The application was connected to a geographical information system (GIS), specifically ArcGIS (ESRI, 2022), to gather high-quality maps with many different layers of information (e.g., linear feature layers such as rivers and roads) and built on JavaScript to provide custom user interface features. Critically for this study, this web application supported different visualizations of the agent-based LPM (Hashimoto & Abaid, 2019), automatic segmentation of the search area around IPP, and assignment of search teams to different search segments (Figure 17). Other features included visualization of UAV path-planners and locations, image pop-ups for detected clues, and map tools (Figure 12). With some customization, this SAR web application prototype can be used by SAR professionals and experimental researchers on any computer with stable internet access. The POAs estimated by the LPM are visualized by overlays on the geographic map. All search teams are assumed to have the same search capability with the same speed and accuracy of surveying each segment.

Figure 17. SAR web application prototype. Teams were assigned to segments and map tools on the right. The image from UAVs is shown by clicking on the spotted clue.

3.2.3 Experimental Design and Manipulation

A within-subjects design was employed to test the single treatment of LOD with four levels – Ring, Weighted map, Heat map, and Trajectory (Figure 18). The four treatment levels represented four spatial resolutions or LODs for the agent-based model as follows:

The *ring* visualization has a high LOD, representing four concentric rings from IPP with 25%, 50%, 75%, and 95% probabilities that the lost person can be located, respectively.

The *weighted map* visualization has a medium LOD, presenting POAs aggregated by search segments shaded in different color saturation. The information may be most efficient for the task of assigning search teams because the POA for each segment is color coded, although the computational mechanism/model process is not represented.

The *heat map* visualization has a low LOD generated with a Gaussian kernel for the entire search area. Unliked weighted map, heat map can highlight variation within a search segment.

The *trajectory* visualization has the lowest LOD, presenting raw data by lines of the possible moving paths generated by the agent-based LPM/Monte Carlo simulation. Thus, the

Trajectory visualization indicated how the model computed the POAs, providing more details than the other three visualizations.

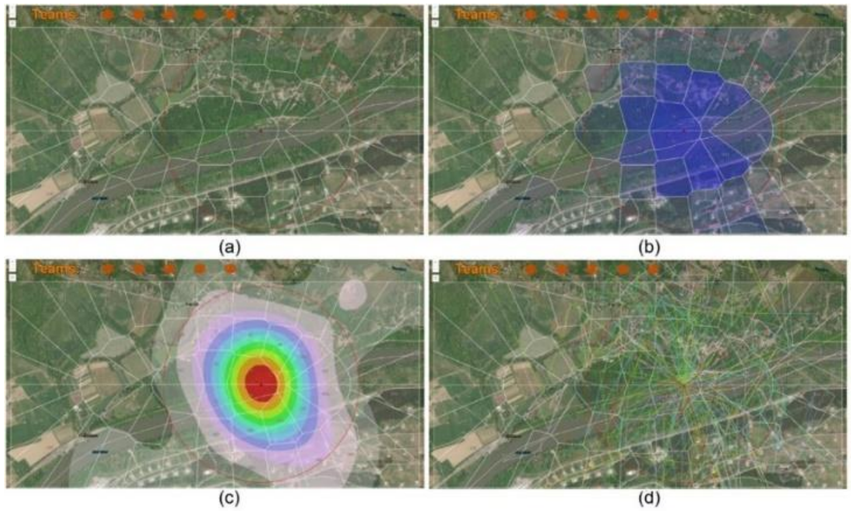


Figure 18. The four treatment levels for the agent-based lost person model for a SAR mission. a) Ring, b) Weighted map, c) Heat map, d) Trajectory.

3.2.4 Procedure

The experiment was conducted over the web through an online meeting software and the SAR web application prototype. Upon joining the online meeting, the participant was first briefed on the experimental procedure, followed by an electronic signature for the online consent form. Then, the participant completed a demographics questionnaire about their age, education, gender, and SAR experience. The participant completed the surveys through the (customized) web prototype during the experiment.

In the training task, the participant could explore the user interface and accomplish one trial of the task. In the formal task, the participant assigned four search teams to segments of the search area (Figure 17). After the participant confirmed the assignment, the display showed results, like nothing, clues, or the target. For each trial, the participant could assign teams for a maximum of five rounds but could complete the scenario prior to this limit. Upon completion of each trial, the participants would complete questionnaires.

After training and a short break, the participants completed four trials, each presented with a different level of LODs (i.e., the four different visualizations). All participant interactions with the web application were logged in to compute task performance metrics. The presentation order of the experimental conditions was counter-balanced, as described in Section 2.1. After finishing all the trials, the experimenter conducted a semi-structured interview on the four treatment levels/visualizations. The whole experiment lasted about 1.5 hours.

3.2.5 Dependent Measures

This study measured the task performance and compliance of the participants based on their interaction with the SAR application prototype. In addition, questionnaires were administered to measure transparency, trust, and workload.

Task performance. Two performance metrics were computed to reflect accuracy and speed in SAR decision-making:

1. *Total rounds* were the number of rounds to assign teams to segments for locating the lost person. In each scenario trial, participants could have a maximum of five rounds to finish the search task. If the lost person was not located within the limit of five rounds, the total rounds were set to six.
2. *Duration per assignment round (DPR)* was the time the participant took to assign the four teams to segments in one round. The first slot starts with the task loaded and ends with the participant clicking the assign button. The rest of the DPR starts with the previous end.

Compliance indicates how well the team assignment strategy of the participants conformed to the agent-based LPM. The compliance of each trial is the means of compliance for all segments. The compliance of one segment was computed by dividing the probability of the assigned segments by the maximum probability of all unassigned segments, see Equation (3.1).

$$C_i = \frac{p_i}{\max\{p_i, p_{i+1}, \ldots, p_N\}} \tag{3.1}$$

where i is the index of the calculated segment, N is the total number of all possible segments of unassigned segments, C_i is the compliance of the current segment, and p_i is the probability of finding the lost person in the assigned segment.

Transparency is based on participant ratings of six items on transparency of the agent-based LPM using a seven-point Likert scale collected after every trial (Table 4). The items were based on previous research on transparency, including the model mechanism (Tjoa & Guan, 2020), understanding of the model (Kulesza et al., 2015), noticing the distribution, understanding why the model looks like this (Rosenfeld & Richardson, 2019), confidence (Wright et al., 2019), and understanding of the system functions (Weller, 2019).

Table 4. Questions of transparency using a seven-point Likert scale.

Questions of transparency (QTR)
QTR1. Do you know, in general, how the model works?
QTR2. I understand what the model shows in this visualization.
QTR3. It is easy to notice the distribution of the lost person in the area by this visualization.
QTR4. I understand why the model looks like this.
QTR5. I'm confident my choice is the best under the circumstances.
QTR6. I understand how the system will assist me with the decisions I have to make.

Trust is based on participant ratings of six items on trust in the agent-based LPM using a seven-point Likert scale collected after every trial (Table 5). The items were based on previous research on trust in automation and autonomy, including general trust in the system (Muir & Moray, 1996), model predictability (Schaefer, 2016), model promptness (X. J. Yang et al., 2021), model reliance (Schaefer, 2016), trust in the model (Muir & Moray, 1996), system function (Schaefer, 2016).

Table 5. Questions of trust using a seven-point Likert scale.

Questions of trust (QT)
QT1. Please select your trust in the system.

QT2. To what extent does the model predict the lost person's location properly?
QT3. To what extent can the model's behavior be predicted from moment to moment?
QT4. To what extent can you count on the model to do its job?
QT5. Your degree of trust in the model?
QT6. I can rely on the system to function properly.

Workload is based on participant ratings of six items in the NASA TLX. NASA TLX was administered after every trial without pairwise comparison between the six dimensions (also known as Raw TLX, Hart, 2006).

3.3 Results

3.3.1 Descriptive Statistics

The Cronbach's alphas for the six transparency items, six trust items, and six NASA TLX items are .93, .95, and .74 respectively. The transparency and trust questionnaires demonstrated high internal consistency (refer to (Cronbach, 1951) on interpretations of Cronbach's alphas), but the NASA TLX questionnaire only exhibited marginal acceptable. All item ratings of transparency, trust, and NASA TLX questionnaires were averaged respectively for analysis.

Spearman's ρ rank-order correlation statistics were used to examine the relationships between task performance, transparency, trust, compliance, and workload (Table 6). Correlation is considered a strong relationship when $r_s \geq 0.7$, a moderate relationship when $0.4 \leq r_s < 0.7$, a weak relationship when $0.1 \leq r_s < 0.4$, and no relationship when $r_s < 0.1$ (Akoglu, 2018; Dancey & Reidy, 2007).

Correlation is considered a strong relationship when $r_s \geq 0.75$, a moderate relationship when $0.5 \leq r_s < 0.75$, a weak relationship when $0.25 \leq r_s < 0.5$, and no relationship when $r_s < 0.25$ at a significance level of .05.

Table 6. Spearman's ρ correlation results between transparency, trust, compliance, workload, and task performance (total rounds and DPR).

Spearman's ρ, N=100	Transparency		Trust		Compliance		Workload		Total rounds	
	$r_s(98)$	p	$r_s(98)$	p	$r_s(98)$	p	$r_s(98)$	p	$r_s(98)$	p
Trust	0.81	**								
Compliance	0.44	**	0.42	**						
Workload	-0.56	**	-059.	**	-0.49	**				
Total rounds	-0.46	**	-0.55	**	-0.54	**	0.77	**		
DPR	-0.04	.69	0.04	.68	0.06	.56	0.16	.11	0.02	.81

Significant codes: p<.01 '**'

Participant transparency and trust ratings were strongly correlated ($r_s(98) = 0.81, p < .001$). The compliance was positively correlated to transparency ($r_s(98) = 0.44, p < .001$) and trust ($r_s(98) = 0.42, p < .001$).

3.3.2 Transparency

The transparency scores were the averages of the ratings for the six items per trial (N=100=25 participants x 4 trials). The Friedman test showed a significant effect of the LOD on the overall transparency scores ($\chi^2(3, N = 25) = 28.7, p < .001$), the median of the four LODs is shown in Figure 19.

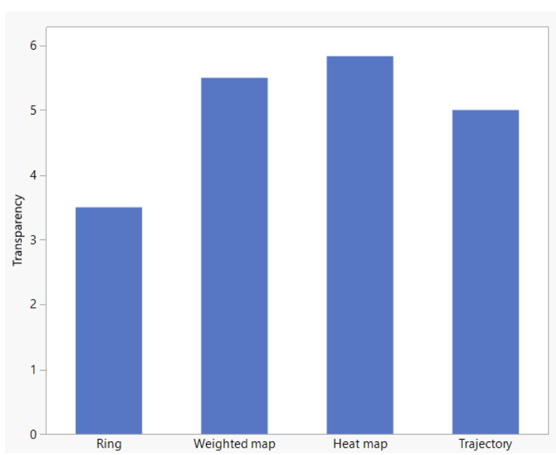


Figure 19. The medians of overall transparency of four LODs.

Post-hoc non-parametric Wilcoxon signed-rank tests revealed that Ring ($Mdn = 3.5$) was rated less transparent than Heat map ($Mdn = 5.8; Z = -4.00, p < .001$), Trajectory

$(Mdn = 5; Z = -3.29, p = .001)$, and Weighted map $(Mdn = 5.5; Z = -3.31, p < .001)$. Participants rated transparency higher for Heat map than Trajectory $(Z = -2.97, p = .003)$.

A Friedman test revealed a main effect across all questions of transparency (QTR) items (i.e., QTR1-6). Figure 20 presents the medians of transparency ratings for the average and all six items across LOD. Visualizations with different LOD led to statistically significant different ratings in the model mechanism (QTR1) $(\chi^2(3, N = 25) = 13.3, p = .004)$, understanding of the model (QTR2) $(\chi^2(3, N = 25) = 14.7, p = .002)$, noticing the distribution (QTR3) $(\chi^2(3, N = 25) = 36.7, p < .001)$, why the model looks like this (QTR4) $(\chi^2(3, N = 25) = 17.0, p < .001)$, confidence (QTR5) $(\chi^2(3, N = 25) = 32.0, p < .001)$, and understanding of the system functions (QTR6) $(\chi^2(3, N = 25) = 16.4, p < .001)$.

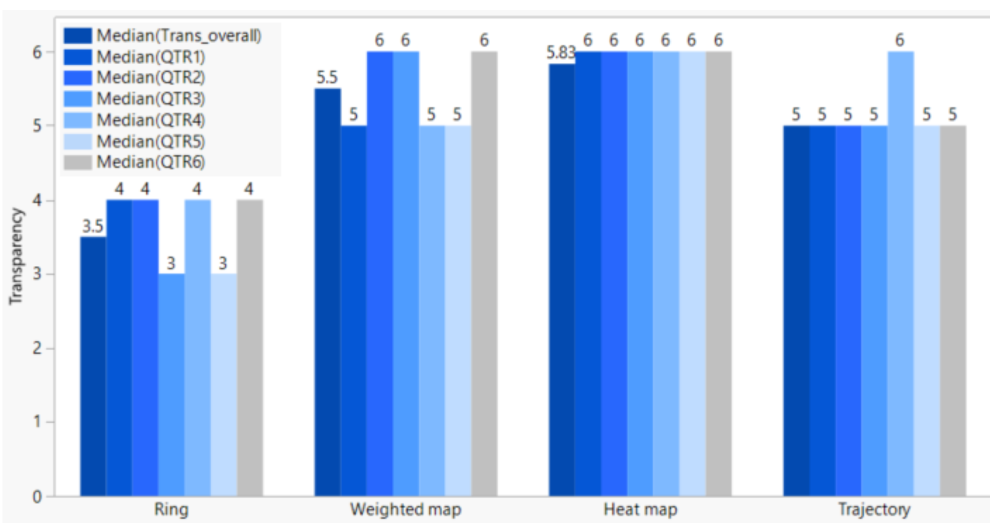


Figure 20. The medians of the overall transparency and the six questions of transparency on the four LODs.

Post-hoc non-parametric Wilcoxon signed-rank test for each pair with a Bonferroni-adjusted alpha level of .008 (i.e., 0.05/6) was used to compare all pairs of groups of QTR1-6. Ring map resulted in the lowest transparency ratings for all transparency items. Heat map was found to be significantly higher than Trajectory $(Z = -3.29, p = .001)$ for QTR3, showing that with Heat map, the participants felt it easier to recognize the distribution of the lost person in the area than with Trajectory. Other comparisons were not significant after the Bonferroni adjustment (all $p > .008$).

3.3.3 Trust and Compliance

The trust scores were the averages of the ratings for six items per trial (N=100). The Friedman test indicated that LOD has a significant effect on (overall) trust ($\chi^2(3, N = 25) = 17.0, p < .001$). Wilcoxon signed-rank tests with a Bonferroni-adjusted alpha level of .008 (i.e., 0.05/6) were used for post-hoc comparisons. The trust in Ring ($Mdn = 3.33$) was lower than Weighted map ($Mdn = 5; Z = -3.09, p = .002$), Heat map ($Mdn = 5.17; Z = -3.09, p = .002$), and Trajectory ($Mdn = 5.33; Z = -3.76, p < .001$). There were no other significant differences after the Bonferroni adjustment ($p > .008$). Figure 21 illustrates the median trust scores for the four LODs.

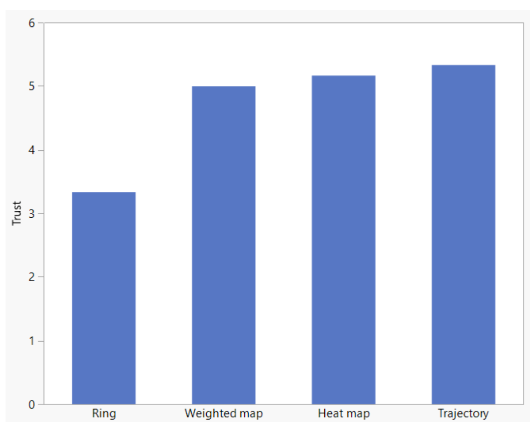


Figure 21. The medians of trust of the four LODs.

Compliance per trial represents how well the participant assignments followed the POA estimates of the agent-based LPM. Friedman test indicated that LOD had a significant effect on compliance ($\chi^2(3, N = 25) = 11.7, p = .008$). Wilcoxon signed-rank tests with a Bonferroni-adjusted alpha level of .008 (i.e., 0.05/6) were used for post-hoc comparisons. The compliance with Ring ($Mdn = 0.27$) was lower than Heat map ($Mdn = 0.72; Z = -3.29, p = .001$), and

Trajectory ($Mdn = 0.69; Z = -2.97, p = .003$). There were no other significant differences with the Bonferroni adjustment (all $p > .008$). Figure 22 illustrates the medians of compliance for the four LODs.

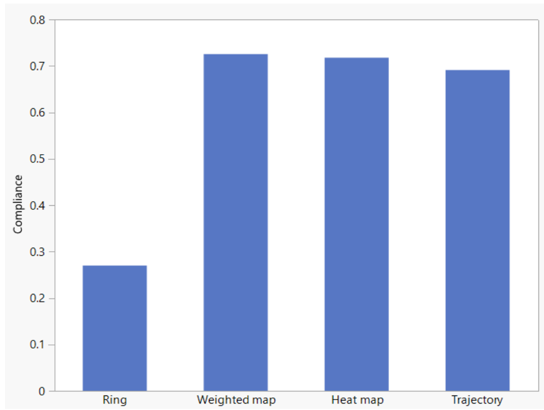


Figure 22. The medians of compliance of the four LODs.

