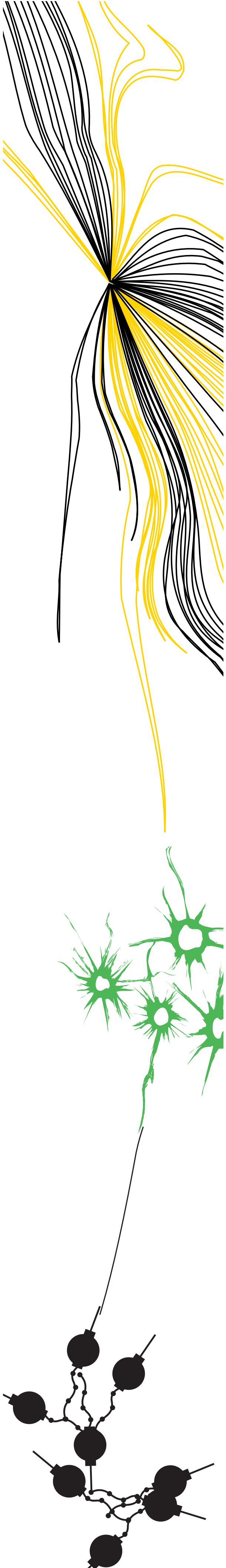

RAM ROBOTICS AND MECHATRONICS

TELEOPERATED CONTROL OF LOCOMOTION WITH TIME DELAYS FOR RECONNAISSANCE IN DANGEROUS FIRE SITUATIONS

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November 7, 2024

Abstract

This thesis explores the effects of time delays on teleoperated robotic systems in high-risk environments, specifically focusing on fire reconnaissance applications. In such hazardous environments, time delays can degrade an operator's ability to control a robotic platform accurately and maintain situational awareness, directly impacting mission success and safety. This research investigates the thresholds at which time delays hinder performance and evaluates mitigation strategies like predictive displays and enhanced interface designs to support operators. Through controlled simulations involving delayed video feedback and situational awareness tests, this study assesses cognitive load, efficiency in task completion, and situational awareness accuracy. Findings reveal that, although operators generally maintained task performance, extended delays notably increased frustration, emphasizing emotional resilience as a key area for improvement. These insights suggest that teleoperation design should prioritize frustration management and adaptability to ensure sustained operator performance in delay-sensitive applications.

Keywords— Situational Awareness (SA), NASA Task Load Index (NASA-TLX), User Workload (UW), Electro-Dermal Activity (EDA), Unmanned Ground Vehicle (UGV), dHRI (delayed Human Robot Interaction).

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Contents

1 Introduction

House fires are an escalating hazard in the Netherlands, with reports indicating a significant rise in incidents in 2023 by the Netherlands Institute for Public Safety (NIPV). It was estimated that over 4,000 house fires were recorded in the first half of the year alone, equivalent to almost one fire every hour (Nivera, 2023). This alarming statistic underscores the urgency of improving fire response strategies in indoor settings, where complex layouts with reduced visibility and structural instability complicate firefighting efforts. By addressing this need, the current thesis explores the potential of teleoperated robotic systems for enhancing situational awareness (SA) and enabling remote reconnaissance in high-risk indoor environments. By providing real-time insights and remote control capabilities, we hope to reduce the direct risks to firefighters while achieving more efficient interventions.

Teleoperated robotic devices are increasingly being used in hazardous areas to reduce the risks experienced by human operators, as described by Chacón (2020). One particularly relevant application is in reconnaissance missions for dangerous fire situations, where rapid response and real-time decision-making are critical. Performance and safety can be significantly impacted in such settings by operator-robot communication delays as well as the cognitive strain on the operator (Chacón, 2020). The development of such robotic systems highlights the growing importance of teleoperation and autonomous control in managing life-critical tasks. However, despite advancements in autonomous capabilities, teleoperation remains essential in situations where human oversight is required to make complex decisions. One of the key challenges in these teleoperated tasks is the presence of communication delays, which can significantly affect the operator's ability to maintain situational awareness (SA) and execute precise control (Moniruzzaman et al., 2022).

Important aspects related to Rots in de Brand's robotic platform concept were identified and addressed in order to enhance the use of teleoperation in dangerous fire scenarios. This study looked at several core topics, such as how time delays affect teleoperation performance, the significance of SA and how to quantify it, and the evaluation of several design approaches to deal with delay-related problems. To assess SA, operator performance, and user workload levels at different delay intervals, the experimental design of the study was designed to replicate the delay conditions commonly encountered in teleoperation. With this strategy, we gained knowledge on how to enhance operator satisfaction and task precision in time-delayed scenarios, ultimately promoting teleoperation as a workable option for remote control in dangerous environments.

1.1 Context

Teleoperation, the remote control of machines over long distances, allows operators to perform challenging tasks in hazardous environments using real-time inputs. In the literature, teleoperation is broadly categorized into bilateral and unilateral types. Bilateral teleoperation provides both control and force feedback: as the robot interacts with its environment, the operator receives tactile feedback that enhances the realism and control necessary for tasks such as tele-surgery or precision manipulation (Zhu et al., 2011; Korte et al., 2014). Unilateral teleoperation, by contrast, relies solely on the operator's visual inputs to navigate and control the robot in real time, offering an effective solution for high-risk scenarios where human oversight and precision are critical (Zhu et al., 2011). In this type of teleoperation, visual cues, rather than tactile feedback, are used to guide the operator's actions, making it well-suited for reconnaissance in dangerous, visually compromised environments.

In firefighting applications, teleoperated systems enable remote reconnaissance missions aimed at victim detection and environment assessment. In situations where visibility is low, such as smoke-filled indoor fires, operators face unique cognitive demands. Skills such as sense-making and cognitive mapping are crucial, allowing operators to construct mental maps of unfamiliar environments to navigate effectively under pressure (Dyrks et al., 2008). Firefighters, for instance, commonly use these cognitive maps to note essential features like entry points, exits, and the number of potential victims, guiding both the reconnaissance mission and informing the rest of the team of critical details.

Integrating teleoperated robots equipped with advanced sensors, such as LIDAR, IMUs, and depth cameras, can significantly enhance these cognitive maps by supplying real-time spatial data to the operator. These sensors provide spatial and situational cues, allowing remote operators to interpret the environment and maintain situational awareness (Hu et al., 2016). However, the goal of teleoperated systems in such high-stakes settings is to supplement—not replace—human judgment. Maintaining operator trust and ensuring that technology supports high-level, qualitative decision-making processes is crucial. When applied to fire reconnaissance, teleoperation platforms can greatly reduce human exposure to danger while also improving mission outcomes by continuously updating the operator with precise spatial data.

The "Rots in de Brand" team is dedicated to enhancing the safety and efficiency of fire reconnaissance operations through the use of teleoperated robotic platforms. Building on the "FireBot" initiative, their focus is to provide firefighters with tools that facilitate navigation in hazardous, low-visibility settings, such as fires in underground parking structures. By deploying teleoperated robots that gather real-time reconnaissance data, the aim is to limit direct human exposure to dangerous environments. This work aligns with studies like Seo et al. (2023), which assess the impact of delayed teleoperation on performance and mental workload. Their findings underscore the importance of minimizing operator cognitive load and maintaining efficient data flow to ensure reliable operation under stressful, delay-affected conditions (Seo et al., 2023). Such insights are invaluable as they inform the design of teleoperated systems that support both operational safety and effectiveness in fire reconnaissance missions.

1.2 Problem Statement

Teleoperation systems are highly sensitive to communication delays, which can severely impact system stability and operator performance. Time delays pose a particular challenge in high-stakes environments, where even minor delays can impair situational awareness and decision-making. For example, space teleoperated robots experience round-trip delays of up to 5 seconds, compromising real-time responsiveness (Penin, 2002). Such delays can affect the operator's ability to effectively control the robot, especially with delayed visual-feedback, this relationship is shown in Figure 1. The delay in this feedback loop disrupts task performance, making remote operations in hazardous environments more challenging (Wojtusch et al., 2018).

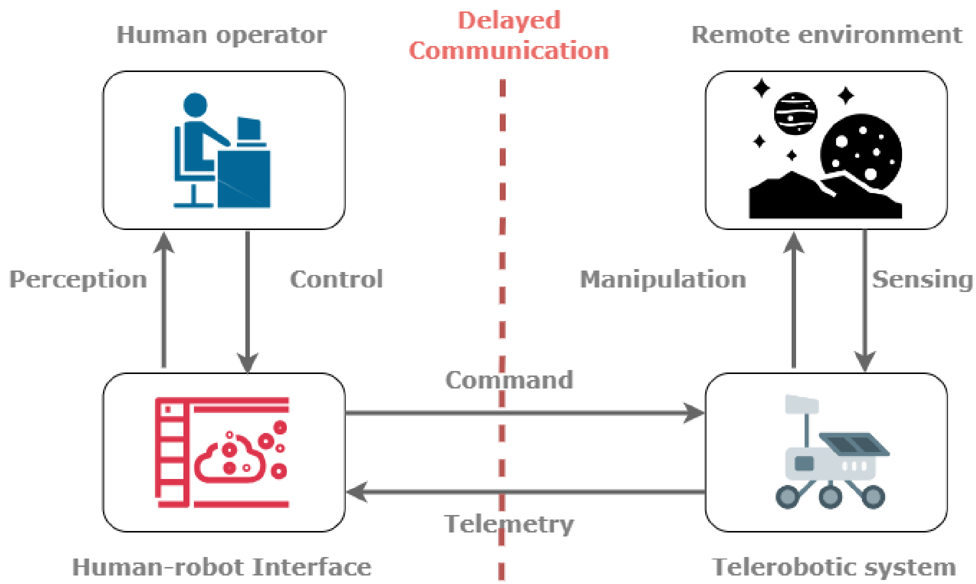


Figure 1: Teleoperation diagram for a delayed scenario between human operator and a telerobotic system (Wojtusch et al., 2018)

This project, in collaboration with Saxion University, builds upon the "Rots in de Brand" and "FireBot" initiatives (Balen et al., 2023). These projects aim to enhance firefighting reconnaissance through autonomous robots equipped with advanced sensors (e.g., infrared and RGB cameras) and SLAM technology for navigation and monitoring. However, a key issue persists: communication delays during remote operation, particularly due to WiFi transmission, which can lead to latencies as high as 2000 ms. Such delays compromise the operator's ability to make real-time decisions, posing risks to mission success and firefighter safety.

Time delays in teleoperation have been studied since the 1960s, with early solutions like the "move and wait" approach providing stability for delayed systems (Ferrell, 1966; Chen et al., 2007). In visual-based teleoperation, where operators rely heavily on visual processing and situational awareness to perform tasks, these delays are particularly disruptive (Seo et al., 2023). Techniques such as predictive displays have been developed to mitigate delay effects, with proven benefits in improving operational efficiency in high-latency environments (Penin, 2002; Chen et al., 2007).

In this project, overcoming latency in camera feedback remains a major difficulty. As reported by the technical team, during the thermal image capture and processing, moderate to large delays were found in the visual channel. Figure 2 illustrates the capturing, conversion, merging, and streaming of these images to the operator's site. According to their insights, "the required time from image acquisition to streaming is about 50 ms to 60 ms. The WiFi ping is generally about 5 ms to 20 ms, but it is not always very stable. Random network delays of up to 2000 ms have been experienced due to interference or range issues."

1.3 Goal

This project's main goal is to evaluate how operator performance and cognitive workload are affected by time delays when operating teleoperated robotic platforms in fire reconnaissance simulations. With an emphasis on detecting the emotional and mental strain caused by delays, this study specifically examines how different delay durations affect important metrics,

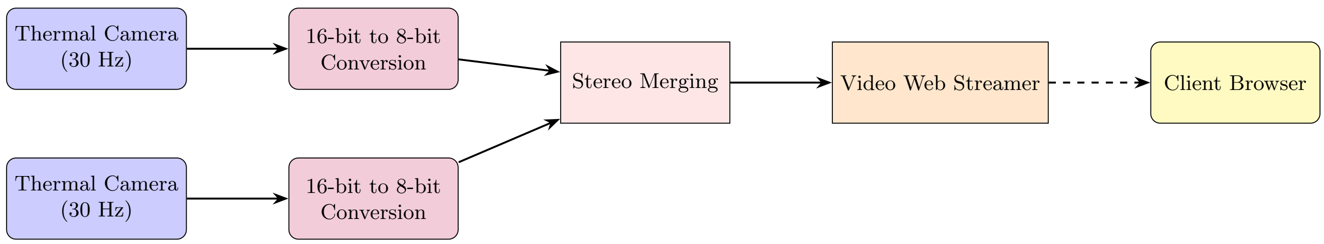


Figure 2: Data Flow Diagram for Thermal Imaging System from Rots in de Brand, Technical Team

including task completion time, navigation accuracy, environment recreation (SA), and dimensions of cognitive load (NASA-TLX). The study looks to offer insights into system design and operator support methods that reduce delay-induced frustration and preserve SA by carrying out a systematic experimental analysis and analyzing pertinent literature. The results provide a basis for creating useful design principles to improve teleoperation effectiveness under time-delay circumstances, which can be applied to high-risk situations like firefighting, where real-time decision-making is primordial.

1.4 Research Questions

The research questions in this thesis are designed to address a number of significant challenges related to teleoperating robotic systems for fire reconnaissance missions. How long can pass before these platforms' controllability begins to deteriorate? This is the primary research question. For safe and efficient operation, it is critical to perform well in areas when lag in communication is unavoidable. The robot platform from this project have reported delays from 80 ms to 1800 ms, so with this in mind we can evaluate this threshold with the ones in literature to compare and evaluate given results or expectations.

