

**ASSESSMENT OF SHARED SITUATION AWARENESS IN HUMAN AUTONOMY
TEAMS**

by

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Abstract

The development of autonomous systems and their implementation within agricultural operations creates an increasing need for effective human–autonomy teaming and remote supervision. This study developed a method to measure shared situation awareness (SSA) between a human supervisor and an autonomous agricultural system, using the FarmBot platform as an experimental case study. Twenty-five participants remotely supervised the FarmBot during four autonomous operational sub-sessions: seeding, soil sensing and watering, weed disruption, and plant imaging. During live operation, participants responded to real-time situation awareness (SA) pop-up questions, while corresponding machine-generated SA responses were simultaneously computed from FarmBot operational data obtained via the FarmBot REST API. Human responses, machine-generated responses, and verified operational reference states were compared to evaluate human SA, machine SA, and SSA performance. Overall human SA accuracy across all sessions was 80.3%, machine-generated SA accuracy was 92.7%, and overall SSA was 78.7%. Results showed significantly higher SSA performance on Level 1 perception-based tasks than on Level 2 comprehension-based tasks. SSA performance also varied significantly across operational sub-sessions, with the weed disruption task producing the highest SSA values and the seeding task producing the lowest. Lower SSA performance was primarily associated with questions that required interpreting operational outcomes and task quality rather than direct observation of current system states. The findings demonstrate that shared situation awareness between human supervisors and autonomous agricultural systems can be measured using synchronized human responses, machine-derived responses, and verified operational reference states. The study additionally highlights the importance of interface transparency, operational feedback, and human factors considerations in the design of autonomous agricultural supervision systems.

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1. Introduction

Autonomous systems are increasingly being integrated into complex operational environments where humans and machines must work collaboratively to achieve shared goals (Sheridan 2016; Endsley 2023). Advances in robotics, sensing technologies, machine learning, and artificial intelligence have enabled autonomous systems to perform tasks with reduced human intervention across domains such as transportation, manufacturing, healthcare, defense, and agriculture. However, despite rapid advancements in automation capabilities, fully autonomous operation remains difficult in dynamic real-world environments where uncertainty, changing conditions, and unexpected events are common (Bechar and Vigneault 2016). As a result, many autonomous systems continue to rely on human supervision and oversight during operation.

Agriculture has experienced significant growth in the use of autonomous and semi-autonomous technologies in response to increasing demands for productivity, efficiency, and sustainability (Vougioukas 2019). Autonomous agricultural systems are now capable of performing tasks such as planting, navigation, crop monitoring, precision spraying, and environmental sensing with limited direct human involvement (Bechar and Vigneault 2016; Vasconez et al. 2019). Despite these advances, agricultural environments remain highly variable and difficult to automate fully due to changing terrain, biological variability, weather conditions, and environmental uncertainty (Reina et al. 2016). Consequently, human operators continue to play an important supervisory role in monitoring autonomous systems and intervening when necessary (Edet et al. 2018; Panfilov and Mann 2018).

Effective supervision of autonomous systems depends heavily on situation awareness (SA), which Endsley (1988) defined as the perception of environmental elements, the comprehension of their meaning, and the projection of their future status. In human-autonomy

teams (HATs), both the human operator and the autonomous system must maintain awareness of the operational environment, system status, and the progression of ongoing tasks to coordinate efforts effectively (Endsley 2020; Endsley 2023). Shared situation awareness (SSA), as described by Endsley and Jones (2001), refers to the degree to which multiple team members possess the same situational understanding relevant to their collaborative tasks. Within HATs, shared SA supports coordination, communication, trust, and team effectiveness (Demir et al. 2017; Ali et al. 2026). Research has shown that degraded SA can contribute to reduced trust, delayed responses, operational inefficiencies, and out-of-the-loop (OOTL) performance problems in highly automated systems (Endsley and Kiris 1995; Kaber and Endsley 2004). A substantial body of research has examined SA and shared SA in domains such as aviation, military operations, transportation, healthcare, and industrial automation (Durso and Sethumadhavan 2008). Researchers have also developed numerous techniques for assessing SA, including the Situation Awareness Global Assessment Technique (SAGAT), the Situation Present Assessment Method (SPAM), and the Situation Awareness Rating Technique (SART) (Endsley 2000; Durso and Dattel 2004; Taylor 2017). While these approaches have contributed significantly to the understanding of SA, most existing methods were designed for human-human teams or simulation environments rather than collaborative human-autonomy systems operating in real-world conditions (Martelaro et al. 2015). Limited research has examined how shared SA can be measured between human supervisors and autonomous agricultural systems during operation.

Human factors research has further demonstrated that SA is closely connected to interface usability, transparency, workload, trust in automation, and information presentation (Hopko et al. 2022; van de Merwe et al. 2024). As automation levels increase, operators may become less engaged in system activities, reducing their ability to effectively monitor autonomous systems and

respond to unexpected situations (Endsley 2017). Consequently, maintaining effective shared awareness between humans and autonomous systems has become an important challenge in the design of autonomous technologies and supervisory interfaces (Schaefer et al. 2017). These issues are particularly important in autonomous agricultural systems, where remote supervisors may oversee machines operating for extended periods with limited direct interaction (Sanchez and Duncan 2009).

This research investigates shared situation awareness between a human supervisor and an autonomous agricultural system using the FarmBot, an open-source autonomous farming platform designed to automate small-scale precision agriculture tasks. The FarmBot operates on a Cartesian coordinate system, like 3D printers and CNC machines, allowing it to move precisely along X, Y, and Z axes within a defined garden area. It is primarily used for growing small crops and can perform a range of agricultural tasks autonomously, including planting seeds, watering plants, controlling weeds, and monitoring plant health using built-in sensors and cameras. During autonomous operation, participants in this study supervised the FarmBot via its online user interface while responding to real-time SA queries presented as pop-up prompts. Simultaneously, machine awareness states are computed directly from FarmBot operational data and system logs using custom Python-based assessment functions. Furthermore, the derived machine awareness states can be conceptualized as the situation awareness provided by the machine's programmers, and the autonomous agricultural equipment is not assumed to possess consciousness and situation awareness in the same way that humans do. By comparing participant responses with machine-derived awareness states, this research develops a novel method for assessing shared situation awareness between humans and autonomous systems during live operational tasks.

The findings of this research contribute to the fields of human-autonomy teaming, situation awareness, human factors engineering, and agricultural robotics by providing a practical framework for evaluating shared awareness between human supervisors and autonomous systems in operational environments. Ultimately, this work aims to support the development of more effective, transparent, and human-centered autonomous agricultural technologies.

2. Literature Review

The purpose of this literature review is to establish the theoretical and applied foundation for evaluating shared situation awareness between a human supervisor and an autonomous agricultural system. The review begins with situation awareness as a human factors construct and then discusses common approaches to measuring it. It then extends the discussion to shared and team situation awareness, human-autonomy teaming, machine situation awareness, agricultural robotics, remote supervision, and interface-related human factors. Together, these areas underscore the need for a method to compare human- and machine-derived awareness during live autonomous agricultural operations.

2.1 Situation Awareness

Situation awareness has become a central construct in human factors because it describes how people understand and act in complex, dynamic environments. Endsley defined situation awareness as the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their future status. This model organizes situation awareness into three levels: Level 1, perception of relevant cues; Level 2, comprehension of the meaning of those cues; and Level 3, projection of future states (Endsley 1988; Endsley 2000). The model is useful for studying operators in dynamic systems because it separates the

ability to notice information from the ability to interpret it and use it to anticipate what may happen next.

The importance of situation awareness is closely tied to decision-making and performance. In dynamic environments, operators must identify relevant information, determine what it means for the task, and decide whether action is required. Durso and Sethumadhavan (2008) described situation awareness as an important construct for understanding operator comprehension in dynamic environments and noted its relevance across many human factors domains. Horswill and McKenna (2004) linked situation awareness to road safety, describing hazard perception as situation awareness in dangerous traffic situations. This chapter's discussion shows that situation awareness is not simply the availability of information, but the ability to perceive and understand the information that matters for safe and effective performance.

Situation awareness is especially important in automated systems because automation changes the human role. Instead of continuously controlling the system, the human may become a supervisor who monitors it and intervenes only when necessary. Endsley and Kiris (1995) described this as the out-of-the-loop performance problem, in which operators supervising automation may lose awareness of the system state and become less able to intervene effectively when automation fails. Their work showed that reduced involvement in active control can reduce situation awareness and slow decision-making after an automation failure. Kaber and Endsley (2004) also found that the level of automation influenced situation awareness, workload, and performance in a dynamic control task. Their findings supported the need for human-centred automation that maintains operator involvement rather than removing humans entirely from the control loop.

These automation-related concerns are directly relevant to autonomous agricultural systems. As agricultural machines become increasingly automated, operators may no longer

directly control every machine action. Instead, they are expected to supervise system activity, monitor task progress, interpret system states, and intervene when abnormal conditions occur. This poses a human factors challenge because the operator must remain aware of the agricultural task, the machine's status, and the broader operational environment despite reduced direct task involvement.

2.1.1 Situation Awareness Measurement Techniques

Since situation awareness is an internal cognitive state, it is often observed and measured indirectly. Researchers have therefore developed objective, subjective, and performance-based methods for evaluating whether operators possess task-relevant awareness. Endsley (2000) emphasized that situation awareness measurement is necessary for evaluating system designs, interfaces, and training methods intended to support awareness. The choice of measurement technique depends on the study context, the information required, and whether the task can be interrupted.

One of the most widely used objective methods is the Situation Awareness Global Assessment Technique. SAGAT uses task freezes during simulation to ask operators situation-relevant questions about the system's current state (Endsley 1988; Endsley 2000). These questions are developed from the operator's goals and information requirements, allowing researchers to determine whether the operator possesses the information needed for task performance. Bolstad and Endsley (2003) applied SAGAT to measure individual, team, and shared situation awareness in a military command-and-control simulation. Their work is important because it demonstrates how situation-awareness questions can be tailored to specific operational roles and used to evaluate shared awareness among team members.

Other methods have been developed to reduce the disruption caused by freeze-probe methods. Durso and Dattel (2004) described the Situation Present Assessment Method as a real-time approach in which operators are asked questions during task performance rather than after a freeze. This approach is useful when the researcher wants to assess awareness without stopping the task. Martelaro et al. (2015) developed DAZE as a real-time situation awareness tool for driving because traditional approaches often required halting a simulation or relying on post-task questionnaires. Their work supports the need for real-time measurement of situation awareness in dynamic systems where stopping the task would reduce ecological validity.

Subjective methods have also been used to assess situation awareness. Taylor (2017) developed the Situation Awareness Rating Technique as a subjective measure of perceived situation awareness. SART can be useful when researchers want to understand how aware participants believe they were, but subjective ratings may be influenced by confidence, memory, or workload. Objective query-based methods are often more directly tied to whether the participant knew specific information at a specific time.

Situation awareness measurement has also been adapted for human-robot interaction. Scholtz et al. (2005) implemented a SAGAT-based assessment tool for evaluating supervisory interfaces for autonomous on-road vehicles. Their study is particularly relevant because it applied situation awareness assessment to a context where a human supervises an autonomous system through an interface. They emphasized that human-robot interfaces must provide information about robot status and the remote environment, especially when users are not co-located with the robot.

2.1.2 Shared and Team Situation Awareness

Although situation awareness was first studied primarily at the individual level, many complex systems depend on teams. Endsley and Jones (2001) distinguished between team situation awareness and shared situation awareness. Team situation awareness refers to the degree to which each team member possesses the situation awareness required for their own responsibilities, whereas shared situation awareness refers to the degree to which team members possess the same situation awareness for shared requirements. This distinction is important because team members do not need identical awareness of all information; rather, they need overlapping awareness for information that supports coordination and shared task goals. Endsley's team situation awareness work emphasizes that shared awareness depends on information requirements, shared displays, communication, and mechanisms for updating team members. In team contexts, failures may occur when relevant information is not shared, when team members interpret the same situation differently, or when team members have incompatible understandings of the task state. These issues become more difficult in distributed teams because team members may not have access to the same environmental cues.

Bolstad and Endsley (2003) demonstrated that shared and team situation awareness can be measured using SAGAT queries in a military simulation. Their results showed variation in situation awareness across teams and highlighted the importance of information sharing. Saner et al. (2009) also examined shared situation awareness measurement and argued that shared awareness scores can be inflated when methods fail to account for both relevance and accuracy. Their work is especially important for this thesis because it supports the idea that shared awareness should not be treated as simple agreement. Instead, shared awareness should reflect correct alignment on information that matters for the task. Shared situation awareness has also been studied in

healthcare. Alnadwi and Al-Moteri (2025) examined individual and shared situation awareness during in-hospital cardiac arrest events and found that shared awareness was associated with team structure and resuscitation success. Although healthcare differs from autonomous agriculture, this study reinforces the broader importance of shared awareness in dynamic, collaborative environments where team members must coordinate under changing conditions.

