# ASSESSMENT OF INTERFACE FOR REMOTE SUPERVISION OF AUTONOMOUS AGRICULTURAL MACHINES

by

**Ebenezer Nunoo**

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**University of Manitoba**

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## Abstract

The increasing use of autonomous agricultural machines (AAMs) demands intuitive and effective human–machine interfaces (HMIs) for remote supervision. This study evaluated the usability and situation awareness performance of two interface designs: one that combines graphical indicators with real-time video, and one that uses indicators only. Twenty participants interacted with both interfaces in randomized trials simulating common sprayer malfunctions. Usability was measured using the System Usability Scale (SUS), while situation awareness performance metrics included error detection accuracy and response time. Results showed significantly higher SUS scores for the video-based HMI, indicating better perceived usability. Although response times did not differ significantly, participants achieved greater detection accuracy with the video interface. These findings suggest that integrating real-time video into HMIs enhances comprehension and operator confidence without compromising efficiency. The study emphasizes the significance of visual feedback and user-centred design in creating interfaces that strengthen trust, accuracy, and informed decision-making in the supervision of autonomous agricultural equipment.

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## 1.0 INTRODUCTION

Agriculture plays a crucial role in ensuring food security by providing high-quality food that sustains human life. The global population is projected to exceed nine billion by 2050 (Steward et al. 2021). The demand for food, fuel, and fibre is expected to rise significantly. To meet this demand, the agricultural sector has increasingly relied on advanced machinery, including tractors, combines, balers, and sprayers, to enhance efficiency and productivity. The continuous improvements in agrarian equipment are driven by rising food demand, increasing production costs, and a shrinking labour pool. Modern technologies, including variable rate technology, autosteer systems, GPS/RTK, and automatic steering, have further revolutionized agricultural operations. Autonomous agricultural machines (AAM) are emerging as the next step in this technological evolution, with scientists and engineers actively working on their development to improve farming efficiency (Berenstein et al. 2012; Edet and Mann 2020). A key aspect of AAMs is the design of an effective automation interface that enables human supervisors to interact with and remotely oversee these machines (Edet et al. 2019). Research in remote supervision reveals that human supervisors play a crucial role in task assignment, resource allocation, task execution monitoring, and emergency intervention (Cornet et al. 2025). To perform these functions effectively, supervisors must be able to assess situations accurately and take necessary actions when required (Edet et al. 2022). This necessitates an automation interface that facilitates real-time monitoring, ensuring usability and situational awareness for remote supervisors (Panfilov and Mann 2018).

Despite significant advancements in the design of automation interfaces for autonomous agricultural machinery, several challenges remain. Human-machine interface (HMI) usability is a considerable issue, particularly in remote supervision. Many studies have focused on the representation and automation of telemetric data, as well as the usability of interface systems. Yet, limited research has been conducted on the supervisor's perspective regarding interface effectiveness (Edet et al. 2018). Another critical challenge is ensuring seamless communication between the automation interface and the agricultural machine, especially in areas with weak cellular signal strength. While Green et al. (2021) recommend real-time video transmission for edge-of-field surveillance in areas with strong network coverage, they also note that alternative methods such as radio-based signalling are needed where connectivity is limited. Although my study did not implement radio transmission, it addressed this challenge by evaluating how interface design and use-case constraints influence the effective use of video under varying bandwidth conditions. Specifically, the work focused on determining whether integrating live video meaningfully improves usability and situation awareness, and whether video can be deployed selectively or contextually. In this way, the study contributes guidance on how video can be adapted, not replaced, to remain usable even when connectivity is imperfect. Additionally, human factors, such as mode confusion, misuse, and disuse of automation, remain underexplored, which affects adoption and trust in AAMs (Albers et al. 2020).

The practical design of automation interfaces for AAMs is crucial not only for optimizing system performance but also for supporting operator well-being by reducing cognitive workload, minimizing stress, and enabling clearer, safer decision-making. This study aims to address gaps in the usability of automation interfaces by evaluating the impact of real-time visual information on the remote supervision of AAMs. This research seeks to enhance the remote supervisor's ability to monitor and manage an autonomous agricultural sprayer effectively by integrating live video and graphical indicators that interpret sensor data (Panfilov and Mann 2018). The findings of this study will provide valuable insights into the development of HMIs that enhance usability, promote safety, and support informed decision-making in agricultural automation.

The **main objective** of this research is to evaluate the interface for remotely supervising autonomous agricultural machines.

## 2.0 LITERATURE REVIEW

### 2.1 Advances in Autonomous Agricultural Machinery

Major agricultural machinery manufacturers have demonstrated strong industry momentum toward autonomous farming technologies. Companies such as John Deere, New Holland, and others are actively showcasing concepts for fully self-governing machines (Bechar & Vigneault, 2016; John Deere, 2017; New Holland, 2016). At the same time, several smaller firms and engineering groups are contributing to this trend by developing aftermarket kits that convert conventional tractors into autonomous units (Demarest 2015; Emmi et al. 2014). Together, these developments show that autonomy in agriculture is no longer theoretical but an active commercial direction supported by both large equipment manufacturers and specialized technology providers. Moorehead et al. (2009) demonstrated that automating repetitive tasks in orchards, such as mowing and spraying, can increase output by substituting for a single supervisor overseeing multiple semi-autonomous tractors. According to Moorehead et al.2012, testing the technology produced a notable 30% increase in productivity compared to the traditional (manual) tractor control method. Better path design, consistent work pace, no breaks, and removing tractor backup are all elements that guarantee increased production. However, the system needs a human supervisor to assign tasks and address issues that automation cannot resolve.

CNH Industrial (New Holland) unveiled its autonomous tractor concept in 2016 (New Holland 2016). The tractor serves as a bridge connecting conventional and fully autonomous tractors. Because it has a regular cab, it can operate manually and carry out tasks independently or in conjunction with other equipment (Figure 1). A desktop computer or a portable tablet can be used to manage and observe the tractor. In this context, supervised automation refers to an intermediate level of autonomy in which the tractor can perform basic navigation tasks—such as following a predefined path and detecting obstacles using onboard sensors but still requires a human supervisor to make higher-level decisions. Although the machine can identify obstructions, it does not autonomously plan avoidance routes. Instead, the supervisor evaluates the situation and decides how the tractor should navigate around or avoid the obstacle.

This places the system at Level 2–3 autonomy of situation awareness, where the machine handles continuous control functions but still relies on human judgment in unexpected situations. The system used in my study aligns with this supervised automation level because the autonomous sprayer followed programmed waypoints independently but required the supervisor to intervene when obstacles, anomalies, or safety-critical events were detected.


**Figure 1:** T8 Blue Power tractor, a concept autonomous tractor by The New Holland (newholland.com)

A study titled "Hands-Free Hectare" was conducted in 2017 by British academics (Hands-Free Hectare 2017). The initiative claimed to be the first to utilize drones and autonomous agricultural equipment for exclusive crop cultivation. According to the researchers, using lighter, more compact equipment rather than the typical type enhances soil health and is better suited to precision farming techniques. The Iseki tractor was used for both seeding and spraying, with a vineyard drill and a precision sprayer. The harvest was conducted using a Sampo harvester, adapted to operate independently, initially intended for harvesting trial plots. The project aimed to demonstrate that all the technologies required to grow crops using self-sufficient machinery had been created.

There are still concerns regarding the safety and dependability of autonomous farm vehicles (Lyon 2017). Large, heavy, and mobile agricultural machinery can be hazardous when used alone if safety measures fail (Conesa-Muñoz et al. 2015). Major manufacturers have developed technologies that ensure the autonomy of agrarian machinery, including RTK-GPS, auto-steer, auto-turn, laser and RGB sensors, machine vision, and computational techniques, which collectively enhance operational precision and serve as critical safety mechanisms by reducing navigation errors, improving obstacle detection, and preventing unintended machine movements (Li et al. 2009; Lyon 2017). These technologies form the foundation for safe autonomous operation. Yet, they still require reliable supervision to manage unexpected hazards, system failures, or environmental conditions that automation alone cannot fully resolve. Until a tractor can respond to and avoid unforeseen impediments, these technologies will only be helpful in autonomous mode, ensuring it can follow a predetermined path (Blackmore et al. 2004). Agricultural devices that are autonomous or semi-autonomous still need a human to oversee operations and address issues that the system cannot resolve (Endsley 2017). Therefore, designing a clear, reliable human–machine interface is essential to ensure operators can safely supervise and control autonomous agricultural machines.

## 2.2 Remote supervision of an autonomous system

In remote supervision of autonomous systems, multiple autonomous machines are monitored and controlled from a central location. This approach is particularly advantageous for managing fleets of autonomous agricultural machines (AAMs), as it enables a single operator to oversee multiple units simultaneously. Remote supervision arises from maximizing human resource efficiency and leveraging automation to enhance operational effectiveness (Sanchez and Duncan 2009).

To support adequate remote supervision, the human–machine interface (HMI) must be designed to provide clear, comprehensive, and real-time information about each machine's status and performance. While remote supervision has shown numerous benefits, including reduced labour costs, improved coordination of farm operations, and faster response to issues (Edet and Mann 2020), it has already been implemented in agricultural tasks, such as grain handling and machine speed control. For example, the one-step automation program enables remote access to real-time bin status and live video feeds via mobile devices. Similarly, Stentz et al. (2002) developed a semi-autonomous tractor for spraying tasks. In their system, the operator first drives the tractor semi-autonomously to map the field layout and identify spray zones, after which the machine can be remotely supervised during operation.

However, remote supervision also presents challenges. A key concern is ensuring the HMI remains intuitive and provides accurate feedback to maintain situational awareness. Advancements in sensor technology, artificial intelligence, and high-speed networks such as 5G have made remote operation a practical method for controlling various types of machinery (Kallioniemi et al. 2021). One significant advantage is the ability to operate equipment in hazardous environments. However, the absence of direct sensory feedback from the machine can hinder the operator’s situational awareness, posing a significant challenge for remote operations.

Ensuring the safe and efficient operation of AAMs under varying and unpredictable field conditions requires robust supervisory systems. Panfilov and Mann (2018) emphasized the importance of real-time monitoring interfaces and human-in-the-loop control. To address these issues, they proposed integrating edge computing and autonomous decision-making systems to support operational reliability while maintaining human supervision as a fallback.

Similarly, Green et al. (2021) investigated the impact of video latency on remote supervision. They found that video delay increased markedly with increasing video resolution. However, in areas with good cellular coverage and at higher resolutions, cellular transmission provided lower latency than radio transmission. These findings underline the critical need to minimize latency in interface design and ensure a reliable communication infrastructure for effective remote monitoring. Together, these studies underscore the need to integrate advanced technologies with user-centred interface design to support the successful deployment and supervision of autonomous agricultural systems.

## 2.3 Tools for Assessment of Human-Machine Interaction

### 2.3.1 USABILITY

The usability of automation interfaces plays a vital role in ensuring effective human-machine interaction, particularly in high-stakes and dynamic environments such as remote supervision of autonomous agricultural machines (Edet et al. 2020). According to ISO 9241-11 (ISO 2018), usability encompasses effectiveness, efficiency, and satisfaction within a specific context. These principles are widely accepted across various disciplines and serve as a foundation for evaluating system performance in real-world applications.

#### 2.3.1.2 Machine Usability

Usability is a property that depends on the interactions among users, products, tasks, and environments. The ISO 9241-11 standard (ISO 2018) offers a standard definition, describing usability as the "*extent to which specified users can use a product to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use*". Other definitions expand on these ideas, emphasizing user engagement and ease of interaction (Nielsen 1993), but the core elements of effectiveness, efficiency, and satisfaction remain central across various perspectives. High usability in remote agricultural supervision interfaces ensures operators can monitor and control autonomous machines effectively, which is critical for safe operations in dynamic field environments. Enhancing usability reduces learning curves, minimizes operational errors, and boosts productivity, making it central to agricultural automation (Adamides et al. 2017). The ISO definition aligns most closely with this thesis, as it captures the multi-dimensional usability relevant to remote supervisory interfaces of autonomous farm machines.

#### 2.3.1.3 Assessment of Usability

Several key elements are essential in assessing the usability of automation interfaces for remote supervision of autonomous agricultural machines: effectiveness, efficiency, learnability, satisfaction, and high tolerance. Effectiveness measures how well users can wholly and accurately achieve their intended tasks, which is essential in remote supervision, where precision in monitoring and control directly impacts productivity and safety in agricultural operations (Ren et al. 2022). Efficiency, on the other hand, refers to the time and resources required for users to complete tasks. A well-designed interface must facilitate quick responses and seamless interactions, enabling users to monitor and control machines without delays remotely (Chang and Johnson 2021). Achieving this efficiency can be challenging, especially with complex systems involving multiple autonomous machines, but it is essential for maintaining workflow continuity in time-sensitive agricultural tasks. Learnability reflects how easily users can learn to use the interface. A simple design enables users to understand and operate the system with minimal training, reducing onboarding time for new operators and facilitating rapid adjustments to system updates (Lee and Ryu 2023). Satisfaction measures how comfortable and pleasant users find the interface. High satisfaction, often assessed through user feedback, is crucial for the long-term adoption of remote supervision technologies, as users are more likely to rely on systems they find enjoyable and straightforward (Lee et al. 2019). Additionally, error tolerance examines the system's ability to prevent, minimize, or assist users in recovering from mistakes. High error tolerance can include features such as error prompts, undo options, and confirmation prompts that help minimize user errors. In remote supervision, reducing errors is essential to prevent accidents or damage to autonomous machinery, as mistakes can lead to costly disruptions in agricultural production (Wu et al. 2021). By evaluating these usability elements, a comprehensive understanding of the interface's strengths and weaknesses can be gained, guiding further development to improve user experience and operational performance in autonomous agricultural systems. In this study, the interface was designed and assessed with a focus on three core usability dimensions: effectiveness, efficiency, and user satisfaction.