Table 1 contains all of the formulated research questions along with a brief explanation for each one of them:

Research Question	**Explanation**
What is the maximum allowable time delay for teleoperated robotic platforms before controllability deteriorates to an unacceptable level?	This question attempts to determine the point at which time delays in teleoperation become undesirable in terms of performance. It seeks to determine the point at which delays hinders the operator's ability to navigate the robot effectively, which is critical to establishing robust teleoperated systems.
How can we assess teleoperation performance with time delays?	This question looks to investigate what are the most important factors that have been used to measure performance in other studies relevant to our project. This can be human factors (e.g., HRV heart rate variability commonly used to measure stress) or objective metrics for a specific goal (e.g., completion time and lane-keeping error during a driving task).
How can we support the operator to operate in time-delay situations?	This question focuses on identifying tools, strategies, and technologies that can mitigate the negative effects of time delays. The goal is to explore ways to improve operator performance when delays are inevitable.

Table 1: Research Questions

1.5 Approach

This thesis adopts a structured approach to examine the effects of time delays on teleoperation performance in fire reconnaissance missions. The methodology spans four primary phases: literature review, theoretical framework development, simulation-based experimentation, and analysis of findings to guide recommendations for teleoperated systems in high-stakes environments.

The study begins with a comprehensive literature review to establish a foundation in teleoperation challenges, delay impacts, and current mitigation techniques. Key studies, such as those by Seo et al. (2023) and Yang and Dorneich (2017), provide insight into the effects of time delay on workload and spatial complexity handling, respectively. Wojtusch et al. (2018) further underscore the importance of situational awareness (SA) and cognitive workload as critical metrics for evaluating human-robot interaction in delay-affected teleoperation (Wojtusch et al., 2018). This literature informs our selection of SA and workload as primary metrics for evaluating operator performance, focusing on their role in maintaining control and decision-making efficiency under delayed feedback conditions.

Building on insights from the literature, a theoretical framework is developed to outline anticipated effects of delay on SA, cognitive workload, and task accuracy. This framework integrates findings on delay sensitivity and SA thresholds, such as those proposed by Wojtusch et al. (2018), to hypothesize that increasing delay intervals degrade SA and increase cognitive load, impacting task performance in complex, low-visibility environments typical of fire reconnaissance missions.

The experimental phase involves a simulation environment where operators control a robot remotely through maze-like structures, chosen to simulate the spatial challenges and limited visibility encountered in real fire scenarios. Delay intervals are systematically varied across trials to measure operator SA and workload under controlled conditions. Inspired by methodologies in Seo et al. (2023) and Yang and Dorneich (2017), this setup uses standardized delay intervals and complex navigation tasks to capture data on performance, SA, and workload in a realistic teleoperation scenario.

Finally, the analysis synthesizes performance patterns across delay intervals, identifying specific thresholds at which delays begin to significantly impact SA and workload. These findings guide practical recommendations, such as implementing predictive displays or adaptive control mechanisms to mitigate delay effects and maintain operator situational awareness. By addressing the impact of delays on SA and workload, this study contributes valuable insights to teleoperated system design for high-stakes environments, supporting safer and more effective fire reconnaissance operations.

1.6 Report Outline

This report is organized as follows:

Introduction 1 introduces the context and motivation for the study, presenting the problem statement, research goals, and the specific research questions addressed throughout the report. Additionally, it outlines the approach taken to investigate the research questions and provides a road-map for the report structure.

Literature Review 2 provides an extensive review of the literature on teleoperation, with a particular emphasis on the impact of time delays on operator performance. The review investigates several approaches suggested for reducing the adverse impacts of delays and discusses pertinent studies that aim at the maximum permitted time delay for teleoperation before performance deteriorates. The hypotheses that motivate the experimental study are also developed in this section, along with the gaps in the current body of research.

Experimental Design 3 describes the experimental design used to investigate the effects of time delays on teleoperation performance. This section details the recruitment of participants, the creation of a simulation environment with specific time delay conditions, and the tasks used to assess the operator's performance. It also introduces the dependent and independent variables, including performance metrics, subjective workload assessments, and time delay conditions.

Results 4 presents the findings of the study. It includes a statistical summary of the data collected from the experiments and highlights the key results regarding driving performance, maze performance, and subjective workload across varying time delays. This section also examines the influence of gaming experience on performance and provides a correlation analysis of all the metrics.

Regression Analysis 4.6 provides a deeper analysis of the results through regression models, exploring the relationships between operator performance, time delays, and cognitive workload. The regression analysis allows for a more comprehensive understanding of the effects of time delays on operator performance. This section also discusses the practical implications of these findings in the context of teleoperation systems.

Conclusion 5 synthesizes the key findings of the research and their theoretical implications. It also acknowledges the limitations of the study and offers recommendations for future research. The report concludes with final remarks on the importance of mitigating time delays to enhance operator performance in teleoperation.

Appendix A provides supplementary analysis, based on the principal experiment results. The extra set of experiments was designed to explore the relationship between varying delay conditions, operator workload, and performance across different ground speeds previously extracted from studied literature. Doing so, the hope was to further improve our analysis and prove valuable points from our hypotheses section 2.3.2. This appendix includes a discussion where technical implications, summary of figures and future work is considered based on these new findings.

2 Literature Review

The goal of this research is to explore how time delays impact the control of robots used in dangerous fire situations and to understand how delays affect operator's performance. By studying these effects, the plan is to improve remote control strategies, making missions safer and more effective. The following sections will address the research questions previously formulated starting from "What is the maximum allowable time delay?".

In this first section a variety of studies were investigated focusing on the effects that delayed operation has on a given task. Research focused on finding magnitudes were delays started to affect a human operator on their performance. Starting from levels where they were barely perceptible to the human brain till they become impossible to ignore and cause teleoperation to fail.

Secondly, the next question will investigate what is being used to mitigate delayed teleoperation. In case that delays effectively reduce performance to critical levels, we would like to be informed about different methods to mitigate this negative effects. Most literature talks about how to get rid of these unwanted delays, but in our case we want to see the options are available in presence of delays. They can come as displays, multi-modal interfaces, side-bars or other kind of interface to alleviate this effect.

2.1 What is the maximum allowable time delay for teleoperated robotic platforms before controllability deteriorates to an unacceptable level?

Time delays have been one of the major challenges in teleoperated tasks, particularly affecting workload, decision-making, and situational awareness (Musicant et al., 2023). In the presence of communication delays, operator's performance seems to decrease in almost every case to some degree. These delays can happen frequently in the connection between operator and teleoperated system. The magnitudes of the delays can vary depending on the communication network and computational processes. Studies like those by Kohrs et al. (2016) have explored the neurological impacts of these delays. Through experimentation, it was demonstrated how even slight delays can alter brain activity, affecting the ability of an operator to respond effectively to dynamic tasks.

It is said by Moniruzzaman et al. (2022) that latency or lag is the time between command input and visual output. As said in 1, these delays often come from data transfer or fails in communication. This study claims that operators can be affected by delays as little as 10 to 20 ms. According to their results, if latency increases from 8.3 ms to 225 ms, teleoperator reaction time increases by 64%, and error rate increases by 214%. One latency goes above 170 ms driving teleoperated vehicles at velocities of 90 km/h (or 25 m/s) becomes significantly more challenging. And for delays around 300 ms, teleoperation becomes virtually impossible for that specific condition.

Time delays have a wide range of implications, affecting everything from simple to more complex tasks with semi-automated and teleoperated systems (Yang and Dorneich, 2017). Teleoperators often rely on visual feedback to make crucial decisions; therefore, any delay can result in a mismatch between the operator's actions and the system's reactions, complicating job execution and potentially leading to operational failures (Chen et al., 2007). For example, research has shown that delays beyond a certain threshold significantly impair the ability to follow and react to changes, thereby increasing cognitive demands and reducing the overall effectiveness of human-machine interaction (Musicant et al., 2023). This discussion sets the stage for a deeper exploration of specific studies and findings to understand the broader implications of time delays in teleoperated systems, emphasizing the need for innovative solutions to mitigate their impact.

Kohrs et al. (2016) studied the effects on brain activity when subjected to delayed feedback by conducting three different fMRI (functional magnetic resonance imaging) experiments. One crucial component of effective human-computer interactions is the temporal contingency of feedback. The timing of this signal can affect the behavior and neural activity of an individual, thus tampering any human-machine interaction. As a secondary test for their experiments, they introduced an auditory categorization task for FM (frequency modulated) tones. Participants were told to respond according to the direction of the modulated signal. A button was pressed when the FM response went upward and another when it went downward. Afterwards, a green check mark would appear to indicate the correctness of the participants' responses. If any of the participants failed to press the correct button in time (at least 1.5 seconds after FM signal), a red mark would appear, terminating the test. This auditory categorization task was helpful to determine delay's thresholds.

The first experiment focused on the effects of unexpected delays in feedback of different magnitudes. In this test, Kohrs et al. (2016) measured the impact of three delay durations. The test conditions consisted of signals where 85% of the feedback was immediate (no delay), while the remaining 15% was delayed by 200 ms (5%), 400 ms (5%), or 600 ms (5%). The main focus of the first test was to identify the noticeable delay of their participants, which was 327.2 ms +/- 89.7. Their results suggest that delays of 200 ms (as used in the context of their fMRI experimentation) are well below the noticeable threshold. On the other hand, 400 ms delays lie in the range of just noticeable, and 600 ms delays are situated above the limit.

The second experiment investigated the adaptability of the users to frequent delays. The results of the second fMRI demonstrated that frequently occurring delays initiate a process of adaptation. Here, the delays were presented pseudo-randomly and equally often as immediate feedback, with an average delay of 500 ms. During these interactions, the user's temporal expectation is adjusted, and the additional neural resources for attention and control are no longer used. Consequently, the difference in brain activity between immediate feedback and frequently delayed feedback is no longer detectable. This validates the assumption that users can adapt to regular delays by changing their work style (Kohrs et al., 2016).

Finally, the third experiment studied the effects of the infrequent omission of feedback. During this test, feedback was omitted in 10% of all trials. In contrast with the second experiment, results showed that there was a greater increase in brain activity. The authors emphasized that introducing rare omissions of feedback can reduce the system's trustworthiness, which leads to an increase of brain activity. Therefore, occasional interruptions in user-system connections can be more detrimental than more frequent delays when controlling a teleoperated system. These communication failures are often caused by network problems or internal errors in the system (Kohrs et al., 2016)(Lu et al., 2019).

Yang and Dorneich (2017) studied the effects of intermittent and variable time delays. Their research focused on the link between human's emotions and task complexity with different time delays in teleoperation. Variable time delays were found to be more influential than task complexity, according to their results. It is mentioned how previous research shows that operators would often resort for a "move and wait" strategy when time delays range between 0.3 s and 3.2 s (Yang and Dorneich, 2017). Chen et al. (2007) also suggests that when system latency surpasses 1 s, the participants begin to do the same strategy, switching their control strategy. During their experiments, participants would often memorize the corners of the mazes to overcome the time delays. However, when delays surpassed a certain threshold, situational awareness was significantly affected, making them struggle even with the simplest tasks (Yang and Dorneich, 2017).

The conducted experiments from Yang and Dorneich (2017) consisted of two tasks: target search and alert detection. In both tasks, the test conditions varied between high and low complexity, with or without a time delay. The target search task consisted of navigating a teleoperated robot from a remote location using a joystick. Participants were only able to see through the video stream from the robot's mounted camera. Two mazes were provided for this task, one more difficult than the other. Inside these mazes, participants had to identify as many identical cylinders as they could and determine if they were "old" or "new." In this way, participant's situational awareness was tested as cognitive load increased. Time delay was varied via the control inputs and feedback, while task complexity was manipulated through the maze's design.

The alert detection task was introduced to measure the workload from the participants. This secondary task consisted in asking the participants to pull a trigger from the joystick control whenever they heard audio beeps. These beeps would occur every 30 seconds during their navigation task. Additionally, specific goals were provided to the participants to increase the cognitive load. This task was to identify new or old objects from the maze would force users to navigate through the whole maze and create a mental map to test their their recollection of the maze. Forcing them to remember and identify objects from an unknown environment.

Yang and Dorneich (2017) identified four traditional mitigation techniques when time delays are inevitable: the "move and wait" strategy, bi-directional control stabilization, the use of predictive displays, and supervisory control. These methods are commonly used to address the performance impact of constant time delays. However, the main focus of this research was not only on the operator's performance but also their emotional responses. By measuring electrodermal activity (EDA), the authors showed that time delays can affect us on a psychological and emotional level. Anger, frustration, and increased workload were present whenever variable time lags were introduced into the feedback signals. A proposal was made for an adaptive system that could be triggered whenever the operator's emotional response surpassed a certain threshold. With the hopes of alleviating the negative effects caused by delays.

The research paper titled "The effects of video frame delay and spatial ability on the operation of multiple semi-autonomous and tele-operated robots" investigates how video frame delays influence operator performance in military contexts, where decision-making speed and accuracy are critical (Sloan, 2005). The study hypothesizes that operators with higher spatial abilities are better suited to challenging control tasks, particularly those involving unmanned aerial vehicles (UAVs), and that video frame delays could impact their ability to effectively operate these robotic systems.

In the experiment, participants were tasked with controlling multiple teleoperated and semi-autonomous robotic platforms under various video frame delay conditions. The experiment was designed to replicate real-world military scenarios, where the precise and timely control of unmanned vehicles is often vital to mission success. The study assessed how delays affected the cognitive load and overall performance of operators, focusing on their ability to complete time-sensitive tasks, identify targets, and maintain situational awareness.

The results showed that operators with stronger spatial abilities performed more efficiently, particularly in UAV-related tasks that required navigation in three-dimensional spaces (Sloan, 2005). These findings highlight the importance of spatial ability in teleoperating unmanned vehicles, suggesting that it should be a key factor in the recruitment and training of operators in military and similar settings. Additionally, while video frame delays did not significantly impact performance across all measures, there was a notable effect on operators with lower situational awareness.