The current work adapts shared situation awareness to a human-autonomy team. In human-human teams, shared awareness is usually described as overlap between human team members' understanding. In a human-autonomy team, one agent is a machine whose awareness is represented through operational data, internal states, sensor information, logs, and task records. Therefore, this study operationalizes shared situation awareness as the simultaneous correct alignment between the human supervisor and the machine-derived operational state relative to an established reference state. This approach preserves the core idea of shared awareness while adapting it for a human-machine team.

2.2 Human-Autonomy Teaming

Human-autonomy teaming examines how humans and autonomous systems work together toward shared goals. This differs from traditional human-machine interaction because autonomous systems may perceive, decide, and act with some degree of independence. Sheridan (2016) described human-robot interaction as a rapidly developing field that includes supervisory control, industrial robots, social robots, medical robots, agricultural robots, and other applications. Sheridan's review emphasized that robots are increasingly used under human supervisory control, making human factors research essential for safe and effective interaction.

In human-autonomy teams, coordination depends on the human's ability to understand the system's activity, status, and intent. Demir et al. (2017) studied team situation awareness in human-

autonomy teaming and found that communication behaviours were related to team situation awareness and team performance. Their work showed that pushing information was positively associated with team situation awareness and performance, whereas human-autonomy teams exhibited lower levels of information sharing than all-human teams. This suggests that autonomous systems may need better mechanisms for communicating task-relevant information to human teammates. Demir et al. (2018) examined team dynamics in human-autonomy teams and proposed that effective performance requires a balance between stability and flexibility. Teams that are too rigid may fail to adapt, while teams that are too unstable may lack coordination. This is relevant to autonomous agricultural systems because the human supervisor and autonomous machine must maintain predictable coordination while still adapting to task changes, operational errors, and environmental variability. Schaefer et al. (2017) focused on communicating agent intent to support shared situation awareness and trust in human-agent teams. They argued that as intelligent agents make more independent decisions, human teammates must be able to interpret the agent's intentions. Misinterpretation can reduce trust, increase unnecessary interventions, or contribute to disuse. This is directly relevant to remote supervision, where the human may rely entirely on interface information to understand what an autonomous machine is doing.

Recent human-AI teaming literature extends these ideas by emphasizing transparency, explainability, and shared situation awareness. Endsley (2023) argued that effective human-AI teams require shared awareness of taskwork, agent state, and teamwork information. This includes not only what is happening in the environment, but also what the autonomous system is doing, what it understands, and what it intends to do. Van de Merwe, Mallam, and Nazir (2024) reviewed studies on automation transparency and found an overall trend suggesting that transparency can support situation awareness and operator performance in supervisory roles without necessarily

increasing workload. Other studies provide examples of transparency and shared awareness interface design. Wright et al. (2020) examined agent transparency and reliability in human-robot interaction and found that reliability influenced trust and perceived reliability. You et al. (2022a) proposed shared situation awareness interface elements for human-machine co-driving, including human-machine state, context, current task status, and plan. Their study showed that these interface elements improved usability, situation awareness, danger prediction, and trust. You et al. (2022b) similarly found that transparency design based on shared situation awareness improved driver understanding and experience in semi-automated driving.

Together, these sources show that human-autonomy teaming depends on awareness alignment, communication, transparency, reliability, and interface design. This literature supports treating FarmBot as an autonomous teammate whose operational awareness can be compared with the awareness of a human supervisor.

2.3 Machine Situation Awareness and Autonomous-System Awareness

Situation awareness has traditionally referred to human cognition, but several researchers have considered how autonomous systems might develop, represent, or evaluate awareness. This is important because autonomous systems must sense and interpret their environment to act appropriately. However, machine awareness is not identical to human awareness. It is usually represented through sensors, internal models, logs, task states, rules, and computational processes. Gehrke (2008) examined situation awareness in autonomous systems and argued that higher-level situation assessment becomes increasingly important as systems operate with greater autonomy and over larger temporal and spatial scopes. Gehrke emphasized that autonomous systems must evaluate the relevance of information, identify missing information, reason about uncertainty, and communicate with other agents or information sources when their own sensors are insufficient.

This is especially relevant in partially observable environments where a system may not have complete information. Müller et al. (2024) argued that situation awareness is important for collaborative robots because humans need to understand how well a robot is aware of its environment before they can trust it and delegate tasks appropriately. Their work proposed a metric and improvement process for robot situation awareness using an intelligent digital twin. This supports the idea that machine awareness can be measured and improved rather than simply assumed from the presence of automation. Doherty et al. (2021) discussed distributed situation awareness in collaborative robotics through Hastily Formed Knowledge Networks. Their framework allowed human and robotic agents to share sensor data and semantic knowledge through distributed knowledge representation. Although their work focused on collaborative robotics in emergency response, it demonstrates how awareness can be distributed across human and robotic agents through shared data and knowledge structures. Gerdes et al. (2025) applied similar concerns to digital-human air traffic control teams. They argued that a digital air traffic controller needs an understanding of current and future traffic situations that can align with the human controller's understanding. Their work is relevant because it frames autonomous systems as needing digital situation awareness to support decision-making, trust, and shared understanding.

For this thesis, machine situational awareness is operationalized in a practical, task-specific manner. FarmBot's machine-derived awareness is inferred from system information such as operational logs, device state data, sensor readings, positional data, tool status, and task records. The study does not claim that FarmBot possesses human-like cognition. Rather, it evaluates whether FarmBot's computed operational response matches the established reference state and whether that machine-derived response aligns with the human supervisor's response.

2.4 Human Factors, Usability, and Interface Design in Human-Robot Systems

Human factors are essential in autonomous systems because system success depends not only on technical capability but also on how humans understand, supervise, and collaborate with automation. Interface usability, workload, transparency, trust, and situation awareness are closely connected. A system may be technically capable, but if the human supervisor cannot understand its state or intent, the human-autonomy team may still fail.

Hopko et al. (2022) reviewed human factors considerations in shared-space human-robot collaboration and found that trust, cognitive workload, and anxiety were among the most frequently measured operator states. Their review emphasized that human factors can affect system efficiency, response time, collaborative performance, quality of work, and operator utilization strategy. Although their focus was on shared-space collaboration, the broader conclusion applies to remote supervision, as the human supervisor's cognitive state influences how the autonomous system is monitored and used. Colceriu et al. (2023) showed how user-centered design can support usability and situation awareness in mobile human-robot cooperation. Their design process included user analysis, interface prototyping, heuristic evaluation, situation awareness measurement, and usability testing. This demonstrates that interface design should be evaluated not only for ease of use but also for its ability to support awareness. Scholtz et al. (2005) made a related argument regarding human-robot supervisory interfaces, noting that such interfaces must provide users with information about robot status and the remote environment, even if they are not robotics experts.

Transparency is another key concern in human factors. Endsley (2023) described that transparency and explainability should support situation awareness and mental models in human-AI teams. Van de Merwe et al. (2024) found that transparency generally supports situation

awareness and operator performance in supervisory contexts. Wright et al. (2020) showed that reliability strongly influences trust and perceived reliability in human-robot interaction. These findings suggest that interface design should support awareness while also helping operators calibrate trust in the system.

The overlap between usability and situation awareness is especially important in remote supervision. A usable interface should not merely be easy to operate; it should help the supervisor perceive relevant information, understand what it means, and decide whether intervention is needed. This is directly relevant to the current study because participant awareness of the FarmBot depends on information presented through the FarmBot interface during autonomous operation.

2.5 Autonomous Machines and Robotics in Agriculture

Agriculture is increasingly adopting autonomous and robotic technologies to address labour shortages, improve productivity, and support precision farming. Bechar and Vigneault (2016), Vougioukas (2019), Vasconez et al. (2019), and Benos et al. (2023) reviewed agricultural robotics and human-robot interaction in agriculture. These reviews show that agricultural robots are being developed for tasks such as seeding, spraying, weeding, harvesting, monitoring, phenotyping, and transport. However, they also emphasize that agricultural environments are difficult to automate because they are unstructured, variable, and biologically complex.

Bechar and Vigneault (2016) note that agricultural robots must operate in changing environments while maintaining safety, reliability, and task quality. They emphasize that robotic systems consist of multiple subsystems that must be integrated and synchronized, and that human operators are often integral to the control loop. Vougioukas (2019) similarly emphasized that agricultural robots face challenges created by environmental variability, complex plant structures,

occlusions, lighting changes, uneven terrain, and biological variation. These challenges mean that even capable robotic systems may still require human supervision.

Vasconez et al. (2019) reviewed human-robot interaction in agriculture and argued that many agricultural tasks remain too complex to automate fully. They emphasized that robots can complement human workers when full replacement is not feasible. They also identified issues such as safety, trust, workload, autonomy level, collaboration, and situation awareness as important concerns in agricultural HRI. Benos et al. (2023) similarly found growing interest in agricultural HRI and noted that collaboration and cooperation are common modes of interaction. Their review indicated that human-robot synergy can improve system performance, workload, and time efficiency, but that safe and functional agricultural HRI remains an ongoing challenge.

Reina et al. (2016) focused on ambient awareness for agricultural robotic vehicles. They emphasized that robust environmental perception is necessary for safe field operation and discussed multisensory approaches using technologies such as stereovision, LIDAR, radar, and thermography. This machine-centred perspective complements the human factors perspective, as the robot's ability to perceive the environment determines which information can be shared with human supervisors.

Rose et al. (2021) discussed responsible development of autonomous robotics in agriculture and emphasized that social, ethical, legal, and adoption issues must be considered alongside technical capability. Spykman et al. (2021) examined public views of autonomous agriculture and noted that societal views may influence acceptance and adoption. These sources show that autonomous agriculture is not only a technical problem but also a human-centred and socially situated design challenge.

2.5.1 Remote Supervision of Autonomous Agricultural Machines

Remote supervision is a key concept in autonomous agricultural systems, given the expectation that many machines will operate autonomously while remaining under human oversight. Research has been conducted on supervision location, user interface requirements, usability, warning modalities, and situation awareness.

Edet et al. (2018) examined farmers' expectations regarding remote supervision of autonomous agricultural sprayers. They found that designers must understand what information operators need to provide effective supervision of an autonomous machine. Their study is relevant because it directly connects interface information requirements with situation awareness in agricultural remote supervision. Panfilov and Mann (2018) examined the importance of real-time visual information in the remote supervision of an autonomous agricultural machine. Their results showed that graphical indicators were the preferred source of machine status information, while live video served as a secondary source that helped participants understand machine functions and feel more secure, which connects to the concept of situation awareness again. Furthermore, Edet and Mann (2020) interviewed experts in autonomous agricultural machine design and identified several remote supervision concepts, including supervision within the field, close to the field, from the farm office, and outside the farm site. Their findings suggested that close-to-field supervision was considered the most viable concept and that live video may reassure farmers that operations are progressing properly. Together, this research indicates that remote supervision in autonomous agricultural settings requires a human factors perspective to ensure that farmers develop reassurance and trust, while designers of these systems must ensure that the interfaces support that relationship. Ezeagba et al. (2025) examined warning cues for the remote supervision of autonomous agricultural machines and linked the perception of warnings to Level 1 situation

awareness. Their study compared visual-auditory and visual-tactile warning cues and found that visual-tactile warnings were preferred and could support supervisor perception during remote supervision. This is relevant because it once again highlights the importance of interface design for the support of supervisors in noticing system states and potential problems.

Research has also discussed operator situation awareness in relation to automation support. Bashiri and Mann (2014) studied situation awareness during the operation of agricultural semi-autonomous vehicles and found that automation affected operators' situation awareness. Their results showed that certain forms of automation support could improve situation awareness, whereas higher levels of automation that removed participants from the task loop could reduce it. Sanchez and Duncan (2009) also discussed automation in agricultural vehicles and emphasized the role of human factors research in understanding operator attention allocation and display design as agricultural vehicles become more automated. In these studies and discussions, situation awareness has been examined in relation to the human supervisor, rather than studied at the shared level between the machine and the remote supervisor.

Together, these studies show that remote supervision of autonomous agricultural machines depends heavily on interface design, operator awareness, and the system's ability to communicate relevant status information. They also show that agricultural automation research has recognized situation awareness as a key issue, but there remains limited work on measuring shared awareness between the human supervisor and the autonomous agricultural system itself.