#### 2.3.1.4 Metrics in assessing the various usability characteristics

Each element of usability effectiveness, efficiency, learnability, satisfaction, and error tolerance is assessed using metrics intended to record the level and reliability of user interaction with the automation interfaces used for remote supervision of autonomous agricultural machinery. For effectiveness, the primary metrics include task completion rate and accuracy, which assess whether users can achieve their objectives and how precisely they can do so. For example, if the interface enables operators to accurately monitor machine status and minimize command errors, it scores higher in effectiveness (Ren et al. 2022). These metrics can reveal potential obstacles to task performance, particularly in the high-stakes environment of agricultural automation, where tasks must be completed without error. Efficiency is typically assessed by measuring time-on-task and the number of actions required to complete a function. These metrics reveal how quickly and effortlessly users can execute commands and gather relevant information. In agricultural settings, where time-sensitive tasks are shared, efficiency metrics highlight problems or inefficiencies in the interface, guiding improvements to streamline remote monitoring and control processes (Lee and Ryu 2023). Learnability is assessed by tracking time to proficiency and frequency of help requests or errors during initial use. These metrics offer insight into how quickly new users can become comfortable and proficient with the interface, which is crucial in remote supervision, where operators must rapidly adapt to new software. A highly learnable interface will show shorter times to proficiency and fewer instances of user confusion or errors, making it more adaptable to various operator skill levels (Lee et al. 2019). Satisfaction metrics are gathered using user feedback surveys and post-task ratings, which gauge users' comfort, perceived ease, and enjoyment when interacting with the interface. These qualitative metrics are crucial for understanding the user's subjective experience, which can significantly influence the long-term use and acceptance of the technology. A high satisfaction rating indicates that users are more likely to embrace and rely on the interface in daily operations consistently (Lee et al. 2019). Finally, error tolerance is measured by recording the error rate, severity, and recovery time. These metrics evaluate the frequency of user errors, their impact on task completion, and the ease with which users can recover from them. In agricultural machinery, errors can have costly and even hazardous consequences; error-tolerance metrics are vital for ensuring that the interface supports safe and effective error management (Wu et al. 2021). These metrics provide a comprehensive view of each usability element, guiding iterative improvements to create a robust and user-friendly interface.

#### 2.3.1.5 Observational and Subjective Measures

Usability studies typically classify measures into observational/objective and subjective measures (Lewis and Sauro 2021). Observational measures often include task completion times, error rates, and the frequency of system failures, providing objective data on system performance. These measures are used to identify usability problems and assess the efficiency of task execution. For example, long task completion times might indicate complex workflows or poorly designed interfaces (Irizarry et al. 2012). Additionally, system response times, user path deviations, and interaction accuracy are standard observational measures that help identify design inefficiencies (Lorenz et al. 2020). On the other hand, subjective measures rely on user self-reports and questionnaires to capture perceptions of ease of use and satisfaction (Lewis 2018). These measures are essential for understanding the emotional and experiential aspects of interaction. Subjective feedback can reveal insights into user frustration or preferences that may not be evident from observational data alone (Pham et al. 2023). Furthermore, subjective assessments can vary significantly based on user experience, cultural background, and expectations, highlighting the importance of diverse participant sampling in usability studies.

**Table 1: Advantages and Disadvantages of Observational and Subjective Measures in Usability Studies**

| Measure Type | Advantages | Disadvantages |
| --- | --- | --- |
| Observational Measures (Lewis and Sauro 2021) | • Objective data<br>• Clear performance measures<br>• Less user influence | • Limited to system performance<br>• Doesn't assess subjective experience<br>• Resource-intensive |
| Subjective Measures (Lewis 2018) | • Captures user perception<br>• Cost-effective | • Response bias<br>• Potential misinterpretation |

| | | |
|---|---|---|
| | • Quick to collect | • Overreliance on self-reports |

#### 2.3.1.6 Subjective usability assessment strategy tools

Some practical subjective tools for evaluating usability and user experience include surveys, interviews, and questionnaires, which are essential for gathering user feedback and insights during interface assessment (Madan and Kumar 2012). Surveys are used to efficiently collect data from large audiences, providing quantitative insights into user preferences, satisfaction levels, and usability challenges. They are handy for identifying common trends and patterns in user experiences. Interviews, on the other hand, provide a more in-depth understanding of user behaviour and needs. Through direct conversations, researchers can explore specific issues, uncover underlying motivations, and clarify ambiguities in user responses. Questionnaires serve as structured tools that combine quantitative and qualitative approaches, enabling researchers to collect detailed feedback while maintaining consistency in data collection. Capturing users' perceptions and feedback is elaborated further in the succeeding sections. In this study, structured questionnaires were adopted as the primary subjective evaluation tool because they provide a consistent, reliable means of measuring users' perceived usability and situational awareness across all participants.

**Table 2: Advantages and Disadvantages of Subjective Data Tools**

| Subjective tools | Advantage | Disadvantage |
|---|---|---|
| Surveys (Lewis and Sauro 2021) | - Efficient for collecting data from a large audience.<br><br>-Standardized responses allow for easy analysis | - Limited depth of responses<br><br>- Misinterpretation of questions can lead to inaccurate data. |
| Interviews (Muddimer et al. 2012) | - Provides in-depth insights into user experiences<br><br>- Allows clarification of responses in real-time | - Time-consuming and resource-intensive<br><br>- Responses may be influenced by interviewer bias |
| Questionnaires (Pham et al. 2023) | - Combines structured and open-ended questions<br><br>- Flexible for quantitative and qualitative analysis | - Risk of low response rates<br><br>- Fixed questions may not fully capture user perspectives. |

#### 2.3.1.6.1 System Usability Scale (SUS)

The System Usability Scale (SUS) is a simple yet effective tool for evaluating the usability of various interfaces, including those used in remote supervision of autonomous agricultural machines. Developed by John Brooke, the SUS consists of a 10-item questionnaire rated on a 5-point Likert scale, in which users indicate their agreement or disagreement with statements about the system's usability (Brooke 1996). Each question alternates between positive and negative wording to encourage balanced responses. SUS provides a quick assessment of usability, with scores ranging from 0 to 100, which can be interpreted using benchmarks to classify usability like "poor," "acceptable," or "excellent." Its simplicity makes it easy to administer and interpret, even without extensive usability training. The application of SUS in remote supervision interfaces is valuable because it enables researchers and designers to gather quick feedback from operators about the usability of complex systems, such as those for autonomous agricultural machinery. It helps identify whether users can efficiently interact with the interface to monitor and control machines remotely, which is critical for time-sensitive farm tasks where usability directly impacts productivity (Muddimer et al. 2012). One significant merit of SUS is its versatility; it can be applied to nearly any system or interface and is effective even with small sample sizes, making it ideal for early-stage usability evaluations and iterative design processes (Lewis 2018c). SUS is also highly reliable and widely recognized in usability studies, allowing comparisons across different studies or systems due to its standardized scoring method. However, SUS has some limitations. Its scores lack context-specific details, so while it indicates overall usability, it does not reveal specific usability problems or areas needing improvement (Martins et al. 2015). Additionally, the language of the SUS items may sometimes feel generic, and without tailoring, it may fail to capture specific nuances in specialized fields, such as agricultural automation. Despite these drawbacks, SUS remains a go-to tool for usability assessment due to its simplicity, efficiency, and strong psychometric reliability.

#### 2.3.1.6.2 Post-Study System Usability Questionnaire (PSSUQ)

The Post-Study System Usability Questionnaire (PSSUQ) is a subjective usability assessment tool developed to evaluate user satisfaction with a system immediately after task completion. Created by James Lewis in 1992 at IBM, the PSSUQ comprises 16 to 19 items, depending on the version, and utilizes a 7-point Likert scale to measure three primary aspects of usability: system usefulness, information quality, and interface quality (Hodrien and Fernando 2021). The PSSUQ aligns closely with the earlier usability metrics. System usefulness reflects effectiveness and efficiency, information quality relates to clarity and cognitive load, and interface quality corresponds to user satisfaction and ease of use. Thus, the PSSUQ directly measures the key usability dimensions defined in this study. This tool provides a quantitative view of user satisfaction. It is well-suited for assessing interfaces used in complex environments, such as the remote supervision of autonomous agricultural machines, where user satisfaction can influence the system's overall effectiveness. In the context of autonomous agricultural systems, PSSUQ can capture user feedback on the sensitive interface and ease of navigation, which are critical for operators who rely on efficient remote control to manage machines in real-time (Vlachogianni and Tselios 2023). PSSUQ's detailed questions about the quality of information and interface layout are beneficial for understanding if the interface provides clear and relevant information for task-oriented decision-making, which is essential in the high-stakes environment of agricultural machinery management. One of the primary merits of PSSUQ is its comprehensive focus on multiple aspects of user experience, which provides a richer view of usability compared to more general scales, such as the System Usability Scale (SUS) (Lewis 2018). Its specific categories allow researchers to pinpoint precise usability issues, making it especially useful for targeted improvements. However, the PSSUQ has limitations; its detailed structure can make it time-consuming for participants, and the 7-point scale can sometimes lead to variability in responses due to subjective interpretations of mid-scale ratings (Tullis and Albert 2013). Furthermore, since PSSUQ is typically administered after task completion, it may not capture usability issues experienced over extended periods. Despite these challenges, PSSUQ remains a valuable tool in usability studies, providing in-depth insights that can guide iterative design improvements for complex, task-driven interfaces, such as those used in agricultural automation.

#### 2.3.1.6.3 NASA Task Load Index (NASA-TLX)

The NASA Task Load Index (NASA-TLX) is a subjective assessment tool developed by the National Aeronautics and Space Administration (NASA) to measure perceived workload during task performance. Introduced by Sandra Hart and Lowell Staveland in 1988, the NASA-TLX evaluates six dimensions of workload: mental demand, physical demand, temporal demand, performance, effort, and frustration level (Said et al. 2020). Each dimension is rated on a scale from 0 to 100, and a weighting process is used to calculate an overall workload score. This tool helps evaluate the usability of interfaces that require intense user interaction, such as those used for remotely supervising autonomous agricultural machines. In such contexts, the NASA-TLX provides insight into how challenging or stressful the interface is, which is crucial for identifying design features that may hinder operators' ability to manage autonomous systems effectively. The NASA-TLX is widely applied in usability studies to evaluate how interfaces contribute to perceived workload, particularly in high-stakes settings such as aviation, healthcare, military operations, and remote supervision of autonomous systems, where performance and safety are top priorities (Grier 2015). When applied to agricultural automation interfaces, NASA-TLX helps determine whether the remote supervision system imposes unnecessary cognitive or physical burdens, thereby affecting operators' efficiency and satisfaction. By identifying workload problems, NASA-TLX can guide interface improvements to reduce mental strain and enhance overall usability. The primary merit of NASA-TLX is its ability to provide a comprehensive picture of workload, going beyond usability to capture how different demands contribute to the overall user experience. This level of detail makes it highly informative for iterative design, particularly for interfaces where task demands vary significantly (Alaimo et al. 2020). However, the weighting process of NASA-TLX can be complex, requiring users to compare workload dimensions, which can be time-consuming and may introduce subjective bias (Wickens et al. 2015). Additionally, the tool's reliance on self-reported measures makes it sensitive to individual interpretations, potentially leading to user inconsistencies. Despite these drawbacks, NASA-TLX remains a valuable tool in usability assessment, particularly in applications where understanding workload is crucial for interface optimization.