The paper emphasizes the need to consider both technological factors, such as video frame delays and bandwidth limitations, and human factors, such as situational awareness, in the design and implementation of teleoperated systems. It suggests that further research is required to better understand the interaction between these factors and their influence on operator performance, with the goal of optimizing the control and operation of unmanned vehicles (Sloan, 2005).

Teleoperation is frequently employed in high-risk industries where the combination of high workloads and communication delays can lead to degraded performance and long-term stress on operators; therefore, workload management is a critical concern in the operation of unmanned vehicles (Lu et al., 2019). Previous studies have shown that even minor delays can significantly increase operator workload and degrade task performance (Chen et al., 2007). However, while much research has focused on the general effects of time delays, there is less information on how delay compensation algorithms, particularly in high-risk environments, impact operator workload (Lu et al., 2019).

Common causes of time delays include limitations in signal transmission speed, bandwidth, long communication distances, and the processing time required to send and receive data (Lu et al., 2019). For example, Zheng et al. (2018) found that delays up to 900 milliseconds in simulated driving tasks dramatically impacted performance, leading to longer task completion times, increased lane-keeping errors, and a greater need for steering adjustments.

In this study, a human-in-the-loop experiment was conducted where participants teleoperated a military High Mobility Multipurpose Wheeled Vehicle (HMMWV) while simultaneously performing a secondary task (Lu et al., 2019). The experiment was designed to test three conditions: delay without compensation, delay with compensation using a model-free predictor, and no delay. It was hypothesized that communication delays would increase operator workload and reduce task performance, but that the model-free predictor would help mitigate these effects by reducing the cognitive load on the operator (Lu et al., 2019).

Participants controlled the HMMWV through simulated tracks using a steering wheel and pedals, while the secondary task—a one-back auditory memory task—measured cognitive workload. The experiment introduced an 800-millisecond delay, a magnitude based on typical communication delays in satellite-linked military operations. The delay condition simulated real-world challenges such as the delays encountered in cross-country teleoperations (Lu et al., 2019).

Results indicated that an 800-millisecond delay significantly increased operator workload and degraded task performance, as expected. However, the model-free predictor effectively reduced the negative impact of these delays on both workload and performance (Lu et al., 2019). The study also revealed that participants were more sensitive to perceived workload, as measured by the NASA-TLX survey, compared to physiological workload indicators. These findings suggest that predictive displays or compensation models are necessary to maintain optimal performance in teleoperation tasks under significant delays.

The study from Musicant et al. (2023) investigates the impact of time delays on the performance of teleoperators controlling vehicles in a simulated environment (Musicant et al., 2023). The experiment focused on how delays influenced driving performance during a sequence of tasks such as following a lead vehicle, responding to sudden breaks, and navigating among other simulated vehicles on a highway. Three different delay durations were tested: 50 ms, 150 ms, and 250 ms. Participants' performance metrics, such as speed consistency, distance to other vehicles, swerving, braking behavior, and crash rates, were meticulously recorded and analyzed.

To simulate realistic driving conditions, participants engaged in a highly controlled simulation where they followed a lead vehicle through various maneuvers. These included following the vehicle along a curved path, reacting to its abrupt stops, and driving in a simulated highway environment with randomized traffic scenarios. The primary measures of operator performance included variations in speed and distance from the lead vehicle, the incidence of swerving, and the frequency of crashes. Notably, as the time delay increased, participants displayed a greater standard deviation in speed and distance when following the lead vehicle on curved roads, indicating decreased control precision (Musicant et al., 2023).

The results demonstrated a significant decrease in driving performance as time delays increased. With a 250 ms delay, participants exhibited more pronounced swerving on highways and more significant variations in following distance on curves compared to shorter delays. Although the crash rates did not show statistically significant differences across different delays, the increased swerving and variability in vehicle control suggest a potential for higher-risk scenarios as delays increase (Musicant et al., 2023).

Additionally, participants completed the NASA-TLX workload assessment, which revealed a higher perceived workload at the longest delay (250 ms). This suggests that increased time delays not only affect physical driving performance but also impact cognitive load, potentially leading to faster fatigue and reduced operator efficiency Musicant et al. (2023). These findings are critical as they highlight the need for advanced compensation mechanisms in teleoperated driving systems, especially as teleoperation becomes more prevalent in managing inter-urban vehicle operations.

Recent research highlights the importance of maintaining situational awareness (SA) for effective task performance in teleoperated systems. Gatsoulis et al. (2010) explored various SA measurement techniques adapted from air traffic control for use in teleoperation scenarios like urban search and rescue. Their findings suggest that higher delays can severely degrade SA, leading to slower response times, increased error rates, and reduced task efficiency. By measuring SA using both objective and subjective metrics, they demonstrated that time delays significantly impact the operator's ability to maintain an accurate perception of the environment and plan actions accordingly.

Studies with their respective findings about different delay thresholds and their implications can be found in Table2:

Study	Delay Magnitudes Findings	Threshold (ms)
Moniruzzaman et al. (2022)	Delays up to 170 ms are manageable for high-speed teleoperated driving, but delays over 300 ms make teleoperation impractical.	170-300
Kohrs et al. (2016)	The noticeable delay threshold in human-computer interaction is around 400 ms, with 600 ms causing pronounced cognitive strain.	400-600
Yang and Dorneich (2017)	Delays from 300 ms to 3.2 s prompt operators to adopt a "move and wait" strategy due to significant SA degradation.	300-3200
Lu et al. (2019)	An 800 ms delay notably increases cognitive load and decreases task performance, suggesting the need for delay compensation.	800
Musicant et al. (2023)	At delays of 250 ms, driving precision and workload are significantly impacted, highlighting the need for delay mitigation in teleoperated driving.	250
Seo et al. (2023)	The study show that time delays not only reduce the operator's performance and perceived workload, but also alter control tactics.	1500 - 3000

Table 2: Delay Thresholds and Effects on Teleoperation Performance

2.2 How can we assess teleoperation performance with time delays?

Wojtusch et al. (2018) presents the results of a Delay Human Robot Interaction Expert Survey (dHRI). The goal was to investigate the most relevant human factors for teleoperation scenarios over to professionals in the field. The survey involved having a simulated scenario where time delays were critical. The simulation consisted of having a a teleoperated robot on the moon controlled from Earth. In this scenario, a signal round-trip would take between 3 and 5 seconds. Forcing a human operator to track the outcome of any given command considering this delay.

Previous studies have talked about human factors such as situational awareness (SA), user workload (UW), and user experience (UE) for robotic platforms (Wojtusch et al., 2018). However, little is known about the application of these metrics during an actual delayed operation test. For this reason, an online survey was conducted to systematically select, rank and weight relevant human factors for teleoperation scenarios with critical time delays based on ratings of experienced experts in the related field. The different metrics with their respective dimensions and description are shown in Table 3.

SA can be described as the ability of the human operator to maintain enough understanding of its surroundings when performing a remote task. UW is the relationship between the mental, physical, and temporal resources that the operator needs to complete the task. Lastly, the user experience UE is the feeling a user experience when using a device or a system, and it can be described in terms of human emotions and attitudes (Wojtusch et al., 2018).

For the dHRI survey, the authors considered three main dimensions for SA: attention demand SA1, attention supply SA2, and understanding SA3. These dimensions were used to approach the different aspects of situational awareness and they align with Endsley (1995) definition of SA. For UW, the authors addressed six different factors: mental demand UW1, physical demand UW2, temporal demand UW3, performance UW4, effort UW5, and frustration UW6. These factors were derived from the NASA Task Load Index (NASA TLX) which is a common metric to assess subjective cognition load of a given task (Wojtusch et al., 2018). This index has been used in many other studies to evaluate the cognitive workload based on a series of questions that . For UE, they also considered six different factors: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty (Wojtusch et al., 2018). At the end of the survey, test participants would have to rate each one of these factors to determine which one was more important for each category.

According to Wojtusch et al. (2018), the results indicated that understanding (SA3), performance (UW4), and dependability (UE4) were rated as the most important factors from each dimension. For situational awareness, SA3 mainly focused on comprehension and control of the situation. While for user workload, UW4 measures the overall success of the task from the operator's point of view. And finally, for user experience assessment, UE4 is the factor that rates to what extent operators feel in control of the interaction.. Their findings suggest that concepts like situational awareness, user workload, and user experience are highly relevant for teleoperated tasks (Wojtusch et al., 2018). Another factor that was considered essential was efficiency (UE3), with a rating surpassing the 75%.

In conclusion, Wojtusch et al. (2018) delivered a systematic approach for selecting, ranking, and evaluating human factors in evaluating delayed human-robot interaction. These findings show that comprehending and monitoring the present surroundings, as well as reducing extra efforts, are critical design factors for teleoperation effectiveness. Integrating these critical human factors—situational awareness, user workload, and user experience—into teleoperation systems allows for more robust and effective designs. This method is especially useful in high-stakes settings where delays are unavoidable, since it highlights the importance of interfaces that enable operator adaptation, situational knowledge, and decision-making precision.

Situational Awareness	
SA1 - Attentional Demand	Factor that rates the amount of attentional resources demanded by the interface or situation, i.e., complexity, variability and instability of the situation.
SA2 - Attentional Supply	Factor that rates the amount of attentional resources supplied by the interface or situation, i.e., division of attention, arousal, concentration and spare mental capacity.
SA3 - Understanding	Factor that rates the understanding of the situation, i.e., information quantity, information quality and degree of acquaintance with situation experience.
User Workload	
UW1 - Mental Demand	Factor that rates how much mental and perceptual activity, e.g., thinking, deciding or remembering, is required for the task.
UW2 - Physical Demand	Factor that rates how much physical activity, e.g., pushing, pulling or turning, is required for the task.
UW3 - Temporal Demand	Factor that rates how much time pressure the operator feels due to the rate at which task elements occur.
UW4 - Performance	Factor that rates how successful the operator is in accomplishing the goals of the task.
UW5 - Effort	Factor that rates how hard the specific operator has to work mentally and physically to accomplish a certain level of performance.
UW6 - Frustration	Factor that rates how frustrated, i.e., insecure, discouraged, irritated, stressed and annoyed, the operator feels during the task.
User Experience	
UE1 - Attractiveness	Factor that rates how much operators like or dislike the interface.
UE2 - Perspicuity	Factor that rates how easy it is to get familiar with the interface.
UE3 - Efficiency	Factor that rates to what extent operators can solve their tasks with the interface without unnecessary effort.
UE4 - Dependability	Factor that rates to what extent operators feel in control of the interaction.
UE5 - Stimulation	Factor that rates how exciting and motivating it is to use the interface.
UE6 - Novelty	Factor that rates how innovative and creative the interface is.

Table 3: Definitions of the Preselected Human Factors (Wojtusch et al., 2018)

Seo et al. (2023) presents a detailed evaluation of performance and mental workload in delayed teleoperation scenarios, specifically focusing on tasks relevant to lunar surface construction. The study investigates how visual feedback delays impact the operator's situational awareness (SA) and cognitive workload, critical metrics previously highlighted by Wojtusch et al. (2018) as fundamental for effective teleoperation. Seo et al. (2023) conducted a set of controlled experiments with operators navigating complex, delay-sensitive tasks. Using delay intervals to simulate the effect of communication lag on task performance, they examined how increased latency influenced the operator's ability to interpret visual cues and make precise navigational decisions.

Central to Seo et al. (2023) approach is the emphasis on mental workload under delayed conditions, which they measured using established cognitive workload assessment tools, including the NASA Task Load Index (NASA-TLX). This aligns with the metrics for user workload (UW) proposed by Wojtusch et al. (2018), who identified mental demand, temporal demand, and frustration as key components. Seo et al. (2023) observed that as delays increased, operators reported heightened mental demand and frustration, corroborating Wojtusch et al. (2018)'s findings on the impact of delay on UW factors. This results are shown in Figure 3, extracted from Seo et al. (2023)'s report.

Notably, the authors found that operators were more prone to making cautious, calculated movements in high-delay scenarios, which resulted in better task accuracy but increased the overall task time and UW. SA was emphasized as a critical factor influenced by delayed visual feedback. In alignment with Wojtusch et al. (2018), they observed that SA deteriorated as delays increased, particularly in terms of understanding (SA3), since operators reported struggles to maintain accurate mental maps of the environment. This decrease in SA under delayed feedback further shows the need for adaptive teleoperation systems that support operator decision-making by minimizing SA loss through predictive visual aids or other delay-compensation mechanisms.

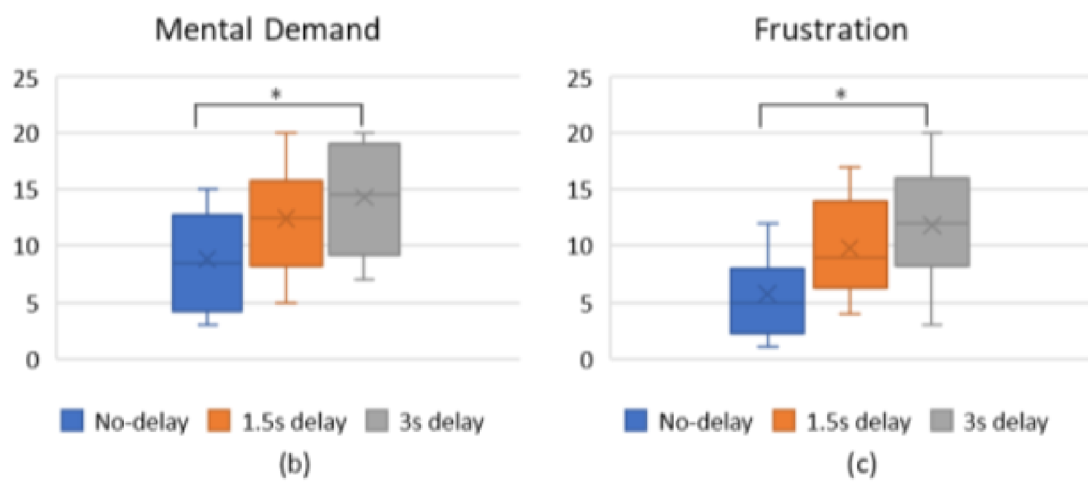


Figure 3: User Workload dimensions: Mental demand and frustration measured with NASA-TLX survey against different delays (Seo et al., 2023)

The findings from Seo et al. (2023) are particularly relevant for our teleoperation scenario, where effective navigation and timely decision-making are crucial despite potential delays. Their approach demonstrates that workload and SA are not only essential metrics for evaluating teleoperation under delay but also critical for identifying effective delay-mitigation strategies. By assessing these factors, Seo et al. (2023) offer a systematic framework for understanding how operators adapt to delay environments.