3.3.4 Workload

The overall workload scores were the averages of the ratings for six NASA TLX items per trial (N=100). A Friedman test indicated that the LOD had a marginal effect on the overall workload ($\chi^2(3, N = 25) = 8.75, p = .033$). Wilcoxon signed-rank test with a Bonferroni-adjusted alpha level of .008 (i.e., 0.05/6) was used for post-hoc comparisons. Ring ($Mdn = 2.67$) was found to be higher than Weighted map on overall workload ($Mdn = 1.83; Z = -2.97, p = .003$). Figure 23 shows the medians of workload scores.

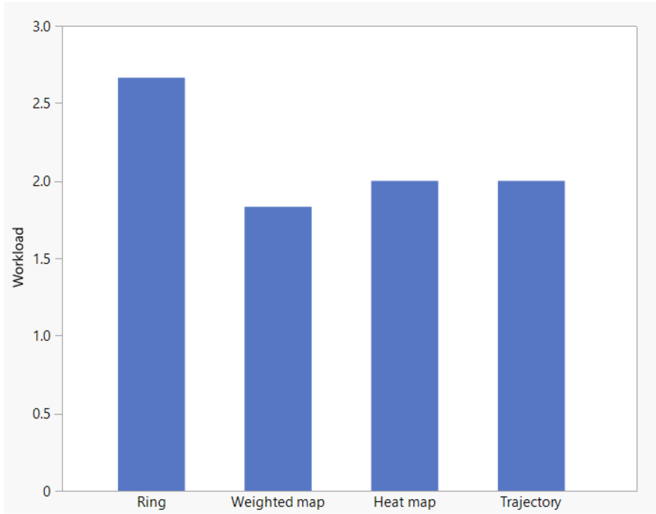


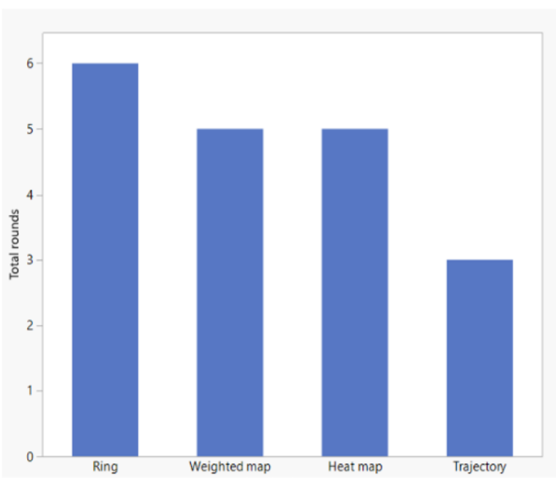
Figure 23. The medians of the workload of the four LODs.

Friedman tests on ratings of individual subscales revealed that LOD had a significant effect on mental demand ($\chi^2(3, N = 25) = 18.8, p < .001$), frustration ($\chi^2(3, N = 25) = 10.3, p = .016$), and performance rating ($\chi^2(3, N = 25) = 9.31, p = .025$). Wilcoxon signed-rank tests with a Bonferroni-adjusted alpha level of .008 (i.e., 0.05/6) were used for post-hoc comparisons. The mental demand for Weighted map ($Mdn = 2$) was significantly lower than Ring ($Mdn = 3; Z = -3.29, p = .001$) and Trajectory ($Mdn = 3; Z = -3.45, p < .001$). The frustration of Ring ($Mdn = 3$) was significantly higher than Heat map ($Mdn = 2; Z = -2.64, p = .008$). The performance rating of Ring($Mdn = 2$) was significantly lower than Trajectory ($Mdn = 6; Z = -3.45, p = .006$). Other post-hoc comparisons were not significant with the Bonferroni adjustment (all $p > .008$).

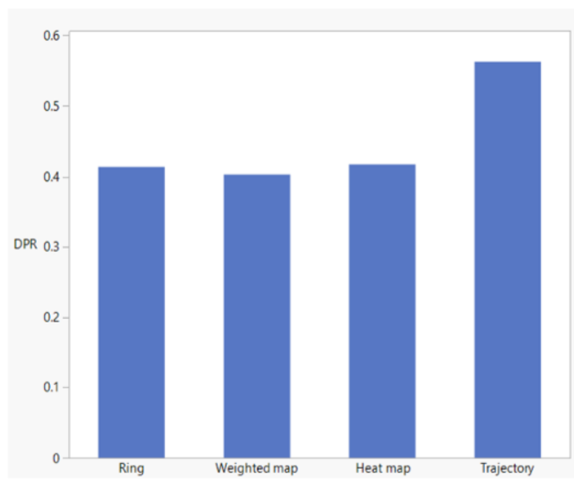
3.3.5 Task Performance

A Friedman test revealed a marginal effect on total rounds of assignment to finding the lost person ($\chi^2(3, N = 25) = 7.4, p = .06$). A Wilcoxon signed-rank test with a Bonferroni-adjusted alpha level of 0.008 (i.e., 0.05/6) was for post-hoc comparison. Participants spend fewer total rounds under Trajectory than Ring with marginal effect ($p = .015$). Participants spend fewer total rounds under Heat map than Ring with marginal effect ($p = .028$). Other comparisons were not significant.

A Friedman test revealed the main effects of LOD on DPR ($\chi^2(3, N = 25) = 10.8, p = .013$). Wilcoxon signed-rank tests with a Bonferroni-adjusted alpha level of .008 (i.e., 0.05/6) were for post-hoc comparisons. Participants spent a longer time per round of assignments on Trajectory ($Mdn = 0.56$) than Heat map ($Mdn = 0.42; Z = -2.97, p = .003$), Weighted map ($Mdn = 0.40; Z = -3.32, p < .001$), and Ring ($Mdn = 0.41; Z = -2.70, p = .007$). Figure 24 presents the bar graphs of total rounds and DPR.



(a)



(b)

Figure 24. The medians of the number of total rounds (a) and DPR (b) of the four LODs.

3.4. Discussion

This study presents the first study explicitly investigating how different LODs about an agent-based LPM developed to enable autonomous UAVs for wilderness SAR could influence transparency (ratings), trust, workload, and task performance. The results indicated that the impact of LOD on transparency is non-linear. As LODs lower (i.e., more detailed), transparency would initially increase and then decline to a moderate level. The impact of LOD on trust was also non-linear in that the highest LOD induced lower trust than the other three LODs. The second highest LOD yielded the lowest workload. Finally, LOD also had a non-linear impact on performance in that number of rounds to find the lost person tended to decrease at lower LODs, whereas the lowest LOD required the longest duration per round (DPR).

3.4.1 Impact of LOD on Transparency, Trust, and Compliance

This study is the first to explicitly examine the impact of LODs on transparency and trust that has been found to be non-linear. The Friedman non-parametric and post-hoc statistical tests (Section 3.2) illustrated that transparency was highest with Heat map, the visualization with the second lowest LOD (rather than the Trajectory visualization with the lowest LOD). Thus, the results suggest that the decrease of LOD can improve transparency up to a point, beyond which the additional information may, in fact, hinder transparency as conceptualized with the notion of transparency resistance (Stohl et al., 2016). The phenomenon is likely due to human limitations in information processing, particularly facing uncertainty under time pressure in complex dynamic environments (Scali & Macredie, 2019). After reaching this limitation, the information should be reduced or synthesized for maximum transparency of autonomy.

The impact of LOD on trust is also non-linear but different from the impact on transparency. The Friedman non-parametric and post hoc statistical tests (Section 3.3) illustrated that trust ratings and compliance were both significantly lower with the Ring visualization, the highest LOD, but negligible between the other three lower LODs. That is, lowering LOD about autonomy can promote trust with diminishing returns and plateau even with lowering LOD further. This suggests that simply presenting some information about autonomy can build trust quickly, as the users may perceive any reasonable forms of disclosure as signs of benevolence or good etiquette that promote trust (Höddinghaus et al., 2021; Mayer et al., 1995; van Straten et al., 2022). This finding shed light on mixed research findings that trust sometimes increased and decreased when comparing one type of display with more information about autonomy against another one with less or none (Göritzlehner et al., 2014; Helldin et al., 2013; Koo et al., 2015; Lyons et al., 2017; Wright et al., 2016). For example, Göritzlehner et al. (2014) found that in low complexity scenarios where the potential aircraft conflict is easy to identify, trust was significantly lower when displaying the heading and speed of aircraft than no information; however, in the high complexity scenario, the impact on trust was not significant.

Transparency appears more sensitive to LOD than trust, which is expected, given that trust is conceptually less connected to the understanding of autonomy than transparency. Trust could be influenced by various factors related to humans, autonomous agents, team design, and the environment and each of these factors contains sub-factors (Hancock, Billings, & Schaefer, 2011). For example, Schaefer et al. (2016) defined four groups of human-related factors: 1) traits, such as demographics, personality, and trust propensity; 2) states, such as attentional control, stress, and fatigue; 3) cognitive factors, such as the ability to use and understanding the automation, expectancy; and 4) emotional factors, such as attitude, comfort, confidence, and satisfaction with the automation. Another example is that a human might understand autonomy very well but not trust it to perform the task due to the high failure rate (Chavaillaz et al., 2016). Because so many factors can influence trust, LOD would simply have less overall impact on trust than transparency, which should only be driven mainly by knowledge and awareness about autonomy.

These transparency and trust results have two major research and practical implications. First, the difference in the impacts between trust and transparency due to LOD calls for a more well-defined and consistent use of the concept - “transparency” and a deeper investigation into the relationships between trust and transparency. On the one hand, an autonomy design (or experimental manipulation) is considered transparent according to some design properties, such as displaying autonomy’s status, functions, mechanisms, intention, and environmental constraints to communicate to humans (J. Y. Chen et al., 2014; Lyons, 2013), but these properties of autonomy cannot guarantee the experience or benefits of transparency. Even if transparency would strictly refer to some collection of design properties of the autonomy, research should specify and investigate such properties, like LOD, with the perspective that most properties are represented by a continuum rather than binary options. On the other hand, if transparency is considered to be some impacts on the user or performance constructs, such as better awareness of autonomy (J. Y. Chen et al., 2014) or matching the user’s capability (Moacdieh & Sarter, 2015), measurements and modeling of transparency with respect to other human performance dimensions and design properties deserve serious research attention (van de Merwe et al., 2022). Such modeling effort would improve our knowledge of the transparency concept in relation to specific design characteristics.

Second, the practical implication of these findings is that designing for the appropriate LOD about autonomy should focus on transparency more than trust, even though both benefit from some information about autonomy. That is, trust is easily supported and robust with some amount of information, whereas (subjective) transparency gradually increases and then decreases with decreasing LODs. However, this implication does need to be interpreted in the light that transparency and trust have significant overlap in both concept and measurements (i.e., high correlations between trust and transparency ratings as presented in Table 6). This also highlights the need to define transparency more precisely with a continuum perspective, as mentioned earlier. The work of Lyons (2013) and J. Y. Chen et al.'s (2014) may help specify the relevant types of information but leave LODs under investigated for each of types of information (Mercado et al., 2016; Nesset et al., 2021).

3.4.2 Impact of LOD on Performance and Workload

The LOD about autonomy on transparency also impacts performance in a non-linear fashion but in a different manner than on transparency and trust. The number of rounds to finding the lost person tends to decrease as LOD decreases, whereas the duration per round (DPR) tends to increase as LOD decreases. The number of rounds of completing a mission scenario and DPR represents decision accuracy and speed as supported by the visualizations of the agent-based LPM at different LODs, respectively. Despite being rated lower in transparency than Heat map, the Trajectory visualization with the lowest LOD facilitated the fewest rounds to completion (i.e., highest accuracy), whereas weighted and Heat maps required fewer rounds than the Ring visualization. However, this improvement in decision accuracy seemed to incur a cost in decision speed, as the Trajectory visualization resulted in the longest DPR compared to the other three visualizations associated with similar DPR. In other words, LODs could induce the speed-accuracy trade-off. That is, with LOD decreased, more cognitive resources are needed to process the increased amount of information; thus, processing speed decreases accordingly. Stowers et al. (2020) observed an increase in response time with additional information that facilitated better correct responses to plans proposed by an intelligent agent for operating multiple UAVs.

Trajectory visualization, Heat map, and Ring visualization all induced similar workload levels that were significantly higher than the level with the Weighted map. This finding suggests that LOD about autonomy catering to the specific control actions would induce the lowest cognitive workload, irrespective of whether the amount of information is sufficient to support the best performance. The Weighted map presented probability information by segments for the human to select for search assignment. This match between LOD and task resulted in the lowest cognitive workload but did not result in the best performance. A major implication of this finding is that designers can manipulate LOD of the LPM visualization to induce different workloads. A proper LOD that supports the task could induce the lowest workload, which may not be necessary consistent with the performance.

The study also presents the first empirical results contrasting impacts of different LODs on transparency, trust, workload, accuracy, and speed that highlights the complexity of designing for HAT. The results did not indicate any one LOD to be universally optimal for all human performance constructs. For example, the lowest LOD or the Trajectory visualization yielded the highest decision accuracy but the worst in speed and intermediate levels of workload and transparency. This level of complexity points to adaptive and/or adaptable user interfaces/interactions (Jameson, 2007; Lavie & Meyer, 2010; Rothrock et al., 2002) that would enable dynamic LODs to the need of the users and systems/situations. The adjustment of LOD can be based on combination of at least transparency, trust, workloads, or potentially prior performance. For example, if trust is well calibrated to capability of autonomy, the user interface or autonomy design can reduce LOD that would likely reduce transparency but also workload with much sacrificing any performance.

3.4.3 Limitations and Future Work

This research has several limitations. The experimental manipulation for LOD cannot be perfectly controlled in that "content" (i.e., LODs) and forms (i.e., visualization methods) cannot be fully separated. That is, the visualizations or representational forms could not be identical across all LODs. (This is related to the philosophical issue that there is no content without form as raised by Hegel.) For example, a Heat map may be more visually appealing besides containing fewer details than the trajectory visualization. Texts are arguable one representation form that may consistently represent all LODs, but prior research has already revealed textual or digital representation would generally cost more time and human efforts than graphical representation (Hollmann & Hanenberg, 2017), indicating low compatibility with real-time system control. Thus, the study results must be interpreted in the light that the effectiveness of the visualizations and LODs cannot be divorced from each other.

Moreover, the effect of LOD on trust calibration still needs further assessment. The maximum transparency did not yield the highest trust, probably because the visualization offers too many details. However, the analysis in this research did not study calibration, which remains an outstanding question. In addition, the reliability of the LPM is experimentally controlled or manipulated in this study. Therefore, future research on LODs should consider experimental manipulating reliability of LPM or autonomy to investigation calibration of trust.

In addition, this study only recruited university students, given the research focused on the influence of LOD on transparency in visualizations. As domain experts may prefer to process more information in different manners and face difficulty building trust in autonomy (Navarro et al., 2021), follow-up research recruiting SAR professionals is necessary to understand the generalizability of the results.

3.5 Conclusion

This study investigated how different LODs could influence human perception of transparency in autonomy and ultimately influence trust, task performance, and workload. Visualization at different LODs for the agent-based LPM was evaluated in an experiment where participants assigned teams to segments of a search area in wilderness SAR missions. The results illustrated that the impacts of decreasing LODs were not linear on transparency, trust, workload, accuracy, and speed. Transparency increased with decreased LODs up to a point before the subsequent decline, providing empirical evidence for the transparency paradox/resistance phenomenon. Further, the impacts of LODs were not uniform across the human performance measurements. The model visualization with the lowest LOD (i.e., trajectory visualization of the LPM) yielded the highest decision accuracy but the worst in speed and intermediate levels of workload, transparency, and trust. Altogether, this research provides insight into different transparency, trust, performance, and workload with respect to LOD that is applicable to designing for HAT.

4. Adaptive LOD for Building Trust

UAVs could provide a bird's eye view from high up in the sky to provide coverage search in SAR missions. With the latest sensors and algorithms, such as object detection and path planning, UAVs could potentially increase the search speed and reduce human resources in SAR missions (Alotaibi et al., 2019; Tomic et al., 2012). However, autonomous UAVs still have limitations and face uncertainty that points to the need to collaborate with human teammates. As discussed in Chapter 1, calibrated trust is essential for the efficiency and effective teaming with autonomy that can be facilitated through transparency – the human subjective feelings and understanding of autonomy through visible and interpretable content about the status, functions, intent, behaviors, and mechanisms of autonomy (refer to Chapter 1.2). When too much information is added in an attempt to promote transparency, the transparency paradox might occur due to information overload, impacting the calibration of trust (as illustrated in the study results presented in Chapter 3). Further, the information necessary for transparency to facilitate trust may differ over time as user trust evolves over repeated interactions with autonomy. This chapter investigates how to adapt levels of details (LODs) in visualization with respect to trust as users interact with autonomy over time. Specifically, the influence of static and adaptive LODs on transparency, trust, workload, and team performance is evaluated during repeated interactions between humans and autonomy in the context of wilderness SAR missions.

4.1 Introduction

Human autonomy teaming (HAT) describes human and autonomous agents working collaboratively toward a common goal (O'Neill et al., 2020). Effective HAT can enhance overall safety, efficiency, and adaptability, ultimately leading to better performance (Z. Chen & Huang, 2017; Freedy et al., 2007). The increasing prevalence and intelligence of autonomy offer many benefits but are accompanied by complexity and uncertainty (Freedy et al., 2007; Helldin et al., 2013; O'Neill et al., 2020) that inevitably challenges the users and operators to access every detail and completely understand autonomy. Differences in cognitive abilities and information processing mechanisms between humans and autonomy can result in potential misinterpretations or challenges in comprehending each other's viewpoints (Abbass, 2019; Arrieta et al., 2020; Tjoa & Guan, 2020). Transparent automation or autonomy, referring to an autonomous system or agent that is both self-governing and understandable to humans (Endsley, 2017; Weller, 2019), represents one approach to resolving this communication need. By providing information about autonomy about its perception, process, and projection, transparent autonomy offers humans more chances to comprehend its current state, intended tasks, and future actions, thus making the autonomy more understandable. However, presenting more information can sometimes lengthen decision-making time (Stowers et al., 2020) and increase workload (Bevan & Macleod, 1994; Helldin et al., 2014). Thus, it is not practical for autonomous agents to provide all available information for a human to perceive, analyze, and operate, given productivity and safety requirements (Westin et al., 2016).