#### 2.3.1.6.4 User Experience Questionnaire (UEQ)

The User Experience Questionnaire (UEQ) is a widely used tool for measuring a system's overall user experience (UX), comprehensively evaluating both usability and emotional aspects of interaction. Developed by Laugwitz, Held, and Schrepp in 2008, the UEQ assesses six key dimensions of user experience: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty. The questionnaire comprises 26 items, each rated on a 7-point Likert scale, enabling researchers to assess users' perceptions of various system aspects (Laugwitz et al. 2008). In the context of autonomous agricultural machinery, the UEQ is particularly useful for evaluating the functional usability of the remote supervision interface and operators' emotional responses, which can influence long-term adoption and user satisfaction. In terms of application, the UEQ helps assess systems with complex interactions, such as interfaces used for remote management of autonomous agricultural machines. It allows researchers and designers to understand how users perceive the interface's practical and emotional aspects, such as whether it feels intuitive, dependable, engaging, or stimulating (Tullis and Albert 2013). This is especially important in agricultural environments, where the human-machine interaction must be efficient and pleasant to maintain user engagement and prevent errors in high-stress, time-sensitive tasks. The principal merit of the UEQ lies in its ability to provide a holistic view of user experience by measuring both usability and emotional responses. Capturing qualitative user impressions that extend beyond pure functional performance is highly beneficial, as it helps identify areas for improvement in interface design that may affect user satisfaction and overall system acceptance (Hassenzahl 2013). Furthermore, the 7-point scale and precise, well-defined categories make it easy to interpret and compare across different systems. However, a notable demerit of the UEQ is that it can be somewhat broad, making it less suitable for highly specialized usability assessments that require in-depth analysis of specific aspects of system use. Additionally, because the questionnaire measures subjective feelings, its results may vary depending on individual user differences, potentially leading to inconsistent feedback when sample sizes are small (Schrepp 2023). Despite these drawbacks, the UEQ remains a popular and valuable tool for measuring overall user experience in various contexts, including agricultural automation.

#### 2.3.1.6.5 Computer System Usability Questionnaire (CSUQ)

The Computer System Usability Questionnaire (CSUQ) is a widely recognized tool for assessing user satisfaction with software interfaces. Developed by Lewis (1995), the CSUQ contains 16 items that evaluate three key dimensions of usability: system usefulness, information quality, and interface quality. The items are rated on a 7-point Likert scale, enabling users to express their level of agreement or disagreement with each statement. The CSUQ is designed to be easy to administer and interpret, making it suitable for quickly gathering user feedback on a system's performance. In the context of autonomous agricultural systems, the CSUQ is particularly valuable for assessing the usability of interfaces used in remote supervision, where both system functionality and ease of interaction are essential for successful task execution (Lewis 2018). By focusing on aspects such as the system's functionality for task completion and the clarity of the information provided, the CSUQ helps evaluate whether the interface meets the practical needs of operators managing agricultural machinery remotely. In terms of application, the CSUQ is highly beneficial for assessing agricultural automation interfaces because it measures key elements that affect an operator's ability to supervise and control autonomous machines efficiently. For instance, it helps identify whether the interface provides clear, accurate, and timely information that aids operators in making critical decisions (Lewis and Sauro 2021). Additionally, the focus on interface quality enables the identification of design flaws that may hinder ease of use, which is particularly important when operators must react quickly to unexpected events in agricultural environments. The primary merit of the CSUQ is its ability to thoroughly evaluate the interface's functionality and quality, offering clear insights into user satisfaction across critical usability dimensions. This makes it an excellent tool for guiding iterative design improvements (Lewis 2018). However, the CSUQ's downside is that, like many usability questionnaires, it may not fully capture the nuances of user experience. It relies on self-reported data, which may vary based on individual perceptions and personal biases, leading to inconsistent responses. Moreover, while it provides valuable feedback on usability, it may not be as detailed in identifying specific usability problems as other assessment methods, such as task-based usability testing (Sauro 2011). Despite these limitations, the CSUQ remains a valuable tool for assessing the overall effectiveness of interfaces, particularly in complex systems such as autonomous agricultural machines.

**Table 3: Comparison of Subjective Usability Assessment Tools: Advantages and Disadvantages**

| Subjective tools | Advantages | Disadvantages |
|---|---|---|
| System Usability Scale (SUS) (Brooke 1996; Martins et al. 2015) | - Simple, quick, and easy to administer.<br>- Effective with small sample sizes.<br>- Standardized scoring allows comparison across systems. | - Lacks context-specific details.<br>- May not identify specific usability issues. |
| Post-Study System Usability Questionnaire (PSSUQ) (Hodrien and Fernando 2021; Sutcliffe and Basapur 2020) | - Provides detailed feedback on system usefulness, information, and interface quality.<br>- Effective for targeted usability improvements | - Time-consuming due to detailed structure.<br>- Long-term usability issues may be missed as they are task-specific. |
| NASA Task Load Index (NASA-TLX) (Wickens et al. 2015; Alaimo et al. 2020) | - Comprehensive evaluation of workload dimensions.<br>- Useful in high-stakes settings.<br>- Helps identify workload issues for interface optimization. | - A complex weighting process may introduce subjective bias.<br>- Subjective self-reported measures can lead to variability in results. |
| User Experience Questionnaire (UEQ) (Laugwitz et al. 2008; Schrepp 2023) | - Measures both usability and emotional aspects.<br>- Easy to interpret and compare across systems.<br>- Holistic view of user experience. | - May be too broad for specialized assessments.<br>- Subjective feedback can lead to variability, especially with small samples. |
| Computer System Usability Questionnaire (CSUQ) (Lewis and Sauro 2021) | - Focuses on system usefulness, information quality, and interface quality. | - Relies on subjective data, leading to variability.<br>- May not identify specific usability |

| | | |
|---|---|---|
| | - Clear insights for guiding iterative design improvements. | problems compared to task-based testing. |

The System Usability Scale (SUS) is chosen as the subjective assessment tool because it provides a quick and reliable measure of usability perception. The SUS is a widely validated instrument with proven reliability, even in complex settings, making it suitable for assessing the overall usability of HMIs for autonomous agricultural machines (Lewis 2018c). SUS is particularly suitable for this context because it allows operators to quickly express their impressions of the HMI, capturing high-level usability perceptions without requiring extensive time or effort. The choice of SUS over other subjective? Usability tools are justified by their flexibility and simplicity, which enable rapid assessment of both strengths and weaknesses in the interface. Additionally, SUS provides benchmarked scores, making it easier to compare usability results across different systems of the same HMI and facilitating improvements that align with user expectations (Lewis and Sauro 2021). Its concise format also minimizes respondent fatigue, which is essential in agricultural automation settings where operators may have limited time for detailed surveys. Overall, SUS is ideal for quickly and effectively capturing subjective usability insights, complementing objective measures to provide a well-rounded assessment of the HMI's performance in supporting remote supervision of autonomous agricultural machinery.

Human-Machine Interface (HMI) plays a crucial role in enabling operators to interact with and effectively manage agricultural machinery from a distance. This interface provides real-time monitoring, control, and decision-making by providing accurate, timely, and relevant information. The HMI should be sensitive, responsive, and provide clear, relevant information to support rapid decision-making, especially when unexpected situations arise in agricultural environments for the operators. It was designed with clear visualizations and user-friendly controls to minimize cognitive load, enabling operators to focus on managing multiple machines under various environmental conditions. Usability assessment of such interfaces aims to ensure that they are functional, reliable, intuitive, and satisfying for end users, ultimately enhancing operational efficiency. Automation interfaces are critical in bridging the gap between human operators and machine operations. They must balance visual information with system indicators to optimize situation awareness, a key element for timely and accurate interventions during machine operation (ISO 2018; Brabec et al. 2024). Real-time responsiveness and clear visualizations are essential for operators to effectively manage multiple machines in dynamic environments such as agricultural fields.

### 2.3.2 Situation Awareness

In addition to usability, the effectiveness of an automation interface hinges on its ability to support the supervisor's situation awareness (SA). Endsley (1995) defines SA in three progressive levels: (1) perception of environmental elements, (2) comprehension of their meaning, and (3) projection of their future status. In the context of agricultural automation, Level 1 SA involves a supervisor detecting system changes, such as alerts or anomalies. Level 2 includes understanding the significance of those changes, while Level 3 entails anticipating potential consequences. Information regarding a particular job or task can often be classified as essential or irrelevant. The task information is only relevant for SA. The person's perception of the information determines the achieved SA level.

According to Endsley et al. (2003)Level 1 SA is attained when an operator detects or knows all the information they need to complete the task.  To maintain situation awareness, various jobs require different types of information.  Usually, the operator perceives information pertinent to the task by combining visual and sensory signals (R.Endsley and J.Garland 2000).  Visual displays and other devices, for instance, provide navigational cues and indicators to an agricultural equipment operator. A system user may struggle to reach level 1 SA if they have too much information to process simultaneously, are distracted, or have other tasks that prevent them from detecting important information (Panfilov 2017). Therefore, ensuring that the user can quickly understand the information provided is a crucial component of achieving level 1 SA.

According to Endsley et al. (2003)Achieving level 2 SA indicates that the operator comprehends the significance of the perceived information related to pertinent objectives. To accomplish the present objectives, the operator needs to process the data, include relevant information, and gain a thorough knowledge. A comprehensive understanding of the system, its tasks, and its operational requirements is essential for achieving Level 2 situation awareness, which can be particularly challenging for operators. If a user lacks experience with a specific task or is unable to accurately interpret the significance of the information, they may struggle to reach level 2 SA.

According to Endsley et al. (2003), achieving level 3 SA indicates that the operator can perceive information, comprehend its significance in relation to pertinent goals, and predict how the situation will unfold. To reach level 3 SA, the operator must understand the existing state of affairs and the system's operation. The operator can be proactive, avoid unfavourable circumstances, and respond swiftly to emergencies by anticipating them. The operator may struggle to reach level 3 SA due to inadequate system understanding or information processing overload. Achieving Level 1 and Level 2 SA can be challenging due to insufficient system design and inexperience, and an operator may never attain Level 3 SA.

Many methods that evaluate SA can be categorized into the following types: i) process measurements, ii) behavioural and performance-based measurements, and iii) subjective and objective measurements (Endsley et al. (2003); Salmon et al. 2006; Bolstad 2008). These methods assess a person's situation awareness by evaluating their responses to task-related questions or SA-specific procedures Endsley et al. (2003).

#### 2.3.2.1 Indirect methods of situation awareness assessment

The indirect measurement approach utilizes the relationship between situation awareness and specific actions or activities. Once these activities or processes are measured, the SA may be ascertained. Process measures (verbal protocols, communication analysis, and psychophysiological metrics), as well as behavioural and performance-based measures (performance outcome measures and behavioural measures), are examples of indirect approaches (Endsley et al. 2003)Salmon et al. 2006.

##### 2.3.2.1.1 Process measures

During the verbal protocol, the participant explains their methods, choices, and thought processes as they perform the activity. To ascertain the proper SA, this is thereafter noted and examined. The verbal protocol is comparable to communication analysis, except that it involves two or more subjects. Rather than thinking out loud, the SA is calculated by recording the subjects' verbal exchanges and analyzing them. The bodily responses associated with the subject's SA are used to calculate SA in psychophysiological metrics. Heart rate and eye movements are part of the response (Endsley et al. 2003).

##### 2.3.2.1.2 Behavioural and performance-based measures

Behavioural and performance measures infer SA from the subject's behaviour or the task's effectiveness. The SA is known as a "behavioural measure" when it is derived from the subject's actions, but it is referred to as a "performance outcome measure" when it is derived from the task's effectiveness or result (Salmon et al. 2006). According to reports, both measurements are less reliable, as several variables, including the task environment and the operator's expertise, can also influence the subject's measured SA Endsley et al. (2003). For instance, operating a tractor over uneven ground. The operator also tends to steer the tractor carefully to prevent overturning, which could impair their performance and result in a low SA rating.

#### 2.3.2.2 Direct methods of situation awareness assessment

It is better to test a person's SA directly to reduce outside influence and improve the accuracy of the results, especially since indirect measurements have potential drawbacks, uncertainties, and inaccuracies. SA can be evaluated using both subjective and objective metrics (Actor 2016).

##### 2.3.2.2.1 Subjective measures

Subjective measurement compares the SA quality of different systems or processes by asking the subject to rate their SA quality over time based on their feelings. The Situation Awareness Rating Scale (SARS), Situation Awareness Subjective Workload Dominance Method (SA-SWORD), and Situation Awareness Rating Technique (SART) are a few examples of subjective measurements. These three factors demand attentional resources, supply of attentional resources, and situational understanding, which are combined to determine the subject's SA using the SART technique. These three aspects mentioned above are covered by the questions the subject responds to. The algorithm SA (calc) = Understanding - Demand - Supply is then used to calculate the SA level Endsley et al. (2003). SARS comprises 31 behavioural components that fall into eight distinct groups. Initially, it was intended for use in the aviation sector. To calculate their SA, participants assess these components on a 6-point scale Endsley et al. (2003). The SA-SWORD, on the other hand, is a modification of the SWORD method, originally developed to evaluate military design concepts. By comparing pairs of design concepts, the SA-SWORD method for evaluating SA finds the designs that maximize SA (Vidulieh 1989).