2.6 Summary and Research Gap

The literature demonstrates that situation awareness is essential for human performance in dynamic systems, especially when automation changes the human role from active controller to supervisor. Foundational research on situation awareness provides a strong theoretical basis for

distinguishing among perception, comprehension, and projection. Moreover, SA measurement research provides methods for assessing awareness through objective queries, subjective ratings, and real-time approaches. Existing research on shared and team situation awareness shows that collaboration depends on overlapping, accurate understanding, not merely on individual awareness.

Human-autonomy teaming literature extends these concerns by showing that autonomous agents must communicate information, intent, and status to support coordination, trust, and shared understanding. Machine situation awareness research suggests that autonomous systems can be evaluated based on their ability to represent relevant task states, identify missing information, and share knowledge with human or robotic teammates. Furthermore, agricultural robotics research shows that autonomous agricultural systems are increasingly feasible but remain challenged by environmental variability, task complexity, safety requirements, and the need for human supervision.

Despite this progress, a methodological gap remains in measuring shared situational awareness between a human supervisor and an autonomous agricultural machine during live operation. Existing situation awareness methods were largely developed for human operators, human teams, simulations, or other domains. Agricultural remote supervision studies have examined interface information needs, visual information, warning cues, and operator awareness, but they have not directly measured shared awareness between the human and the autonomous machine using synchronized human and machine responses. The current study addresses this gap by developing a method for comparing participant responses with machine-derived awareness states and verified operational reference states during FarmBot operation.

3. Research Objectives

The objective of this research is to develop and evaluate a method to measure shared situation awareness (SSA) between a human supervisor and an autonomous agricultural system during live operation, using the FarmBot as the experimental platform. Specifically, this research aims to assess:

- The ability of real-time situation awareness queries and machine-derived awareness states to measure shared situation awareness between a human supervisor and an autonomous agricultural system.
- The degree of alignment between participant responses and machine-derived awareness states during autonomous operation across Level 1 (perception) and Level 2 (comprehension) situation awareness tasks based on Endsley's situation awareness model.

4. Methodology

This study investigated shared situation awareness (SSA) between a human supervisor and an autonomous agricultural system using a FarmBot autonomous gardening robot as the experimental platform. The methodology was designed to evaluate how awareness could be measured and compared between a human participant and an autonomous system operating during live agricultural tasks. Participants remotely supervised the FarmBot while the system autonomously performed a series of agricultural operations. During operation, real-time situation awareness (SA) queries were presented to participants while corresponding machine-generated SA responses were simultaneously computed using FarmBot operational data. Human responses, machine-generated responses, and verified operational reference states were then compared to evaluate human SA,

machine SA, and shared situation awareness. This approach to derive machine SA has not been attempted in other studies and provides the opportunity for SSA computation.

The methodology consisted of a repeated-measures supervisory monitoring experiment involving four autonomous agricultural operational sub-sessions: seeding, soil sensing and watering, weed disruption, and plant imaging. The following sections describe the participant recruitment process, experimental platform and setup, experimental procedure, SA assessment methods, SSA computation procedures, and data analysis methods used in the study.

4.1 Participants

The study involved 25 volunteer student participants recruited from the University of Manitoba. Participants acted as human supervisors within a human-autonomy teaming (HAT) environment involving the autonomous agricultural robot, FarmBot. Prior experience with FarmBot systems, agricultural robotics, or automation technologies was not required. Participants were required to be at least 18 years of age; such individuals were assumed to possess sufficient computer literacy to interact with a graphical user interface and respond to on-screen prompts.

Recruitment was conducted through University of Manitoba recruitment posters. Prior to participation, all participants provided informed consent in accordance with procedures approved by the University of Manitoba Research Ethics Board. Before beginning the experimental sessions, participants received a general explanation of the FarmBot interface, the agricultural tasks being performed, the supervisory monitoring role, the popup response interface, and the format of the SA questions used during the study. Participants were then given an opportunity to ask questions before beginning the experiment.

4.2 Experimental Platform and Setup

The experimental platform used in the study was the FarmBot Genesis v1.7 autonomous agricultural robot. FarmBot is an open-source robotic farming platform that can autonomously perform agricultural operations, including seeding, watering, soil sensing, imaging, and weed disruption. The system was operated via the FarmBot web interface and communicated through a RESTful application programming interface (API) that provided access to system information, including positional data, operational logs, sensor readings, tool status, device states, and operational history. The experiment was conducted in the Department of Biosystems Engineering at the University of Manitoba using a standardized indoor FarmBot setup as shown in Fig. 1, and predefined agricultural task sequences.



Figure 1: Experimental setup of the FarmBot

During each experimental session, participants remotely supervised the FarmBot through the FarmBot web interface while the robot autonomously performed agricultural operations within the planter workspace, Fig. 2.



Figure 2: Top view of the planter workspace of the FarmBot during experimental sessions

Participants observed the FarmBot at a computer workstation Fig. 3, displaying the FarmBot web interface corresponding to the current operational sub-session.

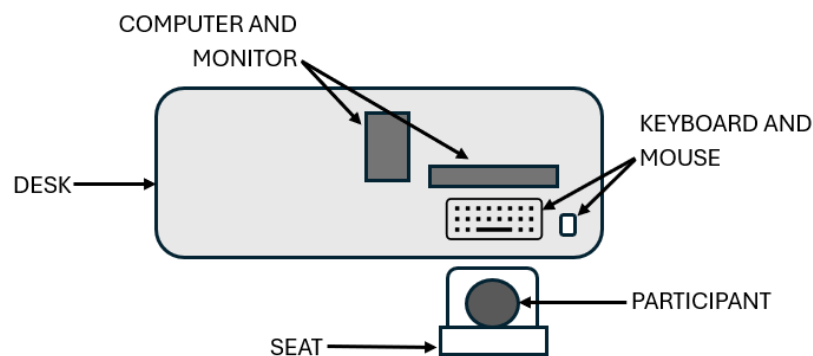


Figure 3: Top view of workstation for remote supervision

The participants did not have an in-person view of the FarmBot throughout its operation. Interface layouts, Fig. 4, varied slightly depending on the agricultural operation being performed so that operationally relevant information was displayed during each task.

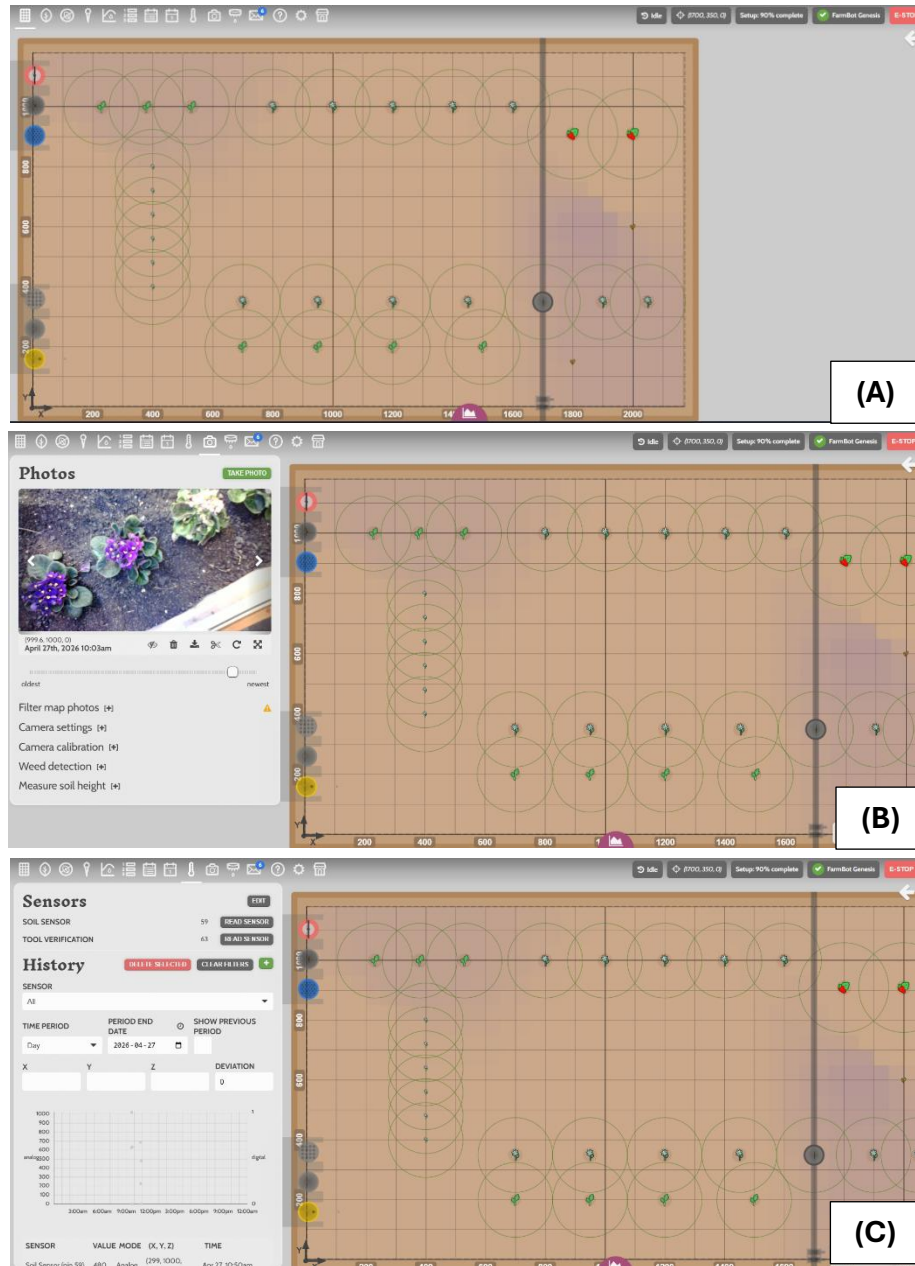


Figure 4: FarmBot web interface for (A) Seeding and Weed Disruption sessions, (B) Plant Imaging session, and (C) Soil Sensing and Watering session

Participants did not directly control the FarmBot during the experiment. Instead, participants assumed the role of remote supervisors responsible for monitoring the autonomous system while simultaneously completing a secondary supervisory monitoring worksheet task (Appendix A2) intended to simulate realistic supervisory workload conditions.

4.3 Experimental Procedure

The experiment comprised of each participant supervising the FarmBot during four separate operational sub-sessions consisting of seeding, soil sensing and watering, weed disruption, and plant imaging operations. Each sub-session lasted six minutes and focused on a different autonomous agricultural operation. All participants observed the same predefined FarmBot task sequences to ensure consistency across experimental trials.

At the start of each session, participants were positioned at the supervisory workstation and instructed to monitor the FarmBot operation using the FarmBot interface while completing the secondary monitoring worksheet task (Appendix A2), which allowed them to make notes on the operation. For the secondary monitoring task, the participants were instructed to take notes during two-minute supervision intervals. A timer on the workstation allowed participants to observe the time. During supervision, participants observed the FarmBot interface while the autonomous system executed the predefined task sequence without direct participant intervention.

Throughout each sub-session, real-time SA popup questions were presented to participants at randomized intervals while the FarmBot continued operating autonomously. Participants responded to each question using predefined multiple-choice response options before continuing supervisory monitoring. Question timing was randomized with a minimum one-minute delay before presentation of the first question and a minimum separation interval between subsequent questions. This timing structure allowed participants to settle into the supervisory task and reduced excessive interruption frequency during monitoring. The order of popup questions within each sub-session was randomized.

Break periods were provided between sub-sessions to reduce participant fatigue and cognitive overload during the experiment. At the conclusion of the experiment, participants additionally completed a short post-session feedback questionnaire regarding their supervisory experience during the study (Appendix A3).

The overall experimental procedure flowchart is provided in Fig. 5.