For this reason, as in complex operations in large human organizations (McAllister, 1995; Salas et al., 2005), trust between agents, human or machine, becomes an essential element in resolving the imperfect understanding and information processing of all the details about different agents (Hancock, Billings, & Schaefer, 2011; Hoff & Bashir, 2015; Lee & See, 2004; Parasuraman & Riley, 1997). Trust may be defined as "the reliance by an agent that actions prejudicial to their well-being will not be undertaken by influential others" (Hancock, Billings, &

Schaefer, 2011, p. 24). Trust in autonomy serves as an inherent yet imperfect solution for a task-oriented human autonomy team when operating under time pressure (Lee & See, 2004).

Trust often needs time and interactions to establish and design for HAT, which could take inspiration from human-human teamwork. Specifically, new teams often rely on frequent communication to build trust for facilitating effective collaboration performance (Derlega & Chaikin, 1977), whereas established ones with a certain level of trust tend to require less communication and fewer interactions to sustain desirable performance. From this perspective, information exchange between humans and autonomy could focus on striving for appropriate transparency or degree of communication for calibrated trust instead of a perfect understanding of individual agents. For example, Park and Lee (2014) found that trust reduces miscommunications and conflicts that may arise from differences in perspectives and still enables team members to be more receptive to feedback and suggestions. Trust can promote the behavioral intention, willingness to rely on, acceptance, and use of autonomous agents (Choi & Ji, 2015; Freedy et al., 2007; Lee & Moray, 1994; Lee & See, 2004; Parasuraman et al., 2008). For this reason, understanding the trust-building process is as crucial as understanding how trust affects the use, disuse, and misuse of automation or autonomy (Parasuraman & Manzey, 2010; Parasuraman & Riley, 1997).

Hoff and Bashir (2015) classified human trust prior to interactions with autonomy or automation to include dispositional, situational, and initial learned trust, whereas trust during interactions is the learned trust. Dispositional trust is influenced by individual differences (e.g., culture, age) and barely changes during interactions (Hoff & Bashir, 2015; Marsh & Dibben, 2003). Situational trust depends on context and tasks, including external variabilities (e.g., environment, system complexity, task difficulty, risks) and internal variabilities (e.g., self-confidence, expertise, and attentional capacity). Initial learned trust includes trust initially set for autonomy based on past experience with other autonomous systems. Learned trust other than initial learned trust is influenced by interactions with the specific technology (Hoff & Bashir, 2015; Marsh & Dibben, 2003) and is the focus of this research.

The nature of trust in HAT is further divided into three groups: stable trust, time-variant trust, and instantaneous trust (Schaefer et al., 2016; Voros et al., 2023). Stable trust is the time-invariant propensity to trust, including trust prior to interactions. Time variant trust is cumulated trust that could be varied after interactions over the long term. Stable trust and time-variant trust are also considered baseline trust and are measured as the subject's overall trust at the beginning or in the aftermath of some major events. Instantaneous trust is influenced by immediate interactions and is usually measured in real-time or right after the interaction (Desai et al., 2013; Holliday et al., 2016; Kroeger et al., 2021).

Extant research tends to focus on time-variant trust as a consequence of interacting with autonomy to accomplish some tasks in various situations (Helldin et al., 2013; Koo et al., 2015; Lee & See, 2004; Lyons, 2013; Skraaning & Jamieson, 2021). Calibrating time variant trust to shape human expectation to match the actual capabilities of autonomous agents involves deciding what and how information about autonomy should be delivered to humans so that the provided transparency could calibrate trust (Boyce et al., 2015; J. Y. Chen et al., 2014; Cramer et al., 2008; Kulesza et al., 2015; Stowers et al., 2020; Wright et al., 2016). Lee and See (2004) applied the research on interpersonal trust to automation and suggested that insufficient communication of automation purpose may negatively influence user trust. For online marketing, Chesney et al. (2017) found that participants exhibited greater trust when immersed in a virtual environment abundant in information, akin to face-to-face interaction, compared to the traditional web-based environment. Other researchers also observed that additional information could bring more trust (Skraaning & Jamieson, 2021; N. Wang et al., 2015; C. Xiong et al., 2019). Knowledge about autonomy does need to be real-time as training could support accurate expectations of the capability of autonomous agents and has been found to promote trust and make overall trust more robust during operations (Johnson et al., 2021; Koustanaï et al., 2012; Muir & Moray, 1996).

While types of information have received substantial attention in research, the appropriate quantity of information required for trust calibration deserves addition attention. A consistent amount of information being communicated yielded more trust (Sanders et al., 2014). Wright et al. (2016) found trust initially increased with information about the suggested route change in reasoning but eventually decreased as information continued to increase. The study finding also highlights that the evolution of trust throughout the interaction may not be accurately captured by trust measurements at the end of prolonged interactions or some major events.

Instantaneous trust can reflect how trust evolves with interactions with autonomy over the course of an event and usage period. Desai et al. (2013) found that although the trust levels were similar at the end of the whole task across different reliability/failure patterns, the evolutions of trust were different. Specifically, Desai et al. investigated how trust evolved across the following four reliability/failure patterns: (1) reliability was constantly high; (2) reliability declined twice, but recovery occurred early in the task; (3) reliability was high at the beginning, then declined and recovered in the midst of the task; and (4) the reliability declined twice, and recovery occurred late in the task. Their study measured trust every twenty-five seconds, with the participants indicating their trust increased, decreased, or unchanged. Trust constantly increased with high reliability, while trust decreased when reliability dropped to a low level and then recovered if reliability rose and stayed at a high level. Yang et al. (2017) uncovered that trust evolved and then stabilized as human operators repeatedly interacted with an automated threat detector in a simulated military reconnaissance scenario. Yang et al. found that the user's instantaneous trust, as reported right after the interaction, was more influenced by the specific momentary interaction, while the overall trust was not influenced. Yu et al. (2017) found that trust tends to rise gradually with successful outcomes but experiences a rapid decline with failures. When autonomy was 90% accurate in detecting faulty glasses, trust initially increased linearly before reaching a plateau, which was lower than the trust plateau for the 100% accurate autonomy but higher than the 80% accurate one. When autonomy dropped to 70% accurate, trust exhibited a linear decline. Establishing calibrated trust in autonomy as quickly as possible is crucial, especially in situations involving time pressure, uncertainty, and concerns about cooperation efficiency (Kroeger et al., 2021). In short, any means to shorten the evolution of trust over time would be invaluable to establishing optimal system performance.

Besides reliability or capability of autonomy, trust can be moderated by exposing the details of the autonomy so that potential malfunctions can be explained and predicted, thereby calibrating the trust in autonomous agents (Ayoub et al., 2021; Edelmann et al., 2019; Matthews et al., 2020; Perkins et al., 2010). Kraus et al. (2020) found that delivering information about system shortcomings in autonomous driving capabilities can avoid the decline of trust during malfunctions and manual take over because information on the potential limitations lowered the performance expectation of autonomous agents during autonomous driving. Holliday et al. (2016) found that, with explanations on the capabilities of the intelligent system put on display to support user understanding, trust initially rose and then reverted back to its initial level, whereas in the absence of explanations, trust declined without experiencing any increase and reached an even lower level.

Several studies have revealed that additional information does not guarantee an improvement in trust or other important human performance constructs (Koo et al., 2015; Wright et al., 2016). Koo et al. (2015) suggested that by providing situational information explaining the reason for autonomous agents' reaction ahead, the driver had more trust in autonomy when presented with information about “why” but less trust when presented with information on “how” the car was acting. Further, the participants showed the safest driving performance when both were presented. Wright et al. (2016) compared how trust changed with respect to displays without any information about autonomy, reasoning information about autonomy, or reasoning information with temporal information for a route selection task for a convoy of three vehicles in a simulated urban environment. The results revealed that trust was lowest for the display condition with reasoning information (i.e., an intermediate amount of information), even by comparison to the display without any information about autonomy. Excessive information disclosure may lead to the transparency paradox, when high “visibility” or a large amount of information may cause the important pieces of information to become inadvertently hidden among a large amount of information leading to opacity (Stohl et al., 2016). The transparency paradox phenomenon requires designers to consider cognitive overload or confusion that can occur with increasing information about autonomy (Kizilcec, 2016).

Some researchers have been investigating the transparency paradox from the perspective of the level of detail (LOD), which refers to the amount of information aggregated or organized in communication for the human to perceive, comprehend, and respond (T. Chen et al., 2014; T. Wang et al., 2023). LOD could be manipulated by changing the granularity of information on the user interface. High LOD delivers less information so that users can obtain an overview and key information about autonomy, such as important functions and outcomes. In contrast, low LOD delivers more information so that information on specific aspects or details of autonomy, such as raw data, technical details, and mechanisms, can be presented to users. T. Chen et al. (2014) found that the medium LOD display yielded the lowest workload when the operator occasionally engaged in autonomy that routed UAVs through hazardous areas; however, no single LOD was found to be universally optimal for every human performance dimension (T. Wang et al., 2023). For example, the lowest LOD yielded the highest decision accuracy but the worst in speed and intermediate levels of workload and transparency (refer to Chapter 3). Furthermore, communication or information exchange for promoting trust usually requires additional human efforts that intrinsically increase workload and operating time, sometimes even risking confusion due to excessive information (Kizilcec, 2016; Moacdieh & Sarter, 2015). Thus, trust could decline or be sub-optimal because performance cannot elevate further due to inefficiency in information exchange or communication (Wintersberger et al., 2020).

The variation of trust as a function of information exchange between humans and autonomy is analogical to human-human relationships. When a human relationship starts, and trust is relatively low, communication tends to be frequent in order to develop trust and gradually decrease with establishing trust for (communication) efficiency (Erdem & Ozen, 2003; Mayer et al., 1995; Nyhan, 2000). In fact, one of the central impetus of trust is to avoid communication and processing of all the information between parties with limited resources through mutual reliance amongst parties to do their jobs without interventions or monitoring (Lee & See, 2004; Moray & Inagaki, 1999). In light of this, an adaptive UI with the ability to dynamically adjust

LOD could potentially improve trust by minimizing unnecessary communication or information overload similar to dynamic human behaviors.

Adaptive UI was defined as "an adaptive interface [that] autonomously adapts its displays and available actions to current goals and abilities of the user by monitoring user status, the system task, and the current situation" (Rothrock et al., 2002, p. 50). Adaptive UI may help to match the diversity of humans, such as the capability of understanding information, cognitive skills, and abilities in particular domains (Jameson, 2007). While adaptive UI catering to improving situational awareness (Stefanidi et al., 2022), workload (Ziegler et al., 2011), and performance (Kortschot et al., 2022) with respect to LODs have demonstrated promise in the literature, there is limited research on applying adaptive UI to enhance trust. Okamura and Yamada (2020) found that UIs providing verbal prompts on whether instantaneous trust represents over and under-trust was beneficial in calibrating trust indicated by manual rates, particularly in scenarios where over-trust was observed. Current literature has not yet thoroughly investigated the evolution of trust while simultaneously manipulating the amount of information presented as a means to avoid excessive communication or information overload.

Figure 25 illustrates a preliminary framework for designing an adaptive UI for calibrating trust after each interaction. The dashed arrows and text in the dashed box are used to be investigated in this study.

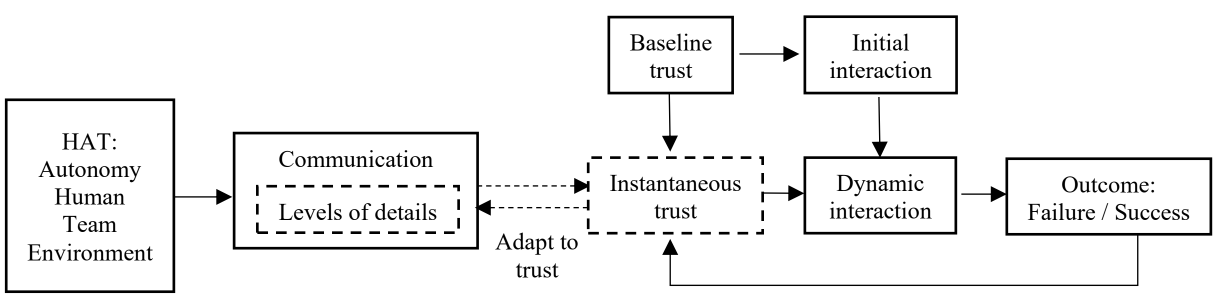


Figure 25. An overview of HAT factors influences instantaneous trust and, thus, outcomes dynamically through communication during dynamic interactions.

HAT is a function of autonomy, humans, team, and environmental characteristics that would shape communication and, thus, trust between team members. The initial strategy of interacting with autonomy is driven by baseline trust and affects early system performance or outcomes. The outcome of these early human-autonomy interactions, in turn, affects instantaneous trust that shapes the subsequent human interaction strategy and system performance, thereby influencing the experience.

To optimize dynamics of trust through interactions between human and autonomy, this study examines how the amount of information about autonomy (LOD) should be adapted for humans with respect to trust evolving over time for accomplishing a collaborative search and rescue task. Specifically, the study compares the effectiveness of static and adaptive UI at different LODs in fostering faster trust-building and plateauing. The study hypotheses are:

H1: Among static LOD, the speed of building trust will be faster with high LOD.

H2: Among static LOD, trust will plateau at a higher value with low LOD.

H3: Adaptive LOD based on trust will accelerate the speed of trust-building and elevate the plateau of trust.

The remainder of the chapter is organized as follows: section 4.2 describes the platform, experimental design, procedures, and measures for conducting the experiment, section 4.3 presents the results in detail, section 4.4 is the discussion, and section 4.5 concludes the research study.

4.2 Method

To evaluate the impact of LODs on trust, transparency, performance, compliance, and workload, this section describes the method of recruiting participants to complete a simulated wilderness SAR task involving collaboration with autonomous UAVs to search for clues and lost persons.

4.2.1 Participants

To establish the appropriate sample size for the experiment, a power analysis was conducted. Given the within-subject design, repeated measures ANOVA was chosen as the analysis method, with a significance level (α) set at 0.05 and an effect size of 0.25. Considering these parameters, a sample size of 36 was determined, resulting in an actual power of 0.95. Consequently, thirty-eight participants (20 males, 18 females) with normal or corrected to normal vision were recruited. The participants had access to a capable computer and stable internet access to perform the experiment through the online platform.

4.2.2 Apparatus

A SAR web application was developed to serve as an experimental platform. The application was connected to a geographical information system, specifically ArcGIS (ESRI, 2022), to gather high-quality 2D and 3D maps with different layers (e.g., terrain feature layers with open water or dense wood) and built on JavaScript to provide custom user interface features (Figure 26). Critically for this study, this web application supported visualizations of the computed/planned flight path of a UAV based on a lost person model (Hashimoto & Abaid, 2019), terrain (Homer et al., 2020), their effects on the path, and SAR mission-related features. The application supported one human operator/participant collaborate with a path planning agent and a UAV search agent. The path planning agent specified a path in terms of longitude, latitude, and altitude for the UAV to search for clues and the lost person in a manner that would balance coverage speed and object detection. To attain higher resolution for better object identification, UAVs must fly a lower and longer path, taking a longer time to cover the search area (Cazzato et al., 2020). Higher altitudes can yield faster search time at the expense of lower resolution images and precision. The UAV search agent autonomously followed the path and identified objects. The human operator decided on whether to comply with the recommendation of autonomous agents and further actions for verification.

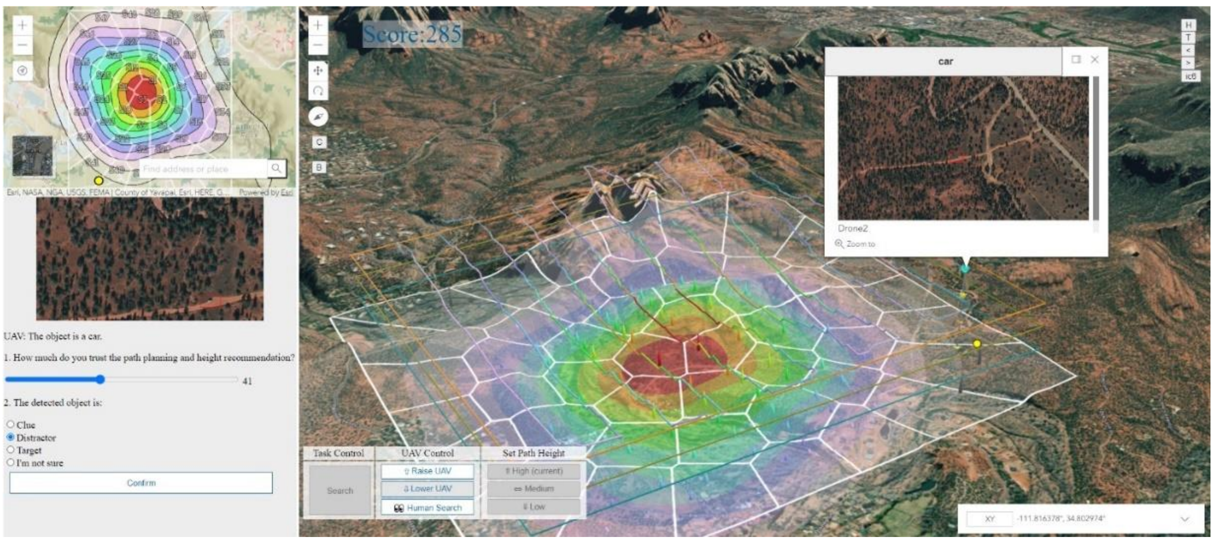
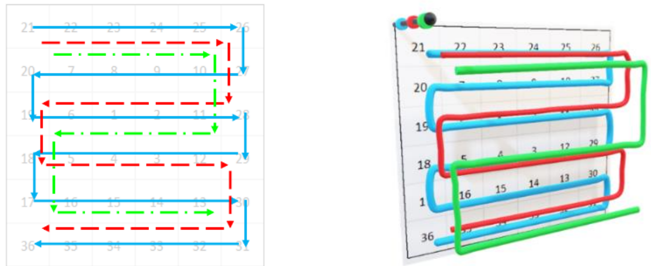


Figure 26. The UI includes three parts.
The left upper panel is a 2D map for lost person model, terrain features, and area segmentation. The left lower panel displays image feedback and results, where the participants can provide a self-reported trust, which is the instantaneous trust and select their judgement of the search result. On the right side is the 3D visualization of the path planning and control panel, with which the participants can control the search, UAV height, human search, and path height.