What is situational awareness and how can it be measured in the context of teleoperated robotic platforms?

Situational awareness (SA) for teleoperated control, which is of crucial importance in dynamic threats such as those faced with dangerous fire situations. Gatsoulis et al. (2010) also mentioned that there had been inadequate SA in human-robot interaction, which led to sub optimal performance of the urban search and rescue (USAR) tasks. These were existing methods of formally measuring SA that had been applied in air traffic control and other domains, with the goal to guarantee operators retained high-fidelity mental representations of their environment so they could make effective decisions acutely under pressure.

In teleoperation, SA refers to the operator's ability to comprehend the spatial and operational dynamics of the environment through remote sensory feedback. According to Endsley (1995) three-tier model (table 4), SA can be broken down into three primary levels:

In the context of a teleoperated platform, SA is directly related to how well operators can perceive and interpret visual data from the remote environment and navigate efficiently under varying levels of time delay. For firefighting practices, a maze reconstruction task poses a challenge for operators to create an accurate cognitive map of an unknown environment's layout, keep track of their navigation, and plan their movements accordingly to avoid dead-ends or delays.

In teleoperated scenarios like fire reconnaissance, maintaining high levels of SA is critical for task success, especially under time delays, which introduce an additional cognitive burden. High delays can disrupt the operator's perception of robot

SA Level	Description
Level 1: Perception	Recognizing key spatial elements such as obstacles, robot position, and target locations.
Level 2: Comprehension	Understanding the significance of the perceived elements in the context of the task at hand.
Level 3: Projection	Anticipating the future states of the system and the environment based on current data and movement patterns.

Table 4: Three Levels of Situational Awareness (SA) in Teleoperation

movements and environmental feedback, making it difficult to anticipate outcomes or adjust strategies dynamically. As such, low situational awareness is often linked to poor task performance and increased operator workload.

How does high cognitive load affect performance when operating a robotic platform?

User workload (UW) in teleoperation refers to the mental, physical, and temporal demands placed on an operator while controlling a robotic platform remotely. It encompasses the cognitive resources required to interpret sensory feedback, make decisions, and execute control commands effectively. High user workload can significantly impact operator performance, particularly in high-stress, time-sensitive environments such as fire reconnaissance, where maintaining a manageable workload is essential for success.

Workload can be systematically measured using various established methods. One of the most widely recognized tools is the NASA Task Load Index (NASA-TLX) (explained in Table 5, which evaluates workload across six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration (Hart, 1988). This method provides a subjective measure of an operator's perceived workload by having them rate their experience across these dimensions, offering insights into the specific aspects of a task that contribute most to the overall workload.

Dimension	Question	Scale (1-100)
Mental Demand	How much mental and perceptual activity was required (e.g., thinking, deciding, remembering, looking, searching)? Was the task simple or complex?	1 (Low) - 100 (High)
Physical Demand	How much physical activity was required (e.g., pushing, pulling, turning, controlling)? Was the task easy or physically demanding?	1 (Low) - 100 (High)
Temporal Demand	How much time pressure did you feel due to the pace at which the task elements occurred? Was the pace slow or fast?	1 (Low) - 100 (High)
Performance	How successful do you think you were in accomplishing the task goals? How satisfied were you with your performance?	1 (Perfect) - 100 (Failure)
Effort	How hard did you have to work (mentally and physically) to accomplish your level of performance?	1 (Low) - 100 (High)
Frustration	How insecure, discouraged, irritated, stressed, and annoyed did you feel during the task?	1 (Low) - 100 (High)

Table 5: NASA Task Load Index (NASA-TLX) Survey Dimensions, Questions, and Scale

In the context of teleoperated robotic platforms, workload measurement is crucial for understanding how different factors—such as interface design, time delays, and task complexity—affect an operator's capacity to manage tasks effectively. For instance, Wojtusch et al. (2018) emphasizes the importance of evaluating workload to optimize teleoperation interfaces and reduce the cognitive burden on operators. High workload can lead to decreased situational awareness, slower decision-making, and increased error rates, all of which are detrimental in critical operations.

Moreover, Seo et al. (2023) highlighted the impact of delayed feedback on operator workload in teleoperation, showing that as delays increase, the cognitive demand on operators also rises, leading to potential performance decrements. This relationship underscores the need for effective workload management strategies, such as adaptive interfaces or assistive technologies, to support operators under varying conditions of delay and task difficulty.

Ultimately, measuring and understanding user workload in teleoperated systems are essential for designing platforms that enhance operator performance, maintain high levels of situational awareness, and ensure successful mission outcomes in challenging environments.

2.3 How can we support the operator to operate in time-delay situations?

A wide variety of robotics and teleoperation applications have been developed, ranging from space missions and military operations to unmanned ground vehicles in urban environments. Some of the major challenges for these applications include latency, channel corruption, and bandwidth, which limit teleoperation efficacy Farajiparvar et al. (2020). Even though several military robots are being designed with semi-autonomous systems, teleoperations will still be an essential element for the foreseeable future. It is said that teleoperations will be the default mode for military robotic systems with a significant role, even for those capable of semi-autonomous and fully autonomous modalities Chen et al. (2007). For safety measures, (Musicant et al., 2023) suggests to separate technological assistance for the operator, such as obstacle avoidance and lane keeping, from the autonomous driving system and keep teleoperation as an alternative. Another recommendation from the same authors is the implementation of predictive and multi-modal displays to enhance teleoperation systems.

Time lags are also known to reduce the control and accuracy of human operators. Performance is heavily affected by the operator's inability to predict the outcome of their actions (Davis et al., 2010). Without this ability, adapting to time lags in control systems can be a very difficult task. Several mechanisms have been studied for the mitigation of time delays, including mathematical predictors, mathematical filters, predictive displays, and command displays (Davis et al., 2010). Predictive displays can provide immediate feedback to the operator to help offset the effects of time delays by using a model representation of the robotic system. This method has proven to significantly reduce lane offset and increase vehicle's speed in driving simulations with both fixed and variable time delays. The use of predictive displays has also been shown to be effective in diminishing operator's perceived workload during teleoperation tasks (Musicant et al., 2023).

Time-delays in teleoperation can be simulated using various methods, each influencing system response and operator performance differently. Rahman (2020) categorizes time-delays as discrete, distributed, or mixed, each adding unique dynamic effects on stability and control accuracy (Rahman, 2020). For this experiment, we implemented a first-order lag through Unreal Engine's camera settings to simulate realistic network latency encountered in remote robotic control scenarios. This approach allows the video feedback to gradually update based on the delay condition, which, while not strictly discrete or distributed, provides a smoother feedback model for operators and reflects real-world latency more closely.

Since the early 1970s, the design and implementation of teleoperation interfaces have been explored (Tener and Lanir, 2022). Robotic vehicles are often used in hazardous situations where human involvement may be dangerous, inconvenient, or impossible. As it was mentioned earlier in this chapter 2.3, one of the main applications for such robotic platforms is in military and space contexts. The operator's situational awareness have been shown to be crucial when teleoperating in the presence of time delays (Wojtusch et al., 2018). The ability to perceive and comprehend their surroundings is crucial for a successful teleoperation task. Works from Chen et al. (2007) addressed the study of various human performance issues and user interface design for teleoperation interfaces, including decision-making and issue commands. They addressed how to increase spatial orientation, object identification, and the effect of reliability, field of view, and depth perception of video images on human performance (Tener and Lanir, 2022).

Delays in the control loop have motivated the development of predictive displays since the 1990s (Moniruzzaman et al., 2022). In teleoperated systems, even the smallest delay in visual feedback can negatively affect task performance (Hu et al., 2016). The study from (Musicant et al., 2023) provided a summary of previous investigations according to time delays and driving tasks. Some of these papers would present different kinds of predictive displays to improve the performance of a teleoperated task. Davis et al. (2010) studied the effect of predictive displays using three conditions: fixed delay on 70 ms, 700 ms, and varied delay between 400 and 1100 ms (average delay = 700 ms). The driving task of their experiment consisted of lane following, sharp turns, and slalom manoeuvres. Besides navigating the vehicle, an additional condition was implemented to test the effectiveness of their predictive display. The driving speed was about 31 km/h. Their results showed that without a predictive display, the lane offset was significantly greater, especially with varying time delays. The driving speed was higher when the display was available, even with the greater delays. A 3 survey was also used, and it showed that the use of the predictive display had better scores than without, and the 70 ms delay condition outscored the other conditions (Davis et al., 2010)(Musicant et al., 2023).

Predictive displays are able to use the operator's input commands to simulate the kinematics of the vehicle without delays and immediately display graphically the system output, usually superimposed on the display of the delayed video. Some predictive displays employ a virtual environment (VE), in which an after-image of the robot would behave accordingly to the teleoperator's commands in real-time (Chen et al., 2007). Although disturbances may exist in the real environment, predictive displays have shown a decrease of 50% to 150% on task time performance (Chen et al., 2007). Ricks et al. (2004) reported that their predictive display (ecological display) made navigation tasks 17% faster and had only 1/5 of collisions compared with standard interfaces like maps, streaming video, or status panels. With the ecological display presented by Ricks et al. (2004), the operator is given an intuitive way of visualizing a robot's position relative to the obstacles around it using range sensors. First, a representation of the robot is shown in a world of obstacles coming from the range sensor's data. The second display element is the video feedback coming from the robot's camera. Lastly, the display is "quickened." This is accomplished by moving the camera and the robot in the virtual world, allowing the operator to see the effects of his actions right away (Ricks et al., 2004).

Davis et al. (2010) reported increased vehicle speeds of about 12% and decreased lane offset by about 26% using a predictive display. These results are consistent with previous research on mitigating time delays. The enhanced speed and accuracy were likely due to the ability to reproduce almost immediate feedback to the operator. This research not only studies the effects of time delays but also examines their effects in the presence of subjective workload (Davis et al., 2010). Incorporating the predictive display resulted in significantly lower reports of mental workload and temporal demand from their participants. Even though the authors considered this method to be feasible, it comes with a set of challenges that need to be addressed before implementing it in real-world situations. For instance, the predictive display would require constant calibration based on the measured misalignment between the predicted and current positions of the vehicle. It is also suggested that for shorter time delays or slow driving speeds, a predictive display that consumes less of the visual field of the operator may be more beneficial (Davis et al., 2010). The relative size of the predictive display in their experiments was proportional to its relative proximity to the operator, and the semi-transparent image consumed most of the operator's visual field. Future work is considered to study the operator's attention focus when predictive displays are present. Eye-tracking data could be useful to test this phenomenon.

Moniruzzaman et al. (2022) presented a teleoperation simulator that can replicate high latency teleoperation driving tasks and can be used to test the effectiveness of assistive interfaces. Their research investigated two 2D visual feedback-based interfaces (sliding-only, and sliding-and-zooming windows) (Moniruzzaman et al., 2022). These assistive interface apply simple but effective video transformations to enhance teleoperation tasks. An operator survey was realized to evaluate the results of the experiments, with and without assistance. The survey showed that delays above 900 ms increased task completion time by 205% for an on-road and 147% for an off-road driving track (Moniruzzaman et al., 2022). Additionally, the over correction-induced oscillations increased to 718%. Their results concluded that a sliding-only predictive window would decrease task completion time by up to 25.53% and oscillation count by up to 66.28%. Meanwhile the sliding-and-zooming interface reduces the task completion time by 21.82% and the oscillation count by 75.58% (Moniruzzaman et al., 2022). This qualitative feedback demonstrates that both interfaces offer better visual situational awareness, comfort, and control, and significantly reduce the negative effects of time delays and intermittency on the teleoperation task.

Time delay, as defined by Yang and Dorneich (2015), can lead to increased frustration, anger, and arousal, while diminishing user satisfaction (Yang and Dorneich, 2015). This is particularly relevant in high-stress environments where delayed responses could lead to compromised decision-making and emotional strain. In teleoperation, managing such emotional factors is critical, as they can substantially affect task performance and operator resilience under time delay. By understanding and mitigating these emotional responses, we aim to improve operator experience, which in turn could lead to enhanced task performance.

In a 2022 study titled *Analytic Review of Using Augmented Reality for Situational Awareness*, Woodward and Ruiz analyze how augmented reality (AR) technologies impact users' situational awareness (SA), especially within high-stakes and complex environments like navigation, aviation, and driving Woodward and Ruiz (2022).This paper provides a comprehensive review of recent research exploring how AR enhances situational awareness, which is critical for effective decision-making and task performance in dynamic situations.

The work by Woodward and Ruiz (2022) also explores a number of mitigating strategies intended to improve situational awareness in AR interfaces. They point out typical issues that can impair a user's capacity to retain SA, include cognitive workload, information overload, and perceptual misalignment. These researchers assess methods like adaptive display approaches, which modify the type and quantity of information presented according to the user's cognitive load or setting, in order to address these problems. Another approach is "information overlapping," which lets users choose what they see depending on the needs of a task by separating important information from secondary material, aligning with studies like Ricks et al. (2004); Yang and Dorneich (2015). They also go over how visual and auditory signals help focus attention on important regions, lower cognitive demands, and improve memory. By analyzing these mitigation techniques, Woodward and Ruiz (2022) provide valuable insights into how AR systems can be optimized to support situational awareness across different applications and contexts.