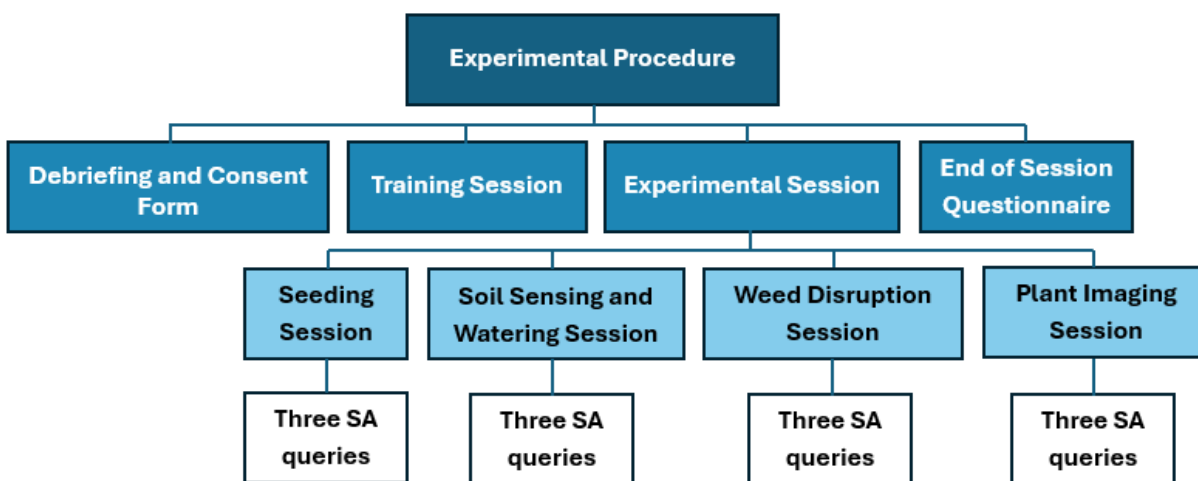


Figure 5: Experimental procedure overview

4.4 Situation Awareness Assessment

Situation awareness assessment was conducted using a modified implementation of the Situation Awareness Global Assessment Technique (SAGAT), like that used by Scholtz et al. (2005), Wright et al. (2020), and Martelaro et al. (2015), with DAZE in the context of autonomous systems. Traditional SAGAT methodologies typically involve freezing system operation before presenting

SA queries to participants. In the study, the FarmBot operation was not paused during questioning. Instead, pop-up questions were presented while the autonomous system continued operating in real time. This continuous-query implementation was selected to better represent real-world supervisory monitoring conditions and is like DAZE and SPAM, in which human operators monitor autonomous systems while tasks continue operating dynamically without interruption. This adaptation is appropriate for remote supervision of autonomous agricultural machines because supervisors are expected to monitor systems while operation continues.

The study focused specifically on Level 1 SA (Perception) and Level 2 SA (Comprehension) based on Endsley's model of situation awareness. Level 3 SA (Projection) was excluded due to the limited predictive functionality available through the FarmBot platform and the supervisory nature of the experimental tasks. The questions, along with corresponding SA level and options for human responses, are shown in Table 1.

The questions classified as Level 1 SA required participants to identify or perceive current system states, environmental conditions, or operational elements directly observable through the FarmBot interface. The questions classified as Level 2 SA required participants to interpret system information, evaluate task progress, or understand relationships between operational states and task outcomes. For example, the question "Are the LED lights currently on?" was classified as Level 1 SA because it required participants to perceive the system's current state. In contrast, the question "Did the soil moisture readings change after watering?" was classified as Level 2 SA because participants were required to interpret changes in system information over time and comprehend the outcome of a completed task.

Table 1: Session questions and corresponding SA level

Experimental Sub-session	Question	Human Response Options	SA Level
Seeding	Have the seeds been evenly spaced so far during this session?	– Yes – No – Not Sure	2
	Is the FarmBot currently seeding or taking a break (no movement)?	– Seeding – Not Moving	1
	Has the FarmBot been in the correct zone for the task it is performing?	– Yes – No – Not Sure	2
Soil Sensing and Watering	What tool is currently attached to the FarmBot?	– Soil Sensor – Water Nozzle – Seeder	1
	Did the soil moisture readings change after watering?	– Yes – No – Not Sure	2
	Was the last task completed successfully without intervention?	– Yes – No – Not Sure	2
Weed Disruption	What quadrant is currently being weeded?	– Q1 upper right – Q2 upper left – Q3 lower left – Q4 lower right – Not sure	1
	Are there any weeds located in the planter still?	– Yes – No – Not Sure	1
	Have any errors occurred during the operation of the FarmBot during this session?	– Yes – No – Not Sure	2
Plant Imaging	What type of plant was the most recent photo of?	– Flower – Strawberry – Lemon Geranium – Not sure	1
	Are the LED lights currently on?	– Yes – No	1
	Has the FarmBot imaged all the plants yet during this session?	– Yes – No – Not Sure	2

4.4.1 Human Situation Awareness Assessment

For the assessment of situation awareness, Python scripts were developed to present real-time SA queries to participants, collect and log participant responses, synchronize response timestamps, and coordinate machine-generated SA assessment functions. Popup questions, as shown in Fig. 6, were presented using full-screen windows generated through Python's Tkinter graphical interface library.

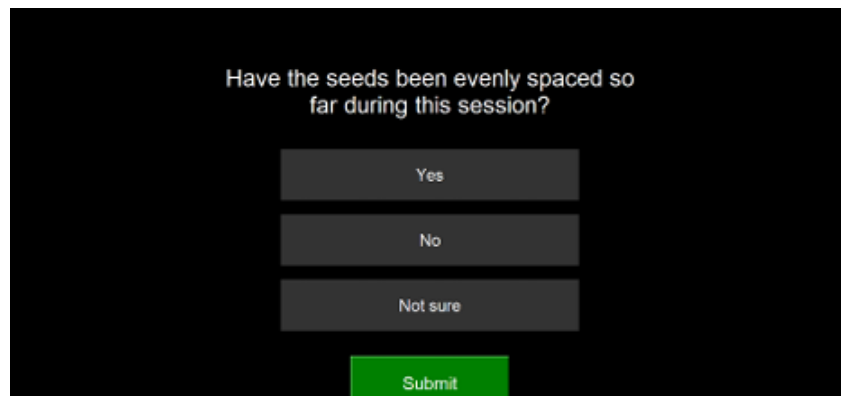


Figure 6: Example on-screen SA question presented to remote supervisor

During each six-minute operational sub-session, participants received three multiple-choice SA questions presented at randomized intervals. Questions were task-specific and corresponded directly to the current operational context and observable FarmBot system state. Participants answered each question by selecting one of the predefined multiple-choice options, then submitted their response and continued supervisory monitoring. Participant responses were automatically logged to timestamped response files. For each popup query, the system recorded the question text, the popup presentation time, the participant response, the participant response submission time, and the session identifier. This approach enabled synchronization between participant responses and FarmBot operational data collected during the same operational period.

4.4.2 Machine Situation Awareness Assessment

Machine-generated SA responses were computed in real time using Python functions, Table 7 (Appendix A5) that retrieved and interpreted FarmBot operational information through the FarmBot REST API. For each SA query presented to a participant, the corresponding machine SA function was executed at the same operational timestamp to determine the FarmBot's machine-derived response. Machine-derived SA states were generated using operational data, including positional data, operational logs, sensor readings, tool status, device state, and task execution records obtained from the FarmBot system during operation. Questions involving current operational conditions, such as active tools, positional location, and operational state, were determined using real-time device state and positional information. Questions involving environmental conditions, task completion, operational outcomes, or historical task progression were determined using combinations of operational logs, task records, sensor readings, and previously recorded system activity. The machine SA functions were executed automatically when participants were presented popup queries.

4.5 Ground Truth Establishment and Shared Situation Awareness

Computation

To establish the correct state corresponding to each SA query, all FarmBot machine activity during the experimental sessions was video recorded and reviewed following data collection. Recorded session footage was synchronized with popup query timestamps to identify the actual operational condition of the FarmBot at the time each question was presented. Operational states including task activity, machine location, tool usage, imaging progress, and task completion were verified through post hoc review of the recorded sessions and associated operational activity. Additionally,

operational abnormalities, such as task interruptions, intervention events, and visible system errors, were documented during live session observation and, when applicable, confirmed during video review. This ground truth verification technique allowed observation of when the human supervisor, the machine, or both held incorrect situation awareness during the sessions.

For each popup query, a reference operational answer ground truth representing the observed FarmBot state at the time of the query was established using the synchronized video review process. Human participant responses and machine-generated responses were independently compared against the established reference operational answer. Responses matching the established reference operational state were assigned a value of 1, indicating correct situation awareness for that query. Responses that did not match the reference operational state, as well as unanswered questions, were assigned a value of 0. The overall process for SSA assessment can be observed in Table 2 and Fig. 7.

Table 2: Shared situation awareness assessment methodology for each SA query per participant

Machine SA	Human Supervisor SA	Shared Situation Awareness
Response matches ground truth, assigned 1	Response matches ground truth, assigned 1	If Machine SA = 1 and Human SA = 1 then SSA assigned 1
Response does not match ground truth, assigned 0	Response does not match ground truth, assigned 0	If Machine and/or Human SA = 0 then SSA assigned 0

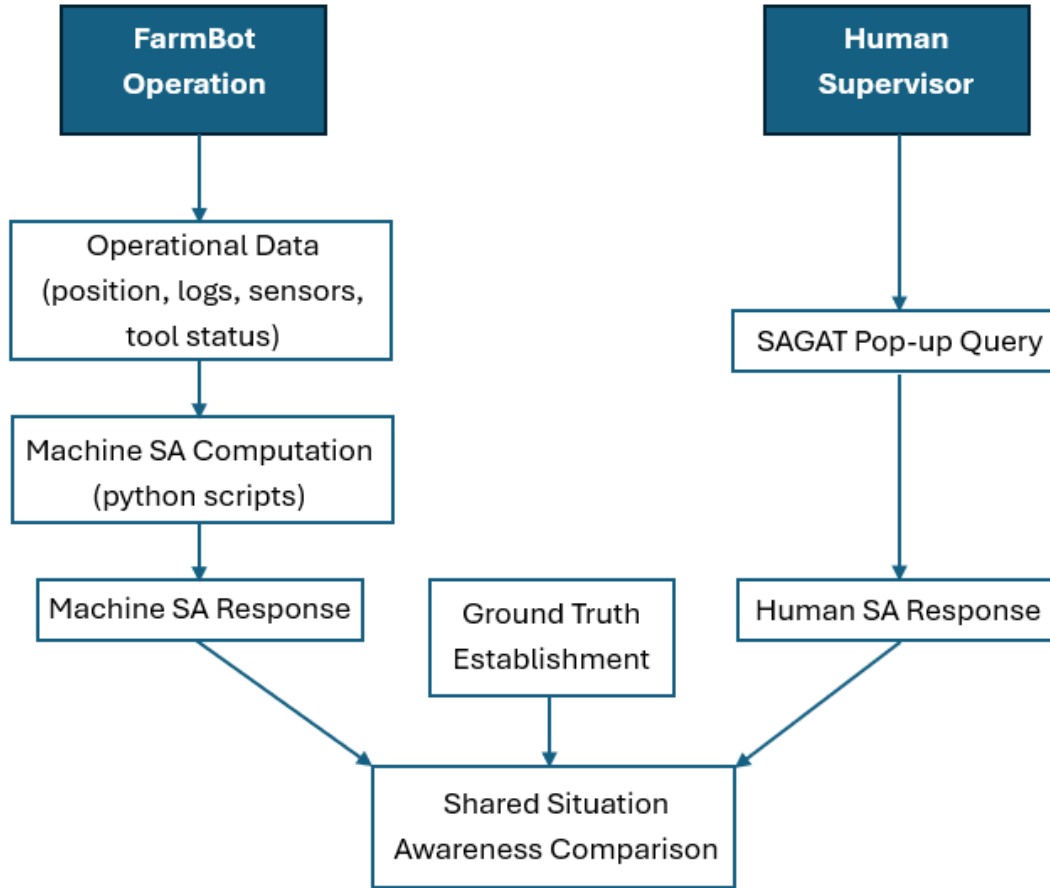


Figure 7: Overall shared situation awareness assessment methodology

Shared situation awareness (SSA) was defined as simultaneous correct awareness between the human participant and autonomous system for the same operational condition at the same point in time. Therefore, SSA was considered achieved only when both the participant response and the machine-generated response correctly matched the established reference operational state for a given query. SSA was computed per participant for each query, then overall the percentage of SSA relationships per question, sub-session, level of SA, and the entire experiment were computed.

4.6 Data Analysis

Participant responses, machine-generated responses, and established reference operational states were compiled for all popup queries across each experimental session. Human SA performance, machine SA performance, and SSA performance were analyzed using descriptive statistical methods. Human SA accuracy, machine SA accuracy, and SSA were calculated as the percentage of correctly identified operational states across all queries.