#### 2.3.2.2.2 Objective measures

While subjective assessment is practical, objective information regarding the design is crucial (Endsley et al. 2003). The Situation Present Assessment Method (SPAM) (real-time probe technique) and the Situation Awareness Global Assessment Technique (SAGAT) (frozen probe technique) are the two most commonly utilized objective measures. To evaluate the subject's SA at a given moment, SAGAT, which is flexible in both design and implementation, pauses the simulation task at random intervals Endsley et al. (2003). The subject's SA is then inferred by comparing the result with the accurate results. Besides the evaluation being included with the job, the online probe is comparable to the SAGAT. Therefore, the response time throughout the exercise is used to determine the person's SA (Gugerty 2011). SPAM offers an alternative when stopping the scenario is not desired. With this method, the operator is presented with questions in real-time, while the system displays are transparent. Situational awareness is demonstrated by the operator's accuracy and response time (Durso and Dattel 2004).

The Situation Present Assessment Method (SPAM) was selected as the objective SA measure in this study? because it delivers moment-to-moment estimates without halting the task. Unlike SAGAT's frozen-probe interruptions Endsley et al. (2003), SPAM's real-time queries preserve visual momentum, which is critical in our remote supervision scenario, where pausing is infeasible and video/indicators continuously evolve. Its transparent probes yield complementary metrics, including response accuracy and latency, capturing both knowledge and access time under varying workloads (Durso and Dattel, 2004; Gugerty, 2011). SPAM scales across scenarios, supports frequent sampling with minimal learning contamination, and integrates seamlessly with our HMI to trigger context-relevant questions at natural events while minimizing disruption and instrumentation overhead. Therefore, SPAM is the most appropriate objective SA measure for this study, given our need for continuous monitoring during dynamic video and indicator supervision.

### 2.4 Research Objectives

The objectives of this research are to assess the effect of real-time visual information on:

- The usability of an HMI developed for remote supervision of an autonomous agricultural machine (AAM).
- The situation awareness experienced by the remote supervisor during a remote supervision task.

# 3.0 METHODOLOGY

## 3.1 Experimental Infrastructure

To evaluate the remote supervision of autonomous agricultural machinery, this section outlines the experimental infrastructure developed for the study. It comprises a modified plot-size sprayer and a custom-designed Human-Machine Interface (HMI) simulator. Together, these components enabled realistic fault simulation, recorded video capture, and operator interaction analysis, providing a robust platform for assessing usability and enhancing situation awareness in agricultural automation systems

### 3.1.1 Instrumented Sprayer

The initial task was to develop an instrumented sprayer that would emulate an autonomous agricultural sprayer. A sprayer was chosen because it is simple and easy to explain to a person without farming experience. It is easy to display the process details using video cameras because all operations occur above ground. The sprayer enables easy fault simulation by allowing modification of various parameters, including boom position, tractor speed, water and pesticide tank levels, flow rates, and nozzle activation. A plot-sized sprayer (model SE-TR12-H25G12B) was upgraded to prototype functions anticipated for an autonomous platform (Figure 2). Solenoid valves were integrated at each nozzle to enable automated section control and deliberate fault injection. At the same time, a boom-control toggle was mounted beside the tractor operator's seat for convenient manual overrides. To test height-related errors, a simple actuator–stop mechanism was added, allowing the boom to be adjusted precisely and creating off-height conditions on demand. Complementing these actuation features, the sensing suite and its placement were designed to yield stable, interpretable signals under motion. Non-contact ultrasonic level transducers were mounted on top of the pesticide and herbicide tanks, aligned with the vertical centerline and aimed at the liquid surface, allowing the headspace distance to serve as a robust proxy for fill level. Boom height was tracked by an ultrasonic distance sensor fixed near mid-span and oriented toward the ground plane, allowing vertical clearance to be measured independently of terrain undulations. The electromagnetic flow meter was installed in the main discharge line, downstream of the pump and upstream of the boom manifold, to capture total system flow. These placements were chosen to maintain stable readings during motion, minimize hydraulic disturbance, and simplify cable routing to the controller.

The placement and integration of sensors were essential for simulating sprayer issues in a controlled and measurable manner. The ultrasonic tank level sensors allowed us to replicate depletion or refill faults by adjusting fluid volumes and monitoring whether the interface correctly detected abnormal changes in headspace distance. The boom-mounted ultrasonic distance sensor enabled simulation of off-height errors, since intentional actuator adjustments could be validated against real-time clearance readings. Similarly, the electromagnetic flow meter supported fault injection by quantifying flow reductions or surges when individual nozzles were shut off using solenoid valves. Together, these sensors ensured that induced malfunctions such as low tank levels, irregular boom height, or nozzle blockages were translated into stable and interpretable signals for participants to detect through the interface.

For experimental purposes, it was necessary to provide a video showing the sprayer in operation. Inspired by previous work by Edet and Mann (2018), it was determined that videos of the right and left booms, as well as a forward-facing view depicting the field ahead of the sprayer, would be relevant. A Raspberry Pi 4 was used as the core component of the video capture system. It was mounted on a Bolens Model 2028 lawn tractor that pulled the instrumented sprayer. Acting as both the capture device and video encoder, the Raspberry Pi 4 was connected to three cameras, with recordings stored locally on the device. Its affordability, flexibility, and strong community support made it an ideal choice. At the same time, its Broadcom chip enabled H.264 hardware-accelerated video encoding via OpenMAX, allowing efficient video processing and seamless visual feedback for the simulator.

The camera configuration included one front-facing camera mounted on top of the Bolens tractor and two side-mounted cameras (one on each boom), positioned at the same height as the nozzle spray cones to monitor nozzle performance and spray coverage (Fig. 2). The system was powered by a battery pack. A computer initiated the recording process, while the Raspberry Pi handled video storage. The recorded footage featured staged malfunctions that would commonly happen in real farming conditions for experimental validation and training, following a predefined yet randomized sequence to avoid recognizable patterns and enhance dataset robustness. During testing, recorded video feeds from the side cameras were displayed on separate monitors labelled “Left” and “Right” for precise real-time observation and post-analysis.

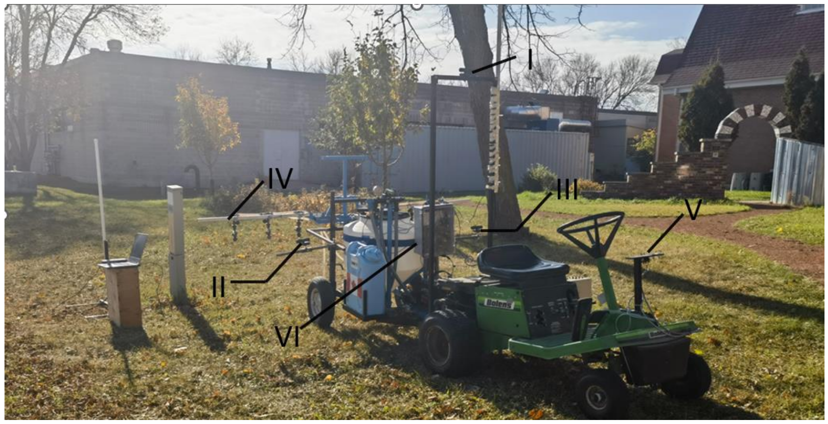



**Figure 2.** Plot size tractor and the sprayer modified for video recording

I-Front Camera, II-Right Camera, III-Left Camera, IV-Nozzle with Solenoid valve, V-Switch to Control Boom, VI-Electric Box

### 3.1.2 Automation Interface Simulator

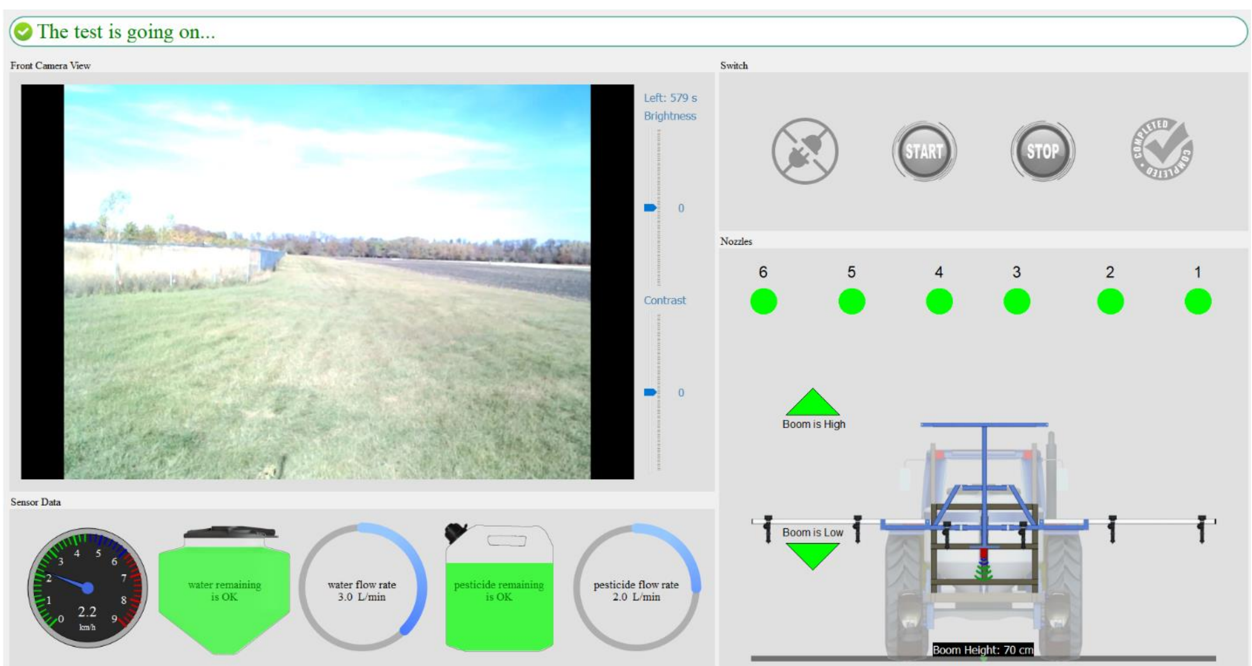



**Figure 3.** Design Layout of the Automation Interface Simulator.

To facilitate controlled testing and observation of operator responses to sprayer faults, an automation interface simulator (AIS) was developed for the instrumented sprayer. The AIS consisted of an HMI designed to display information for remote supervision of an agricultural sprayer (Fig. 3) and code that caused the HMI elements to change over time. The HMI was developed using a user-centred design approach that focuses on understanding the operator's needs, abilities, and limitations. At the same time, the design process was goal-oriented, meaning that each interface component was created to support specific operational goals—such as monitoring machine status, detecting anomalies, or responding quickly to hazards. These two approaches are not contradictory; instead, they work together. User-centred design ensures the interface matches the operator, while goal-oriented design ensures it supports the tasks and system objectives. Both were guided by established usability principles and situation-awareness theory to create an interface that is both intuitive for users and effective for operational performance. Based on the interface design principles utilized by previous researchers (Rakhra and Mann 2013; Panfilov and Mann 2018; Edet and Mann 2020), the HMI adopts a multi-screen layout inspired by professional supervisory control environments, enabling operators to monitor multiple subsystems of the autonomous sprayer simultaneously (Fig. 3). A notification bar was incorporated at the top of the interface to alert users to abnormal conditions and guide the supervisor during testing. It includes a message panel and a status icon that convey both the nature and priority of each alert, enabling rapid visual parsing before more detailed inspection. Recorded video from the forward-facing camera supports the first two levels of situation awareness perception, and comprehension - by maintaining a continuous visual context of field operations (Endsley 1995).

Graphical indicators display essential parameters, including tractor speed, tank levels, flow rates, boom height, and nozzle status, in a manner that reduces cognitive load and facilitates quick anomaly detection (Sweller 1988). Logical grouping follows the proximity-compatibility principle and the Gestalt laws of proximity and similarity. Parameters that must be interpreted together (e.g., tank level, flow rate, and nozzle state) are co-located, whereas action controls are visually segregated to avoid split attention.