Table 6, summarizes the reviewed mitigation technologies, outlining the challenges they aim to address and the methods used to support SA and UW in teleoperated missions:

Challenge	Mitigation Technique	Description
Latency	Predictive Displays	Simulates immediate feedback using a robotic system model, helping operators anticipate the effects of commands despite visual delays Davis et al. (2010); Musicant et al. (2023).
Control Accuracy	Ecological Displays	Provides intuitive representations of the robot's environment, such as obstacle proximity and spatial orientation, reducing navigation errors and improving task completion Ricks et al. (2004).
Operator Perceived Workload	Adaptive Visual Cues	Employs visual cues that dynamically adjust based on task demands and user workload to prevent cognitive overload, enhancing control Woodward and Ruiz (2022).
Task Performance	Sliding-and-Zooming Interface	A visual feedback system with sliding and zooming functions to help operators compensate for time delays, reducing oscillation errors and improving task completion times Moniruzzaman et al. (2022).
Visual Feedback	Virtual Environment (VE) Based Predictive Display	Creates a virtual after-image of the robot that responds in real-time to operator commands, allowing operators to see action outcomes without delay Chen et al. (2007).
Emotional Strain	Multi-Modal Feedback	Integrates auditory and visual feedback to reduce frustration and mental strain, supporting smoother operation under high-latency conditions Yang and Dorneich (2015).

Table 6: Time-Delay Mitigation Techniques for Teleoperation

To sum up, the existing literature highlights the significant effects that time delays have on the cognitive load, decision-making, and situational awareness of operators in teleoperated systems. As evidenced by studies such as those conducted by Kohrs et al. (2016), minimal delays can significantly disrupt operator performance, creating cognitive effort and potentially decreasing performance. These results are corroborated by Stark et al. (1988), who highlights the neurological challenges posed by delays, disrupting the human-machine interaction. Furthermore, Yang and Dorneich (2017) and Wojtusch et al. (2018) highlighted the importance of situational awareness and important User Workload factors, while also offering ways to improve system design and mitigate the negative effects of time delays through training. Lastly, addressing these delays through technological developments and improved operator training is necessary to increase the efficacy and safety of teleoperated systems in a variety of operating scenarios.

2.3.1 Gaps in Knowledge

The current literature on time delays in teleoperated systems provides a solid foundation for understanding the basic impacts on operator performance, UW and SA. However, several critical knowledge gaps remain, particularly regarding how these effects translate to real-world conditions and different robotic applications. Addressing these gaps is crucial for advancing teleoperation safety and efficacy, especially with high-risk scenarios like dangerous fire situations.

One significant gap is the limited understanding of how different types of delays impact operator performance under realistic conditions. While most studies have investigated discrete, consistent delays, real-world teleoperation often involves more complex delay patterns, such as intermittent, distributed, or mixed delays due to fluctuating network connectivity and environmental interferences (Rahman, 2020). This gap is especially relevant for unmanned ground vehicles (UGVs) operating in challenging environments where network conditions can vary unpredictably. For our experimental design, we adopted a wider range of delays, employing smoother distributed delays to simulate more realistic network conditions rather than discrete delays, therefore providing a more robust analysis that better reflects real-world operations.

Additionally, a notable limitation in existing research is the lack of insights into how moderate time delays affect UGVs operating at lower speeds. Much of the current literature has focused either on scenarios with high velocities and low delays (e.g., military or aviation applications) (Musicant et al., 2023; Moniruzzaman et al., 2022) or low velocities with significant delays (e.g., space exploration) (Seo et al., 2023; Wojtusch et al., 2018). However, UGVs in reconnaissance missions often operate at low to moderate speeds where moderate delays may still impair decision-making and control accuracy. This research gap underscores the need for a specific analysis for UGVs under moderate to high delay conditions, since findings from high-velocity scenarios may not directly translate to lower-speed operations.

Furthermore, while predictive and multimodal interfaces have demonstrated promise in controlled conditions, there is insufficient evidence to support their effectiveness in a variety of practical situations. Studies by Musicant et al. (2023) and Davis et al. (2010) indicate that predictive displays can reduce UW and improve task performance under time delay conditions, yet the variability of situations with fluctuating network latency and unforeseen obstacles (e.g., limited visibility caused by smoke from a burning building) remains largely unexamined (Dyrks et al., 2008). More scientific research is needed to test these measures in unknown real-world settings, especially where operator mental demand and frustration are more prominent.

Lastly, individual operator differences, including experience and situational awareness (SA) capabilities, are lacking in the literature. Although evidence suggests that individuals with stronger spatial abilities perform better under delayed conditions (Sloan, 2005), there is limited knowledge about how training or adaptive interfaces could enhance the performance of operators with varying SA and experience levels. A better understanding of these individual differences could inform the development of tailored training programs and interface designs that optimize performance and safety in teleoperated systems.

In conclusion, addressing these knowledge gaps, particularly in terms of mitigation strategies and individual factors, will be essential for advancing teleoperation capabilities. Such progress will enhance the efficacy of teleoperated robotic platforms while providing safer operator experiences in hazardous environments.

2.3.2 Hypotheses

Our study project's goal is to examine and lessen the impact of different time delays on robotic locomotion teleoperated control, with an emphasis on fire reconnaissance scenarios. The impact of increasing delay magnitudes on operator performance, task success, and situational awareness in fire response scenarios can be methodically investigated by developing focused hypotheses. In order to improve the efficacy of teleoperation and strategic planning for high-risk scenarios, each hypothesis is designed to guide the experimental setting and data analysis.

H1: Delay Threshold of Perceptible Impact: As demonstrated by Kohrs et al. (2016) and Yang and Dorneich (2017), delays from 300 ms up to 600 ms can cause significant decrease in navigation precision and situational awareness (SA). After reaching 300 ms of delays, a modest decrease in performance should be noticeable, and after 900 ms performance will drop to an unacceptable level.

H2: Incremental Effects of Time Delay after 1 second: Based on findings by Chen et al. (2007) and Seo et al. (2023), we hypothesize that incremental increases in time delay length have a linearly proportional impact on task completion time after 1000 ms. Chen et al. (2007) emphasizes that when system latency exceeds this magnitude, operators tend to shift their control technique to a "move and wait," strategy rather than driving with continuous commands. We hypothesize that this will cause a higher recorded times during the navigation experiments.

H3: Effects of Time Delays on User Workload: In line with the research by Lu et al. (2019), Wojtusch et al. (2018) and Seo et al. (2023), we hypothesize that as time delays increase, cognitive load will also increase. Results in similar teleoperation tasks (Seo et al., 2023) have shown that user workload (UW) dimensions: mental demand and frustration were significantly impacted by delayed conditions.

H4: Time Delays Impact for Rots in de Brand: Given the delays reported by the Rots in de Brand project (80 ms to 1800ms) and the maximum speed of the vehicle (2 m/s), driving performance should not be significantly affected by low and moderate delays (170 ms to 400 ms)(Moniruzzaman et al., 2022; Kohrs et al., 2016). This is based in prior research on minimal delay thresholds where the working speeds were around 6 m/s (Musicant et al., 2023).

These hypotheses are structured to assess how delayed teleoperation affects driving, situational awareness, and the subjective user workload in a teleoperation tasks in the presence of time delays. Through a series of controlled experiments simulated delay conditions, the influence of how delays affect operator performance across key variables will be studied. The robotic platform used in the Rots in de Brand project is designed for high-risk environments where precise control and accuracy is vital for mission success. Like most UGVs with similar applications, this robotic platform features a unilateral control configuration, which means that only visual feedback is received from the operator's side (Zhu et al., 2011). With a robot moving at speeds as low as 2 m/s (7 km/h), this vehicle provides a slower pace than previously studied systems, offering a unique opportunity to analyze delays under conditions not previously studied in teleoperation research.

3 Experimental Design

To test the formulated hypotheses in section 2.3.2, a series of tasks were designed to evaluate the impact of time delays on a teleoperated environment. The primary task consisted of a driving course where operators faced different delays from the robot's video feedback. It involved driving a simulated UGV through a maze using simulation software Unreal Engine 4 (UE4). After each run, a secondary task was introduced to test the participant's situational awareness (SA). This task required the participants to recreate the maze based on their recollection of the driving test. Finally, a NASA-TLX (NASA Task Load Index) survey was given to the participants to measure their cognitive workload (UW) and use these results to analyze the effects for each delay condition.

The duration of each test was set between 30 to 45 minutes including briefing, test runs, driving test, SA test, UW assessment and de-briefing. To increment the robustness of our experiments, a decision was made to have participants test the experiment multiple times with different randomized delays. Each measure (completion time, SA and UW) was taken three times per participant, since the goal of this experiment is to have a score for all different delays and to minimize individual factors and variability on the results.

3.1 Recruitment

Sixteen participants were recruited specifically for the experiment, most participants were students and workers from the University of Twente due to practical and methodological considerations. Since participants were close to the experimental site making the experimental set up more efficient. The sample size was chosen carefully to balance between practical constraints and a robust analysis. For each participant, 3 different randomized delay conditions (0 to 1800 ms) were tested along with SA and UW assessment making. Given that a total of 12 different delays were tested, this sums up to 48 observations in total for each metric.

Before each test, each participant was asked wether they have gaming experience or not. As discussed in Section 2.3.1, it was hypothesized by Sloan (2005) that people with more experience (or spatial abilities) might perform better than the rest. To determine if their gaming experience was significant or not, we asked them the frequency and amount of time that they played any video game in the present year. The majority of the participants revealed to have considerable gaming experience, but there is still a number of those who did not have any experience.

3.2 Consideration of Time Delay Thresholds in Experimental Design

As Korte et al. (2014) demonstrate, time delays exceeding 1.5 seconds typically lead to a degradation in task performance as operators adopt a move-and-wait strategy to maintain accuracy under delay conditions (Korte et al., 2014; Chen et al., 2007). For our study, we chose time delays within the minimum and maximum magnitude reported from Rots in de Brand which ranged from 80 ms to 1800 ms. This range of delays was randomly distributed among participants. In difference from reviewed literature, this study takes more delays into consideration with the hopes of obtaining more accurate results. The analyzed delays consists of: 0, 80, 160, 320, 400, 600, 800, 1000, 1200, 1400, 1600 and 1800 ms.

3.3 Simulation Environment

The virtual environment was created with Unreal Engine 4 (UE4) to imitate the Rots in de Brand robotic platform, with a first-person view and a remote controller. This game engine was chosen for its ability to deliver high realistic graphics and physics simulations, which have been proved crucial for modeling real-world conditions in teleoperation tasks. UE4 allows for seamless control of environment variables like lightning and textures, thus facilitating the virtual simulation of environments with low visibility, unknown structures, such as the ones presented in fire situations.

For consistency with the Rots in de Brand platform's real performance, the robot's velocity was set at 2 m/s as specified in the real technical specifications of the robotic platform (see Table 7). Within the simulated environment, a simple maze layout was designed inspired by the studies from Yang and Dorneich (2017) for their task analysis. Their findings suggested that increasing task complexity coming from different maze layouts have an impact in both driving task and UW (Yang and Dorneich, 2017). Hopefully, the control of this variable will allow the study to isolate and accurately measure the impact of various delay intervals on task performance, situational awareness, and operator workload.

Furthermore, the type of time delays introduced from the simulation are differ from the ones reviewed from literature. Instead of having discrete or fixed delays, which are not realistic for real-world scenarios (Rahman, 2020), a choice was made to include distributed delays within UE4. With this novel approach, the simulation is closer to a real-world scenario where delays magnitudes are still the same, but delivered differently.

3.3.1 Camera Lag in UE4's Spring Arm Component

According to UE4's documentation, the camera lag effect can create smooth transitions between the camera's position and target position using the Spring Arm component Unreal Engine Documentation (2023). This technique is especially useful

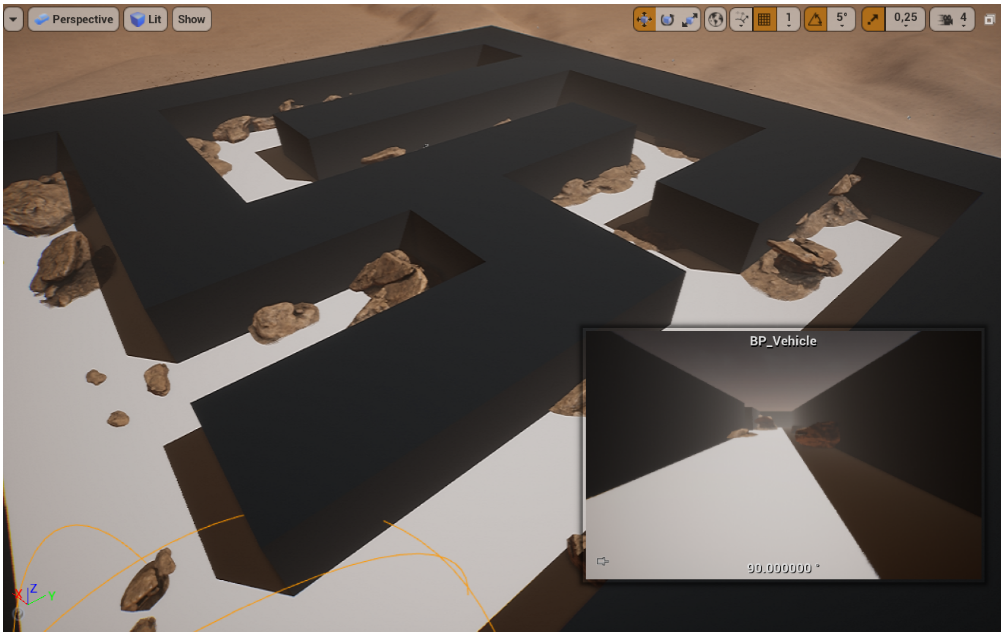


Figure 4: Simulation Environment. A screenshot of the UE4-based simulation environment used for the teleoperation task, showing the robot's perspective during the maze navigation task.

in third-person POV games, where a slight lag in camera movement relative to the player pawn adds a modest delay that enhances gameplay. After experimenting with different approaches, such as "Emulating bad Network Connectivity" and "Buffering camera frames," we found that the Spring Arm component produced a delay effect that closely matched our intended requirements for creating a first-order lag.