Additional analyses were conducted to evaluate overall participant SSA performance, overall Level 1 SA performance, overall Level 2 SA performance, SSA performance within each operational sub-session, SSA performance for individual question types, human SA accuracy relative to the established reference operational state, and machine SA accuracy relative to the established reference operational state. Level 1 SA and Level 2 SA performance were analyzed separately to examine differences between perception-based and comprehension-based supervisory awareness tasks. SSA performance was additionally analyzed across the four experimental sub-sessions consisting of seeding, soil sensing and watering, weed disruption, and plant imaging operations.

Inferential statistical analysis was conducted using nonparametric statistical methods due to the binary nature of the SA scoring data. Wilcoxon signed-rank tests were used to compare Level 1 and Level 2 SA performance. Friedman tests were used to evaluate differences in SSA performance across the four operational sub-sessions. Tables and graphical visualizations were used to compare human SA, machine SA, and SSA performance across SA levels, operational sub-sessions, and individual question categories.

5. Results and Discussion

This section presents the results of the shared situation awareness (SSA) assessment conducted during the FarmBot supervisory monitoring experiment. Human situation awareness (SA), machine-generated SA, and SSA performance were evaluated across all experimental sessions, situation awareness levels, operational sub-sessions, and individual question types. Descriptive and inferential statistics were used to evaluate supervisory awareness performance and differences between experimental conditions.

5.1 Overall Human SA, Machine SA, and Shared Situation Awareness

Overall human SA accuracy across all experimental sessions was 80.3%, indicating that participants correctly identified the operational state of the FarmBot for the majority of pop-up queries presented during the supervisory monitoring tasks. Machine-generated SA responses achieved an overall accuracy of 92.7% relative to the verified operational reference states. Overall, shared situation awareness across all sessions was 78.7%.

Table 3: Overall human SA, machine SA, and SSA summary

Human SA (%)	Machine SA (%)	SSA (%)	Mean Response Time (s)	Standard Deviation Response time (s)
80.3	92.7	78.7	7.3	3.0

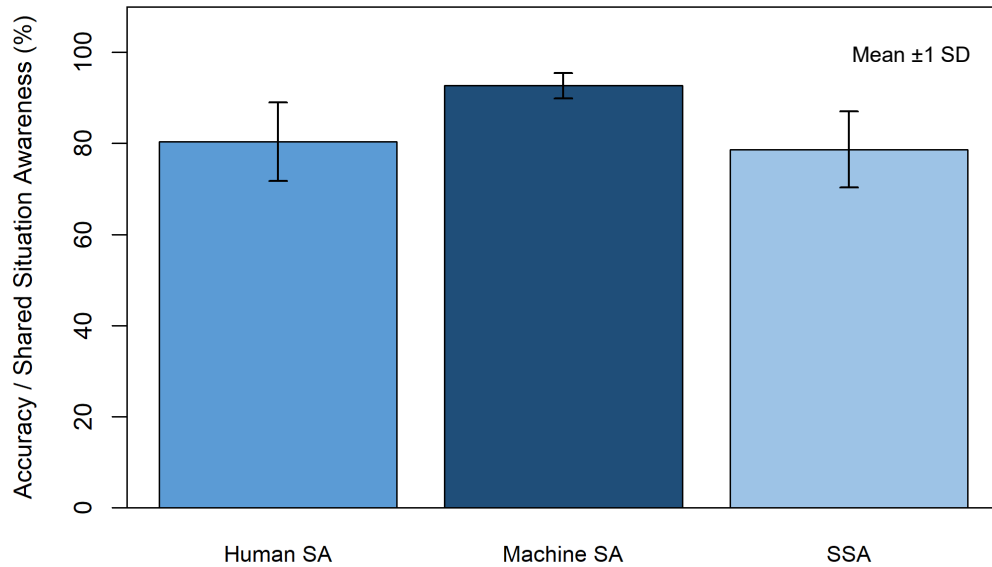


Figure 8: Overall human SA, machine SA, and SSA

The results demonstrated that machine-generated SA maintained the highest overall performance, while participant responses showed greater variability across operational tasks. Shared situation awareness values were slightly lower than overall human SA values because SSA required both the participant and machine-generated responses to correctly match the verified reference operational state simultaneously.

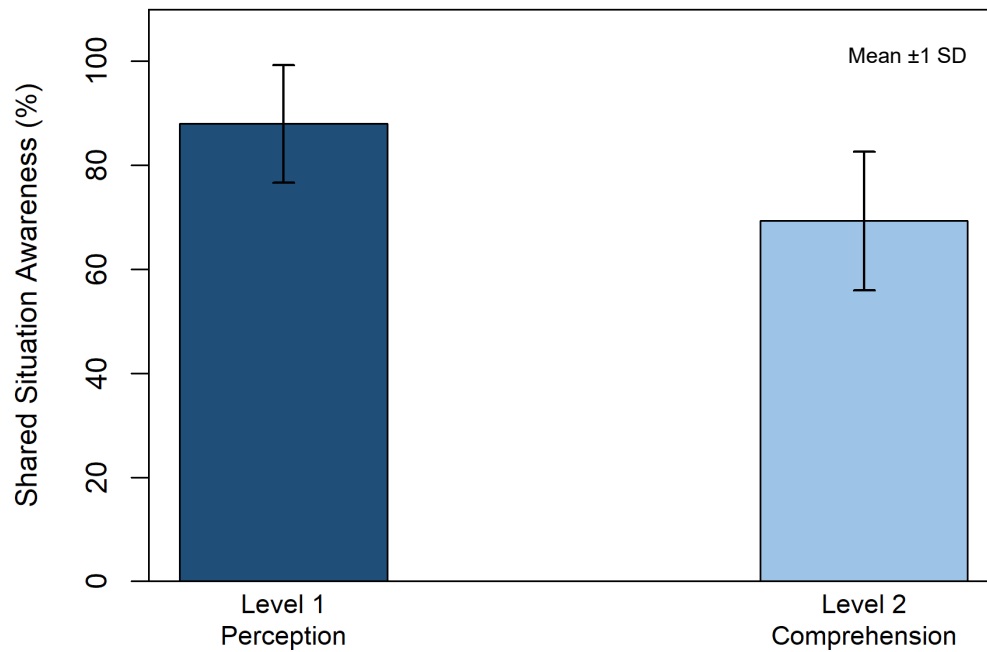
Shared situation awareness performance was evaluated individually for each participant across all operational sub-sessions and popup questions. Overall SSA values across participants generally ranged between approximately 67% and 92%.

5.2 Shared Situation Awareness by Situation Awareness Level

SSA performance differed substantially between Level 1 and Level 2 situation awareness tasks.

Table 4: SSA performance by SA level

SA Level	Human SA (%)	Human SA sd	Machine SA (%)	Machine SA sd	SSA (%)	SSA sd
1	88	11.3	100	0	88	11.3
2	72.7	14.3	85.3	5.5	69.3	13.3

**Figure 9: Shared situation awareness by SA level**

Level 1 SA tasks produced an overall SSA value of 88.0%, while Level 2 SA tasks produced a lower overall SSA value of 69.3%. Participants demonstrated stronger performance on questions involving direct perception of operational states and interface conditions, including tool identification, LED status, current machine activity, and positional location. Lower SSA performance was observed during questions requiring comprehension of operational outcomes, environmental changes, or overall task completion status. The results indicated that perception-based awareness tasks were consistently easier for participants to supervise remotely than comprehension-based tasks requiring interpretation of operational progress over time.

5.3 Shared Situation Awareness by Operational Sub-Session

SSA performance additionally varied across the four operational sub-sessions consisting of seeding, soil sensing and watering, weed disruption, and plant imaging.

Table 5: SSA performance by operational sub-session

Sub-Session	Human SA (%)	Human SA sd	Machine SA (%)	Machine SA sd	SSA (%)	SSA sd
Seeding	70.7	20	70.7	11.1	64	13.3
Soil Sensing and Watering	78.8	23.3	100	0	78.7	23.3
Weed Disruption	93.3	13.6	100	0	93.3	13.6
Plant Imaging	78.7	28.7	100	0	78.7	28.7

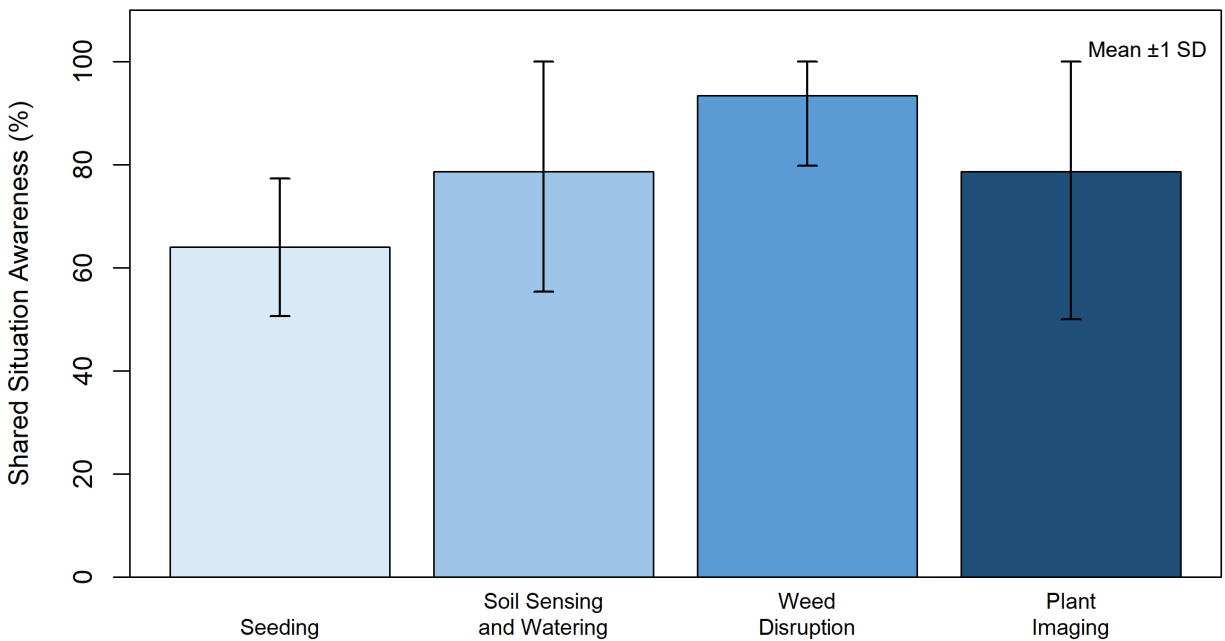


Figure 10: Shared situation awareness by operational sub-session

The weed disruption sub-session produced the highest overall SSA value at approximately 93.3%.

Soil sensing and watering and plant imaging produced intermediate SSA values of approximately

78.7%, while the seeding sub-session produced the lowest overall SSA value at approximately 64.0%.

The lower SSA observed during the seeding sub-session was primarily associated with the seed spacing evaluation question. Participants and the machine frequently interpreted the seed placements as evenly spaced despite missed seed placements occurring during operation. The FarmBot often would attempt to pickup a seed and continue onto seeding but an actual seed was not present based on the ground truth recording. In contrast, the weed disruption sub-session involved more directly observable operational states, such as current quadrant location and visible weed presence, resulting in substantially higher supervisory awareness performance.

5.4 Shared Situation Awareness by Individual Question

SSA performance was evaluated individually for each popup question presented during the experimental sessions.