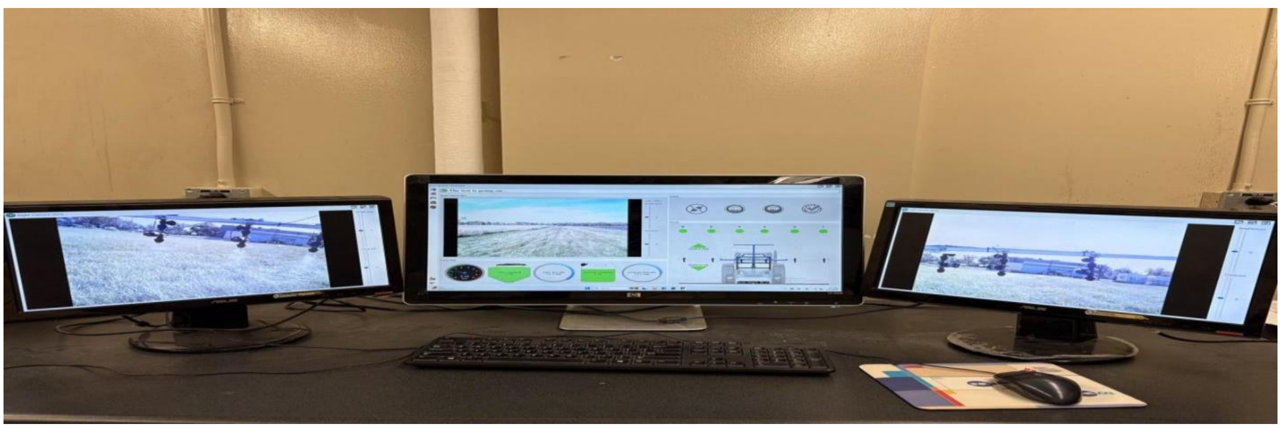
Control placement follows natural mapping and stimulus–response compatibility (Wickens and Hollands 2000). The boom-height readout aligns with the “Boom is High/Low” indicators it describes, nozzle icons are arrayed above the boom diagram to reinforce their spatial correspondence, and global actions (Start, Stop, Complete) are grouped near the notification bar they influence. Consistent iconography and labels create redundancy gain (colour, shape, and text), supporting preattentive recognition under glare or colour-vision variance(Wickens and Hollands 2000). Frequently used controls are positioned along the resting cursor path and sized to minimize movement time in accordance with Fitts’ Law (Fitts 1954). Less-frequent camera adjustments (brightness/contrast) are placed immediately adjacent to the video pane to reduce clutter and accidental activation, while preserving quick access under changing light conditions. Collectively, these ergonomic choices enhance usability and situation awareness and are expected to shorten detection and response times while reducing selection errors.

The HMI was developed using Python on a Raspberry Pi 4, with PyQt5 employed for graphical user interface (GUI) design, PyMySQL for data management, and the Requests module for external communication. This combination ensured seamless functional integration and real-time responsiveness.

The HMI depicted in Figure 3 was assumed to represent the baseline condition, an HMI devoid of video information about the spraying operation. Although a video of the field ahead of the sprayer was displayed on the HMI, it did not provide any information relevant to the sprayer's operation. To enable an investigation of the usability of video information for the task of remotely supervising an agricultural sprayer, two additional monitors were added on each side of the HMI (Fig. 4).

These additional screens showed video footage captured by cameras mounted on the instrumented sprayer, offering a comprehensive view of the spraying operation. The left and right cameras, strategically positioned on brackets at the nozzle level and centred on their respective booms, provided detailed visual information crucial for detecting issues such as nozzle clogging. Alongside the video feed, the Automation Interface Simulator (AIS) displayed machine status information and simulated agricultural equipment failures, enhancing its ability to replicate real-world scenarios. This integrated approach provided a more immersive, practical experience, enabling operators to effectively monitor and respond to a range of conditions and challenges encountered with agricultural sprayers.

**A.**



**B.**

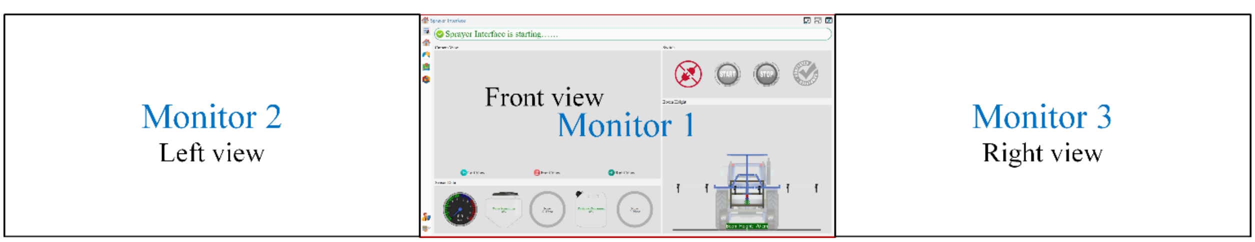



**Figure 4.** Multi-screen setup of the Automation Interface Simulator.

### 3.2 Video Dataset Generation (Pre-recorded Stimuli for AIS)

It is important to note that the instrumented sprayer was not in operation in real-time during the experimental trials. Instead, it was operated before the study to record video footage that could be integrated into the Automation Interface Simulator (AIS). Video generation took place on a rectangular lawn located east of the University of Manitoba's Fort Garry campus. This setting provided a consistent, controlled environment. 20 video clips, each approximately 10 minutes in length, were recorded to capture different operating conditions of the sprayer. Sprayer faults were intentionally staged during these sessions by manipulating system parameters, including flow rate, boom height, nozzle activation, and tank levels. For instance, nozzle clogging was simulated by obstructing specific nozzles, while boom misalignment was created by adjusting the boom position. These staged malfunctions were distributed across clips to provide varied fault scenarios for the experimental trials, ensuring realism and randomness in the testing environment.

### 3.3 Experimental Method

The Human-Machine Interface (HMI) usability evaluation was conducted through a structured process at the University of Manitoba. First, the HMI system was set up in the Agricultural Ergonomics Lab, where all hardware and software components were installed and tested to ensure full functionality. The lab environment was configured to simulate real-life conditions, allowing for effective participant interaction. The participant will monitor the interface to respond to any errors. Following the setup, a detailed ethics application outlining research protocols, consent forms, and data handling procedures was submitted to the university's Research Ethics Board to ensure compliance with ethical standards for human participant research. Upon receiving ethics approval, participants aged 18–35 were recruited through university networks. Individuals were selected based on at least 1 to 3 years of experience with agricultural machinery or precision farming technologies, or on their direct relevance to the target user group—such as students, technicians, and operators who regularly interact with farm equipment or autonomous systems. Participation was voluntary and based on informed consent. During the experiment, participants interacted with the HMI to complete predefined tasks that simulated real supervisory activities, such as monitoring machine status, identifying anomalies from indicators or video feeds, responding to probe questions, and making decisions based on the information presented on the interface. These tasks were designed to reflect typical responsibilities of a remote supervisor and to evaluate how effectively the HMI supported usability and situation awareness. The key parameters measured to assess situation awareness included response time (the time participants took to identify and respond to issues), accuracy (measured by participants' correct identification of faults based on the interface), and a usability assessment conducted using the SUS questionnaire. These parameters were measured through task performance metrics, structured observations, questionnaires, and interviews. The results were then used to assess the HMI system's effectiveness and pinpoint areas for improvement.

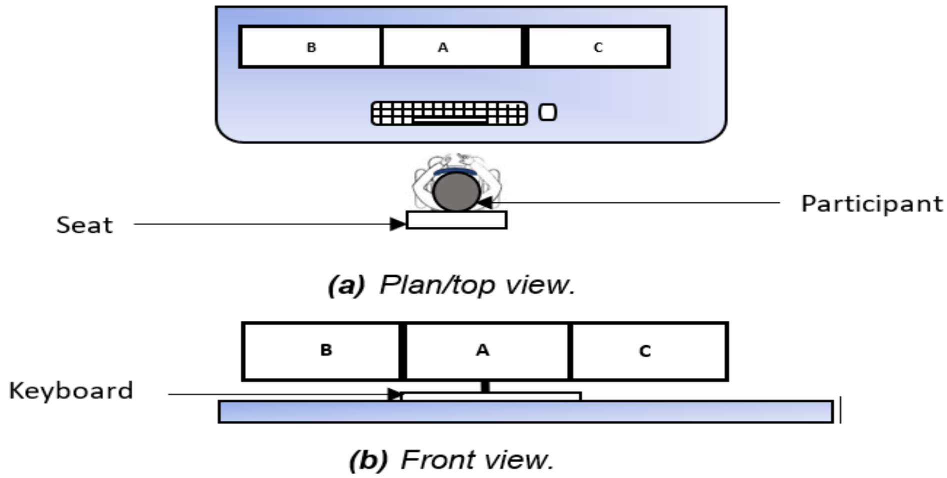



**Figure 5:** Experimental setup for assessing the error modalities.

### 3.4 Experimental Protocol

Participants first reviewed and signed informed consent approved by the University of Manitoba Research Ethics Board, then completed a standardized 5-minute orientation to the Automation Interface Simulator (AIS) and task procedures. Following training, they proceeded to the experimental session, which evaluated the Human–Machine Interface (HMI) for remote supervision of an autonomous agricultural sprayer. The session emphasized usability and situational awareness, with the primary objective of assessing each participant's ability to detect sprayer malfunctions in controlled scenarios. Performance was quantified by detection accuracy and response time, using standardized stimuli and instructions to ensure comparability across participants, as shown in Figure 5 below. Each session consisted of two trials presenting identical sprayer status information in two HMI formats: (1) HMI without videos of the sprayer, and (2) HMI complemented by a video of the sprayer. The order of the trials was randomized to minimize learning effects. The forward-facing camera view, displayed in the center of the HMI, was present in both conditions to mimic windows. This experimental design enabled us to isolate the impact of visual input on the HMI's usability and the supervisor's situation awareness. In video-supported trials, some malfunctions were visible in both the indicators and video footage, while others appeared only in the indicators to simulate sensor failure.

Participants were instructed to immediately click on-screen upon detecting any malfunction with the sprayer. Each trial lasted approximately 10 minutes and included 8 simulated malfunctions across six categories: water tank, pesticide tank, boom height, water flow rate, pesticide flow rate, and nozzle clogging. A colour-coded system, with green indicating normal operation and red indicating malfunction, was used to signal errors. After clicking an indicator, participants selected the identified issue from a predefined list, including low water tank level, low pesticide tank level, incorrect boom height, reduced water flow rate, reduced pesticide flow rate, and nozzle clogging. This allowed researchers to measure detection response time and accuracy rate.

Following each experimental trial, participants evaluated the HMI under both conditions (i.e., with and without video) using the SUS tool. The effectiveness of the HMI in supporting situation awareness was assessed using several key metrics, including response time and error-detection accuracy, user feedback on interface usability, and comparative performance between the video-supported and indicator-only conditions. These data comprehensively evaluated the HMI's design and its potential to support accurate and timely decision-making in the remote supervision of agricultural machines.

After the experimental procedure, participants completed a supplementary questionnaire where they could express their opinions on the usefulness of the video footage for supervising autonomous agricultural machines and provide open-ended feedback on the HMI's clarity and overall functionality.

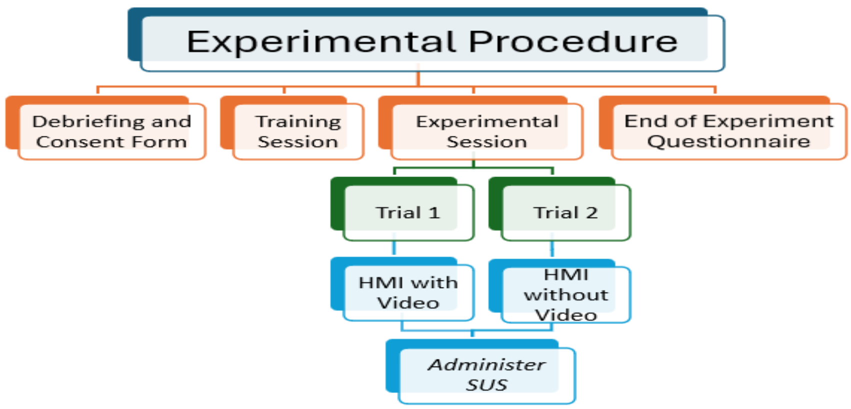



**Figure 6.** Experimental Protocol

### 3.5 Data Analysis

For usability, we converted each participant's System Usability Scale (SUS) rating for the two interface conditions (video vs. no-video) to the standard 0–100 metric and interpreted scores using the Sauro–Lewis curved grading scale (Lewis 2018), in which ≈85 indicates Excellent, 70–80 Good, 68 above average, and <50 Poor; operationally, we treated SUS ≥80% as a "good" usability outcome. SUS questionnaires were administered separately for each interface so that perceived usability could be compared directly; group differences were tested with an independent two-sample t-test at $\alpha = 0.05$. To enrich interpretation beyond a single composite score, We coded participants' comments using a simple thematic analysis: key statements were labeled, grouped into recurring themes (e.g., learnability, clarity of feedback, discoverability, visual clutter, workload), and then used to help interpret differences in SUS scores and workload impressions and used these qualitative categories to contextualize any observed SUS differences. Situation awareness (SA) was evaluated independently through two performance measures captured during scripted fault-detection tasks. Response time was defined as the interval from the programmed onset of an error to the participant's on-screen acknowledgment, as derived from simulator timestamps. To mitigate the undue influence of extreme values, we applied a 2 standard deviations (SD) outlier removal rule before conducting inferential testing. Accuracy was defined as the proportion of trials in which participants correctly identified the specific fault that occurred. We compared SA across interface conditions using a one-way repeated-measures ANOVA for response times and a chi-square test of independence for accuracy, both with $\alpha = 0.05$, thereby quantifying differences in detection speed and correctness under each HMI. Finally, we compared the SUS patterns with the SA results to investigate the relationship between perceived usability and objective detection performance, for interpretation purposes only, and not for hypothesis testing. To avoid confusing subjective assessments with performance-based measures and to maintain the study's goals (usability and situational awareness), we reported usability and situational awareness independently.