However, it is essential to note that our implementation is not fully aligned with the distributed delay approach described by Rahman (2020), which simulates delays more realistically by distributing them across different networks to replicate varied delay behaviors. In our instance, we used UE4's Spring Arm component to implement a more seamless, continuous delay that was dependent on the target's position in relation to the cameras'. Despite this distinction, the Spring Arm component provides a close approximation suitable for simulating a controlled delay effect. This allows consistent testing of operator performance under modest, adjustable delay conditions.

With this configuration, by adjusting the alpha parameter fixed delay values can be approximated. For example, an alpha value of 1 would result in the camera reaching the target position in approximately 1 second, effectively simulating a 1000 ms delay (Unreal Engine Documentation, 2023). Operator responses to incremental delay conditions can be systematically tested thanks to this controlled approach. Although this is not the same as distributed network latencies in the real world, the configuration offers important information on how users adjust and how well tasks operate at different delay levels. In order to confirm these results in settings with varying, dispersed delays, future research could expand on this by using more intricate delay models.

This implementation can provide valuable insights, especially when testing gradual delay effects and smooth response adjustments rather than fixed or discrete delays (Rahman, 2020). In alignment with this study, our focus is to explore how operators respond to real-world network fluctuations. Hence, the decision was made to include this addition to the simulated environment of our project.

The behavior of Unreal Engine's Spring Arm component, is modeled by the following formula. While a lower α introduces more lag, a higher α value causes a faster camera response.

$$\mathbf{p}_{\text{camera}}(t + \Delta t) = \mathbf{p}_{\text{camera}}(t) + \alpha \cdot (\mathbf{p}_{\text{target}}(t) - \mathbf{p}_{\text{camera}}(t)) \cdot \Delta t$$

where:

- $\mathbf{p}_{\text{camera}}(t)$ is the current camera position at time t,
- $\mathbf{p}_{\text{target}}(t)$ is the target's position at time t,
- α is the lag speed factor, determining how quickly the camera catches up to the target,
- Δt is the time step for each update.

Figure 5 compares the effect of simulated delays on target and camera movement, comparing responses with and without smoothing across different delay values. The plot displays the target's movement simulating a wait and move maneuver, overlaid with delayed responses under both models. Solid lines show fixed delays without smoothing, with the response trailing sharply behind the goal, resulting in a more abrupt, ramped effect as the target moves. Dotted lines show the smoothed delay model, using exponential smoothing with different delay settings (e.g., 50 ms, 500 ms, and 1000 ms). Smoothing inserts a steady, continuous lag into the reaction, making it appear more fluid and allowing the delayed position to gradually catch up to the target.

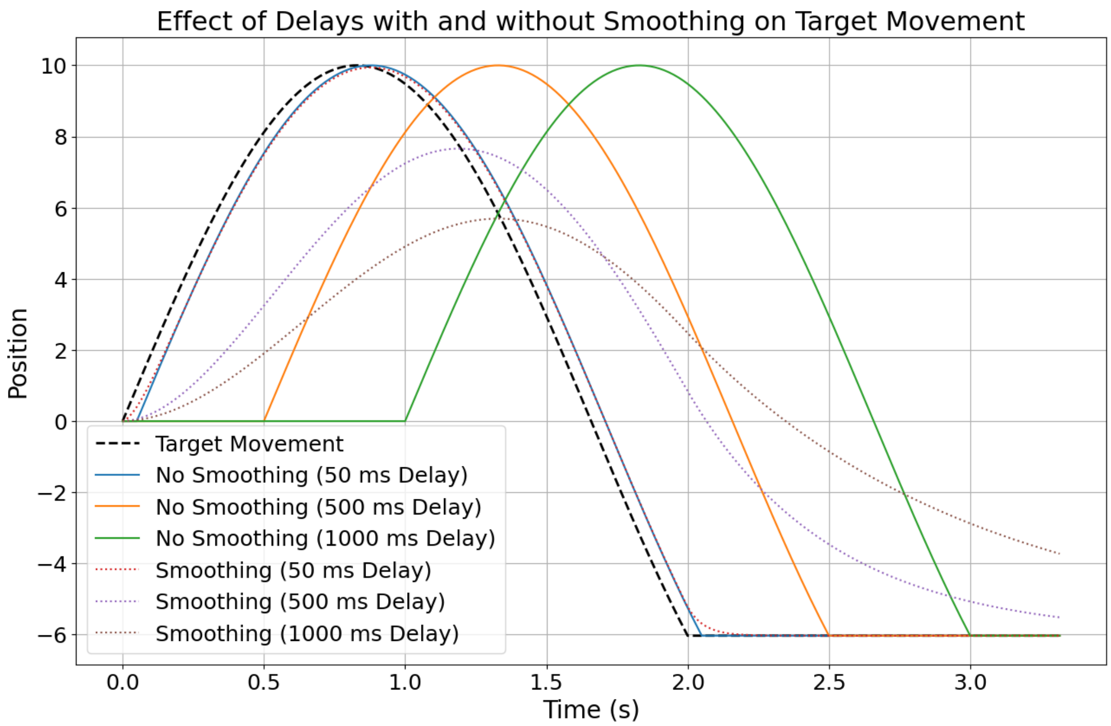


Figure 5: Delays with and without exponential smoothing with respect on target's position.

3.4 Navigation Task

The primary task involved navigating the robot through a maze (see Figure 6). Driving performance was assessed by measuring the time taken to complete the track in each run, which served as an indicator of the participant's proficiency in controlling the robot under different time-delay conditions. Participants had to rely on video feedback from the robot's camera to navigate the maze, mimicking real-world teleoperation scenarios such as search and rescue missions or reconnaissance in dangerous environments (Seo et al., 2023).

Thanks to the game engine, we were able to design a stop-watch component and an action block for securely measure each and every run. Using keyboard actions, a trigger was made to apply the delay condition to the robot's camera and starting a stop-watch at the top of the screen. Before pressing this key, participant's movement is set locked to prevent false starts in the test. Additionally, to precisely record each run, UE4 permits us to create a programmable object which we can assign all set of rules and behaviors. In our case, we created an instance of a box with transparent material placed at the end of the maze. Inside the blueprint (or programming blocks), from the stop watch component, we added a collision condition that whenever the pawn-actor (the robot) comes into contact with this box, the stop-watch stops allowing us to record the exact results of the driving test to the millisecond.

To ensure that the experiment closely simulated real-world conditions, the robot's speed and dimensions were adjusted to match the technical specifications of the robotic platform used by the Rots in de Brand. Specifically, the experimental robot was designed to emulate the ClearPath Jackal UGV, the same model used by our research team (Figure 7).

Technical Specifications	
Size and Weight	
External Dimensions	508 x 430 x 250 mm (20 x 17 x 10 in)
Internal Dimensions	250 x 100 x 85 mm (10 x 4 x 3 in)
Weight	17 kg (37 lbs)
Maximum Payload	20 kg (44 lbs)
Speed and Performance	
Max Speed	2.0 m/s (6.6 ft/s)
Runtime (Basic Usage)	4 hours
User Power	5V at 5A, 12V at 10A, 24V at 20A
Drivers and API	ROS Melodic, ROS Kinetic, Windows 10, Mathworks

Table 7: Rots in de Brand Platform Technical Specifications

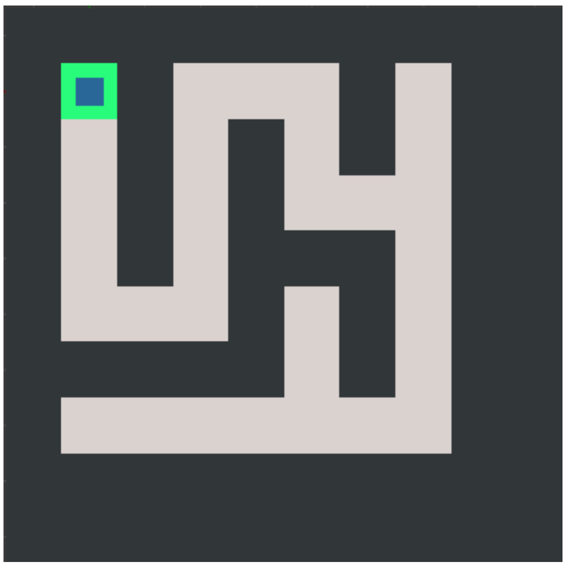
The driving task replicates the type of challenges encountered in real-world high-risk teleoperation, particularly in environments where operators must rely on delayed visual feedback. Where time delays can significantly affect driving performance, as they introduce a lag between the operator's commands and what the operator's perceives. For this task, the max speed was set at 2.0 m/s which is significantly lower from previous studies with similar delay magnitudes (Musicant et al., 2023; Moniruzzaman et al., 2022). The speed, however, is congruent with UGVs in mapping or reconnaissance missions where unknown conditions and/or obstacles might be present (e.g., smoke, debris, walls).

Driving through a long-distance course is completely different than navigating a robot in an enclosed environment where the operator does not have a complete view of the layout. Musicant et al. (2023), for example, created a simulation for a teleoperated car in an urban setting at high velocities with different delay conditions. For this experiment, however, the velocity and the track dimensions were chosen to comply with the project reported specifications. So, it is possible that the results from our experiments does not align completely to their findings because of the velocity condition. And the same applies for Seo et al. (2023), where the authors simulated a robotic platform with similar physical and speed conditions, but with delays higher than ours.

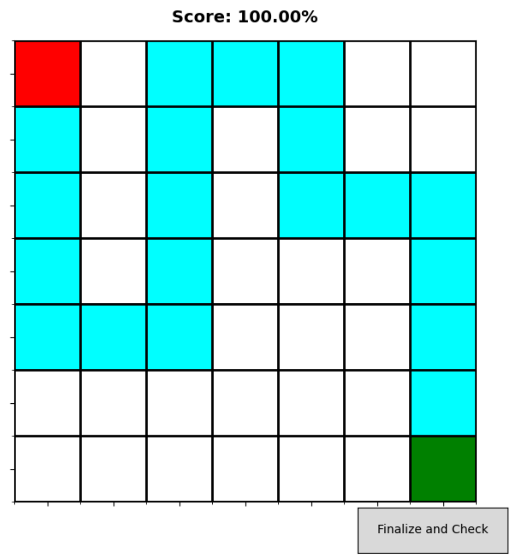
3.5 Situational Awareness assessed by Maze Reconstruction Task

The maze task was used to assess the participant's SA during teleoperation. After each driving session under varying delay conditions, participants were required to reconstruct the maze from the driving course on a 7x7 grid (Figure 6). This task tests their ability to remember and recreate the environment. As delay increases, it is expected that SA scores will deteriorate, which aligns with Hypothesis 3 from Section 2.3.2.

The maze layout (Figure 6a) was generated using a recursive backtracking algorithm, and its dimensions were carefully chosen to allow a single run to take around one minute when no delay is applied. As mentioned in Experimental Design 3 the maze design was kept consistent across all runs, with this it was possible to compare the effects of time delay under identical driving conditions. Participants' SA was evaluated with their accuracy at reconstructing the maze from the grid blocks using a weighted error formula, taking into account both incorrect and missed selections (Figure 6b).



(a) Maze Layout used in the driving task.



(b) Maze reconstruction by a participant.

Figure 6: Comparison of the maze layout and a participant's reconstruction.

SA was measured based on the framework proposed by Endsley (1995):

- *SA1- Perception* involves the recognition of key spatial elements, such as obstacles, pathways, and the operator's current position.
- *SA2- Comprehension* refers to understanding the significance of these elements in relation to the task, such as determining the correct path through the maze.
- *SA3- Projection* requires anticipating future movements, particularly how time delays will affect the robot's navigation and actions.

The maze task (Figure 6a) is designed to evaluate situational awareness (SA) by assessing participants' ability to reconstruct the maze after each run. With time delays introduced into the visual feedback, it is theorized that the recreation of the maze would be significantly more challenging than without them. The reliance on spatial memory makes the maze reconstruction an effective method for examining how well participants maintain SA particularly at the SA2-comprehension level.

The maze reconstruction offers an objective metric for SA assessment. By taking into account how well the participant is able to recreate and understand the environment, we can compare this results with variables like time delays and the navigation ability. Additionally, the use of subjective measures like User Workload (UW) can give valuable insights on their relation with maze accuracy and overall SA. The following section describes how UW was assessed in this project.

3.6 Subjective metric: User Workload (UW)

NASA Task Load Index (NASA TLX) introduced Hart (1988) is a widely used tool for assessing perceived workload (UW) under teleoperation tasks (Wojtusch et al., 2018).

To provide a better understanding of the different factors affecting user workload (UW) during teleoperation, a brief review of the UW dimensions is outlined below:

- Mental Demand: The amount of mental and cognitive effort required.
- Physical Demand: The level of physical effort required.
- Temporal Demand: The time pressure experienced.
- Performance: The perceived success in accomplishing the task. Where a score of 1 is being considered perfect and 100 failure.
- Effort: The amount of effort expended.
- Frustration: The level of stress and frustration felt.

For this experiment, an equally-weighted NASA-TLX survey was used to evaluate overall user workload (UW). Each of the six NASA-TLX dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration were included into our analysis. Each dimension offers a different perspective of the UW perceived from each participant.

After each driving and SA assessment, each participant is asked to rate each dimension on a scale from 0 to 100. This rating provides a subjective assessment of UW, where higher scores indicated increased demand or frustration in that area. Each workload component can contribute equally to the final workload score providing a balanced view of participants' subjective UW. With this approach, we can obtain knowledge about the particular characteristics of teleoperation that are most affected by time delays in an emotional level by examining these NASA-TLX ratings.