The path planning agent specifies a path in terms of longitude, latitude, and altitude for the UAV to search for clues and the lost person in a manner that would balance coverage speed and object detection. The search time depends on flight speed, altitude, and size of the search that interacts with the frame rate and resolution capabilities of the optical camera on the UAV. Within the limits of the optical camera, a larger area is covered for every frame flown at a higher altitude. Figure 27(a) and (b) illustrate the differences in the flight path for three altitudes in two-dimensional and three-dimensional space, respectively. The blue path is the longest at the lowest altitude, whereas the red path is the shortest at the highest altitude.



(a) (b)

Figure 27. As the UAV flies higher, the path of the flat dimension could change accordingly. (a) The path of the UAV on a flat surface. (b) The lowest path (blue line) has the longest length. The highest path (green lines) has the least density and the shortest length.

Given the experimental setup for the web application, the path planner would recommend the altitude of the coverage path considering two parameters: the lost person model and terrain.

The lost person model estimates the probability of the lost person's location in a given area, providing invaluable information recommending flight altitude. Lower altitude would be necessary for searching more probable areas for higher resolution video streams and better image recognition to minimize misses of likely clues or even the lost person.

The density of the terrain can also influence the difficulty and, thus, necessary image resolution of identifying objects. For example, the accuracy of detecting objects in the open water area could be very different from the evergreen forest or heavy foliage. The terrain is classified into one of the sixteen classes according to the 2016 National Land Cover Database (Homer et al., 2020). In the study, the sixteen classes of terrain are categorized into three levels of difficulty for identifying the objects: open water, perennial ice, developed open space, and barren land are considered level 1, which is the easiest for object detection; low intensity developed area, herbaceous, wetlands, developed medium intensity, shrubland, planted area are considered level 2, which poses moderate challenge for object detection; and high density developed areas, evergreen forest, mixed forest, and deciduous forest are considered level 3 which poses severe challenge for object detection.

This study prescribes the altitude of the UAV to be negatively correlated to the probability of area for finding the lost person and terrain difficulty for identifying objects, shown in Equation (4.1)

$$H \propto \frac{1}{P_l} \times \frac{1}{D} \times X \times H_b \tag{4.1}$$

, where H is the altitude of the UAV. P_l is the probability of the lost person in the location, which is estimated using the lost person model. D is the terrain difficulty for object identification, which includes three levels. X is the human choice of the general level of altitude, including three levels. H_b is the baseline altitude.

The UAV Search Agent has two autonomous capabilities: autonomously follows a flight path to survey the area and autonomously identifies objects deemed relevant to the mission. The two capabilities interact with each other slightly in that flight altitude impacts image resolution and, thus, object identification capabilities (Cazzato et al., 2020). To attain higher resolution for better object identification, UAVs must fly a lower and longer path, taking a longer time to cover the search area. The increased resolution may increase the likelihood of identifying more clues to estimate the direction of travel by the lost person. Further, clues can have different sizes that demand different resolutions for accurate detection (e.g., humans, tents, backpacks, jackets, keys, water bottles). Higher altitudes can yield faster search time at the expense of lower-resolution images and precision.

For simplification in this study, the UAV search agent has the following characteristics:

1) The UAV flows a sweeping search pattern because obstacles are generally rare in wilderness or rural areas.
2) The UAV flies at a constant speed.

4.2.3 Experiment Design

The experiment followed a within-subject design in that each participant completed four SAR missions using different LODs. The study had two treatments: Levels of Detail (LOD) and Trial. The experiment consists of four blocks, including three static LOD blocks at high (Figure 29), medium (Figure 30), and low LODs, respectively (Figure 31), and one adaptive LOD block that switched LODs based on Algorithm 1 that needed the input of instantaneous trust measured after each trial. Each block includes seven to nine trials depending on the success in target identification. The order of these blocks was randomized to minimize order effects.

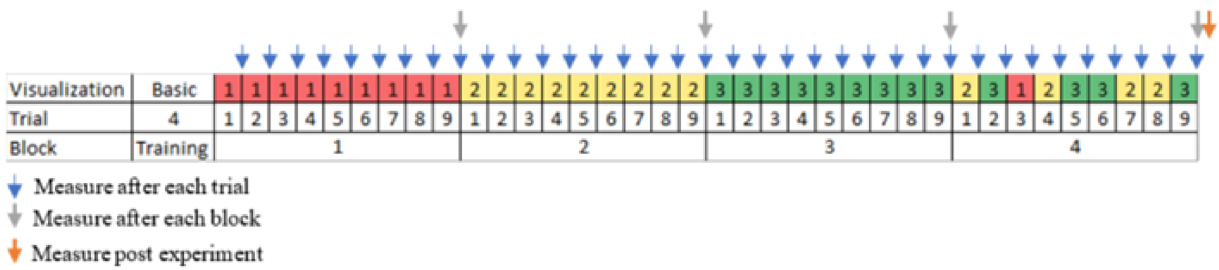


Figure 28. The experimental flow of the task. The first line of the flow is visualizations in three LODs, high is marked as 1, medium as 2, and low as 3. Measures are conducted after each trial, after each block, and post experiment.

4.2.3.1 Static LODs

A map of the search area with the path of a UAV is displayed with a 3D line above the area and a 2D line on the ground. The paths of UAV are the same across different LODs. The visualization of LPM, terrain features, and their effects on the UAV path changes across the three LODs. For the high LOD (Figure 29), the LPM is visualized as a *basic map*, representing four concentric rings from IPP with 25%, 50%, 75%, and 95% probabilities that the lost person can be located, respectively. For the medium LOD (Figure 30), LPM is visualized as a *weighted map*, terrain features are visible, and the joint impacts of terrain and probability estimates of the LPM on the altitude are marked on the flight path. For the low LOD (Figure 31), the LPM is visualized as a *heatmap* with terrain features. The impact of terrain and probability estimates of the LPM on altitude are marked with 3D cones on the map and different colors on the flight path.

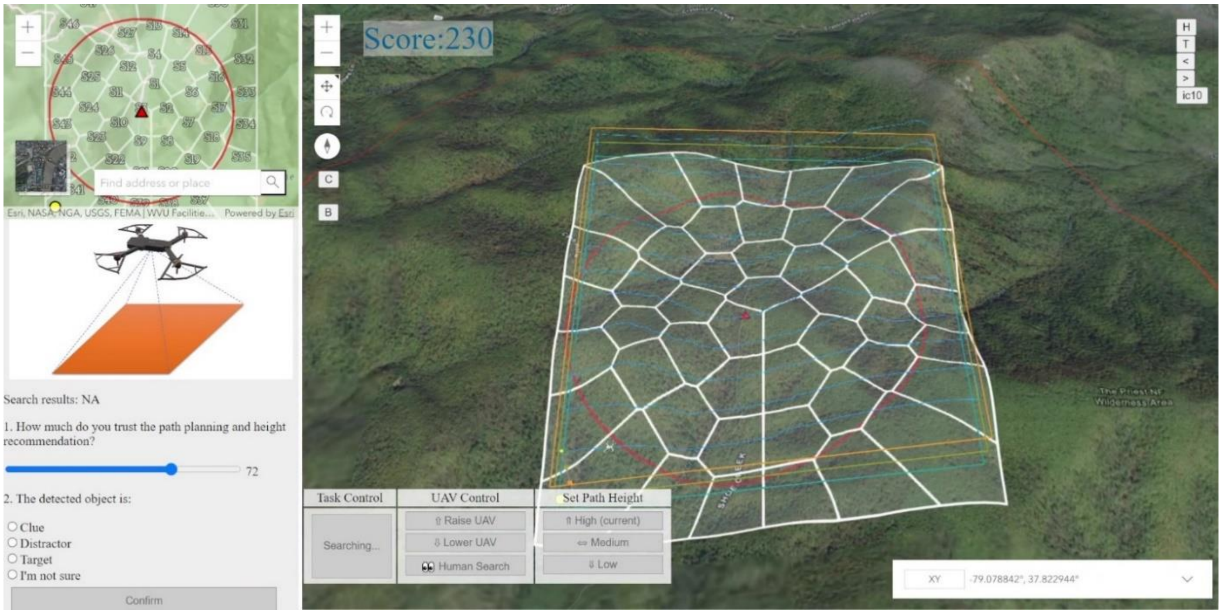


Figure 29. High LOD.
The visualization shows the least amount of information. A map of the search area with the path of a UAV is displayed with a 3D line above the area and a 2D line on the ground. The LPM is visualized as a ring map, representing four concentric rings from IPP with 25%, 50%, 75%, and 95% probabilities that the lost person can be located, respectively.

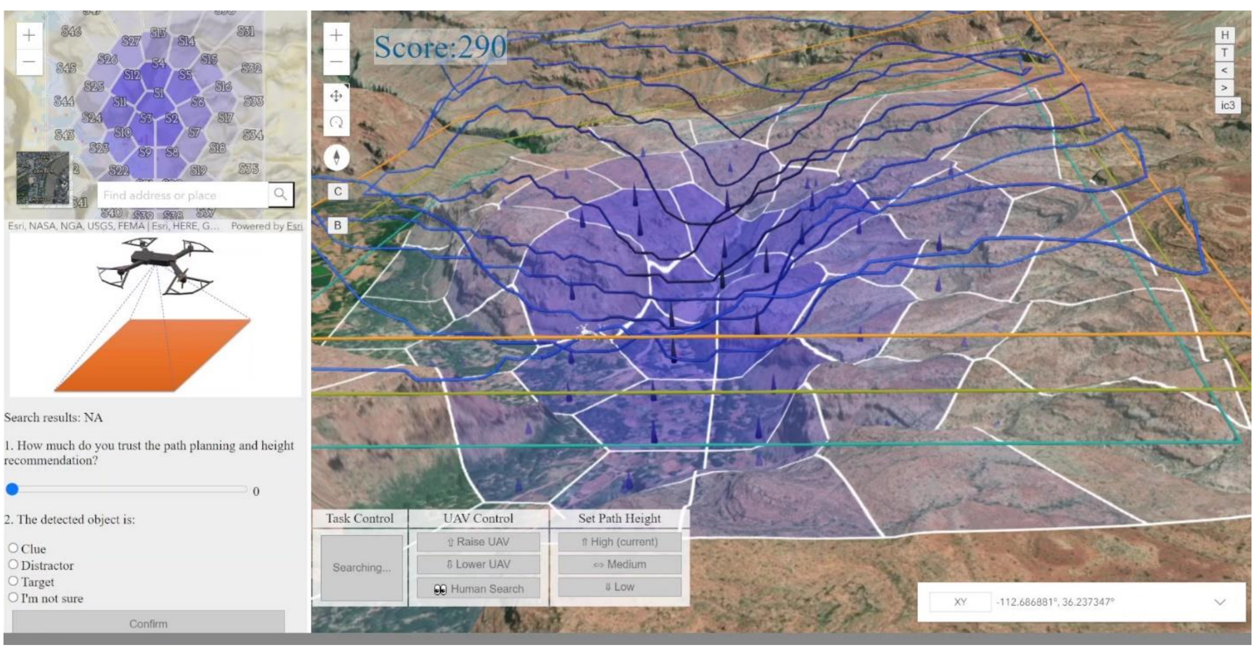


Figure 30. Medium LOD.
The visualization shows a medium amount of information. The purple area marks weighted map and terrain features. The influence on the flight path is also marked in colors with different brightness.

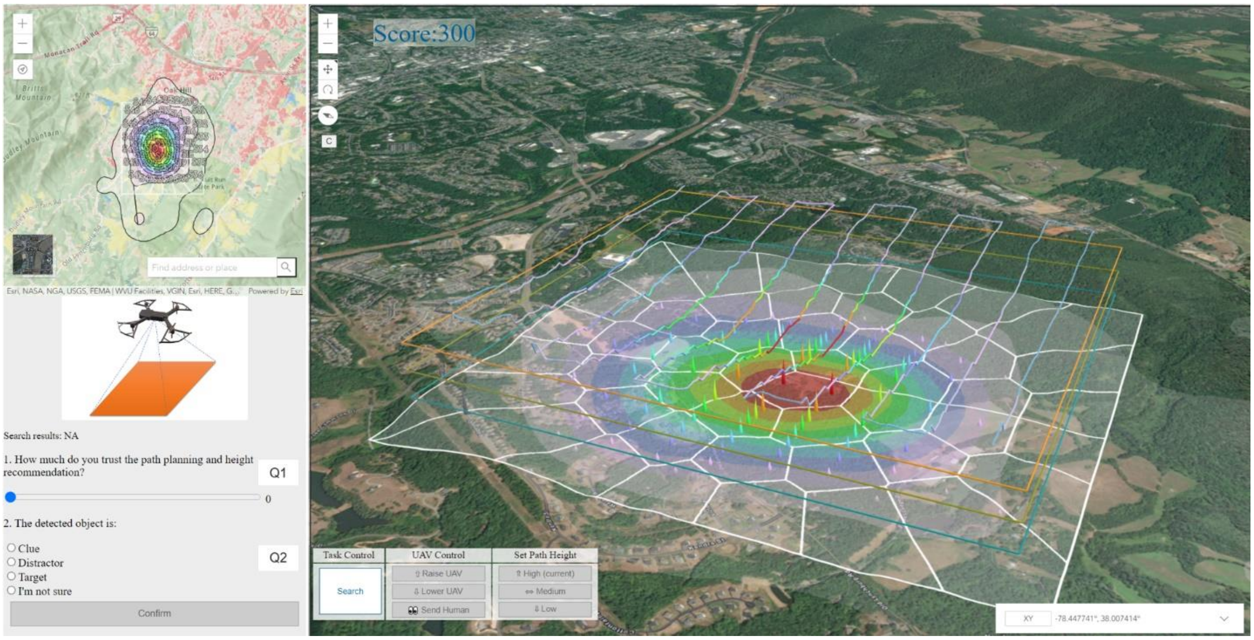


Figure 31. Low LOD.
The visualization shows the most amount of information. The lost person model is shown in the heat map with a yellow cone showing the influence on the path. The terrain is purple, with purple (upside down) cones showing the decreased altitude due to the dense wood and blue cones showing the risen altitude due to the open water area.

4.2.3.2 Dynamic LODs

The adaptive visualization switches between the three LODs about autonomy based on participant trust. As mentioned, each mission is divided into several trials, and the UAV sends an image to the human operator to verify object identification. The visualization might switch to a different LOD after each trial, depending on the participant's trust rating at the end of the trial. Algorithm 1 shows the LOD adaptive strategy for this study. The core concept is that increasing information by lowering LOD (i.e., increasing details) would enhance the understanding of the mechanism of the height change in the path planning so that trust may increase at the potential expense of increased cognitive load. As people get more familiar with and trust the path planning, higher LOD or less information would be enough to maintain trust of the users.

Algorithm 1 Get the adaptive LOD

1: $Input$:
2: $Change\_of\_LOD$ $(initial\ value\ is\ 1)$
3: i $(index\ of\ current\ trial, with\ range\ of\ 3, 4, \ldots n)$
4: LOD_{i-1} $(initial\ LOD_0 \leftarrow 1)$
5: $Trust$ $(average\ trust\ of\ the\ previous\ three\ trials)$
6: $\Delta T \leftarrow Trust_i - Trust_{i-1}$
7: $Output: LOD_i$
8: $\boldsymbol{procedure}$ $AdaptiveLOD$ $(LOD_{i-1}, Change\_of\_LOD, \Delta T)$
9: $\quad \boldsymbol{if}\ \Delta T > 0\ \boldsymbol{then}$
10: $\quad\quad LOD_i \leftarrow LOD_{i-1}$
11: $\quad \boldsymbol{else\ if}\ \Delta T < 0\ \boldsymbol{then}$
12: $\quad\quad Change\_of\_LOD \leftarrow (-1) * Change\_of\_LOD$
13: $\quad\quad LOD_i \leftarrow LOD_{i-1} + Change\_of\_LOD$
14: $\quad \boldsymbol{else\ if}\ \Delta T = 0\ \boldsymbol{then}$
15: $\quad\quad LOD_i \leftarrow LOD_{i-1} + Change\_of\_LOD$
16: $\quad \boldsymbol{if}\ LOD_i > 3\ \boldsymbol{then}$
17: $\quad\quad LOD_i \leftarrow 3$
18: $\quad \boldsymbol{if}\ LOD_i < 1\ \boldsymbol{then}$:
19: $\quad\quad LOD_i \leftarrow 1$
20: $\quad \boldsymbol{return}\ LOD_i$

Algorithm 1. Adaptive LOD.