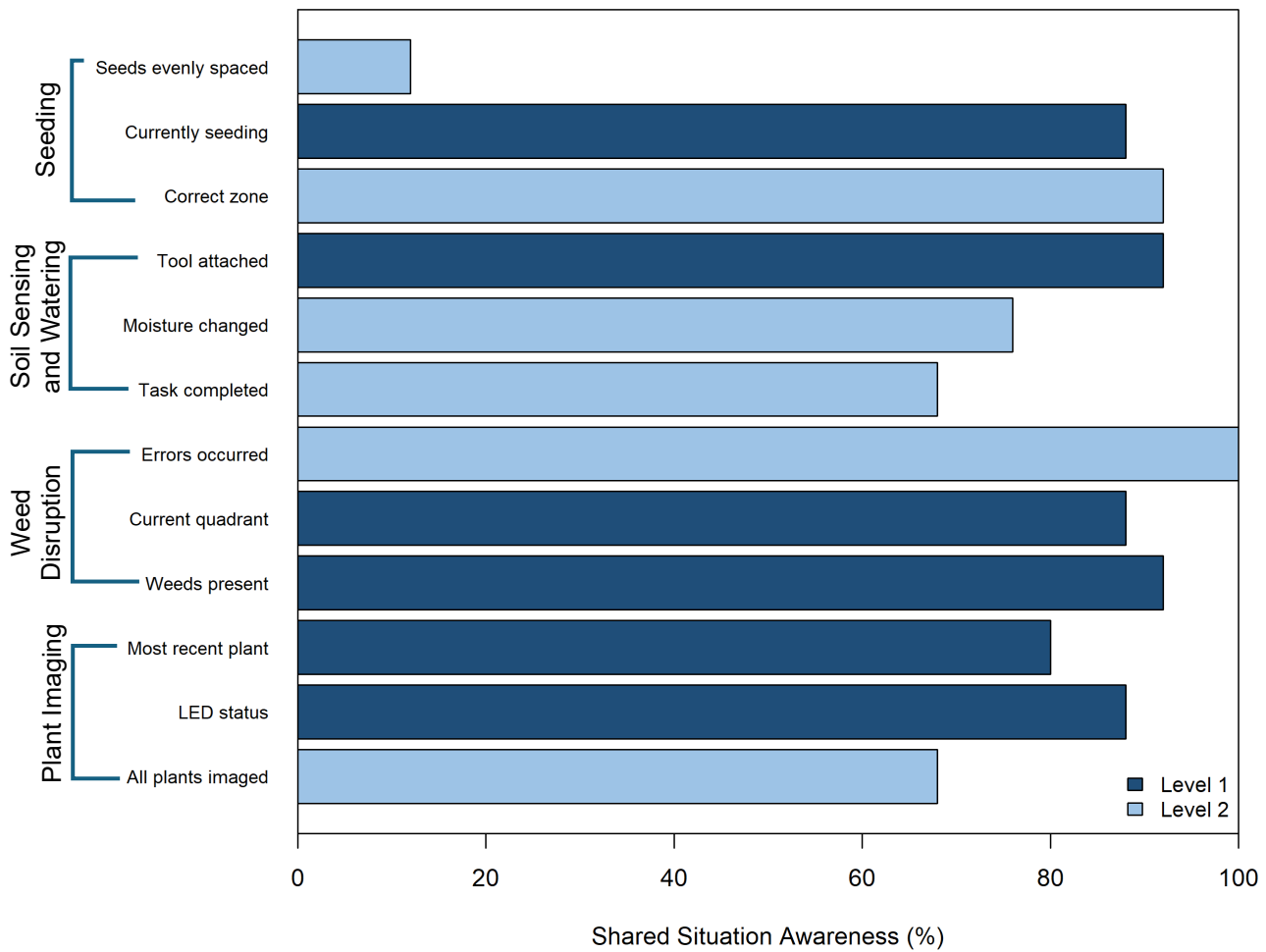


Figure 11: Shared situation awareness by question

Questions involving direct observation of current operational conditions generally produced higher SSA values than questions involving interpretation of cumulative task outcomes or environmental changes. The highest SSA value was observed for the question regarding operational errors during the weed disruption sub-session, which achieved 100% SSA. High SSA values were also observed for questions involving tool identification, current machine activity, LED status, weed presence, and current operational quadrant.

The lowest SSA was observed for the seed spacing question during the seeding sub-session, with an SSA of approximately 12%. Lower SSA values were also observed for questions involving soil

moisture change following watering and determining whether all plants had been imaged. These tasks required participants to interpret operational progress or environmental outcomes rather than directly perceive current system states.

5.5 Inferential Statistical Analysis

A Wilcoxon signed-rank test was conducted to compare SSA performance between Level 1 and Level 2 SA tasks. The analysis indicated a statistically significant ($p = 0.000615$) difference between Level 1 and Level 2 SSA performance, with significantly higher SSA observed during Level 1 perceptual tasks compared to Level 2 comprehension-based tasks.

A Friedman test was conducted to evaluate differences in SSA across the four operational sub-sessions. The Friedman test indicated a statistically significant difference in SSA performance across the operational sub-sessions, $\chi^2(3) = 20.95$, $p < 0.001$. This result demonstrated that supervisory awareness performance varied significantly depending on the operational task being monitored.

Post hoc pairwise comparisons using Wilcoxon signed-rank tests with Bonferroni correction were subsequently conducted to determine which operational sub-sessions differed significantly.

Table 6: Post hoc pairwise comparison results

SSA Comparison	Raw p Value	Adjusted p Value
Seeding vs Soil Sensing and Watering	0.003891	0.023347
Seeding vs Weed Disruption	4.18E-05	0.000251
Seeding vs Plant Imaging	0.006576	0.039455
Soil Sensing and Watering vs Weed Disruption	0.029182	0.17509
Soil Sensing and Watering vs Plant Imaging	0.923713	1
Weed Disruption vs Plant Imaging	0.049911	0.299469

Post hoc analysis demonstrated that the seeding sub-session produced significantly lower SSA values compared to the soil sensing and watering sub-session (adjusted $p = 0.023$), weed disruption sub-session (adjusted $p < 0.001$), and plant imaging sub-session (adjusted $p = 0.039$). No statistically significant differences were observed between the weed disruption, plant imaging, and soil sensing and watering sub-sessions following Bonferroni correction.

Overall, the inferential statistical analyses demonstrated that shared situation awareness performance varied significantly according to both the operational context of the agricultural task and the level of situation awareness required by the supervisory query.

5.6 Post-Session Questionnaire

At the conclusion of the experimental session, participants completed an end-of-session questionnaire (Appendix A3) designed to evaluate their subjective experience supervising the FarmBot system. The questionnaire included one Likert-scale statement related to supervisory confidence as well as several open-ended questions regarding interaction quality, shared awareness, coordination, and potential improvements to the system.

Participants responded to the statement: “I was confident in monitoring and managing the FarmBot during the session.” using a five-point Likert scale ranging from Strongly Disagree to Strongly Agree. Overall, participants reported generally positive confidence levels while supervising the FarmBot system as demonstrated in Fig. 12.

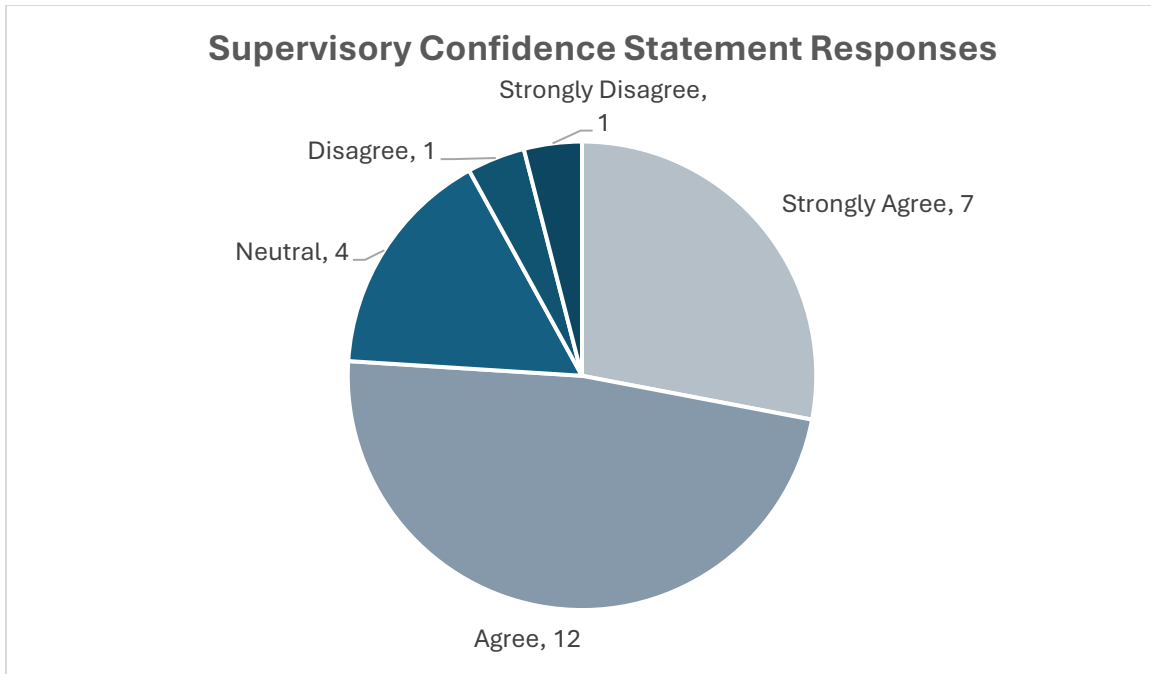


Figure 12: Participant responses to supervisory confidence questionnaire

The majority of participants selected either “Agree” or “Strongly Agree,” suggesting that most participants felt capable of supervising the FarmBot during the experimental tasks. A smaller number of participants selected “Neutral,” while very few participants reported disagreement with the statement. These findings suggest that participants generally felt comfortable interacting with the FarmBot supervisory interface.

The open-ended responses additionally indicated that participants found directly observable interface elements, such as machine movement and current operational states helpful during supervisory monitoring. Several participants noted that the popup questions were generally understandable and that the interface provided sufficient information for many operational tasks. However, some participants reported difficulty interpreting operational outcomes. Participants suggested that additional visual feedback, clearer task-status indicators, or improved notifications regarding operational errors and task completion could improve coordination and awareness

during supervision. These subjective responses were generally consistent with the quantitative SSA findings. Tasks involving directly observable operational states produced higher shared situation awareness values, while tasks requiring interpretation of operational outcomes produced lower shared situation awareness performance. The questionnaire responses therefore provided additional support for the importance of interface transparency and operational feedback in autonomous agricultural supervision systems.

5.7 Discussion

The purpose of this study was to develop and evaluate a method for measuring shared situation awareness between a human supervisor and an autonomous agricultural machine during remote supervision tasks. The results demonstrated that the proposed method could measure shared situation awareness by directly comparing participant responses, machine-derived responses, and verified operational reference states. Overall, the findings suggest that shared situation awareness between human supervisors and autonomous agricultural systems can vary substantially depending on the complexity of the awareness requirement and the operational context of the task being supervised.

One of the most important findings of this study was the significant difference in shared situation awareness performance between Level 1 and Level 2. Level 1 shared situation awareness values were consistently higher than Level 2 values, indicating that participants were more successful at perceiving directly observable operational states than at comprehending broader task outcomes or operational progress. This result aligns strongly with Endsley's three-level model of situation awareness, where Level 1 involves the perception of relevant cues and Level 2 involves the comprehension of their meaning in relation to task goals (Endsley 1988; Endsley 2000). The results

suggest that participants could generally identify current system states, such as tool position, LED status, or the current quadrant location, but had greater difficulty interpreting more abstract or cumulative task conditions.

This difference between Level 1 and Level 2 awareness was particularly visible during the seeding sub-session. The seeding tasks produced the lowest shared situation awareness values and were significantly lower than the soil sensing and watering, weed disruption, and plant imaging sub-sessions. The largest contributor to reduced performance during the seeding task involved the seed spacing question. Although the FarmBot frequently failed to place seeds correctly during operation, participants often believed the spacing was correct because the missed seed placements were not always immediately obvious through the interface. This finding reflects a broader challenge in autonomous supervision systems: supervisors may struggle to accurately interpret task quality when failures are subtle, cumulative, or not directly visible.

These results are consistent with literature on automation and out-of-the-loop performance problems. Endsley and Kiris (1995) demonstrated that operators supervising automation may lose awareness of system state and become less effective at identifying automation failures. In the present study, participants were not actively controlling the FarmBot but instead monitoring its operation remotely through the interface. This supervisory role required participants to infer whether agricultural tasks were being completed correctly based on indirect cues rather than direct physical interaction with the task environment. The lower Level 2 awareness observed during seeding, therefore, supports the argument that supervisory automation can reduce operator comprehension of task outcomes when important operational details are difficult to perceive.

The weed-disruption sub-session yielded the highest overall shared situation-awareness values. Questions within this sub-session largely involved directly observable operational states, such as identifying the current quadrant or determining whether weeds remained in the planter. These tasks relied more heavily on Level 1 perception than on interpretation of longer-term task outcomes. Participants were therefore able to identify relevant interface information quickly and accurately. This result supports prior research suggesting that shared awareness is easier to maintain when relevant operational information is clearly visible and directly represented to the operator (Schaefer et al. 2017; Endsley 2023).

The machine-derived situation awareness results also provide important insights into the proposed methodology. Machine-derived responses demonstrated high overall agreement with the verified operational reference states across most experimental conditions. This suggests that operational data available through FarmBot logs, positional data, system states, sensor readings, and task records can be used effectively to generate machine-derived awareness states. The methodology therefore demonstrates a practical approach for operationalizing machine situation awareness without assuming that the autonomous system possesses human-like cognition.