For our experiments, and easier application of the survey, we utilized a programming GUI (Graphical User Interface) offered by Tkinter and implemented with Python. Thanks to this method, the data processing for each participant was considerably more efficient and easier to analyze once the experiments are done. This was particularly useful, since our approach consists on making the analysis of UW once for each run, resulting in 48 samples considering 16 participants are assigned to 3 different conditions.

In general, the NASA-TLX survey will be used to quantify the cognitive load associated with the delayed teleoperation, offering a comprehensive measure of UW. With this approach, we aim to identify the areas where delays have the greatest impact, allowing for a better design and user interface improvements to mitigate these effects.

4 Results: Interpretation of Findings

4.1 Summarized Statistics

Measure	Count	Mean	Std	Min	25%	50%	75%	Max
Mental Demand	45.00	38.64	22.89	5.00	20.00	40.00	60.00	80.00
Physical Demand	45.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Temporal Demand	45.00	25.11	23.66	0.00	5.00	20.00	40.00	80.00
Performance	45.00	33.02	20.59	0.00	20.00	30.00	40.00	80.00
Effort	45.00	39.67	25.17	0.00	15.00	40.00	60.00	80.00
Frustration	45.00	22.07	24.84	0.00	0.00	10.00	35.00	85.00
NASA-TLX Overall Score	45.00	26.47	13.04	3.17	18.33	24.17	31.67	58.17
Delays (ms)	45.00	784.00	602.50	0.00	320.00	800.00	1200.00	1800.00
Completion Time (s)	45.00	69.86	14.01	56.80	60.23	63.96	74.63	119.29
SA score (%)	45.00	55.85	17.49	35.89	43.06	50.24	65.61	100.00

Table 8: Descriptive Statistics for NASA-TLX, Delays, Time Scores, and Maze Performance

Descriptive statistics for the test performance measures are shown in Table 8. A total of 45 observations were recorded for each measure, providing enough data to support a reliable analysis of completion time, SA and UW.

The average mental demand was 38.64 and a high standard deviation (Std = 22.89), indicating that participants reported a moderate mental demand with high variability between themselves. Physical demand was consistently rated at 0.00 by all participants, suggesting that the tasks were not perceived as physically demanding. The average temporal demand was 25.11, with a significant variation in responses (Std = 23.66), showing that participants did not feel rushed by the pace of the experiment.

The subjective assessment of UW performance produced a mean score of 33.02, indicating that individuals thought their performance was somewhat above average. Effort has a mean of 39.67, but the highest Std (= 39.67) out of all subjective metrics. Highlighting the diverse responses from participants in this dimension. Frustration reported one of the lowest averages with 22.07 and a Std of 24.84, but it also counts with a reported max value of 85%.

The NASA-TLX Overall Score had a mean of 26.47, and a Std of 24.47. This indicates a relatively low overall UW from the test participants, with the lowest value recorded being of 3.17% and the highest 58.17%.

The completion time score, had an average of 69.86 seconds, with a relatively small Std of 14.01, suggesting that most participants completed the task in a similar time frame just above the one minute mark. And the maximum value reported was just under two minutes (119.29 s).

Finally, SA score, measured by the maze reconstruction task, averaged 55.85% with a Std of 17.49 indicating moderate SA performance across participants, with some obtaining higher scores than others with a reported max score of 100% and the lowest at 35.89%.

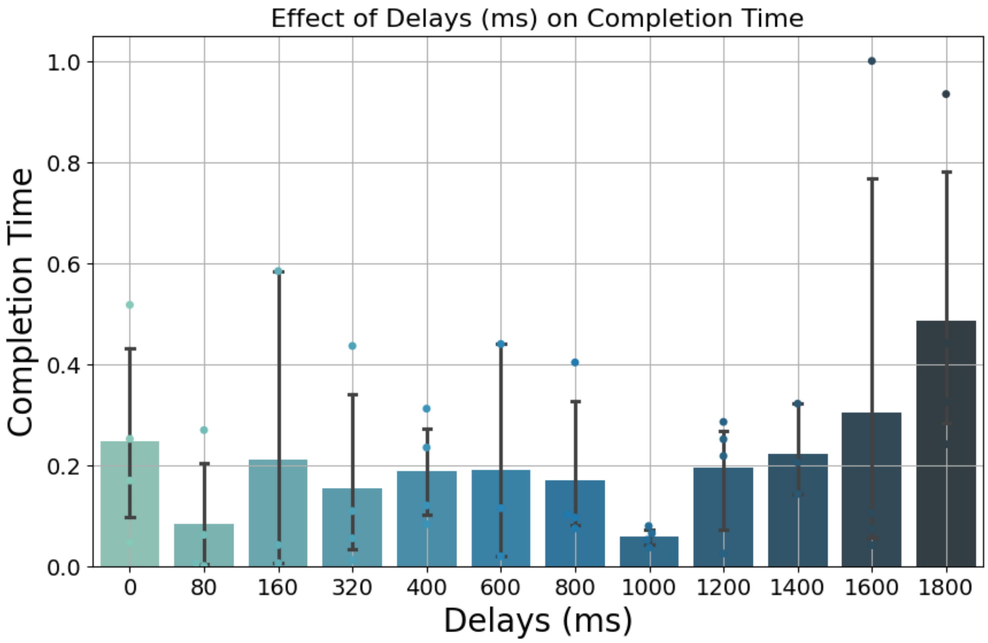
4.2 Objective Metrics: Completion Time and Situational Awareness (SA)

The driving task results under high delay conditions align with Korte et al. (2014), who identified a threshold of 1.5–2.0 seconds, beyond which teleoperators typically adopt a cautious move-and-pause approach resulting in higher completion time. However, in our study, we observed that both driving and SA metrics were barely affected by the lowest delays. In fact, the results suggested that even with delays as high as 1000 ms participants still were able to achieve compelling driving results. But for SA assessment, there was no clear indicator that increasing delays had any effect on this metric. The maze scores fluctuate across the board even with increasing delays, with no signal of correlation between both variables. This comparative analysis highlights the importance of different underlying factors that could have come into play when fulfilling this set of experiments.

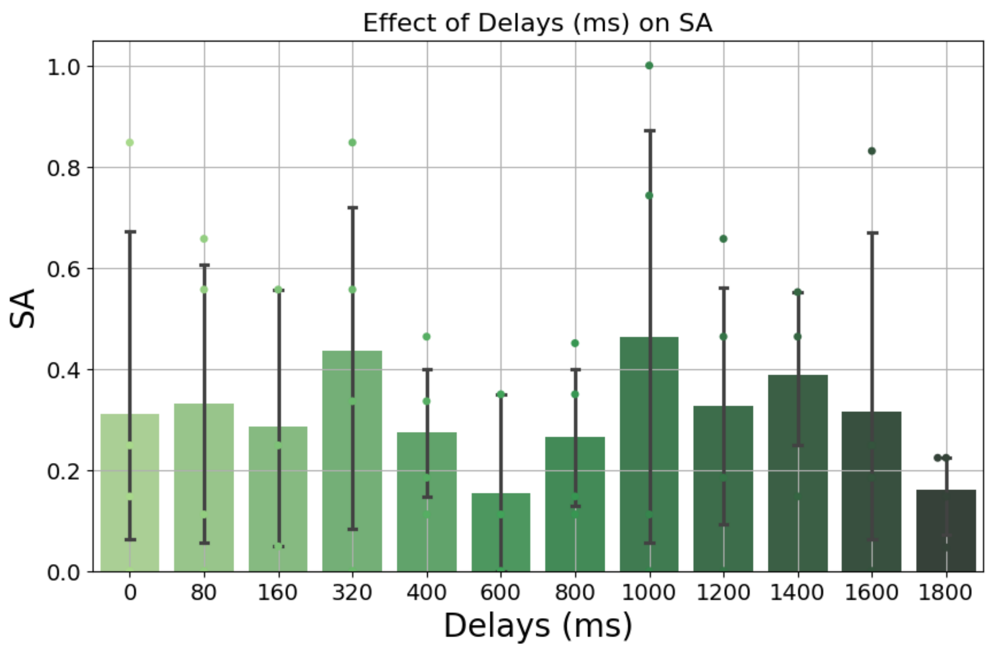
Following subsections show the results of the objective metrics: navigation and SA performance against the introduced time delays (Figure 7) and reported levels of User Workload (UW) (Figure 8). With these results we can study the effects of delays and UW in delayed teleoperation.

4.2.1 Objective Metrics vs Delays

The experimental results from the driving task, as visualized in Figure 7a, shows fluctuating results until the 1000 ms mark. After that, there exists a linear increased in the completion time reported by participants. This discovery aligns with what was previously stated in 2.3.2, which hypothesizes that after 1000 ms, the completion time of the teleoperation task will increase proportionally to the delays.



(a) Completion time (normalized) vs Time Delays (ms)



(b) SA scores vs Time Delays (ms)

Figure 7: Effect of Time Delays on Navigation and SA Scores

Figure 7a illustrates the participants' driving performance, measured in task completion time, across varying delay conditions. Time delays, ranging from 0 ms to 1000 ms, did not result in slower times or reduced performance. Participants' navigation results fluctuated but remained relatively stable even under low-moderate delays, indicating that some individuals were able to adjust to the increased lags without significant loss of performance. However, there is a modest increase of this measure when delays surpassed 1000 ms, with the highest average time scores being reported at the 1800 ms delay, following a linear relationship after the 1200-1400 ms delays corroborating with findings from Korte et al. (2014).

These results also confirmed previous hypotheses (H3), that due to the velocity of our vehicle we might not find a significant decline in the driving performance. This is also corroborated by Rahman (2020) who shares that under moderate delayed conditions, cognitive and emotional load are often more affected than the control accuracy. On the other hand, our navigation results are somewhat comparable with studies that utilized delays as high as 1.5 s and 3.0 s (Seo et al., 2023; Yang and Dorneich, 2017) which used a similar experimental design as ours.

Figure 7b illustrates the Situational Awareness (SA) score using maze reconstruction, which was notably unaffected by growing time delays. SA scores, which reflect how accurately participants were able to rebuild the maze, varied depending on the delay condition and did not decrease as delays progressed. The 800 and 1800 ms delay categories had the lowest marks, while the 320 and 1000 ms delay categories had the highest.

4.2.2 Objective Metrics vs User Workload (UW)

The following figures (Figure 8) illustrate the relationship between completion time and Situational Awareness (SA) with the overall NASA TLX scores, which provides a measure of the perceived workload across the different objective metrics. These visualizations help in analyzing how task performance (measured in terms of normalized completion time and SA) correlates with the perceived cognitive as captured by the NASA TLX survey.

In Figure 8a, the normalized completion time is compared against the overall recorded UW. With low UW (0.0 - 0.6), the time results fluctuate without a clear increasing pattern. However, after reaching higher UW (0.6-1.0) a linear increase for the driving results is made visible. This trend implies that participants who reported higher cognitive took longer to complete the maze, indicating a potential relationship between perceived workload and task efficiency. Or that participants who did poorly in the driving test, recorded higher UW.

In Figure 8b, the SA score is compared against the overall UW.SA results were consistent across almost all degrees of UW. The maze reconstruction accuracy did not seem to decrease when participants experienced low to moderate UW. However, the SA scores experienced a significant plummet when UW was at its, suggesting that higher perceived workload may correlate with lower SA results. Nevertheless, further analysis needs is needed in order to confirm (or deny) the relation between these two metrics for this specific experiment.

4.3 Subjective Metric: User Workload vs Delays

The UW scores across different time delays reveal some important patterns in cognitive and workload-related dimensions during teleoperated tasks (as shown in Figure 9). Mental demand fluctuates across delay conditions but generally decreases as delays increase. For instance, the median mental demand is higher at 0 ms and 80 ms but decreases noticeably at delays of 400 ms and above. This trend suggests that participants experienced a slight reduction in perceived cognitive load as they adjusted to the delays, perhaps due to the slower pace or more deliberate actions taken during the tasks with higher delays.

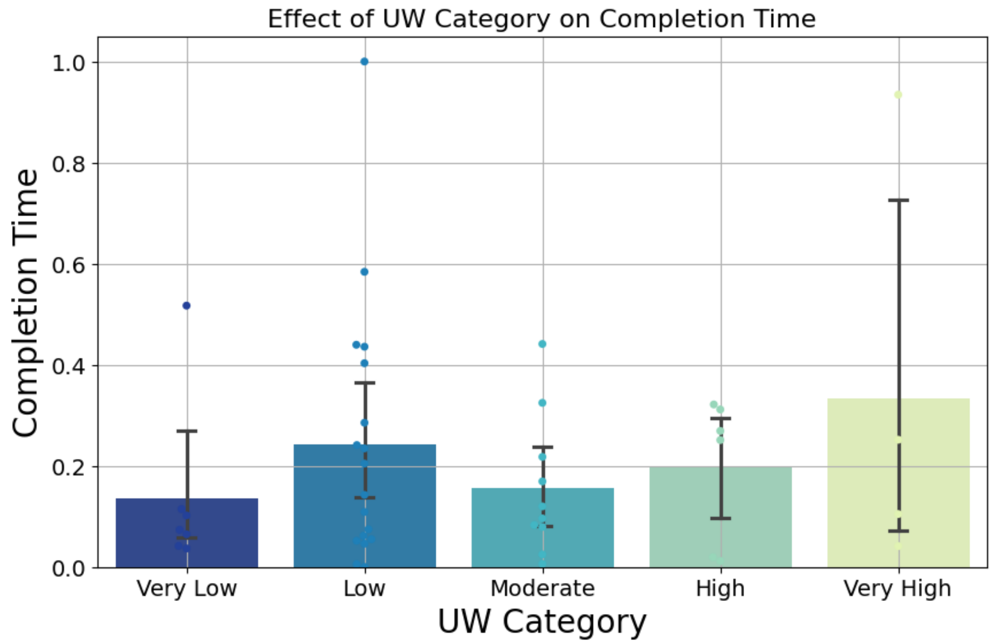
Temporal demand, on the other hand, shows a sharp decline with increasing delays. The highest temporal demand is observed at 0 ms, but as delays increase, particularly from 400 ms onward, temporal demand steadily drops. This pattern indicates that participants felt less time pressure with longer delays, likely because they adapted their behavior, taking more time to ensure correct inputs when faced with delayed responses.