At the beginning of the mission, this LOD adaptive strategy seeks to increase the information about autonomy in the visualization by shifting from higher to lower LOD for promoting trust (as measured by a trust rating after each trial). If trust increases between trials, meaning that visualization is effective for building trust, the LOD of the visualization remains the same (lines 9 and 10 of Algorithm 1). When trust is stable, visualization will switch to a lower LOD (i.e., providing more details) to establish a higher level of trust (lines 14 and 15 of Algorithm 1). However, lowering LODs may become ineffective in increasing trust (lines 11 to 13 of Algorithm 1), especially when trust is well-established. For this reason, when the adaptive strategy is decreasing LOD and LOD is at the lowest, the adaptive strategy would switch to increasing LODs when trust is stable and maintain the highest LOD until the trust rating declines between trials (lines 11 to 13 of Algorithm 1). This adaptive strategy rests on the assumption that less information could be good at maintaining a high level of established trust. Trust is considered to be stable if the last trial rating is within five scores of the average of the last three trials. When trust decreases, the visualization will reverse from increasing or decreasing LOD.

4.2.4 Procedure

After an introduction about the experiment, participants were asked to provide informed consent followed by a demographic questionnaire. Then, a training session was conducted to familiarize them with the experiment. An introduction of all four visualizations with LODs was provided to get participants to know the aims, context, flows, and the UI system of the experiment. The participants performed a mission before the formal experiment to get familiar with the user interface, the actions they could take, the corresponding consequences, the score system, the flow of the decision-making, the steps in the mission. They also had the opportunities during this period to ask experiment-related questions. The participants could take as long as they would like to until they were confident with the experiment apparatus and simulated mission.

For the formal data collection, each participant experienced four blocks, each of which contained seven to nine trials. As mentioned, each block provided one of the four LODs. Before the start of the block, the participants received a briefing about the lost person. Figure 32 describes the flow of one trial. The search starts with the UAV search agent surveying an area at a default path altitude. Upon UAV finding an object, the UAV indicates the identification as a clue, a distractor, or a target, along with an image. Then, the human operator could take additional actions to verify by selecting actions between no action, lowering the altitude of the UAV by 1, 2 or 3 times, or sending a human team. If the human operator identifies the object as a clue or distractor, the system checks whether the whole area is covered by the UAV. Otherwise, if the human operator identifies the object as the target, a rescue team would be sent to determine whether the object was a true or false target. A true target leads to the end of a mission, while a false target leads to the check of area. If the whole area is covered, then the mission ends. Otherwise, the autonomy then recommends the path altitude of the next search, based on which the human operator decides to adjust or comply. Then, the next search starts. The terms of target, clue, and distractor are explained in Table 7

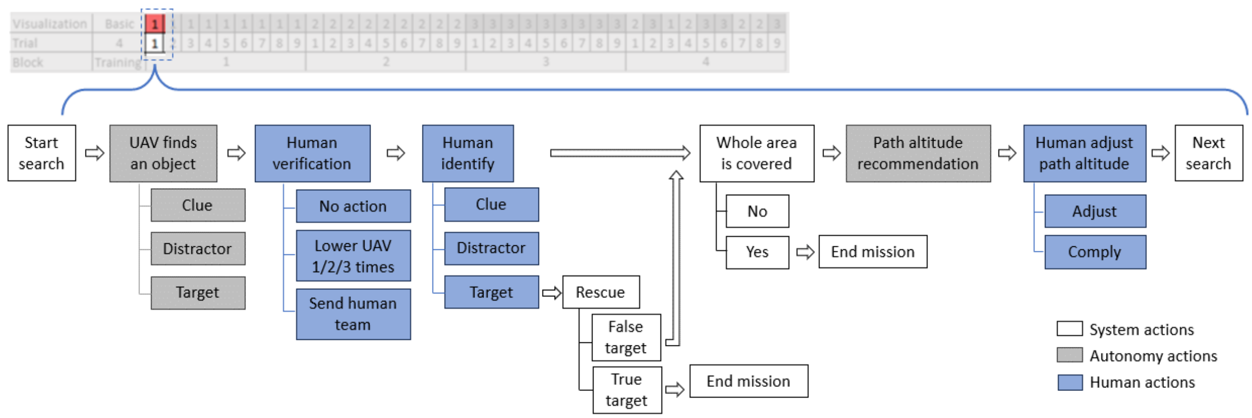


Figure 32. The flow of one trial of the mission.

Table 7. Terminology of the Search Outcome

Terminology	Description	Other details
Target	The lost person(s)	Not all detected humans are the target. Search team members are also people but not the target.
Clue	The objects relevant to the target include belongings, footprints, unusual objects, and other physical clues associated with the lost person.	Not all detected objects are considered clues since distractor objects may be detected. For example, the background investigation for the mission might indicate that the target wears a red jacket and carries a blue bag. A yellow bag would not be considered a relevant clue.
Distractor	Irrelevant objects or false clues.	Objects detected by the UAV that are not considered relevant to the mission.

4.2.5 Dependent Variables

4.2.5.1 Subjective Measures

This study used subjective questionnaires on seven-point Likert scales to measure trust after each trial with a single item (Table 8) and after each block with seven items (Table 9). Transparency was also measured using subjective questionnaires with seven items on seven-point Likert scales (Table 9). The workload was measured with raw TLX with ratings of six dimensions in the NASA TLX without the additional weighting questions, as raw TLX could quickly assess mental workload with similar sensitivity to the NASA-TLX (Hart, 2006). A semi-structured interview was conducted at the end of data collection (Table 10).

Table 8. Measures after Each Trial

Measure	Questions	Anchor
Trust	1. How much do you trust the height recommendation and path planning?	Very little vs Very much

Table 9. Measure after Each Block

Measure	Questions	Anchor
Trust	1. Please select your trust in the system.	Not trust vs Trust
	2. To what extent do you rely on the autonomous system for decision making?	Not at all vs Totally
	3. To what extent does the UAV survey the area properly?	Not at all vs Totally
	4. To what extent does the searching process is proper for achieving the goal?	Not at all vs Totally
	5. To what extent do you think the autonomous system helps you achieve the goal under uncertainty and vulnerability?	Not at all vs Totally
	6. To what extent do you think the autonomous system is hindering disturbing your decision-making?	Not at all vs Totally
	7. To what extent are you confident on whether your choice is the best given the circumstances/scenarios?	Not at all vs Totally
Transparency	1. To what extent do you understand how the system works?	Not at all vs Totally
	2. To what extent do you think the responsibility of the autonomous system is clear or easily understandable to you?	Not at all vs Totally
	3. To what extent do you think the capabilities of the autonomous system are clear or easily understandable to you?	Not at all vs Totally
	4. To what extent do you think the activities of the autonomous system are clear or easily understandable to you?	Not at all vs Totally
	5. To what extent do you think the mechanism of the autonomous system is clear or easily understandable to you?	Not at all vs Totally
	6. To what extent does the system provide you get appropriate information to make any decisions?	Not at all vs Totally
	7. To what extend do you understand why the result looks like this?	Not at all vs Totally

Table 10. Post Experiment Interview

Questions
1. Which visualization do you like the most? The least? Why? (A: Basic map, B: Weighted map, C: Heat map, D: Adaptive mode)
2. Which visualization helps you understand the path planning most effectively? Least? Why?
3. Which visualization helps you understand the path recommendation most effectively? Least? Why?
4. What graphical elements are helpful or distracting? (e.g., Color? Lines? Cones?)
5. What is your strategy for deciding to lower the UAV, raise the UAV, or send the human search team? On what condition?
6. Do you understand the reward and penalty when you make decisions? Do you have any particular strategy in maximizing rewards and penalties? What is confusing to you?

4.2.5.2 Objective Measures

Compliance with altitude and object identification recommendations served as a behavioral measure of trust, as participants were required to make two decisions concerning automation in each trial. The actions are shown in Table 11. The rate of compliance was calculated by block, specifically, the number of compliance actions was divided by the number of trials in each block.

Table 11. Compliance actions

Measure	Action
Altitude Compliance	Comply with the recommended flight path altitude or make changes to it.
Object-identification Compliance	Comply with the recommendation for object verification or lower the UAV (Unmanned Aerial Vehicle) to capture higher-resolution images for the purpose of verifying the detected object.

Performance was measured with an objective score on the mission outcomes resulting from participant decisions. In each trial, the participants received rewards and penalties based on their decisions. The fundamental score system is increasing scores for the target or a clue discovered and decreasing the scores for actions consuming (more) time and false identification of a target or clue. The scoring system is based on the general decision-making process in search and rescue missioned described in (section 4.2.4; also refer to Heintzman et al., 2021; Koester, 2008; Phillips et al., 2014), although the numeric values of rewards and penalties for the decisions and outcome are assigned by the research team in a simplistic manner to minimize training time. For instance, flying at the highest altitude consumes less time than low and medium, and results in the least reduction in score, while the human team, known for taking the most time to perform actions, experiences the most significant score reduction.

The scoring system has four components: (1) penalty/cost as a function of flight path altitude, (2) penalty for the verification actions of objects identified as clue or target, (3) reward (or penalty) for correct (or incorrect) classification of the identified object, and (4) penalty for sending the rescue team. The integrated score for each block was then standardized by the geographical location of the block for data analysis.

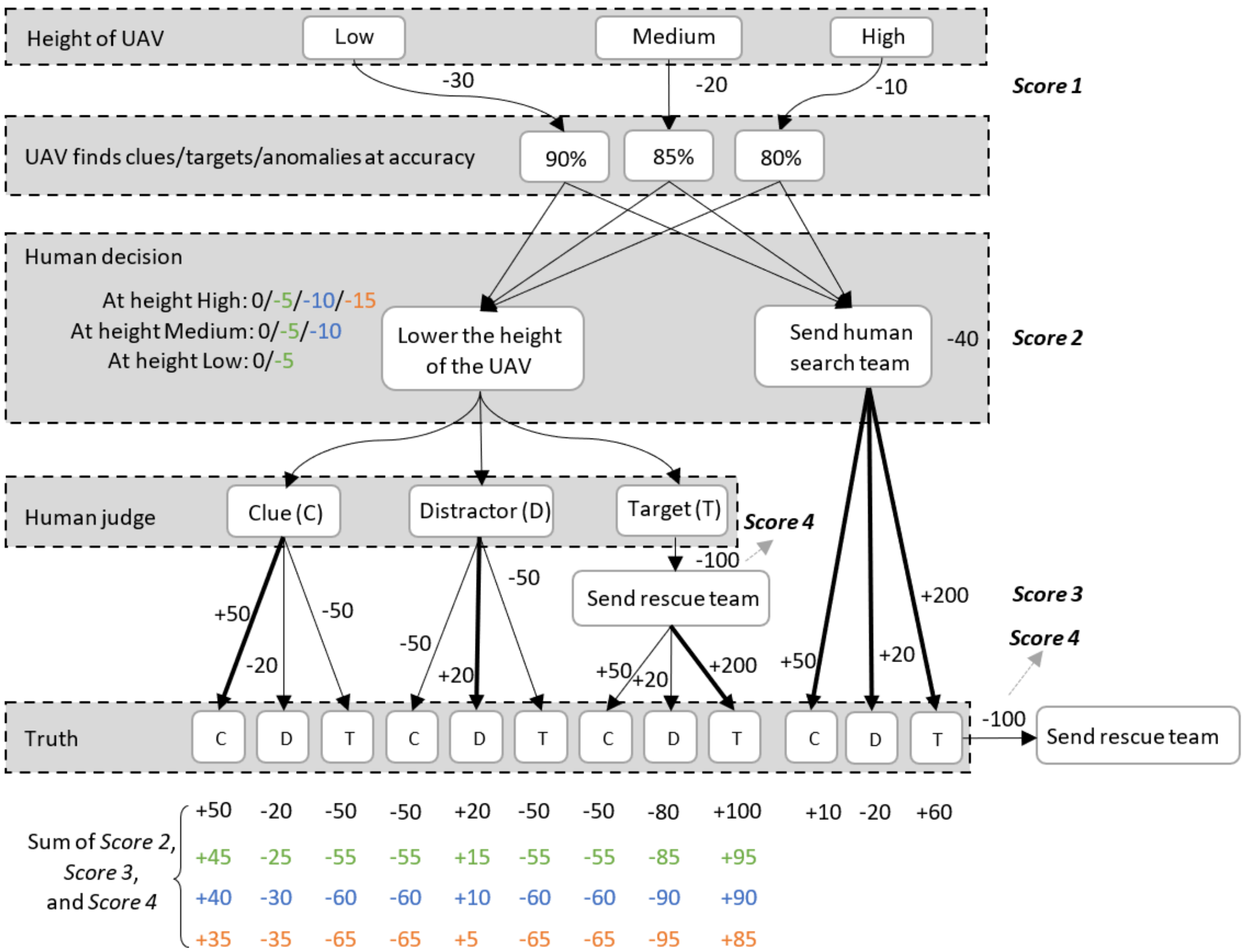


Figure 33. The reward system for every trial.

Score 1 was a penalty/cost of -30, -20, and -10 for directing the UAV to survey the area at a low, medium, or high altitude, respectively. As mentioned, the total distance of UAV flying would be shorter at higher altitudes. The accuracy of the UAV detection at altitudes of low, medium, and high altitudes were 90%, 85%, 80%, respectively.

Score 2 was a penalty/cost for choosing one of the three verification actions after the UAV provided an image of the identified object and a recommendation on whether the object detected was a clue or target. Then, the participant may choose to (1) omit any verification actions with zero penalties; (2) send the UAV for a higher-resolution image with a penalty between -5 and -15 depending on the levels of altitude being lowered; or (3) send a human search team for 100% accurate identification of the detected object with a penalty of -40. If the participant initially chose a low-altitude UAV flight path (refer to Score 1 above), the altitude can only be lowered for one more level with a penalty of -5 (green text in Figure 33). If the initially chosen flight path was the medium altitude, the participant could choose to lower UAV one or two levels at a penalty of -5 or -10, respectively. Similarly, if a flight path is at a high altitude, the UAV can lower one, two, or three altitudes with a penalty of -5, -10, and -15, respectively.

Score 3 was the reward (or penalty) for the correct (or incorrect) participant classification of the object identified as a clue, distractor, or target. Figure 33 presents the rewards for various correct and penalties for various incorrect classifications (i.e., participant classification matching/mismatching the ground truth). The likelihood of clue, distractor, and target for all the trials are 40%, 40%, and 20%, respectively. For example, if the participant classification was the target and that was true, Score 4 would be a reward of +200. Note that when the participant decides that the detected object is a target (i.e., the lost person), then a rescue is automatically sent, and Score 4 cost is incurred.

Score 4 was the penalty of -100 for sending the rescue team, which occurred automatically when the participant decided that the identified object was the target. The final score of each trial was the sum of Score 1 to 4.

4.2.6 Analysis

Transparency, trust, and workload rating scales were assessed on internal consistency with Cronbach's alpha (Cronbach, 1951). Cronbach's alpha above 0.70 is considered acceptable for further analysis (Taber, 2018). Normality of averaged transparency ratings, overall trust ratings, workload ratings, performance, altitude compliance rates, and object-identification compliance rates of every block (i.e., four LOD) were assessed with the Shapiro-Wilk. As the sample size is large (>30), the impact of the deviation from normality should be negligible, so parametric tests were still adopted despite the violation of some conditions (Ghasemi & Zahediasl, 2012; Pallant, 2020). Relationships between transparency, trust, workload, and performance scores were analyzed with Repeated Measures of Correlation (Bakdash & Marusich, 2017) as denoted by r_s, which quantifies the strength and direction of the linear relationship between the four measures.

To evaluate the main effects of LOD, one-way repeated-measures ANOVAs (Girden, 1992) were performed on all measurements aggregated per block (N=4). The univariate approach to one-way repeated measure is appropriate because it can provide valuable insights into the characteristics of individual variables and determine whether there is a statistically significant difference between the means of the four groups in which the same participants experienced each group. Though robust to normality violation, a repeated measures ANOVA is not robust to sphericity (Howell, 2012). The assumption of equal variance was assessed with Mauchly's test of sphericity (Mauchly, 1940). In cases of violation, either Greenhouse-Geisser or Huynh-Feldt adjustment to degrees of freedom and corresponding p-value would be adopted. If the Greenhouse-Geisser epsilon (ε) is less than .75, this study will use the Greenhouse-Geisser estimate of sphericity and otherwise, the Huynh-Feldt estimate of sphericity (Girden, 1992).

To evaluate the evolution of trust, instantaneous trust ratings were aggregated into phases of three trials. Specifically, phase one included instantaneous trust ratings from trials one, two, and three, phase two included ratings of trials four, five, and six, and phase three included the ratings of the remaining trials. A two-way repeated-measures ANOVA of LOD (four levels) and phases (three levels) was adopted to examine instantaneous trust. The same treatment of assumptions was adopted as described above. Furthermore, the initial instantaneous trust values were interpolated to nine data points for fitting curves to observe the trend of instantaneous trust over trials of interactions.

Statistically significant results from the one-way and two-way repeated ANOVAs were followed by post-hoc comparisons of means between experimental conditions. Multiple t-tests were used for post-hoc comparisons with Bonferroni adjustment to control the risk of making false positive conclusions due to the increased chance of Type I errors when performing multiple comparisons (Armstrong, 2014). Bonferroni adjustment is appropriate because it helps maintain the desired level of significance across multiple tests. This becomes particularly important when the assumption of sphericity is not met, making the Bonferroni method a more appropriate choice for post hoc analysis in the context of repeated measures designs compared to Tukey's test (Maxwell, 1980). To maintain type 1 error rate $\alpha=0.05$, the alpha level for post-hoc analysis was produced by dividing the original alpha level by the number of tests.

4.3 Results

4.3.1 Descriptive statistics

The Cronbach's alphas for the seven transparency items, seven trust items, and six workload items are .94, .85, and .78, respectively (Cronbach, 1951), indicating sufficient internal consistency (Taber, 2018). All item ratings of transparency, trust, workload questionnaires, and performance scores after the block were averaged for analysis, respectively.