**4.0 Results and Discussion**

## 4.1 Participant demographics

A total of 20 individuals (M = 26.2 years, SD = 4.8; age range = 18–35 years) participated in the study. The sample comprised 17 males and 3 females, representing a predominantly young adult population. None of the participants reported prior experience in farming or agricultural machinery operation, so the group reflected naïve or non-expert users rather than professional operators. This demographic profile was appropriate for assessing how first-time or infrequent users might interact with a video-enhanced human–machine interface for remote supervision of an autonomous agricultural sprayer. All participants provided informed consent in accordance with the University of Manitoba Research Ethics Board guidelines and received a modest monetary honorarium in recognition of their time and contribution. Demographic data such as age, gender, and prior farming experience were collected through a brief pre-experiment questionnaire and were used to describe the sample and contextualize any observed differences in usability ratings and situation-awareness measures.

## 4.2 Effect of real-time visual information on usability

The SUS questionnaire consists of 10 standardized items; each rated on a 5-point Likert scale from "Strongly Disagree [1]" to "Strongly Agree [5]". Standard usability benchmarks from the literature were applied to support the interpretation of the SUS scores. Bangor et al. (2009) report benchmarks on the standard SUS 0–100 scale, we linearly converted our 0–5 usability ratings to a SUS-equivalent score by multiplying each mean rating by 20 (SUS-equivalent = $\text{rating}_{0\text{–}5} \times 20$). For example, a mean usability rating of 3.4/5 corresponds to 68/100, which aligns with the reported “above average” SUS threshold. More detailed thresholds classify scores of 70–80 as good usability and scores above 85 as excellent usability (Lewis and Sauro 2021). These standards were used to assess the acceptability of each interface.

An independent two-sample t-test was conducted to examine the effect of video information on participants' usability ratings, as measured by SUS. The results revealed a significant main effect of video information on SUS scores, $T(2, 38) = 2.46928$, $p < .01815$, $\eta^2 = .23$. This indicates that adding video information significantly influenced participants' response times, confidence in the system, and overall comfort during use. According to the SUS benchmark, usability scores were significantly higher for the HMI with video (Mean? = 80%, SD = 23.24) compared to the HMI without video (M = 64%, SD?), suggesting that the HMI with video better supports users in achieving their goals and is perceived as easier to use than the HMI without video, as seen in Fig. 6.

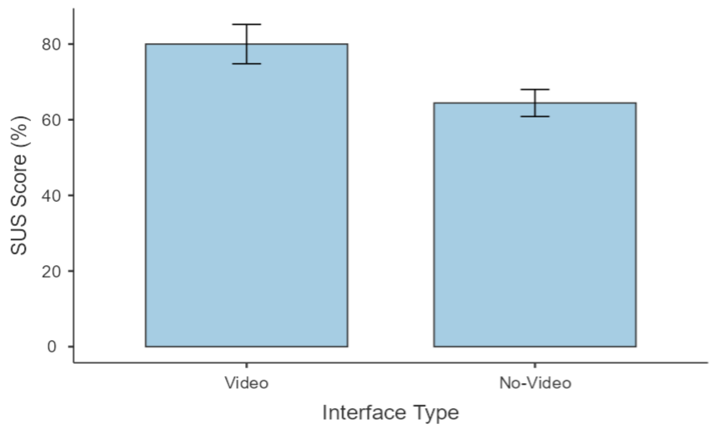



**Figure 7.** Mean System Usability Scale (SUS) score by interface type.

## 4.3 Effect of real-time visual information on situation awareness

### 4.3.1 Response Time

A one-way ANOVA was conducted to examine the effect of real-time information across different interface types, HMI with video and HMI without video, on participants' response times when projecting future system status. The analysis revealed no significant main effect of interface type on response time, $F(1, 19) = 0.715$, $p = .408$, $\eta^2 = .04$, indicating that interface type did not reliably affect response time. Mean response times were similar for the video HMI ($M = 3000$ ms, $SD = 759.9$) and the non-video HMI ($M = 2858$ ms, $SD = 747$). However, this difference was not statistically significant, as shown in Fig. 7 and Appendix 5. These findings suggest that both interface types support similarly efficient user performance in processing and projecting system status.

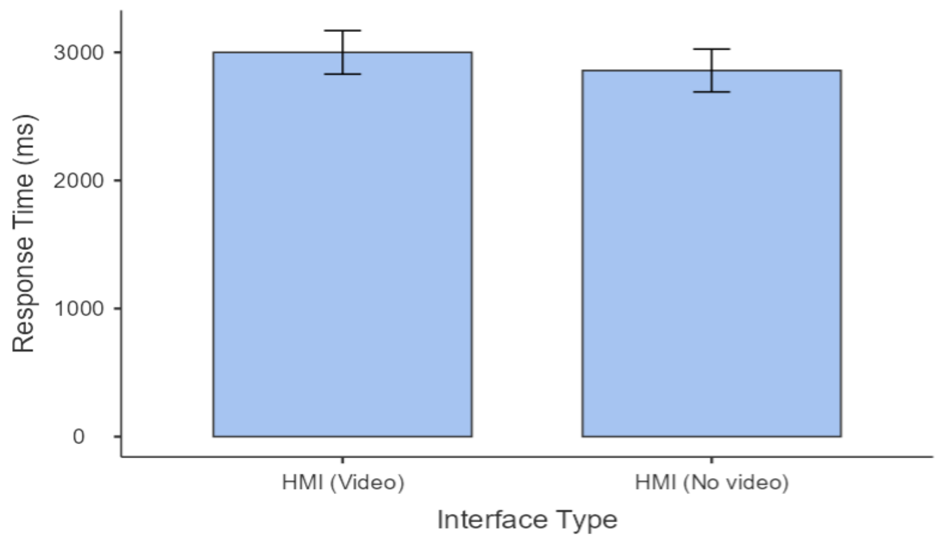



**Figure 8.** Mean response time (ms) by interface type. Error bars represent one standard error**.**

**4.3.2 Accuracy**

A chi-square ($\chi^2$) test of independence was conducted to examine the relationship between interface type (HMI with video and HMI without video) and response accuracy (correct vs. incorrect). The distribution of correct and incorrect responses varied significantly across the two interfaces, $\chi^2$ (1, N = 320) = 13.94, $p < .005$. The HMI with video yielded a very high proportion of correct responses, with 150 out of 160 trials answered correctly and only a small number of errors (Fig. 8). In contrast, the HMI without video showed poorer performance, with 34 out of 160 trials answered incorrectly, indicating lower comprehension effectiveness relative to the video-supported interface. These findings suggest that the type of interface significantly influences participants' ability to interpret system status correctly.

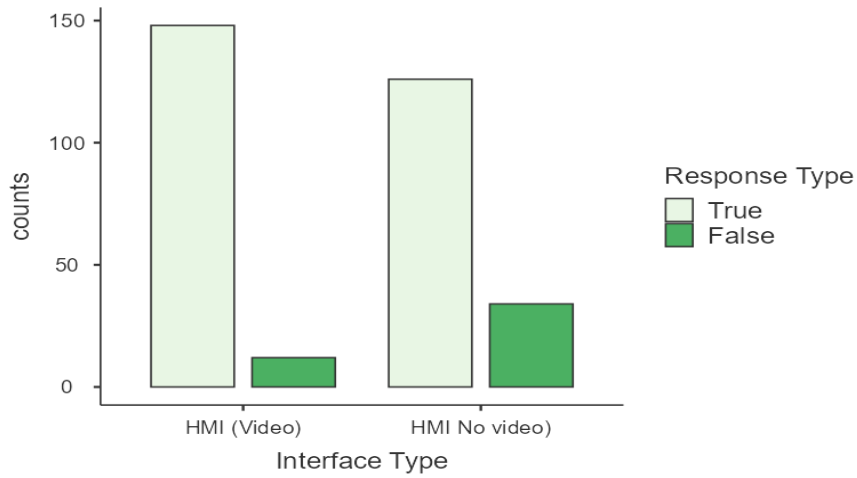



**Figure 9.**Number of True and False responses by interface type.

#### 4.3.3 Subjective Responses

The questionnaire responses showed that all participants preferred the HMI with video overall. However, when asked how they would like to receive information during supervision, 75% indicated a preference for accessing video on demand rather than having it displayed continuously or relying solely on the non-video HMI. This suggests that participants valued video as a supportive resource but were mindful of potential distraction, visual clutter, and information overload. Additionally, 75% of participants reported that the inclusion of video improved their understanding of the machine's status, whereas 25% felt that it reduced their understanding. Similarly, 75% indicated that they felt more confident using the HMI when video was available. Despite these mixed perceptions, 75% of participants agreed that the HMI with video helped detect problems, reinforcing the role of video as a valuable but context-dependent aid to remote supervision.

## 4.4 Discussion

This study examined the impact of real-time video input on the usability and SA of an HMI designed for remote supervision of autonomous agricultural machinery. The results highlight the importance of HMI feedback in enhancing user confidence, decision-making accuracy, and overall satisfaction during remote supervision activities.

The HMI with video achieved significantly higher SUS scores (M = 80%) than the HMI without video (M = 64%), indicating that video information substantially enhances perceived usability. According to Lewis and Sauro (2021), SUS ratings above 68 indicate above-average usability, suggesting that the video-enhanced HMI in this study meets high usability standards. While previous studies have integrated video into automation interfaces, the present work extends this evidence by directly comparing video and non-video HMIs within the same experimental framework and quantifying the impact of video using standardized SUS scores. This controlled comparison, conducted in the specific context of remote supervision of an autonomous agricultural sprayer, highlights the unique contribution of this study in demonstrating how real-time visual information improves perceived usability relative to an equivalent indicator-only interface. This aligns with earlier findings that integrating video into automation interfaces enhances user engagement, perceived control, and overall satisfaction (Panfilov and Mann, 2018; Lewis 2018). Moreover, the results are consistent with user-centred design principles, which emphasize the importance of contextually rich and intuitive feedback to improve operator experience and system engagement (Endsley 1995; Lorenz et al. 2020).

The video-based HMI yielded high comprehension accuracy (94% correct responses), outperforming the indicator-only interface (79%). This suggests that visual cues play a critical role in supporting SA Level 2 comprehension of system states, even though response times did not differ significantly between interface types. This result aligns with Endsley's (1995) SA model, which holds that understanding is facilitated by perceiving pertinent environmental cues. The interface design, which included contextual visual cues from the left and right cameras, evidently facilitated a better mental model of the system state, allowing for more informed and accurate decisions, a finding consistent with Panfilov and Mann (2018) and Rakhra and Mann (2013). Interestingly, the HMI with video support improved comprehension but did not significantly impact response time. This may reflect a trade-off between thorough visual inspection and reaction time; users may have taken longer to confirm issues by visually validating their perceptions through graphical indicators. Similar findings have been reported in other domains, where improved accuracy through visual feedback sometimes comes at the cost of marginally slower responses (Douglas and Kirkpatrick 1999; Steinkrauss et al. 2023).

Subjective feedback further supported the quantitative findings. Most participants (75%) preferred the HMI with video and felt more confident using it. Interestingly, while some users preferred video on demand rather than continuous streaming, this pattern emerged from the post-experiment questionnaire, which collected participants' feedback on video preferences and the usefulness of visual feedback. Overall, their questionnaire responses indicated that visual feedback enhanced understanding of machine status and supported faster problem detection. This insight could inform future interface designs by promoting adaptive or user-controlled video integration to balance situational needs with data bandwidth considerations.

### 4.5 Limitations

This study is subject to several significant limitations. The participant sample consisted entirely of individuals without prior experience with farming or agricultural machinery. While this allowed for a consistent evaluation of the human–machine interface (HMI), the absence of professional operators limits the generalizability of the findings. Experienced agricultural workers, who possess well-developed mental models of machine behaviour, may interact with the interface in ways that differ significantly from novice users, particularly in terms of situation awareness and the interpretation of visual cues.

Another limitation arises from the experimental context. The study was conducted in a controlled laboratory environment using prerecorded video footage of staged malfunctions. Although this design ensured uniformity across participants, it did not replicate the dynamic and unpredictable nature of real farm operations. Environmental factors, such as variable weather, uneven terrain, and concurrent task demands inherent to agricultural work, were not represented in the experimental setup and may influence both workload and decision-making in practical settings.

The relatively short trial durations also restrict the scope of the findings. Sessions averaging approximately ten minutes provided valuable insights into immediate usability and comprehension, but did not capture the long-term effects of extended monitoring. In real supervisory contexts, operators may engage with autonomous machines for prolonged periods, during which fatigue, cognitive strain, and fluctuations in trust may alter performance outcomes.

A further limitation concerns the absence of data communication related challenges. Because prerecorded video was used, participants were not exposed to network latency, bandwidth limitations, or connectivity interruptions, which are likely to influence the effectiveness of remote supervision in field applications.

Finally, the modest sample size and narrow demographic profile reduce the extent to which results can be generalized. Broader studies involving professional operators, larger participant groups, and field-based trials are required to confirm the robustness and scalability of these findings.