The present findings also support literature emphasizing the importance of transparency and interface design in human-autonomy teaming. Studies by You et al. (2022a; 2022b), Wright et al. (2020), and van de Merwe et al. (2024) suggested that interface transparency can improve situation awareness, trust, and operator understanding in supervisory tasks. In the present study, participants generally performed well when the interface provided clear and directly interpretable information. However, performance declined when successful task completion required interpretation of subtle environmental outcomes that were not explicitly communicated through the interface. This

suggests that future agricultural supervisory interfaces may benefit from improved feedback mechanisms that communicate task quality, task confidence, or uncertainty to the supervisor.

The results additionally contribute to human-autonomy teaming literature by demonstrating that shared situation awareness can be operationalized and measured between a human and an autonomous agricultural system. Existing shared situation awareness research has primarily focused on human-human teams or simulated environments (Endsley and Jones 2001; Bolstad and Endsley 2003). In contrast, the present study evaluated the alignment of awareness between a human supervisor and a physical autonomous system performing real agricultural tasks. This represents an important extension of shared situation-awareness concepts to agricultural human-autonomy teaming.

The findings also have broader implications for the remote supervision of autonomous agricultural machines. Prior research on agricultural supervision has emphasized the importance of interface information, visual feedback, and warning systems (Edet et al. 2018; Panfilov and Mann 2018; Ezeagba et al. 2025). The present study supports these findings and extends them to shared awareness measurement. The results suggest that remote supervision systems should not only provide operational information but also support the supervisor's ability to comprehend task progress and task quality over time.

Overall, the study demonstrates that shared situation awareness between human supervisors and autonomous agricultural systems can be measured objectively using synchronized human responses, machine-derived responses, and verified reference states. The results suggest that awareness alignment depends strongly on the complexity of the awareness requirement and the transparency of the operational information available to the supervisor.

6. Conclusion

The purpose of this study was to develop a method to measure shared situational awareness between a human supervisor and an autonomous agricultural machine during remote supervision tasks. Using the FarmBot as an experimental platform, the study combined participant responses, machine-derived responses, and verified operational reference states to evaluate alignment of awareness during autonomous agricultural operation.

The results demonstrated that the proposed methodology could measure shared situational awareness between the human supervisor and the autonomous system. Overall, shared situational awareness performance varied with both the operational task being supervised and the complexity of the awareness requirement. Participants demonstrated significantly higher shared situation awareness during Level 1 perception-based tasks than during Level 2 comprehension-based tasks. These findings aligned closely with Endsley's situation awareness framework and suggested that operators supervising autonomous systems may experience greater difficulty when task assessment requires interpretation of broader operational outcomes rather than direct perception of system states.

The seeding sub-session produced the lowest shared situation awareness values and differed significantly from the other operational sub-sessions. This result highlighted the challenges of interpreting subtle task-quality failures during autonomous supervision and that the machine is not always correct in its situation awareness. In contrast, tasks involving directly observable operational conditions, such as weed disruption and current system states, produced substantially higher shared situation awareness values. These findings suggest that transparency and observability strongly influence the alignment of awareness between human supervisors and

autonomous systems. The machine-derived situation awareness methodology also demonstrated strong agreement with verified operational reference states across most experimental conditions, but not all of them due to the errors which are more difficult to catch. This supports the use of operational logs, positional data, system states, and sensor information as practical sources for estimating machine-derived awareness during autonomous agricultural operation and the requirement of the ground truth comparisons.

Beyond the experimental findings themselves, the study contributes to the broader literature on human-autonomy teaming and agricultural automation by extending shared situation awareness concepts into the context of autonomous agricultural supervision. Existing shared situation awareness research has focused primarily on human-human teams or simulated systems, whereas the present study evaluated awareness alignment between a human and a physical autonomous agricultural system performing live operational tasks. The findings additionally reinforce the importance of human factors considerations in autonomous agricultural system design. Interface transparency, operational feedback, warning systems, and task-status communication all appear important for supporting supervisory awareness during autonomous operation. The results therefore suggest that future agricultural automation systems should be designed not only for technical performance, but also for effective human supervision and awareness support.

Overall, this study demonstrated that shared situation awareness between human supervisors and autonomous agricultural systems can be measured during operation using synchronized human responses, machine-derived awareness states, and verified operational reference states. The methodology developed in this thesis provides a foundation for future research examining

awareness alignment, supervisory interaction, and human-autonomy collaboration in agricultural automation systems.

6.1 Limitations

Several limitations should be considered when interpreting the results of this study. First, the experiment was conducted with a single FarmBot platform in a controlled laboratory environment. Although the FarmBot provided a suitable platform for studying autonomous agricultural supervision, the system does not fully capture the complexity, scale, or environmental variability of commercial agricultural machines operating under outdoor field conditions. As a result, the findings may not generalize directly to larger autonomous agricultural systems such as autonomous sprayers, tractors, or harvesters.

Second, the experimental tasks represented a limited set of agricultural operations. The study focused on seeding, soil sensing and watering, weed disruption, and plant imaging tasks. While these activities provided meaningful opportunities to evaluate Level 1 and Level 2 situation awareness, they do not represent the full range of supervisory tasks encountered in agricultural automation. More complex agricultural operations involving navigation, obstacle avoidance, weather variability, or multi-machine coordination may produce different shared situation awareness patterns. The study additionally focused only on Level 1 and Level 2 situation awareness. Level 3 situation awareness involving projection of future system states was not evaluated directly due to the capabilities of the machine. While this decision simplified the experimental design and supported more objective assessment, future studies may benefit from examining predictive awareness and anticipation in autonomous agricultural supervision.

Another limitation concerns the method used to develop machine situation awareness. Machine-derived responses were generated from FarmBot operational data, including logs, positional information, sensor states, and task records, and were computed at the exact moment a question was asked. While this approach provided a practical and objective method for estimating machine awareness, it does not imply that the autonomous system possessed human-like cognition or understanding. Instead, the machine-derived responses represented task-specific operational states inferred from available system data. For the human supervisor responses, there was also a response-time delay, which may slightly impact situation awareness. Participants may be answering the SA queries based on what they believe is happening at the moment the screen is blanked out, rather than what occurred at the exact moment the question was asked. This time delay or way of responding to the questions may contribute to reduced shared situation awareness. Alternative approaches to machine awareness representation may produce different results.

The study was also limited by the number and type of situation awareness questions used during the experimental sessions. Only a small number of questions were presented during each sub-session in order to reduce disruption to the task. Although the questions were designed to evaluate Level 1 and Level 2 awareness requirements, additional question types may have provided a broader understanding of participant awareness.

The participant population represents another limitation. Participants may not have possessed extensive prior experience with agricultural robotics or autonomous agricultural supervision systems. Although this was appropriate for evaluating general supervisory awareness performance and the methodology of shared situation awareness, experienced operators or agricultural professionals may respond differently to the same tasks. Prior familiarity with agricultural systems,

automation, or remote monitoring interfaces could influence shared situation awareness performance. In this study, the focus was on the methodology of assessment, therefore, in the future a larger group of participants with varying agricultural and supervisory experience could be implemented.

Finally, the study evaluated shared situation awareness during relatively short experimental sessions. Shared awareness and trust may evolve over longer-term interaction with autonomous systems. The experimental design therefore may not fully capture how human supervisors adapt to autonomous systems over time or how familiarity influences awareness alignment.

6.2 Recommendations

Based on the findings of this study, several recommendations can be made for the design of autonomous agricultural supervision systems and future shared situation awareness research. First, supervisory interfaces for autonomous agricultural systems should prioritize clear presentation of task-relevant operational information. The results showed that participants performed well when operational states were directly observable through the interface. Interface designers should therefore ensure that critical operational states, warnings, task progress indicators, and machine status information are presented in a manner that supports rapid perception and interpretation.

Furthermore, future supervisory interfaces should provide improved support for Level 2 situation awareness. The lower shared situation awareness observed during seeding tasks suggests that supervisors may struggle to evaluate task quality when operational outcomes are subtle or difficult to observe. Interfaces should therefore include clearer feedback regarding task completion quality, operational success, uncertainty, and potential task errors. Additional graphical indicators,

confidence metrics, or automated notifications may help supervisors better comprehend task outcomes.

Third, remote supervision systems should support transparency between the human supervisor and the autonomous system. Prior human-autonomy teaming research has shown that transparency can improve trust, awareness, and operator understanding. The present findings similarly suggest that supervisors benefit when machine behaviour and operational status are clearly communicated.

Another recommendation concerns the development of machine-derived awareness representations. The methodology developed in this study demonstrated that operational data can be used to generate machine-derived awareness responses that can be compared directly with human responses. Future supervisory systems may benefit from incorporating real-time awareness-monitoring tools that identify mismatches between human and machine awareness states. The study also suggests that agricultural autonomy research should continue integrating human factors principles into system development. Autonomous agricultural systems should not be designed solely from a technical automation perspective. Instead, designers should consider how operators monitor, interpret, trust, and collaborate with autonomous systems during real supervisory tasks.

6.3 Future Work

Several opportunities exist for future research extending from this study. One important direction involves evaluating shared situation awareness in larger-scale and more complex agricultural systems. Future studies could modify and expand upon the proposed methodology to autonomous sprayers, tractors, harvesters, or multi-robot agricultural systems operating in outdoor field conditions. These environments would introduce additional variability, uncertainty, and supervisory demands beyond those present in the laboratory-based FarmBot environment. The challenge with this future work is the access required to machine data in order to compute the machine's SA. Therefore, a recommendation is to work with industry during the design phase of autonomous agricultural machines to test shared situation awareness and potentially expose areas for improvements in the user interface design and communication within the system.

Future work could also examine shared situation awareness during longer-term human-autonomy interaction. Repeated exposure to autonomous systems may influence operator trust, familiarity, workload, and awareness alignment over time. Longitudinal studies may therefore provide valuable insight into how shared situation awareness evolves as supervisors gain experience with autonomous agricultural systems.

Another important area for future work involves evaluating Level 3 situation awareness. The current study focused on perception and comprehension tasks because these levels could be assessed more objectively during live operation due to the FarmBot's capabilities. Future studies could investigate predictive awareness by asking participants to anticipate future machine states, task outcomes, or environmental changes and programming the FarmBot or similar autonomous agricultural machine to include predictive abilities.

Future research could additionally examine how different interface designs influence shared situation awareness. The study used the existing FarmBot supervisory interface, but alternative interfaces incorporating additional transparency features, visualizations, warning systems, or predictive information may improve awareness alignment between the human supervisor and the autonomous system.

Future studies may also benefit from comparing experienced agricultural operators with inexperienced participants. Differences in agricultural knowledge, automation familiarity, or supervisory expertise may influence both human situation awareness and shared situation awareness performance. Finally, future work could explore real-time shared situation awareness monitoring systems capable of identifying awareness mismatches dynamically during operation. Such systems could potentially detect when the human supervisor and autonomous system no longer share the same understanding of task conditions and provide corrective support before operational problems occur.

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Appendix A: Study Materials

A1: Informed Consent



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Assessment of Shared Situation Awareness in Human-Autonomy Teams.

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Professor and Head

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CONFLICTS OF INTEREST AND UNDUE INFLUENCE: None of the researchers have any conflicts of interest in this study.

You are being invited to participate in a research study. This consent form, a copy of which will be left with you for your records and reference, is only part of the process of informed consent. If you want more details about something mentioned here, or information not included here, feel free to ask any of the people named above. Please take the time to read this document and any accompanying information carefully. It is very important that you understand:

- **What is being asked of you,**
- **What the risks and benefits of participation are, and**
- **How the information you provide will be used and stored.**

PURPOSE OF THE STUDY: I am doing this research for my MSc thesis under the supervision of Dr. Danny Mann. The purpose of this study is to evaluate the shared situation awareness between the FarmBot autonomous planting robot and human supervisors. Participants will be asked questions related to planting tasks while remotely supervising the autonomous machine. The study should take no longer than one hour to complete.

STUDY PROCEDURES: You will be asked to monitor a farming robot's activity and status on a web interface (computer screen) while answering questions related to the tasks being conducted on a supervisor sheet (paper). The experiment comprised of 4 sub sessions which will be completed

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in order of (1) Seeding, (2) Soil Sensing and Watering, (3) Weed Disruption and (4) Plant Imaging. Also, there will be verbal training to enable you to become familiar with the experiment. Each sub session will be 6 minutes of duration where 3 pop-up questions will appear on the computer screen related to the perception and comprehension of the situation. You are expected to answer based on your perception and comprehension. After you have finished the session, you will be given an “end-of-session questionnaire” to comment on your overall experience.