Repeated Measures Correlation was used to examine the relationships between transparency, trust, workload, and performance scores (Table 12). Correlation is considered a strong relationship when $r_s \geq 0.7$, a moderate relationship when $0.4 \leq r_s < 0.7$, a weak relationship when $0.1 \leq r_s < 0.4$, and no relationship when $r_s < 0.1$ (Akoglu, 2018; Dancey & Reidy, 2007).

Table 12. Correlation Results between Transparency, Trust, Workload, Performance Score

Variable	n	M	SD	1	2	3	4
1. Trust	152	5.02	0.60	___			
2. Transparency	152	5.57	0.84	0.68^{***}	___		
3. Workload	152	2.98	0.86	-0.12	-0.02	___	
4. Performance score	152	-0.83	0.42	0.26^{**}	0.27^{**}	0.07	___

*p<.05, **p<.01, ***p<.001

Participant transparency and trust ratings showed moderate and positive correlations, $r_s(113) = 0.68,\ p < .001$. The performance score had a weak and positive correlation with trust $r_s(113) = 0.26,\ p < .01$, and weak and positive correlation with transparency, $r_s(113) = 0.27,\ p < .01$.

4.3.2 Transparency

A one-way repeated-measures ANOVA was performed to evaluate the effect of LOD (four levels) on transparency ratings averaged by blocks. The means and standard deviations for transparency are presented in Table 13. Mauchly's test indicated that the assumption of sphericity had been violated, $\chi^2(5)=22.94$, p<.001, and therefore degrees of freedom were adjusted with Greenhouse-Geisser estimates of sphericity (ε=.74). The effect of LOD on transparency was significant, F(2.21, 81.60)=5.50, p=.004, $\eta_p^2=.13$; Figure 34. Post-hoc pairwise comparisons using a t-Test with a Bonferroni-adjusted alpha level of .008 (i.e., 0.05/6) indicated that transparency was significantly larger for low LOD (M=5.83, SD=0.97) than high (M=5.30, SD=1.12, p=.002) and medium LOD (M=5.45, SD=0.95, p=.007). Other comparisons were not significant after the Bonferroni adjustment (all $p > .008$).

Table 13. Descriptive Statistics for Transparency by LOD

LOD	n	M	SD
High	38	5.30	1.12
Medium	38	5.45	0.95
Low	38	5.83	0.97
Adaptive	38	5.70	0.95

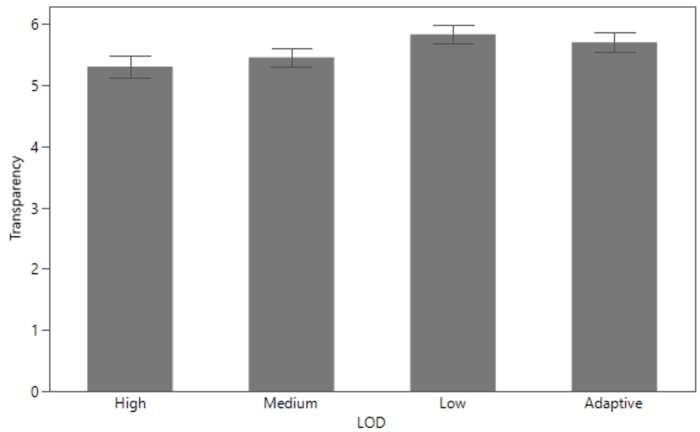


Figure 34. Transparency means with the standard error by LOD.

4.3.3 Trust

A one-way repeated-measures ANOVA was performed to evaluate the effect of LOD (four levels) on trust per block. The means and standard deviations for trust are presented in Table 14. Mauchly's test indicated that the assumption of sphericity was satisfied, $\chi^2(5)=6.36$, p=.273. The effect of LOD on trust was significant, $F(3, 111)=8.48$, $p<.001$, $\eta_p^2=.19$; Figure 35. Post-hoc pairwise comparisons using a t-Test with a Bonferroni-adjusted alpha level of .008 (i.e., 0.05/6) indicated that trust was significantly larger in low LOD (M=5.45, SD=0.82) than high LOD (M=4.76, SD=0.87, p<.001), medium LOD (M=4.83, SD=0.77, p<.001), and adaptive LOD (M=5.02, SD=0.85, p<.001). Other comparisons were not significant after the Bonferroni adjustment (all $p > .008$).

Table 14. Descriptive Statistics for Trust by LOD

LOD	n	M	SD
High	38	4.76	0.87
Medium	38	4.83	0.77
Low	38	5.45	0.82
Adaptive	38	5.02	0.85

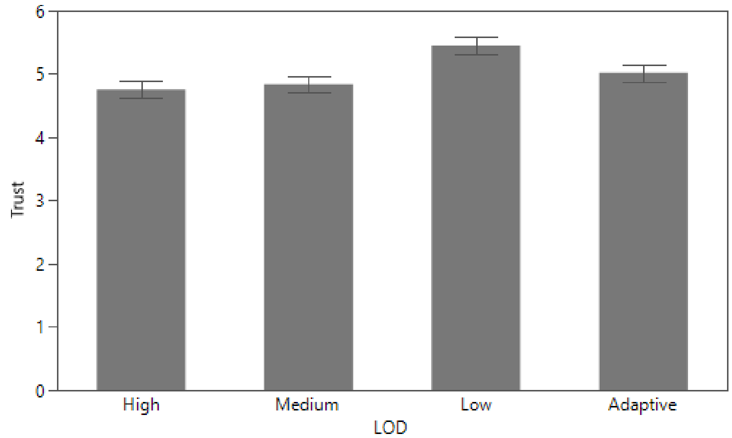


Figure 35. Trust means per block with the standard error by LOD.

A block might have seven to nine measurements of instantaneous trust depending on the decisions of the participants (Figure 36).

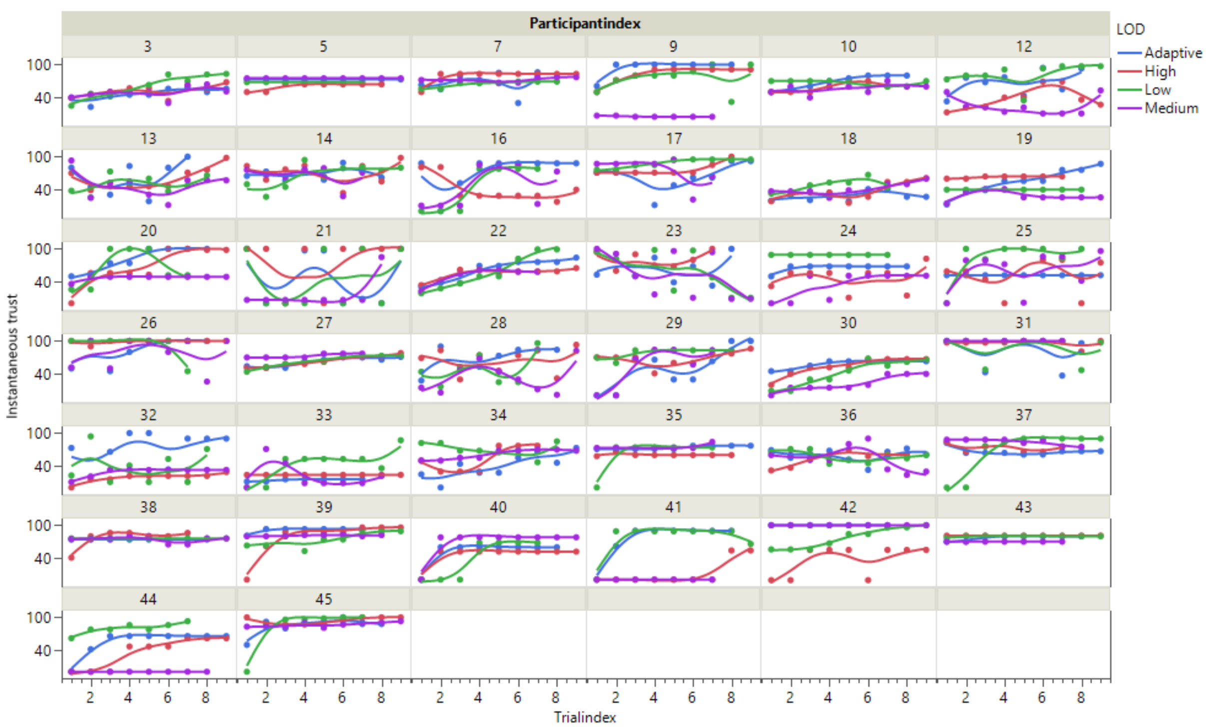


Figure 36. Instantaneous trust of all participants.

To evaluate the evolution of trust, instantaneous trust ratings were aggregated into phases of three trials, as described in section 4.2.6. A two-way repeated-measures ANOVA was performed to evaluate the effect of LOD (four levels) and phase (three levels) on instantaneous trust. The means and standard deviations for trust of each phase are presented in Table 15. Mauchly's test indicated that the assumption of sphericity had been satisfied for LOD, $\chi^2(5)=8.42$, $p=.135$. The effect of LOD on instantaneous trust was significant, $F(3, 111)=5.63$, $p=.001$, $\eta_p^2=.13$. Mauchly's test indicated that the assumption of sphericity had been violated for phase, $\chi^2(2)=7.76$, $p=.021$, and degrees of freedom were adjusted with Huynh-Feldt estimates of sphericity $\varepsilon=.87$. The effect of phase on instantaneous trust was significant, $F(1.75, 64.58)=39.00$, $p<.001$, $\eta_p^2=.513$. Mauchly's test indicated that the assumption of sphericity had been violated for LOD*phase, $\chi^2(20)=55.67$, $p<.001$, and degrees of freedom were adjusted with Greenhouse-Geisser estimates of sphericity $\varepsilon=.68$. The interaction effect of LOD and phase on instantaneous trust was significant, $F(4.09, 151.28)=3.30$, $p=.012$, $\eta_p^2=.08$, Figure 37.

Table 15. Instantaneous Trust by Phase for LODs.

Phase	n	High LOD		Medium LOD		Low LOD		Adaptive LOD	
		M	SD	M	SD	M	SD	M	SD
1	38	52.68	24.4	50	28.8	54.69	23.77	56.08	20.03
2	38	60.13	21.93	54.89	29.39	71.16	18.44	68.34	19.99
3	38	69.2	21.13	54.79	26	73.11	17.58	73.16	18.89

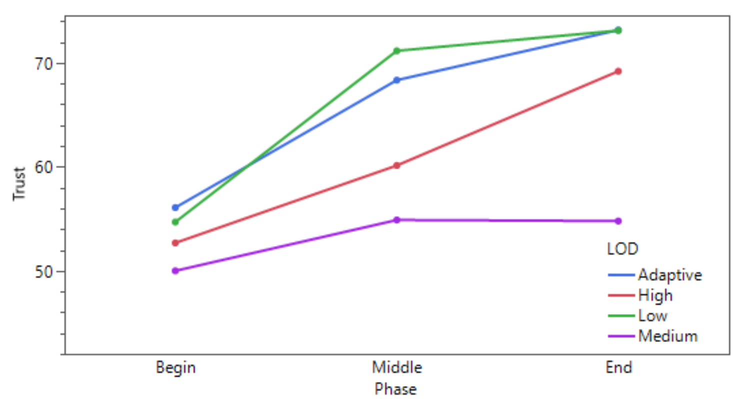


Figure 37. Means of instantaneous trust at each phase.

Post-hoc pairwise comparisons between LODs were performed using a t-Test with a Bonferroni-adjusted alpha level of .008. The descriptive statistics for instantaneous trust by LODs are shown in Table 16. The result indicated that for all phases, instantaneous trust was significantly smaller in medium LOD (M=53.23, SD=30.97) than low LOD (M=65.73, SD=27.42, p=.003) and adaptive LOD (M=65.15, SD=25.34, p=.005). Other comparisons were not significant after the Bonferroni adjustment (all $p > .008$).

Table 16. Descriptive Statistics for Instantaneous Trust by LOD

LOD	Mean	SD	95% CI	
			LL	UL
High	60.10	27.34	57.11	63.07
Medium	53.23	30.97	49.81	56.66
Low	65.73	27.42	62.68	68.79
Adaptive	65.15	25.34	62.34	67.95

Post-hoc pairwise comparisons between phases were performed using a t-Test with a Bonferroni-adjusted alpha level of .008. The descriptive statistics for instantaneous trust by phases are shown in Table 17. The result indicated that for all LODs, instantaneous trust was significantly smaller in phase one (M=53.36, SD=24.31) than in phase two (M=63.46, SD=23.38, p<.001) and phase three (M=68.45, SD=19.07, p<.001). Instantaneous trust was significantly smaller in phase two (M=63.46, SD=23.38) than in phase three (M=68.45, SD=19.07, p=.003).

Table 17. Descriptive Statistics for Instantaneous Trust by Phase

Phase	Mean	SD	95% CI	
			LL	UL
1	53.36	24.31	49.47	57.26
2	63.46	23.38	59.70	67.20
3	68.45	19.07	65.40	71.51

Post-hoc pairwise comparisons between different combinations of LOD and phase were performed using a t-Test with a Bonferroni-adjusted alpha level of .008. The descriptive statistics for instantaneous trust of phases are shown in Table 18. The result indicated that in phase two, instantaneous trust was significantly larger for low LOD (M=71.05, SD=18.22) than medium

LOD (M=54.22, SD=29.00, p<.001) and high LOD (M=60.18, SD=21.96, p=.007). In phase three, instantaneous trust was significantly smaller for medium LOD (M=61.00, SD=22.39) than low LOD (M=72.66, SD=15.36, p<.001), adaptive LOD (M=70.90, SD=17.55, p<.001), and high LOD (M=69.25, SD=18.88, p=.002). Other comparisons were not significant after the Bonferroni adjustment (all $p > .008$).

Table 18. Descriptive Statistics for Instantaneous Trust by LOD and Phase

Phase	LOD	Mean	SD	95% CI	
				LL	UL
1	High	52.68	24.40	44.66	60.705
	Medium	50.00	28.80	40.54	59.46
	Low	54.69	23.77	46.88	62.51
	Adaptive	56.08	20.03	49.49	62.66
2	High	60.18	21.96	52.97	67.40
	Medium	54.22	29.00	44.69	63.75
	Low	71.05	18.22	65.06	77.04
	Adaptive	68.37	19.84	61.85	74.89
3	High	69.25	18.88	63.04	75.45
	Medium	61.00	22.39	53.65	68.36
	Low	72.66	15.36	67.61	77.71
	Adaptive	70.90	17.55	65.13	76.67

A fit curve was used to model the pattern of trust evolving over trials to characterize and understand how trust changes over interactions. Before modeling, to make the number of measurements balanced across blocks, the value of instantaneous trust was interpolated to nine data points, as described in Table 19.

Table 19. Interpolate Instantaneous Trust to Nine Data Points

The number of trials for the block	Previous value	Interpolated value
7	trust estimates of trial 6	average trust of trials 5 and 6
	trust estimates of trial 7	trust of trial 6
	trust estimates of trial 8	average trust of trials 6 and 7
	trust estimates of trial 9	trust of trial 7
8	trust estimates of trial 8	average trust of trials 7 and 8
	trust estimates of trial 9	trust of trial 8

Then, for each LOD, the instantaneous trust was standardized using the max-min scale in Equation (4.2), where i is the trial index, j is the block index, $trust_i$ is the instantaneous trust, std_trust_{ij} is the standardized value.

$$std\_trust_{ij} = \frac{trust_{ij} - \min_j trust_{ij}}{\max_j trust_{ij} - \min_j trust_{ij}} \tag{4.2}$$

The standardized trust value was fit into the curve using Equation (4.3), where i is the trial index, c is the asymptote, a is the growth rate, and b is the inflection point. Table 20 shows the parameters of the fit curve.

$$fitted\_trust_i = \frac{c}{1 + e^{-a*(\mathrm{i}-b)}} \tag{4.3}$$

Table 20. Parameter for Trust Curve Fitting

LOD	R-Square	Growth Rate (a)	Inflection Point (b)	Asymptote (c)
High	0.15	0.31	3.48	0.96*
Medium	0.03	0.88	0.77	0.51*
Low	0.14	0.85*	1.74*	0.69*
Adaptive	0.17	0.61*	2.11*	0.77*

* p<.01

For each visualization/block, the new trust value, $new\_trust_{i,}$ was recalculated for rescaling standardized trust data to the original scale using Equation (4.4), where i is the trial index.

$$new\_trust_i = fitted\_trust_i * \left(\max_i trust_i - \min_i trust_i\right) + \min_i trust_i \tag{4.4}$$

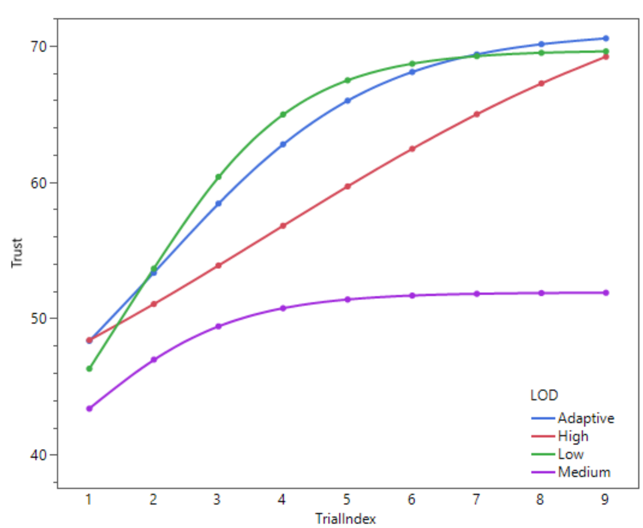


Figure 38. Means of recalculated trust after fit curve.