### 4.6 Recommendations

The findings of this research demonstrate that integrating real-time video into a human–machine interface (HMI) enhances both usability and situation awareness during the remote supervision of autonomous agricultural machinery. Based on these findings, it is recommended that future HMI designs of farming applications incorporate live visual feedback alongside graphical indicators. However, such integration should carefully balance interpretability, cognitive workload, and error communication to ensure that visual elements enhance rather than overwhelm the user. Adaptive or on-demand video functions may offer a practical approach, allowing operators to access detailed visual information when required while managing bandwidth and reducing potential distractions.

HMI designers and agricultural equipment manufacturers should prioritise testing interfaces with experienced agricultural workers in real farm environments. Field-based evaluations carried out over extended periods are recommended to understand better operator trust, workload management, and long-term usability. Industry and research teams should incorporate these longer-term, real-world trials into their development process to verify that HMIs not only perform well in controlled laboratory settings but also provide reliable and robust support under the demanding conditions of everyday agricultural practice.

### 4.7 Future directions

Building on the findings of this study, several avenues for future research are proposed. A key priority is to extend evaluation to experienced agricultural workers. Unlike novices, professionals possess established mental models of machine behaviour and may employ different supervisory strategies when interacting with automation interfaces. Comparative studies involving both novice and expert operators would provide a deeper understanding of how user background influences perceptions of usability, situation awareness, and reliance on visual feedback.

Another direction involves conducting field-based experiments in real farm environments. While the controlled laboratory setting ensured consistency, it did not replicate the variability and operational pressures of real-world conditions. Evaluating human–machine interfaces across diverse agricultural contexts that include environmental factors, connectivity limitations, and multitasking demands will yield more robust insights into system performance and operator decision-making.

Longitudinal studies are recommended to assess extended use, as short experimental sessions capture only immediate usability; factors such as fatigue, learning curves, and sustained cognitive load shape performance over time. Investigations of farming seasons would provide evidence on the long-term effectiveness, trust, and adaptability of video-supported HMIs. Future work should also address technical issues, such as network latency, bandwidth efficiency, and adaptive video streaming, as rural settings often face connectivity challenges. Ultimately, integrating emerging technologies such as augmented reality, multimodal feedback, and machine learning-driven decision support could enhance usability, awareness, and resilience in supervisory platforms for autonomous agriculture.

## 5.0 Conclusions

This thesis evaluated the effect of incorporating real-time visual information into a human–machine interface for the remote supervision of an autonomous agricultural machine. Compared with an indicator-only display, integrating live video enhanced HMI usability, as reflected in higher SUS scores. The same integration enhanced situation awareness, evidenced by more accurate and faster responses to task-relevant probes during supervision. These findings support the conclusion that incorporating real-time visual information has an overall positive effect on both the usability of the developed HMI and the supervisor's real-time situation awareness.

Beyond meeting the goals, the results emphasize that successful agricultural automation depends not only on machine capability but on interfaces that present timely, interpretable visual context alongside graphical indicators. Placing the operator at the center of design, balancing clarity, cognitive workload, and error communication, ensures that automation supports rather than complicates decision-making. Practically, modest changes, such as on-demand or contextual video, can enhance user performance and confidence while managing bandwidth and minimizing distractions. Overall, by combining usability and situation-awareness principles with field-relevant constraints, this work provides actionable guidance for designing usable, trustworthy, and adaptable HMIs for autonomous agricultural machinery.

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## 7.0 APPENDIX A: STUDY MATERIALS

### A1: Informed Consent

Department of Biosystems Engineering
E2-376 EITC
Winnipeg MB R3T 5V6
CANADA
Tel: 204-474-6033
Fax: 204-474-7512

**ASSESSMENT OF INTERFACE FOR REMOTE SUPERVISION OF AUTONOMOUS AGRICULTURAL MACHINES**

***Principal investigator:***
**Ebenezer Nunoo**
MSc Student
Dept. of Biosystems Engineering
University of Manitoba
Email: nunooe@umanitoba.ca.

***Advisor:***
**Danny Mann,** Ph.D., P.Eng.
Professor and Head
Dept. of Biosystems Engineering
University of Manitoba
Phone: 204-474-7149
Email: Danny.Mann@umanitoba.ca.

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**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:** The purpose of this study is to assess the effect of real-time visual information on the usability of a Human Machine Interface (HMI) developed and the situation awareness experienced by the remote supervisor during a remote supervision task. Real-time visual information refers to live, continuously updated visual data during operations. Participants will be asked to provide feedback that will inform future design. The study should take no longer than one hour to complete.

**STUDY PROCEDURES:** The experiment will be conducted in an office environment inside the Agricultural Ergonomics Laboratory. A simulation has been developed that displays information on three computer monitors placed side-by-side-by-side. Video recordings of a plot sprayer will be displayed on the left and right monitors, with sprayer status information displayed on the center monitor. The experimental procedure will include a training session, an experimental session composed of two distinct trials (with video recordings present and without video recordings present), and an end-of-experiment questionnaire.

During the experimental session, various errors with the operation of the plot sprayer will be introduced at random intervals. Upon the occurrence of an error, participants will be expected to interact with the simulation using the centre (touchscreen) monitor. The participant's response time will be recorded and used as a measure of situation awareness. In one experimental trial, the error information will be presented to participants using both video (left or right monitor) and with normal machine status information display (centre monitor). In the second experimental trial, the error information will be presented only using the normal machine status information display (centre monitor). At the end of each trial, you will be asked to complete a short questionnaire to obtain a subjective assessment of situation awareness.

The questions presented in this study are **NOT** intended to test your intellectual competence. They are only meant to gather your opinion with regards to the effect of real-time visual information on the usability of an HMI developed and the situation awareness during the remote supervision task.

**STUDY RISKS:** You will be exposed to a computer workstation equipped with three monitors. The experimental protocol requires a vigilance (monitoring) task within a comfortable office environment with scheduled breaks. 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:** There are no direct benefits to the participants.

**COMPENSATION:** You will be offered a $25 Tim Hortons gift card as an honorarium upon receipt of your consent as compensation for your time. We will collect additional personal 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.

**STORAGE AND USE OF DATA:** All the information you provide as part of this study is confidential. Only members of the research team, including both the principal investigator (PI), Mr. Ebenezer Nunoo, and his advisor, Dr. Danny Mann, will have access to directly identifying information. This access is necessary from the outset of the project, such as when participants email either the PI or the advisor to express interest in participating. The data will be stored on a University of Manitoba-approved secure platform to ensure confidentiality. It will not be cited but may be used directly for analysis, publications, or presentations. In all cases, only group averages or summary data will be presented to protect your identity. To safeguard your privacy further, documents containing identifiable information will be stored in a locked drawer within a secured filing cabinet. All de-identified information will be stored separately in a second locked drawer of the same filing cabinet. The data will be stored securely on a password-protected laptop used to access and analyze the information. By September 2034, hard copies of consent forms and other documents containing personal information will be deleted. If you consent, your anonymized data may be shared with researchers outside of the University of Manitoba, for further analysis or research purposes. This will only be done if anonymized, ensuring that no personally identifiable information is included. It may also be shared with other organizations or made publicly available, if required for research purposes, funding, or publication.

**DISSEMINATION:** Results from this study will appear in research 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. However, despite efforts to keep your personal information confidential, absolute confidentiality cannot be guaranteed. Your personal information may be disclosed if required by law. 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 June 2025 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, and you do not have to explain why. You will not be penalized in any way for withdrawing. You will be able to withdraw from the study until June 2025. Should you withdraw, all gathered responses will be destroyed, unless you consent to the use of partial data (e.g., data collected up until your withdrawal) for analysis. After this date, we will begin to analyze the information, and it may not be possible to withdraw your data. To withdraw, please contact the Principal Investigator, Mr. Ebenezer Nunoo, at the phone number or email provided above.

**QUESTIONS OR CONCERNS:** A designated University of Manitoba auditor may check that this study is being done safely and properly. 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 auditor 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.**

**CONSENT:**
By signing this document, I have read the above information and have had the opportunity to ask and have answered any questions I may have.

I understand that:

- I will be taking part in a research study.

- I may freely leave the research study activities at any time.
- 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 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**. | ☐ YES ☐ NO |

| | |
|---|---|
| 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: _______________________________________________

**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: Participant's Information

Name: ________________________________ Subject ID: ___________

**Instruction:** Please answer the questions below as honestly and accurately as possible. Circle the answer that best describes you. For questions with a blank, open responses are encouraged.

**Participant's information:**

1. Age?

   18 - 24 25 – 30 31 - 35

2. Do you live on a farm?

   Yes No

3. Have you ever operated an agricultural machine?

   Yes No

If yes, please indicate the number of years of experience operating agricultural machines:

____________________

## A3: SYSTEM USABILITY SCALE QUESTIONNAIRE

Trial Number: ________________ Subject ID: ____________

Error Cue: ___________________________________

| | The System Usability Scale<br>Standard Version | Strong Disagree | | | Strongly Agree | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| 1 | I think that I would like to use this system frequently. | | | | | | |
| 2 | I found the system unnecessarily complex. | | | | | | |
| 3 | I thought the system was easy to use. | | | | | | |
| 4 | I think that I would need the support of a technical person to be able to use this system. | | | | | | |
| 5 | I found the various functions in this system were well integrated. | | | | | | |
| 6 | I thought there was too much inconsistency in this system. | | | | | | |
| 7 | I would imagine that most people would learn to use this system very quickly. | | | | | | |
| 8 | I found the system very awkward to use. | | | | | | |
| 9 | I felt very confident using the system. | | | | | | |
| 10 | I needed to learn a lot of things before I could get going with this system. | | | | | | |

## A4: SUS SCORES FOR HMI (VIDEO AND NO VIDEO)

HMI WITH VIDEO

| Participate ID | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | Average SUS Score |
|---|---|---|---|---|---|---|---|---|---|---|---|
| P1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 100 |
| P2 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 2 | 97.5 |
| P3 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 100 |
| P4 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 100 |
| P5 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 100 |
| P6 | 5 | 1 | 4 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 97.5 |
| P7 | 5 | 1 | 5 | 2 | 4 | 1 | 5 | 1 | 5 | 1 | 95 |
| P8 | 3 | 2 | 3 | 1 | 3 | 2 | 3 | 2 | 2 | 3 | 75 |
| P9 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 100 |
| P10 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 100 |
| P11 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 100 |
| P12 | 1 | 2 | 2 | 2 | 3 | 2 | 3 | 2 | 2 | 3 | 50 |
| P13 | 1 | 2 | 2 | 1 | 3 | 2 | 3 | 2 | 2 | 4 | 52.5 |
| P14 | 2 | 3 | 1 | 3 | 3 | 2 | 4 | 2 | 1 | 1 | 50 |
| P15 | 4 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 2 | 87.5 |
| P16 | 1 | 2 | 1 | 3 | 2 | 3 | 2 | 3 | 2 | 4 | 40 |
| P17 | 1 | 2 | 2 | 1 | 4 | 2 | 3 | 2 | 2 | 3 | 57.5 |
| P18 | 2 | 3 | 3 | 1 | 3 | 2 | 3 | 2 | 2 | 4 | 52.5 |
| P19 | 1 | 2 | 2 | 1 | 3 | 2 | 3 | 2 | 2 | 4 | 50 |
| P20 | 5 | 1 | 5 | 2 | 4 | 1 | 5 | 1 | 5 | 1 | 95 |
| **Mean** | | | | | | | | | | | **80** |

HMI WITH NO VIDEO

| Participate ID | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | Average SUS Score |
|---|---|---|---|---|---|---|---|---|---|---|---|
| P1 | 1 | 2 | 2 | 1 | 3 | 2 | 3 | 2 | 2 | 4 | 47.5 |
| P2 | 1 | 2 | 2 | 1 | 2 | 2 | 3 | 2 | 2 | 3 | 45 |
| P3 | 2 | 1 | 3 | 2 | 3 | 1 | 3 | 1 | 3 | 1 | 67.5 |
| P4 | 1 | 1 | 2 | 2 | 3 | 2 | 3 | 2 | 2 | 4 | 45 |
| P5 | 1 | 2 | 3 | 1 | 3 | 2 | 3 | 2 | 2 | 4 | 50 |
| P6 | 1 | 2 | 1 | 2 | 3 | 2 | 3 | 2 | 3 | 3 | 52.5 |
| P7 | 1 | 2 | 2 | 1 | 2 | 2 | 3 | 2 | 2 | 3 | 57.5 |
| P8 | 1 | 2 | 3 | 1 | 3 | 2 | 3 | 2 | 2 | 4 | 60 |
| P9 | 1 | 2 | 2 | 1 | 2 | 2 | 3 | 2 | 2 | 3 | 57.5 |
| P10 | 1 | 1 | 2 | 1 | 3 | 2 | 3 | 2 | 1 | 1 | 56 |
| P11 | 4 | 1 | 4 | 2 | 4 | 1 | 5 | 1 | 2 | 3 | 77.5 |
| P12 | 5 | 1 | 4 | 1 | 5 | 1 | 5 | 2 | 5 | 2 | 92.5 |
| P13 | 3 | 1 | 4 | 2 | 4 | 1 | 3 | 1 | 3 | 1 | 77.5 |
| P14 | 4 | 1 | 4 | 2 | 5 | 1 | 5 | 1 | 5 | 2 | 85 |
| P15 | 1 | 2 | 2 | 1 | 3 | 2 | 3 | 2 | 2 | 4 | 50 |
| P16 | 2 | 1 | 2 | 2 | 3 | 2 | 3 | 2 | 2 | 3 | 55 |
| P17 | 5 | 2 | 4 | 1 | 5 | 1 | 4 | 2 | 4 | 2 | 75 |
| P18 | 4 | 2 | 5 | 1 | 4 | 2 | 5 | 1 | 5 | 1 | 67.5 |
| P19 | 3 | 1 | 4 | 1 | 3 | 2 | 4 | 2 | 4 | 3 | 70 |
| P20 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 100 |
| **Mean** | | | | | | | | | | | **64.425** |