The questions presented in this study are **NOT** intended to test your intellectual competence. They are only meant to gather your perception and comprehension of the situation with regards to supervising an autonomous machine.

STUDY RISKS: You will be exposed to a web interface that presents visual depictions of the FarmBot, however, the web interface will not present flashing lights or physical disturbance. However, there is a risk of cognitive load as monitoring requires sustained attention. To reduce cognitive load, the duration of the sub sessions is only 6 minutes with sufficient breaks between. Nevertheless, if you indicate fatigue and/or discomfort during the experiment, you can either request an unscheduled break or discontinue the experiment if it persists.

STUDY BENEFITS: The research will expose you to monitoring an autonomous agricultural machine, an advanced farming robot. It will also give you a better understanding about how autonomous agricultural machines can be employed when they become commercially available, and what remote supervision tasks may be applicable.

COMPENSATION: You will be offered a twenty-five-dollar Tim Hortons gift card as an honorarium upon receipt of your consent as compensation for your time. We may collect additional personal contact information from you to record giving you an honorarium. The researchers will keep this information separate from any research information. This information will be kept in a secure location for 7 years in case the University of Manitoba has to account for the money during a financial audit.

CONFIDENTIALITY: All the information you provide as a participant in this study is confidential, which means we as the research team must keep it safe. We will do our best, however, it is not possible to guarantee absolute confidentiality. We will only share your personal information if required through court order law.

STORAGE AND USE OF DATA: For safety, your information will be kept on a UM-approved secure platform. In all cases, only the group average or summary will be presented to protect your identity. To further ensure the safety of participants’ information, only the research team will have access to participant data. A password protected laptop will be used to access and analyze participants’ information. Any personal information will be stored separately from your research data. By December 2032, all data (identifiable and anonymized) will be securely destroyed or deleted.

At the end of this document, you will have a chance to tell us whether you will allow your information to be shared outside of the University of Manitoba. Your information may be shared with researchers outside of the University of Manitoba; shared with other organizations; made publicly available. The information is being shared for further analysis or testing; as part of the

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research study; because it is required by a funder or journal. It will not include your name or any information that could identify you, meaning that it will be anonymized.

DISSEMINATION: Results from this study will appear in a MSc. thesis of the Department of Biosystems Engineering at the University of Manitoba as well as articles published through MSpace, in peer-reviewed scientific journals and conferences. The results will also be included in oral presentations that are open to the public. Some data and information from this study may be sent outside of the University of Manitoba to other researchers, organizations, or made publicly available. This is for further analysis, testing, as part of the research study, or a requirement by a granting agency or journal. Any information sent out of the University of Manitoba will not show your name or address, or any other identifiable personal information about you. However, despite efforts to keep your personal information confidential, absolute confidentiality cannot be guaranteed. Your personal information may be disclosed if required by law. A formal feedback will not be provided immediately after the experiment. However, the principal investigator will be willing to answer any questions that may arise. A summary of the study will be made available upon completion by April, 2026 to participants who will indicate interest by providing their email addresses at the end of this consent form.

WITHDRAWING: Your participation in this research is voluntary. You can choose to do only the activities and/or answer only the questions that you are comfortable with. You may withdraw from the study for any reason. You do not have to explain why. You will not be penalized in any way. The honorarium is yours to keep. If you withdraw partway through the study, all your information will be destroyed unless you allow us to keep it. You may withdraw from the study until April 2026. Should you withdraw, all gathered responses will be destroyed. After this date, we will start to analyze the information so it may not be possible to withdraw your information. To withdraw, please contact the Principal Investigator, Ms. Makenna Coldwell at the phone number or email above.

QUESTIONS OR CONCERNS: Designated University of Manitoba personnel may look at your information to see that the research is being done in a safe and proper way. To do this, they may visit the study site or review the research records. We will tell you if someone outside the research team will be there while you are participating. If this makes you uncomfortable, please tell the Principal Investigator, who will ask the personnel to return at another time.

This study has been reviewed and approved by the Research Ethics Board at the University of Manitoba, Fort Garry Campus. However, this does not mean that participation is risk-free. If you have any questions or concerns, or complaints about this study, you may contact any members of the research team listed on the first page or the office of Human Research Ethics at humanethics@umanitoba.ca or 204-474-7122.

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CONSENT:

By signing this document, I agree that:

- I have read the above information or had it read to me.
- I have had the opportunity to ask and have had all of my questions answered.
- I understand what is being asked of me.
- I will be taking part in a research study.
- I may freely stop or leave the research study activities at any time.
- I understand what the researchers will do with the information I give them.
- I do not waive my legal rights by participating in the study.

Please review the following statements. For each statement, please check if you agree or do not agree.

I agree to participate in this study.	☐ YES	☐ NO
---------------------------------------	------------------------------	-----------------------------

I agree to have (check one):		
☐ a general descriptor used instead of my name when results are shared for this study.		
☐ a pseudonym (fake name) used when the results are shared for this study.		
I would like my pseudonym to be _____		

I agree that the information I provided to the research team can be used for future research purposes by members of this study's research team and/or their students.	☐ YES	☐ NO
I agree that the information I provided to the research team can be share with or used by other researchers, funders, research or community organizations, journals, or other third parties for any future research purposes only if anonymized unless explicit consent for identifiable/coded data is obtained.	☐ YES	☐ NO

I agree to be contacted by a member of this research team for future phases related to this research study.	☐ YES	☐ NO
If yes, please provide an email address: _____		
By agreeing to be contacted, you are not required to participate in any future phases. If you wish to withdraw your name from this list, please contact Ms. Makenna Coldwell-coldwel1@myumanitoba.ca		

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If I choose to withdraw partway through the study, I agree that the research team may still include the responses I have completed in their analysis.	☐ YES ☐ NO
---	--

Name of Participant

Participant's Signature

Date

I read and explained all of the information in this consent form to the participant before receiving the participant's consent, and the participant had knowledge of its contents and appeared to understand it.

Name of Participant

Researcher's Signature

Date

SUMMARY OF RESULTS: Please provide an email address below if you would like to be sent a summary of the results and/or my individual results.

Email address: _____

PARTICIPANT INFORMATION:

Please answer the following questions as honestly and accurately as possible. Circle the answer that best describes you.

Name: _____

What is your age in years? 0-17 18-35 36-50 51-65 66+

Are you a student at the University of Manitoba? YES NO

Notice Regarding Collection, Use, and Disclosure of Personal Information

Your personal information is being collected under the authority of *The University of Manitoba Act*. The University of Manitoba is committed to preserving your right to privacy. The information you provide will be used by the University to support our research. Your personal information will not be used or disclosed for other purposes, unless permitted by *The Freedom of Information and Protection of Privacy Act* or *The Personal Health Information Act*. If you have any questions about the collection of personal information: Ph: 204-474-9462 or Email: fippa@umanitoba.ca

A2: Supervisor Task Sheet

Subject ID: _____

Supervisor Task Sheet

1. Seeding Session

Time	Are seeds evenly spaced? (✓/✗)	Any spots missed? (✓/✗)	Where were issues? (if any)	Notes
00:00–02:00				
02:01–04:00				
04:01–06:00				

2. Soil Sensing & Watering Session

Time	Overwatering seen? (✓/✗)	Dry patches? (✓/✗)	Any missed plants? (✓/✗)	Notes
00:00–02:00				
02:01–04:00				
04:01–06:00				

3. Weed Disruption Session

Time	Any plant damage? (✓/X)	Weeds missed? (✓/X)	Where were issues? (if any)	Notes
00:00–02:00				
02:01–04:00				
04:01–06:00				

4. Plant Imaging Session

Time	Plant Type Observed	Growth Stage (e.g., seedling, vegetative, flowering)	Any Plants Missed? (✓/X)	Notes
00:00–02:00				
02:01–04:00				
04:01–06:00				

A3: End of Session Questionnaire

Subject ID: _____

APPENDIX E: End-of-Session Questionnaire

Instruction: Please answer the questions below as honestly and accurately as possible. For the statement, fill in the box of the answer that best describes your experience. For questions with blank spaces, written responses are encouraged.

1. I was confident in monitoring and managing the FarmBot during the session.
☐ Strongly Disagree ☐ Disagree ☐ Neutral ☐ Agree ☐ Strongly Agree

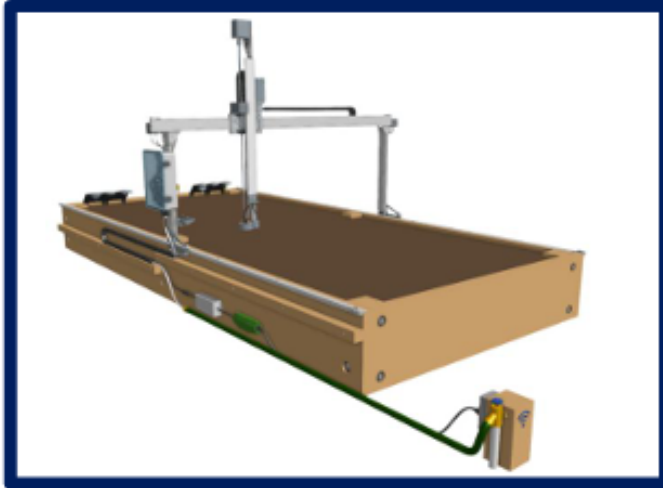
2. What aspects of your interaction with the FarmBot worked well?

3. What aspects of your interaction could improve to enhance shared awareness and coordination with the FarmBot?

4. Do you have any suggestions that might be beneficial to this study?

A4: Recruitment Poster

PARTICIPANTS NEEDED



Purpose of Study:

You are invited to participate in a study that will be carried out in a Lab to evaluate the shared situation awareness between the FarmBot autonomous planting robot and a human supervisor. The study should take no longer than one hour to complete.

Role of Participants:

You will be asked to do the following: (1). Conduct a supervisor task to answer specific seeding, watering, weeding and imaging questions (on paper) while monitoring the behaviour of the FarmBot (on a computer screen) (2). You are to select the right choice of response to questions (on the computer screen) based on your comprehension of the situation. (3). You will be presented with an end-of-session questionnaire to give your personal experience during the entire experiment.

Inclusion/Exclusion Criteria:

Potential participants should be University of Manitoba students 18 years old or older. Experience with and knowledge of farming is not required. Participants who are less than 18 years would not be eligible.

Participants will be provided a \$25.00 CAD gift card to Tim Hortons as an honorarium.

This research has been approved by the Research Ethics Board at the University of Manitoba, Fort Garry Campus. If you have any concerns or complaints about this project, you may contact any of the below-named persons or the Human Ethics Coordinator at 204-474-7122, humanethics@umanitoba.ca

Interested?

Email Makenna

(Principal Investigator):

coldwel1@myumanitoba.ca,

or

Dr. Danny Mann (Advisor):

danny.mann@umanitoba.ca for more information

FarmBot Study coldwel1@myumanitoba.ca	FarmBot Study coldwel1@myumanitoba.ca	FarmBot Study coldwel1@myumanitoba.ca	FarmBot Study coldwel1@myumanitoba.ca	FarmBot Study coldwel1@myumanitoba.ca	FarmBot Study coldwel1@myumanitoba.ca	FarmBot Study coldwel1@myumanitoba.ca	FarmBot Study coldwel1@myumanitoba.ca	FarmBot Study coldwel1@myumanitoba.ca	FarmBot Study coldwel1@myumanitoba.ca
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A5: Machine Situation Awareness Implementation

Table 7: Machine Situation Awareness Implementation

Experimental Sub-session	Question	Python Functions Applied	SA Level
Seeding	Have the seeds been evenly spaced so far during this session?	fb.api_get("logs")	
	Is the FarmBot currently seeding or taking a break (no movement)?	fb.get_xyz()	1
	Has the FarmBot been in the correct zone for the task it is performing?	fb.get_xyz()	2
Soil Sensing and Watering	What tool is currently attached to the FarmBot?	fb.api_get("device")	1
	Did the soil moisture readings change after watering?	fb.api_get("logs")	2
	Was the last task completed successfully without intervention?	fb.api_get("logs")	2
Weed Disruption	What quadrant is currently being weeded?	fb.get_xyz()	1
	Are there any weeds located in the planter still?	fb.api_get("points")	1
	Have any errors occurred during the operation of the FarmBot during this session?	fb.api_get("logs")	2
Plant Imaging	What type of plant was the most recent photo of?	fb.api_get("points") fb.api_get("logs")	1
	Are the LED lights currently on?	fb.read_status() fb.state status.get("pins")	1
	Has the FarmBot imaged all the plants yet during this session?	fb.api_get("logs") fb.api_get("points")	2