Figure 38 illustrates that the low LOD presented the highest growth rate and plateaued at the highest value of (instantaneous) trust. The adaptive LOD presented a similar growth rate and plateau of trust as the low LOD. The high LOD presented a linear growth rate and reached a similar trust as the heat map and adaptive map at the last trial index. The medium LOD presented the worst growth rate and plateau of trust. The result suggests that the dynamics of trust vary with different LODs as captured by different visualizations. Among the static visualizations, more information led to a quicker increase in trust and reached a higher plateau value. Adaptive LOD led to a quicker increase than the high LOD, with the least information reaching a higher plateau value than medium LOD.

4.3.4 Workload

A one-way repeated-measures ANOVA was performed to evaluate the effect of LOD (four levels) on workload per block. The means and standard deviations for workload are presented in Table 21. Mauchly's test indicated that the assumption of sphericity had been satisfied, $\chi^2(5)$ =7.09, p=.214. The effect of LOD on workload was not significant at α=0.05 level, F(3, 111)=0.37, p=.778, η_p^2=.01.

Table 21. Descriptive Statistics for Workload by LOD

LOD	n	M	SD
High	38	2.95	0.90
Medium	38	3.01	0.96
Low	38	3.00	0.90
Adaptive	38	2.95	0.87

4.3.5 Performance

A one-way repeated-measures ANOVA was performed to evaluate the effect of LOD (four levels) on performance scores per block. The means and deviations for performance scores are presented in Table 22. Mauchly's test indicated that the assumption of sphericity had been violated, $\chi^2(5)=17.73$, $p=.003$, and therefore degrees of freedom were adjusted using Huynh-Feldt estimates of sphericity ($\varepsilon=.89$). The effect of LOD on performance score was not significant, $F(2.65, 98.19)=0.37$, $p=.75$, $\eta_p^2=.01$.

Table 22. Descriptive Statistics for Performance Score by LOD

LOD	n	M	SD
High	38	-0.88	0.66
Medium	38	-0.86	0.49
Low	38	-0.81	0.68
Adaptive	38	-0.78	0.45

4.3.6 Compliance

A one-way repeated-measures ANOVA was performed to evaluate the effect of LOD (four levels) on altitude compliance per block. The means and deviations for altitude compliance are presented in Table 23. Mauchly's test indicated that the assumption of sphericity had been satisfied, $\chi^2(5)=0.55$, $p=.99$. The effect of LOD on altitude compliance was not significant, $F(3, 111)=1.15$, $p=.33$, $\eta_p^2=.03$.

Table 23. Descriptive Statistics for Altitude Compliance by LOD

LOD	n	M	SD
High	38	0.79	0.28
Medium	38	0.74	0.30
Low	38	0.83	0.25
Adaptive	38	0.81	0.25

A one-way repeated-measures ANOVA was performed to evaluate the effect of LOD (four levels) on object-identification compliance per block. The means and deviations for compliance are presented in Table 24. Mauchly's test indicated that the assumption of sphericity had been met, $\chi^2(5)=5.49$, $p=.36$. The effect of LOD on object-identification compliance was not significant, $F(3, 111)=1.64$, $p=.19$, $\eta_p^2=.04$.

Table 24. Descriptive Statistics for Object-identification Compliance by LOD

LOD	n	M	SD
High	38	0.46	0.33
Medium	38	0.45	0.29

Low	38	0.50	0.31
Adaptive	38	0.43	0.29

4.4 Discussion

This study assessed the influence of static and adaptive LODs on transparency, trust, workload, and performance during repeated interactions between humans and autonomy in the context of wilderness SAR missions. The results indicated that when provided visualization with LOD adapted to instantaneous trust to vary the amount of information on display, users could maintain similar trust dynamics as with low LOD that yielded the highest level of trust. Hence, the study addresses the research gap by demonstrating how adaptive LOD aimed at facilitating communication efficiency in HAT could enhance trust development.

4.4.1 Overall transparency and trust

Though differences in performance and compliance were not observed, transparency and trust ratings collected at the end of a block were different across LODs. Low LOD brings more transparency than high and medium LOD (Figure 34). More information in visualization helped participants trust the responsibility, capability, activities, and mechanism of the autonomous system. In addition, since the participants were novices to SAR, more information could enhance participants' comprehension of the UAV's actions and the search process. In situations where the existing knowledge does not align with the task at hand, research has found that individuals prefer user interfaces that provide more detailed instructions (Ziegler et al., 2011).

Low LOD induced the most trust (Table 14). This finding suggests that presenting information about autonomy could build trust, as the users may perceive any reasonable forms of disclosure as signs of benevolence or good etiquette that promote trust (Höddinghaus et al., 2021; Mayer et al., 1995; van Straten et al., 2022). Furthermore, based on ratings of some items in the trust measure, the greater availability of information fosters participants' confidence in selecting the optimal action.

Concerning the relationship between trust and transparency, the study indicates that while trust and transparency are interconnected, they are distinct concepts. On the one hand, trust and transparency are strongly and positively correlated. On the other hand, the adaptive LOD induced less trust than low LOD (as indicated in Table 14), but there was no significant difference in transparency compared to low LOD (as shown in Table 13). Transparency of adaptive LOD was expected to be as effective as low LOD because when the information was insufficient for trust, the algorithm of adaptive LOD would provide more information in an attempt to improve understanding and trust. The findings suggest that displaying more details about the system functions can increase trust. However, not all the improvement of trust comes from transparency because trust could also be influenced by other factors (Hancock, Billings, & Schaefer, 2011). The adaptive LOD presents variable contents, and the variability of information being communicated could potentially lead to less trust (Sanders et al., 2014).

4.4.2 Instantaneous trust

The relationship between the LOD and instantaneous trust is complex. In general, trust increased and then plateaued after several trials of interactions. Regardless of the quality of the visualization, trust requires a certain period to stabilize (Yu et al., 2017). With the rate of change and plateau value varies among LODs, the trust development follows a similar sigmoidal growth curve in low LOD, medium LOD, and adaptive LODs, while high LOD follows a linearly increasing rate of change with a lower plateau value (Figure 38).

The lowest LOD was the heatmap coupled with a color-coded UAV path that resulted in the highest plateau of trust. Displays providing explanations on the capabilities of autonomy could increase trust, but lack of explanation would decrease trust (Holliday et al., 2016). In the debriefing of this study, the participants mentioned that the use of colors to highlight the likelihood of finding the lost person in the areas on the heatmap helped them to comprehend the path taken by the UAV. This implies that more details can be effective for expediting the process of building trust. The low LOD visualization is likely most suitable in situations where trust needs to be established quickly within a limited number of interactions, especially when communication or processing resources are not constrained.

Among the three static LODs, the weighted map at medium LOD had the lowest growth rate and quickly plateaued at the lowest trust. The weighted map presents a simplified version or greater abstraction of the heat map that may be beneficial when the underlying mechanisms of autonomy are well understood. During the debriefing, six participants mentioned that the weighted map was confusing. Two participants expressed that the weighted map provided no more information than the basic map, offering limited assistance in understanding path planning. One even indicated that the weighted map was too complicated to understand. A weighted map may have provided a more abstract representation, but the abstraction may have distorted the explanation of the underlying path-planning rationale, thereby hindering trust. Intermediate abstraction or medium LOD might demand that the users have a deep understanding of the task and autonomy for them to infer (or overlook) the missing details. This possible explanation needs further research.

The basic map with the highest LOD followed a different trend from the other sigmoidal growth curves. Specifically, trust showed a slower, consistent, and linear increase, eventually reaching a similar level to the heat map. This result implies that the experience provided through repeated interactions and consistent visualization could help build trust, albeit at a slow pace.

Given that the basic map lacks details or information about the autonomy, the users or operators cannot exploit any information about the autonomy to explain any positive and negative outcomes of their decisions for moderating or accelerating their trust. The users or operators can only rely on repeated interactions to gradually reach the same plateau of trust as with low LOD and adaptive visualizations.

Debriefing provides additional insights into this linear increase of trust with the high LOD or basic map. Among the 38 participants who took part in the post-experiment interview, seven participants regarded the basic map as the most effective for comprehending altitude due to its straightforward display without additional coloring and clear identification of the UAV and terrain, and ten participants ranked the basic map as their most preferred visualization, attributing its effectiveness to its simplicity, ease of information extraction, and reduced distractions. Conversely, seven participants regarded the basic map as the least effective, citing its limitation in conveying supplementary information beyond the path and noting its overly simplistic representation and lack of details. The mix of positive and negative debriefing responses offered another potential explanation for linear, rather than sigmoidal, development of trust over interactions with autonomy. On one hand, some users prefer the less information-rich and distractive communication that can be helpful in building trust. On the other hand, others prefer more details or information, so the lack of details in the basic map could hinder the development of trust. The mix of results led to a linear increase in trust with interactions.

The three static LODs resulted in three distinct curves of instantaneous trust over the nine trials of interactions, while the adaptive LOD visualization yielded a curve similar to the low LOD in terms of rate of change and plateau value. For adaptive LOD, the trust first increased at a fast speed, then slowly reached the plateau at a similar level of trust as with low LOD. At the beginning phase, the four curves showed similar trust values. The adaptive LOD was initialized using high LOD. The increase in trust reflected that the participants felt they were learning about autonomy during this phase (refer to Figure 37). After the initial climb in trust, the speed of high LOD started to slow due to the limited information, while low LOD included more information to enable the trust to keep growing. Due to the potential confusion caused by abstraction in the visualization, the speed of trust growth in medium LOD was slow early on and stopped growing quickly. As the visualization started to switch based on the instantaneous trust in adaptive LOD, participants would get more information to develop trust with a similar speed and value as the low LOD. Finally, the trust of low and adaptive LOD plateaued. In addition, because the change of LOD was to prioritize the development of trust, and adaptive LOD did not provide more information than low LOD, a similar plateau value was expected. In contrast, trust in high LOD visualization did not plateau and increase to a similar value as the low LOD at the end (refer to Figure 37).

The low overall and instantenous trust consistently observed for the medium LOD visualization deserves further disussion. Unlike certain existing studies where a moderate amount of information often results in moderate or even higher trust compared to too little or too much information (Boyce et al., 2015; Wright et al., 2016), a medium LOD in this study instilled less trust compared to other LODs. The medium LOD representing a weighted map in this study closely resembles what the human search team might use (and thus relatvely effective for Study 1), but UAV path planning is not based on discretized search areas in the weighted map. The absence of a direct connection between the weighted map (i.e., or discretized areas) and path planning (i.e., continuous paths) might challenge participants in to identifying the utility of the medium LOD or such visualization. In contrast, the heat map employed for the low LOD aligned better with the task of searching clues and tagets on a continuous path. The low LOD effectively maintained focus on the path rather than information about the search segment or area even though the visualizations at both low and medium LOD occasionally obstructed the view of terrain features, which could aid participants in estimating the lost person's directional movements. This could explain why high and medium LODs displayed similar trust patterns in the first phase but high LOD exhibited gradual trust growth, while medium LOD stagnated in the final phases. Interestingly, in the adaptive mode, the presence of the medium LOD did not appeared to hinder the trust evolution probably because the adaptive mode mitigated the drawback of weighted map or medium LOD by providing participants with some opportunities to examine unobstructed terrain for an overview that would facilitate the alignment of the path with the task. Communication facilitating understanding of the task could promote trust (Hancock, Billings, & Schaefer, 2011). In addition, similar to the study of Kortschot et al. (2022) adapting UI by adjusting amount of information dynamically to reduce cognitive overload, the adaptive mode in this study would swiftly transitions to another LOD in an attempt to promote trust. when trust plateaued with the weighted map

As complex visualization of autonomy may demand substantial information processing resources of the users, adaptive visualization offers the potential advantage of maintaining trust at a comparable level to that of the low LOD without presenting all the information. In addition, UI adaptive to different factors besides trust can provide a more personalized and tailored experience for the user. For example, Kortschot et al. (2022) illustrated that UI adaptive to information processing demand could benefit workload management and overall performance when collaborating with autonomy to identify the most efficient subway routes. In adaptive mode, the granularities of the information on display vary, and the participants could avoid being given either the minimum or maximum amount of information. This approach could prevent situations where comprehension is hindered due to either insufficient or excessive information about the autonomy system or computational models (refer to Kizilcec (2016)). Hence, visualization with adaptive LOD could enhance the effectiveness of information exchange during specific interaction opportunities and promote the speed and efficiency of communication.

Despite some recent evidence supporting adaptive UI (Jameson, 2007; Stefanidi et al., 2022; Ziegler et al., 2011), static LODs still have the advantage of being more predictable than dynamic LODs; thus, users would know exactly what to expect each time they interact with the autonomy, and do not need to learn or adapt to new features or visualization changes. In the context of adaptive UI, the human operator might get confused by the complex variation in the UI when the visualization frequently changes during the interactions and potentially poses a drawback to trust-building. For this reason, the adaptive LOD might not have developed trust better than low LOD.

The study results highlight how both overall trust and instantaneous trust are both critical measures. Instantaneous trust measurements capture trust levels after specific interactions to reflect the temporal nature of trust, showing that overall trust measurements may lack insight into nuances of evolving trust. Precise, fine-grained temporal precise measurements of trust are necessary to comprehend trust evolution and its impact. However, frequent trust ratings are intrusive, and relying on a single item is less reliable while incorporating more items becomes more obtrusive. Although the overall trust measured after each block was different from the instantaneous trust measured after each trial, both the overall level of trust and instantaneous measures for granular interaction-specific insights are necessary to fully understand user experiences.

4.5 Contribution and Practical Implications

This research produced two major contributions to the literature. First, this study presents the first examination into how the amount of information or LODs (about autonomy) can influence the development of trust towards autonomy, advancing our understanding of trust in HAT. Specifically, this study illustrated that trust evolved over interactions in a linear curve when information about autonomy is minimal but in a sigmoidal curve when the information includes more details or variable levels of detail. Further, the development of trust is generally faster with more details about autonomy. Whereas prior work largely highlights more information about autonomy would lead to higher time-invariant trust after an extended period of interactions, this study presents that the growth speed of trust is generally higher with more details about autonomy. This finding is significant because methods for establishing trust faster could potentially lead to earlier adoption of autonomy that would reduce workload and facilitate performance.

Second, this study is also novel in adapting UI based on instantaneous trust with a simple algorithm to vary the amount of information on display in an attempt to improve trust and task performance. Adapting LOD based on instantaneous trust can reach very similar growth speed and pattern as well as the plateau value of trust as in the lowest LOD, although there were no statistically significant differences observed in terms of performance, compliance, or workload. At least for building trust, this novel approach of adapting UI based on instantaneous trust and a variable amount of information about autonomy presents promise and is thus significant in extending current research on adapting UI based on workload.

Autonomous systems directing UAVs for SAR mission is increasingly necessary not only because of dwindling volunteers but also because of the potential to promote search speed and survival of lost person. Accelerating trust in the system could be important for accelerating the decision time to deploy autonomy, improving confidence in the capabilities of autonomy during operations, and reducing unnecessary interruptions of search path decision-making. This study designed visualizations for static LODs and an adaptive LOD to support the understanding of UAV path, lost person location estimation, and terrain features. The UI with low LOD shows higher trust than high LODs. The adaptive UI led to a trust development pattern akin to that of the static user interface with a low LOD while demanding less information exchange during the task. Thus, the LOD in UI holds significance for attaining an efficient search process with effective communication. Therefore, a higher survival rate and faster detection time for the lost person searching should be expected.

4.6 Future work

Future research on adaptive or static LOD is necessary to address several knowledge gaps. First, the information processing requirement for the tasks in this study might not be sufficiently demanding to overwhelm the users or participants, so the potential advantage of adaptive UI in lowering the amount of information exchanged on displays might not yield sufficient benefits for compliance, workload, and performance. Future studies need a wider range of LODs to determine the potential benefits of adaptive LOD for the UI based on trust or other indicators. Second, the displays across all four LODs have overlapping contents for achieving the task, such as geographic maps, area arrangement, and search path. Since all the information components in the display are novel to the participants without prior SAR experience, the influence of this information on task outcomes could be substantial, forming such a high baseline of information processing that renders any changes in LOD for this study insignificant on compliance, workload, and performance. Last, the adaptive trust algorithm is simple and straightforward, relying on one immediate rating of trust. Future studies can explore other methods of measuring instantaneous trust for adapting the UI. In summary, future research should introduce more variation in information contents and formulate more diverse and sophisticated trust measurements and trust adaptive algorithms.

4.7 Conclusion

This study investigated how the amount of information about autonomy should be adapted for humans with respect to trust evolving over time for facilitating communication efficiency in a collaborative task. The results revealed that the low LOD with the maximum information gained the most overall trust among the four LODs and gained higher transparency than medium and high LOD. For instantaneous trust, among the static visualizations, more information led to a quicker increase in trust and reached a higher plateau value. Adaptive LOD led to a quicker increase than the high LOD, with the least information reaching a higher plateau value than medium LOD. Thus, this unique adaptive method based on human trust and communication illustrated that instantaneous trust could be an adaptive factor in addition to the commonly investigated workload or task load.

Chapters 2, 3, and 4 present all the empirical and methodological research of this dissertation. The next chapter is a general discussion of the empirical results of all the studies on LOD, trust, transparency, and adaptive automation to illustrate the overall contribution to research and industry.

5. General Discussion

Information exposing the details of autonomy for promoting transparency has been used to calibrate trust, but the transparency paradox, in which high visibility of the autonomy may actually decrease transparency and produce opacity, has been under-investigated. This dissertation investigates this transparency paradox in the context of human autonomy teaming in wilderness SAR. The specific research aims of this dissertation are:

1) to understand how visualization at different LODs about autonomy could have different impacts on users with respect to transparency and trust after interacting with autonomy,
2) to understand how static and adaptive UI designs with different LODs could be better in elevating the speed of building trust and plateau of trust as users interact with autonomy over time.