## A5: RESPONSE TIME FOR HMI (VIDEO AND NO VIDEO)

| | A | B | C | D |
|---|---|---|---|---|
| 1 | PARTICIPATE | RespnseTime (ms)- Video | ResponseTime (ms)- NO Video | |
| 2 | A1 | 2676.797539 | 2573.547512 | |
| 3 | A2 | 2421.660006 | 2361.172467 | |
| 4 | A3 | 2551.789999 | 3209.442043 | |
| 5 | A4 | 2572.706699 | 3037.336667 | |
| 6 | A5 | 3013.722479 | 2420.607477 | |
| 7 | A6 | 2383.693981 | 3125.001465 | |
| 8 | A7 | 2312.342465 | 2072.371415 | |
| 9 | A8 | 2698.538343 | 2589.839965 | |
| 10 | A9 | 2421.824932 | 2293.962887 | |
| 11 | A10 | 2372.233351 | 2081.212521 | |
| 12 | A11 | 2344.961929 | 2053.927481 | |
| 13 | A12 | 2594.085038 | 2223.832518 | |
| 14 | A13 | 2577.384336 | 3289.346774 | |
| 15 | A14 | 2399.399936 | 2078.930003 | |
| 16 | A15 | 2430.009985 | 2521.321433 | |
| 17 | A16 | 2648.309994 | 3083.907127 | |
| 18 | A17 | 2287.08005 | 2279.790044 | |
| 19 | A18 | 2538.786809 | 2420.138687 | |
| 20 | A19 | 2960.108399 | 2091.71626 | |
| 21 | A20 | 2808.680058 | 2447.61576 | |

## A6: ACCURACY FOR HMI (VIDEO AND NO VIDEO)

| Participant | HMI (Video) | HMI (NO-Video) |
|---|---|---|
| A1 | TRUE | FALSE |
| A1 | TRUE | FALSE |
| A1 | TRUE | TRUE |
| A1 | TRUE | TRUE |
| A1 | TRUE | TRUE |
| A1 | TRUE | TRUE |
| A1 | TRUE | TRUE |
| A1 | TRUE | TRUE |
| A2 | TRUE | TRUE |
| A2 | TRUE | TRUE |
| A2 | TRUE | TRUE |
| A2 | TRUE | FALSE |
| A2 | TRUE | FALSE |
| A2 | TRUE | TRUE |
| A2 | TRUE | TRUE |
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| A10 | TRUE | TRUE |
| A11 | TRUE | TRUE |
| A11 | TRUE | TRUE |
| A11 | TRUE | TRUE |
| A11 | TRUE | FALSE |

| | | |
|---|---|---|
| A11 | TRUE | TRUE |
| A11 | FALSE | FALSE |
| A11 | TRUE | TRUE |
| A11 | TRUE | TRUE |
| A12 | TRUE | TRUE |
| A12 | TRUE | TRUE |
| A12 | TRUE | TRUE |
| A12 | TRUE | FALSE |
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| A16 | TRUE | TRUE |
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| A16 | TRUE | FALSE |
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| A16 | FALSE | TRUE |
| A16 | TRUE | TRUE |

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|---|---|---|
| A16 | TRUE | TRUE |
| A17 | TRUE | TRUE |
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| A17 | TRUE | TRUE |
| A17 | TRUE | TRUE |
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| A20 | TRUE | TRUE |
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| A20 | TRUE | TRUE |
| A20 | TRUE | TRUE |
| A20 | TRUE | TRUE |

## A7: END OF SESSION QUESTIONNAIRE

Subject ID: _____

**Instruction:** Please answer the questions below as honestly and accurately as possible. Circle the answer that best describes your experience. For questions with blank spaces, written responses are encouraged.

1. Does video of the sprayer make it easier to complete the task of supervising the operation of the sprayer?
   a. Yes
   b. No

2. Does video of the sprayer enhance your understanding of the operational status of the sprayer?
   a. Yes
   b. No

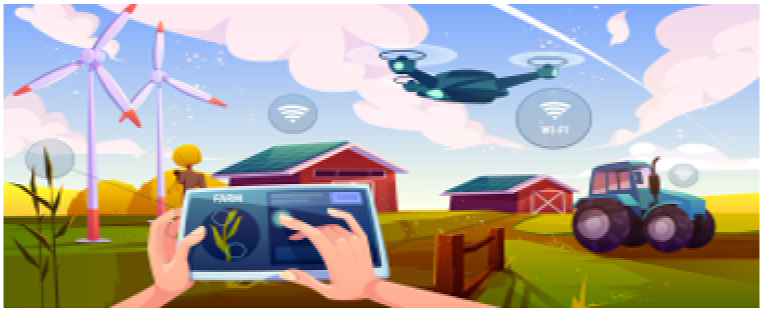
3. Which design would you recommend for remote supervision of an autonomous sprayer?
   a. I recommend that video be present during remote supervision of an autonomous sprayer
   b. I recommend that video NOT be present during remote supervision of an autonomous sprayer

4. Why do you make this recommendation?

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

A8: RECURIMENT POSTER

# PARTICIPANTS NEEDED



**Purpose of Study:**

You are invited to participate in a study that will be carried out in a Lab to assess the effect of real-time visual information on the usability of a Human Machine Interface (HMI) developed and the situation awareness experienced by the remote supervisor during a remote supervision task. The study should take no longer than one hour to complete.

**Role of Participants:**

The experiment will be conducted in an office environment inside the Agricultural Ergonomics Laboratory. A simulation has been developed that displays information on three computer monitors placed side-by-side-by-side. Video recordings of a plot sprayer will be displayed on the left and right monitors, with sprayer status information displayed on the centre monitor.

During the experimental session, errors with the operation of a plot sprayer will be introduced at random intervals. The participant's response time will be recorded. In one experimental trial, the error information will be presented to participants using both video (left or right monitor) and with normal machine status information display (centre monitor). In the second experimental trial, the error information will be presented only using the normal machine status information display (centre monitor). At the end of each trial, you will be asked to complete a short questionnaire to obtain a subjective assessment of situation awareness.

**Inclusion/Exclusion Criteria:**

We are seeking University of Manitoba students between the ages of 18-35 who have at least one year of experience operating agricultural machines.

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

Tim Hortons Gift Card ($25) Will be provided as Honorarium

## Interested?

**Email Ebenezer Nunoo (Principal Investigator): nunooe@myumanitoba.ca,**

**or**

**Dr. Danny Mann (Advisor): Danny.Mann@umanitoba.ca for more information**

A9: Post-Training Assessment

Subject ID: _____

- Please select the response that best describes the HMI (human machine interface) that was used during the experiment:

  Its layout is not reasonable  Its layout is very reasonable

- How comfortable or uncomfortable were you when presented with the HMI?

Very Uncomfortable 0 1 2 3 4 5 6 7 8 9 | 10 Very Comfortable

- Please select the response that best describes the HMI with video that was used during the experiment:

  It makes remote supervision difficult  It makes remote supervision easily

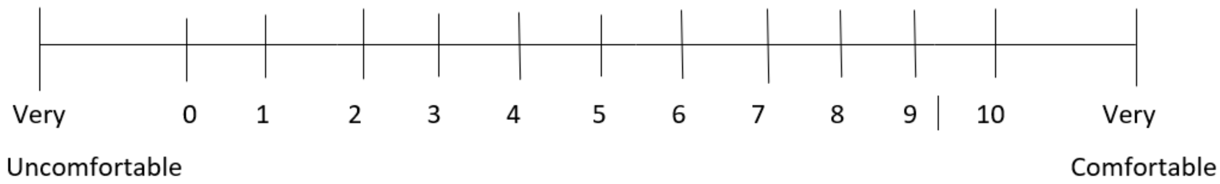
- How comfortable or uncomfortable were you when presented with the HMI with video?

Very Uncomfortable 0 1 2 3 4 5 6 7 8 9 | 10 Very Comfortable

- Please select the response that best describes the HMI without video that was used during the experiment:

  It makes remote supervision difficult  It makes remote supervision easily

- How comfortable or uncomfortable were you when you felt the HMI without video?


Very
Uncomfortable
0
1
2
3
4
5
6
7
8
9
10
Very
Comfortable

## A10: RECURIMENT EMAIL

University of Manitoba | Faculty of Agricultural and Food Sciences

Biosystems Engineering
E2-376 EITC
Winnipeg MB R3T 5V6
CANADA
T: 204-474-6033
F: 204-474-7512

**To: University of Manitoba Students**

**Subject-** Study: Assess the effect of real-time visual information on the usability of a Human Machine Interface.

Hello Students,

I am conducting research as part of my MSc thesis project in the Department of Biosystems Engineering at the University of Manitoba. The focus of my study is to assess the effect of real-time visual information on the usability of a Human Machine Interface and the situation awareness experienced by the remote supervisor during a remote supervision task. You are invited to participate in this study if you are between the ages of 18 and 35 and have at least one year of experience operating agricultural machines. If you meet these criteria, your input will be highly valued.

The study will take no longer than one hour. During this time, you will be asked to participate in tasks related to operating a remote agricultural machine, using the developed Human Machine Interface, and providing feedback on its usability. As compensation for your time, you will receive a $25 CAD Tim Hortons gift card.

The research is being conducted under the supervision of Dr Danny Mann within the Agricultural Ergonomics team, and has been approved by the Research Ethics Board (REB) at the University of Manitoba (contact: humanethics@umanitoba.ca, 204-474-7122). The risks involved are no greater than those encountered in everyday life, and your participation is voluntary. You may withdraw at any time without penalty.

If you are interested in participating and meet the inclusion criteria, please contact me by email at [nunooe@myumanitoba.ca]. Should you have any questions or concerns, feel free to reach out.

***Principal investigator:***
Ebenezer Nunoo
MSc Student
Email: nunooe@myumanitoba.ca

***Advisor:***
**Danny Mann,** Ph.D., P.Eng.
Professor and Head
Phone: 204-474-7149
Email: Danny.Mann@umanitoba.ca

## A11: EMAIL TO DEAN

University of Manitoba | Faculty of Agricultural and Food Sciences

Biosystems Engineering
E2-376 EITC
Winnipeg MB R3T 5V6
CANADA
T: 204-474-6033
F: 204-474-7512

**Dear Dean Scanlon,**

**RE: Request for assistance in recruiting student participants in a research study**

I am an MSc student at the University of Manitoba, working in the Agricultural Ergonomics Laboratory in the Department of Biosystems Engineering with Dr. Danny Mann. Dr. Mann and I have formulated an experimental plan to assess the effect of real-time visual information on the usability of a Human Machine Interface (HMI) and the situation awareness experienced by the remote supervisor during a remote supervision task. This study will involve recruiting student participants, specifically those with knowledge of and experience operating agricultural machines. Therefore, we intend to target our recruitment efforts at students in the Faculty of Agricultural & Food Sciences.

We are requesting the assistance of the Faculty of Agricultural & Food Sciences staff to send an email to current undergraduate students, including diploma students in the School of Agriculture, to invite them to participate in the study. The recruitment email has been approved by the Research Ethics Board at the University of Manitoba Fort Garry Campus as part of the Human Ethics Protocol for this experimental study. The study will be conducted using a simulation located in the Agricultural Ergonomics Lab (A115 AEB). Participants will interact with the simulation in a manner consistent with the task of remotely supervising an autonomous agricultural sprayer. The entire experimental session is expected to last approximately one hour. Students will receive a $25 Tim Hortons gift card as appreciation for their time.

For your reference, I have attached the recruitment email to this message so you can review the content that would be sent to students. We are seeking your permission to distribute this recruitment email to students in your faculty and to place recruitment posters on designated bulletin boards in the various buildings managed by the Faculty of Agricultural & Food Sciences.

Thank you for considering this request. I look forward to your response

***Principal Investigator:***
Ebenezer Nunoo
MSc Students
Email: nunooe@myumanitoba.ca

***Advisor:***
**Danny Mann,** Ph.D., P.Eng.
Professor and Head
Phone: 204-474-7149
Email: Danny.Mann@umanitoba.ca