This section discusses the research contributions and practical contributions, followed by a conclusion.

5.1 Research Contributions

This research expands on the limited research on transparency and trust of autonomy with respect to LODs in visualization or UI. The two empirical studies in this dissertation consider LOD as a critical factor of trust and transparency. Study one provides the first empirical evidence indicating that the impact of LODs on trust and transparency is not linear, which has not been explicitly investigated in prior studies about autonomy. Study two investigates trust as an adaptive factor for communication efficiency and provides empirical evidence that adapting LOD to trust can support the speed of growth and plateau value of trust.

This research manipulated LOD by changing the granularity of information in the user interface. High LOD delivers less information so that users can gain an overview with selected information about autonomy, while low LOD delivers more information on each aspect of autonomy to users in a more detailed manner. Among static LODs, study one reveals that the lowest, the second lowest, and second highest LODs among the four LODs earned more trust than high LOD, while study two reveals that the lowest LOD earned the most trust. These results are not necessarily contradictory because the LODs across the two studies cannot be directly comparable as the objectives between the studies introduced different design properties for the LODs. In both studies, the high LOD offers minimal information, providing an overview of the geographic area, except the high LOD in study two also presented the UAV path (that was available across all LODs in study two). For the second highest LOD, study one provides area segments identical to the team assignment area that matches the task requirements well, whereas in study two, the medium (static) LOD presents a similar area segmentation, but the task in study is no longer about assigning teams to search areas. The second lowest LOD in study one and the lowest LOD in study two featured a heatmap representation of LPM that reflected more details or lower granularity. Given the research objective, the lowest LOD in study two also presented the impact of the heatmap on the UAV path. Finally, study one takes the LOD one step lower (i.e., the lowest LOD) to present all potential paths accounted for by the LPM. This lowest LOD level in study one enhanced the task performance in the number of rounds of sending search teams. However, this lowest LOD representation of the LPM was absent in study two.

The overall interpretation of the influence of LOD on trust across the two studies that contain different designs of LOD is that low LOD generally helps develop trust more than the other higher LODs. As indicated by substantial transparency research (e.g., Chesney et al., 2017;

Hoff & Bashir, 2015), limited information constrained (perceived) transparency and trust in autonomy as more information could promote comprehension and increase the overall reliance on autonomy. Further, the best practice for developing trust may still be presenting most information at low LOD (as efficiently as possible) rather than medium and high LOD, which may distort or lack information about autonomy. For example, Mooney & Juhász (2020) discovered that the use of incorrect scales and inappropriate units of aggregation could mislead users. Caution is still necessary to avoid information overload. In addition, complex scenarios can favor simple presentations with high LOD, provided that interaction time is flexible or unconstrained.

It is worth noting that study one revealed no significant difference in trust levels across the three lower LODs. This finding should not be haphazardly considered to reflect the same dynamics or evolution of trust in reaching a particular level or plateau since the evolution of trust reaching a particular level could be different (Guo & Yang, 2020). Study two measured instantaneous trust after every interaction during the task to trace the evolution of trust, providing the directions and speed of building trust for comparison across different LODs. The highest, lowest, and adaptive LOD showed similar instantaneous trust at the end of the task or scenario, but the path to the trust plateau differed. The speed of building trust in high LOD was consistent but slower, while the low and adaptive increased faster at the beginning and plateaued earlier. This finding is significant in that the support for the dynamics of trust must become part of the design considerations rather than trust after extended interactions.

Other research suggests that trust and transparency could be impacted by a lack of information (Chesney et al., 2017; Hoff & Bashir, 2015; Lee & See, 2004) and information overload (Kizilcec, 2016; Moacdieh & Sarter, 2015; Parasuraman et al., 2008; Wintersberger et al., 2020). In other words, optimal transparency is likely a careful balance of information. This research shed light on this issue by providing an empirical assessment on visualization at several different LODs, varying in the amount of information and impacting trust and transparency differently. Future work needs to improve our understanding of the benefits of providing different granularity and levels of LOD for different types of information across different tasks and settings. Instead of conducting research focusing on the binary option of whether to include a certain type of content, researchers and practitioners could benefit from a taxonomy that would define types of information and the granularity of information in visualization with precision. The lack of such taxonomy is limiting the systematic approach to selecting and designing LODs in visualization for research and applications.

Communication fostering trust in human-autonomy teaming could take inspiration from the influence between communication and trust in human-human interactions despite unique social features (Lewandowsky et al., 2000; Maehigashi, 2022; Whyte, 1991). Teamwork can be long-term when members might have a history of interactions with established norms, or temporary or task-specific when members unknown to each other have limited time or number of interactions to learn about each other and complete some tasks (Goodman & Goodman, 1976; Musick, 2022). For long-term human relationships, trust can increase open and reduce defensive communication (Savolainen et al., 2014). Further, trust in long-term human relationships is often robust to the momentary violation of expectations (Rempel et al., 1985).

For temporary or ad hoc teams, the speed of establishing trust is even more important than for long-term teams (Derlega & Chaikin, 1977). Temporary teams are time-constrained to prioritize immediate performance over establishing coordination norms, processes, and mutual understanding (Bell & Kozlowski, 2002; Kelly & Loving, 2004; Saunders & Ahuja, 2006). The focus in adaptive automation must shift from emotions, commitment, and interpersonal communication to actions, cognition, and communication efficiency (Meyerson et al., 1996). Effective transmission of specific information within a given or minimum number of interactions becomes essential.

A central impetus of trust is to overcome time and resource constraints by minimizing communication and processing of all the information between parties through mutual reliance among parties to do their jobs without unnecessary interventions or monitoring (Lee & See, 2004; Moray & Inagaki, 1999). The communication requirements differ during the periods of building and maintaining trust. In the early trust-building period, study two revealed no significance difference in trust for the first three trials or phase of using a visualization of a specific LOD, suggesting that a large amount of information may not be necessary for initial interactions. This could be because not all information in low LOD could be effectively processed within the limited interaction opportunities. However, during the middle phase of study two, providing more information resulted in higher trust levels meaning that more information in communication could promote trust building. Once trust is established and transitions into the maintenance period (i.e., the end phase in study two), some information become less essential, leading to a similar plateau in trust levels in both adaptive and low LODs. Consequently, a less information is sufficient to sustain trust. This pattern mirrors human relationships, where the initial stages of building trust involve high communication levels that gradually decrease as trust is established in order to promote efficiency (Erdem & Ozen, 2003; Mayer et al., 1995; Nyhan, 2000). However, the adaptive UI did not yield any observable workload and performance benefits, so the effectiveness of adapting LODs based on trust still needs further investigation.

There are several alternative explanations for the lack of performance or workload difference despite the effectiveness of building trust for the adaptive UI. First, the enhanced trust associated with the adaptive UI may be attributed to the dynamic switching between visualizations. This switching could provide participants with glimpses of previously unprovided, concealed, or less evident information compared to static LODs, consequently fostering trust. Second, participants might simply find the UI switching feature appealing or engaging, contributing to trust-building. Third, the experimental tasks and information on display may not overwhelm or challenge participants as anticipated, as suggested by the low absolute value of workload. If most of the information could be processed, there would be no observable difference in performance. Alternatively, participants may remain unknowledgeable about the experimental SAR task, resulting in limited variation in decisions and leading to a lack of performance difference.

In addition, study one and study two revealed the existence of a transparency paradox that too little information could lead to a lack of transparency, while excessive information could be overwhelming and harm transparency. Applying the adaptive method could potentially solve the transparency paradox by adjusting the amount of information in visualization. This research highlights a likely prerequisite to achieve this goal is to precisely delineate the relationship between transparency and trust that has not been subjected to systematic, empirical assessment. Study one and study two both show that trust ratings cannot reflect the exact difference in ratings on transparency across LODs. Transparency is commonly considered to have an impact on calibrating trust (Lee & See, 2004; Lyons, 2013; Miller, 2021), but its impact relative to other factors of system performance, such as reliability, accuracy, and success rate, impacting trust is under-investigated, and might not be as strong as the literature might suggest. On the one hand, a person might understand how autonomy works but might not trust it due to concerns about possible failures or lack of practical experience (Desai et al., 2012; Gao et al., 2006). On the other hand, when users have the same experience of autonomy over time, even consistently, autonomy failures can still increase trust (Freedy et al., 2007). One explanation reconciling both findings is that the transfer of transparency into trust might involve a lag. A person may understand autonomy intellectually but may not fully trust it until they have experienced it for themselves or until they have seen it work reliably over time. For example, human still need time to develop trust through experience with easy-to-understand autonomy or, simple automated system (Manzey et al., 2012). Additionally, future efforts should address the question of whether the initial condition should be high LOD with less information or the lowest LOD with more information.

Moreover, the existing approach to visual design concerning LODs might be effective for managing a limited number of autonomous agents or providing specific interventions for individual agents. However, as the agent count increases (Hussein et al., 2020; Ramchurn et al., 2004), the design of LODs becomes more intricate and necessitates additional considerations. For instance, the literature shows research on trust of one agent could be influenced by the collective trust (Okuoka et al., 2022; Walliser et al., 2023), but lacks research on trust established in one agent would impact on the dynamics of trust among other agents based on that agent's performance. Another scenario to consider is the impact of diverse environmental conditions managed by autonomous agents. The suitability of a particular LOD across all conditions or methods of adapting the visualization to the environment becomes a key question. For diverse environment conditions or operating situations, the current approach of assessing immediate trust through subjective questionnaires encounters challenges that the single item might not be sufficient to reflect diversity of factors and the frequent measure of trust might interrupt the interaction between the human and autonomous agents, and thus potentially reduce the efficiency of trust measures in complex situations. Alternative measures for instantaneous trust should be considered and tested, including performance metrics such as behavioral/interaction patterns and reliance and eye tracking to identify gaze patterns revealing what critical information are being sought by the user.

SAR professionals can offer distinct insights into the design of LOD visualizations due to their extensive knowledge and domain experiences compared to novice study participants. An informal interview with a SAR professional who evaluated the LOD visualizations and tasks provided two insights. First, professionals expressed a preference for predictions or probabilities of area for the lost person in the future than LPM results merely for the current moment. They found value in having access to LPM results predicting future probabilities of area to assist their judgments regarding the potential direction a lost person might take. The UI prototype was initially designed with the capability to display LPM results for the current moment and up to next 12 hours, but during the pilot study with novice participants indicate confusion about this feature as the volume of information for the current moment LOD was already overwhelming. As expected, the SAR professionals seemed less overwhelmed by the higher volume of information. Further, despite high level of trust in LPM data, SAR professionals consistently ranked maps as their primary information source for making decisions. Years of field experience had cultivated a habit of relying on maps to estimate the location of lost persons. Consequently, any visualizations of the autonomy should be designed with care to avoid obstructing the use of maps, as such obstructions could influence their attitude and willingness to rely on autonomous agents. In general, visualizations including designs for different LOD should be approached with a broader perspective of accounting for user background and potential obstruction effects. Domain expertise can significantly affect how information is used and trust is developed and maintained in autonomous agent collaboration.

Research and observation on human-human relationships and communication provides inspiration for research and design for HAT beyond this dissertation. As suggested in the findings in study two, the adaptation of LOD might enhance communication efficiency and, in the broader context, potentially address the transparency paradox. Other human interactions also can offer valuable opportunities for consideration. For instance, in scenarios involving multiple human operators collaborating with multiple autonomous agents, it is very unlikely that all operators would have identical trust in every autonomous agent. Studies have proposed a conceptual framework for understanding trust among multiple humans and agents within a team, addressing issues such as how one human's trust in autonomous agents can impact another human's trust in the agent (Ulfert et al., 2023). However, empirical evidence supporting these concepts is currently lacking. The consideration of the potential asynchrony of multiple human operators' trust towards the autonomous agents leads to the question: what initial LOD should be presented to facilitate efficient collaboration? While allowing individuals to set their own LOD may suit user preference, the collective outcome might be asynchrony of trust within the team. Studies have demonstrated the importance and potential applications of sharing awareness regarding others' actions and intentions in collaborative multi-user interfaces (Morris & Horvitz, 2007; Yuill & Rogers, 2012). Although research concerning the establishment of trust in this context is lacking, the idea could be borrowed to inspire the UI design for trust. One solution could be the introduction of a shared, general LOD, but the question remains: Which LOD or other design characteristics should take precedence for the display? Alternatively, since communication has shown influence on team assembly and performance before the team forming (Ren et al., 2020), should human operators calibrate their trust within the team before undertaking the task, or should considerations to baseline trust begin prior to team formation? The possibility of enhancing trust by enabling human operators to select team members based on autonomous agent information also merits exploration. As the team satisfaction, relationship commitment and perceived task performance was shown positively related to trust in human teams (Costa et al., 2001; Morgeson et al., 2005), such pre-task selections may have implications for trust dynamics during the task in HAT. Finally, since dispositional trust and history of human interacting with autonomous agent could have impact on trust (Merritt & Ilgen, 2008), the design of LODs could also reflect agent or team performance in comparison to historical data to help human operators in calibrating their trust.

5.2 Practical Implications

This research offers several practical implications for designing user interfaces or human-computer interactions. The findings on trust inform designers on how to develop UI adapting LOD based on instantaneous trust for reaching the trust plateau on autonomy. An adaptive UI based on instantaneous trust levels represents a useful technique to promote trust in a short time and sustain trust by adjusting LOD dynamically. The adaptive algorithm started with high LOD, conveying fewer details during early interactions before trust is established to minimize the risk of information overload. As trust increases, lower LOD visualization with more details is presented to the user to exploit information about autonomy, but then fewer details are presented as a trust plateau when the user may find detailed information redundant given the history of interactions. This approach varies the amount of information exchanged between users and autonomy in a manner that yields similar development and plateau of trust as visualization with the most details and the lowest LOD. For establishing trust quickly to a high level without maximum information exchange, adapting LOD based on instantaneous trust presents promise.

The web application represents a prototype for the SAR domain to adopt or simply examine for new features in developing their software applications for managing human-UAV teams. The various visualization designs for representing the lost person model, UAV flight paths, object identification can be readily deployed in existing SAR software applications (e.g., SAR Topo which is developed by a non-profit organization) to improve their operations if deemed meaningful by SAR professionals. Further, the web application also includes UI functions for allocating teams and adjusting path planning in parallel with the visualization of the LPM that could simplify the process of directing search and distributing situation awareness about identified objects across team members. This could, in turn, promote faster search speed and a higher survival rate of the lost person.

5.3 Conclusion

This dissertation research investigates the impact of LODs in the visualization of autonomy to support human autonomy teaming in SAR involving UAVs. A web-based application was developed for wilderness SAR, which can support different visualizations of the lost-person model and UAV path planner. The visualization adapting LOD in the web application could advance UI design to support humans in collaborating with autonomy in planning, managing teams, and identifying clues and targets for wilderness SAR missions, thereby speeding up the search process and improving mission outcomes. Two studies were conducted: (1) study one investigated how LODs in visualization affect transparency, trust, workload, and performance, and (2) study two investigated how the visualization of (static) LODs and LOD adaptive to trust affect trust over time. Through a combination of qualitative and quantitative methods, this research provides insights into the effect of LODs delivered in static visualization and dynamically adjusted visualization on transparency and trust. This research could be useful for both academics and practitioners by improving our understanding of the LODs in visualization design for facilitating transparency and trust and ultimately improving overall performance during human autonomy teaming.

This research extends the limited research on transparency and trust of autonomy with respect to LODs in the visualization. This research is among the first to consider LOD as a critical factor of transparency and trust. The study provides the first empirical evidence indicating that the impact of LODs on transparency and trust is not linear, which has not been explicitly demonstrated in prior studies about human autonomy teaming. The impact of LOD on transparency is more sensitive than trust, calling for a more defined and consistent use of the term or concept - “transparency” and a deeper investigation into the relationships between trust and transparency. Study one produced the first empirical results on contrasting impacts of different LODs on transparency, trust, workload, and performance, highlighting the complexity of designing for HAT. The study did not reveal any universally optimal LOD for all human performance constructs. This level of complexity points to adaptive interactions that can cater LODs to the states of human and autonomy.

Study two in this dissertation research investigated how trust evolves over time with visualizations at different LODs and visualization adaptive to trust for switching LODs. Visualizations with different LODs in both static and adaptive modes present their own set of benefits and drawbacks, resulting in trade-offs concerning the speed of promoting trust and information quantity transmitted during communication. The algorithm for adapting LOD for the adaptive visualization based on user trust is novel, and adaptive LODs in visualization could switch between detailed and abstract information to influence trust without always transmitting all the details about autonomy. Automatically adjusting the level of aggregation of detailed information, variables of lost person behavior model, and visualization of UAV paths, adaptive LOD presents the potential to limit possibilities of too much or too little information. This research contributes to the HAT literature on how UI adapting LOD could help develop trust.

This research investigated the influence of LOD on HAT through quantitative and qualitative evidence, exploring its effects on transparency, trust, workload, compliance, and performance in team assignment and path planning for human and autonomy collaboration in search and rescue operations in the wilderness. The findings of this research contribute to the HAT literature by revealing that there are non-linear relationships between LODs, with transparency, trust, workload, and performance, confirming the phenomenon of transparency resistance. Furthermore, LOD has an influence on the evolution of trust in terms of growth speed and plateau value. The adaptive LOD could facilitate the development of trust while maintaining communication efficiency. These findings indicate that LOD is an effective factor for designing and analyzing visualization for transparency and trust in HAT. With these features in the UI, the application can further facilitate the efficient team assignment and deployment of UAVs to supplement the dwindling volunteers for SAR missions in the wilderness.

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