Subjective performance (Figure 9) shows a varied pattern across delay conditions. While performance is relatively low at 0 ms, it increases at intermediate delays (160-800 ms) and then decreases again at the highest delays (1400 ms and 1800 ms). This non-linear trend suggests that participants perceived their performance as improving slightly at moderate delays but felt it declined significantly at the highest delays, likely due to increased difficulty in managing control at very high latencies.

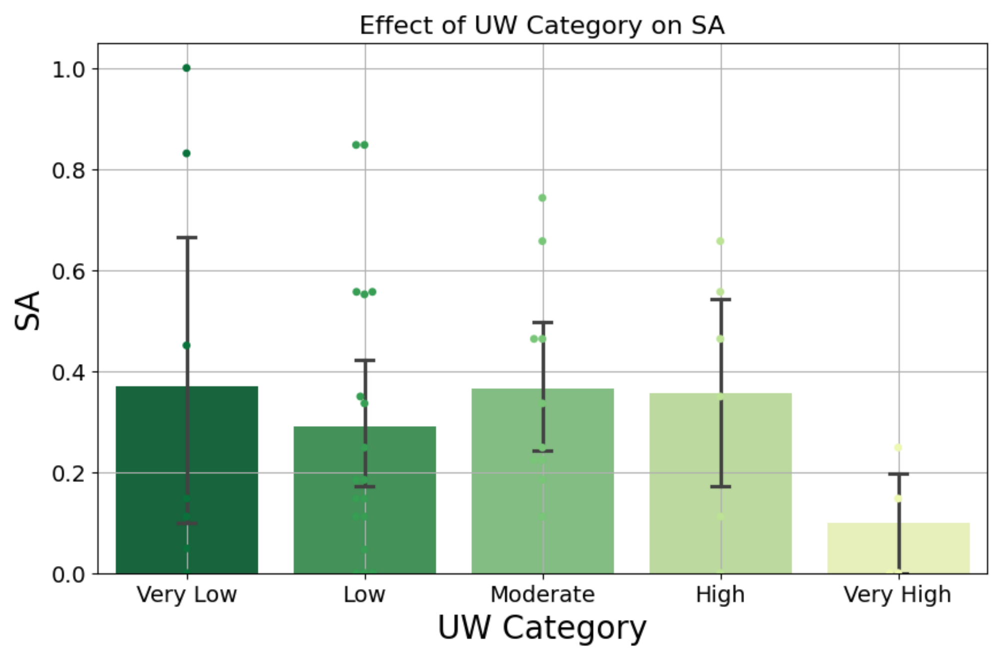
Effort follows a more erratic pattern. It is higher at shorter delays (0 ms, 80 ms) but decreases as delays increase, stabilizing at moderate levels (400 ms to 1000 ms) before rising again at the longest delays (1600 ms, 1800 ms). This suggests that participants initially exerted more effort at lower delays but required less effort to maintain performance at moderate delays, with effort increasing once more as delays became extreme.

Frustration levels generally follow the same pattern as effort, with participants reporting higher frustration at shorter delays and moderate levels of frustration at delays between 400 ms and 1000 ms. Frustration increases again at 1600 ms and 1800 ms, indicating that long delays led to higher emotional strain and difficulty in controlling the task effectively.

The overall UW score reflects these patterns as well, with scores decreasing steadily from 0 ms to around 1000 ms, then increasing sharply at the highest delays (1600 ms and 1800 ms). This trend suggests that participants found the task less demanding as delays increased to a moderate level, but the highest delays significantly impacted their perceived workload and performance.



(a) Relationship between Normalized Completion Time and Overall NASA TLX Scores.



(b) Relationship between SA score and Overall NASA TLX Scores.

Figure 8: Comparative analysis of SA score and Normalized Completion Time in relation to Overall NASA TLX Scores. (a) shows the normalized completion time from the driving task and (b) shows the normalized SA scores, both across NASA-TLX score.

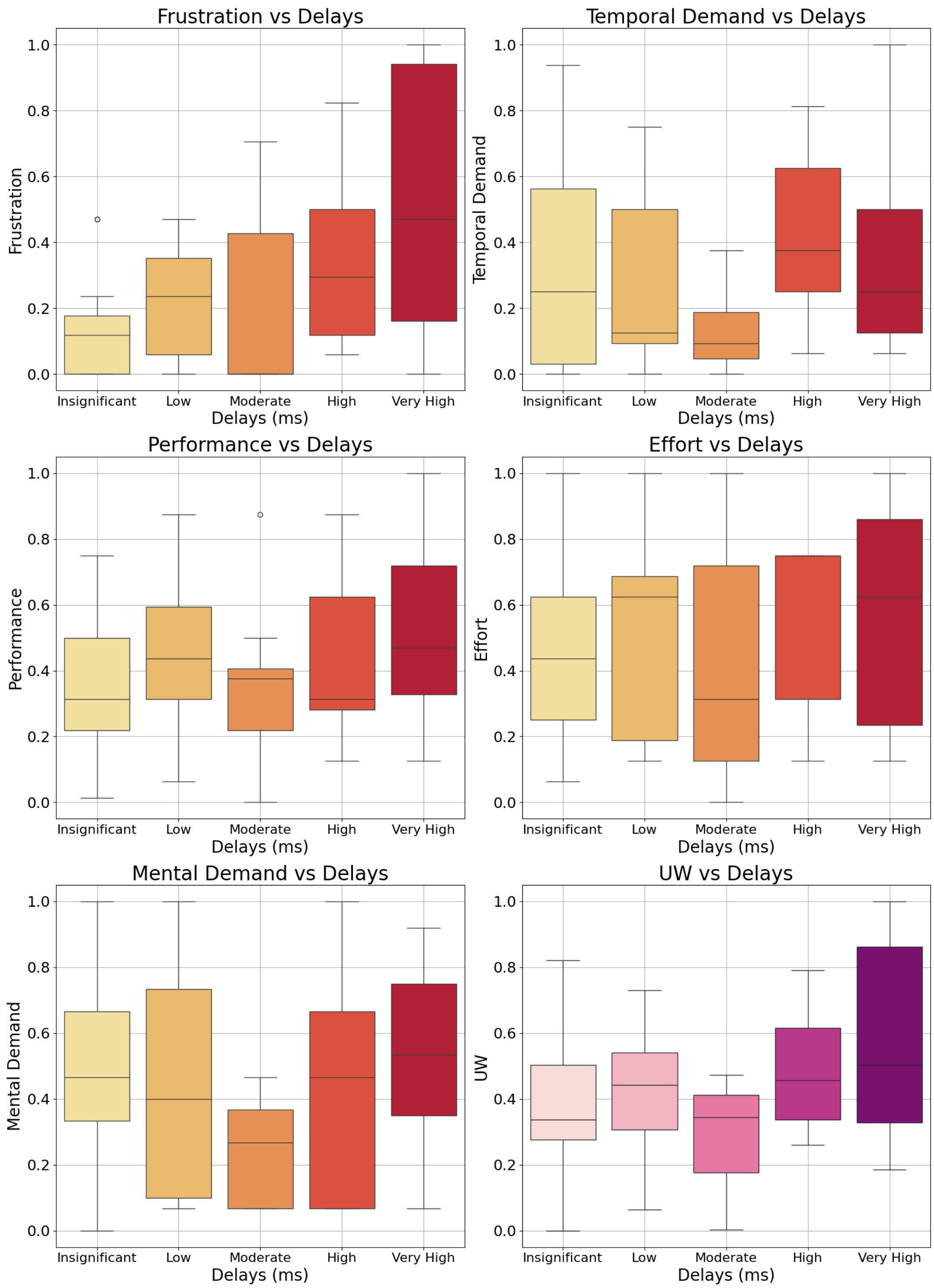


Figure 9: User Workload vs Delays

Physical demand, was not significant enough to be included since it was consistently low across all delay conditions, highlights that the tasks were primarily cognitively and emotionally challenging, with minimal physical exertion required from participants. Which is expected coming from a simulation environment where no physical task is asked from the participants.

In summary, Figure 9 shows that while participants did not reported higher UW overall results, frustration and effort increased significantly at the highest delays. This suggests that time delays primarily affect frustration and perceived effort above all metrics for this specific application, with participants adjusting well to moderate delays but struggling to cope with extreme latencies.

The significant increase in frustration with prolonged time delays is consistent with the findings by Yang and Dorneich (2015), who observed increased emotional arousal and reduced user satisfaction in human-robot interaction with time delays (Yang and Dorneich, 2015). This suggests that time delay in teleoperation not only impacts task performance but also has considerable emotional and cognitive effects on the operator. Understanding these emotional impacts is essential for designing teleoperation systems that support user well-being in high-latency scenarios. This results also align with studies from Seo et al. (2023) where the author made had similar results from a simulated teleoperation task that also involved time delays from 0 to 3s in 1.5s increments. The author reported that frustration and mental demand from UW assessment using NASA-TLOX resulted to be the most influenced dimensions from UW along with their completion time and success rate from their simulated task.

4.4 Impact of Gaming Experience on Performance

An important factor in assessing participants' driving and spatial abilities was gaming experience, which has been shown to influence performance in interactive, delay-sensitive environments (Claypool and Claypool, 2010). The analysis compared individuals with and without prior experience in similar locomotion control across the three core performance metrics: task completion time, situational awareness (SA), and user workload (UW). The impact of different time delays and increased cognitive strain on participants with gaming experience is illustrated in the following figures, providing insights into how previous exposure to interactive virtual environments can shape teleoperation performance. For this analysis, all delays were categorized from insignificant to very high for better visualization and understanding of the results.

Figure 10 shows the influence completion time of those with and without gaming experience. Starting from the left part of the graph, participants who claimed not having game experience reported the longest completion time when delays were insignificant or very high relative to the others. These participants recorded the best driving results when the delay was in the "High" category, and had worst results with a lower delay condition. These results suggests that there is not a proportional effect in performance in comparison with delays for this group, the plot shows inconsistency and variability among the time scores reported in all delay conditions.

In the right side of Figure 10 , participants with prior experience reported lower completion time results. The worst performance from this group was also encountered when delays reached the upper limit of the specified range (0- 1800 ms). The lowest time achieved, however, can be seen in the "Moderate" delay category (1000 ms). After the moderate delays, the completion of the task augmented as the delays went up, in contrast with the other participants of the study. This could suggest that individuals with gaming experience can perform better under moderate to low delays than the ones without, but are more sensitive to bigger delays in the visual feedback.

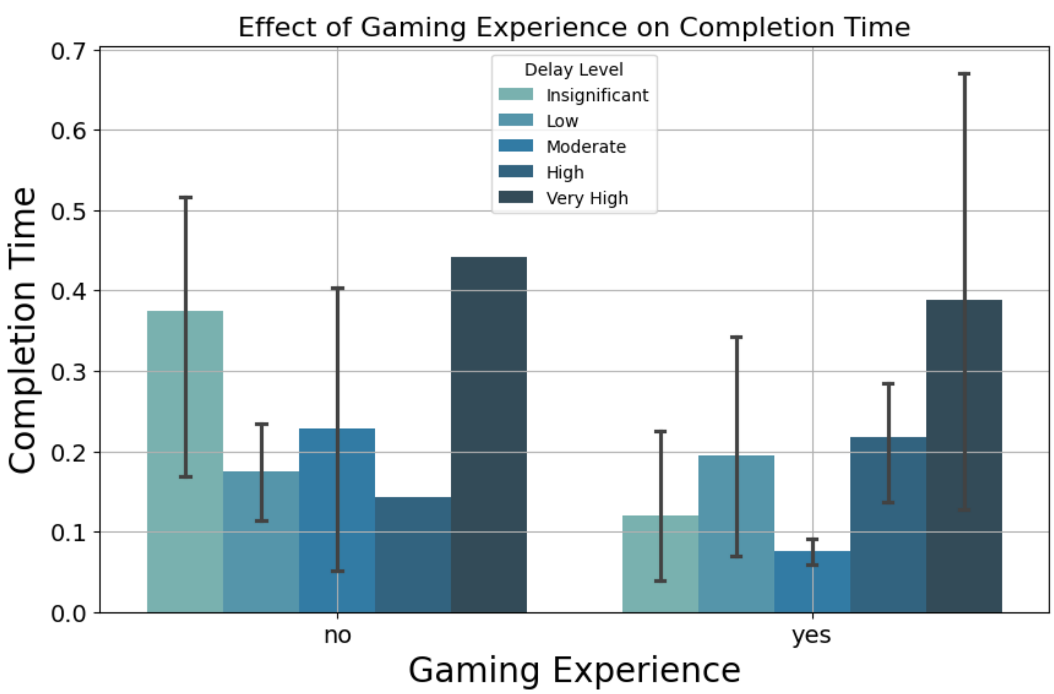


Figure 10: Comparison of task completion time between individuals with and without gaming experience with different delay conditions.

In the next Figure 11, a comparison of SA results, assessed by the maze reconstruction task, was made between participants with and without prior game experience. By taking a glance a this figure, results from SA are significantly higher for participants who have game experience. Participants who do not, reported the lowest results across all delay conditions with little variability from each other. In contrast, participants with prior experience recorded scores twice as big as the former group. Interestingly, the lowest average SA score, for this group, was recorded at the highest delay condition. Showing us again that delays could have a more significant impact with the more experienced sector of participants.

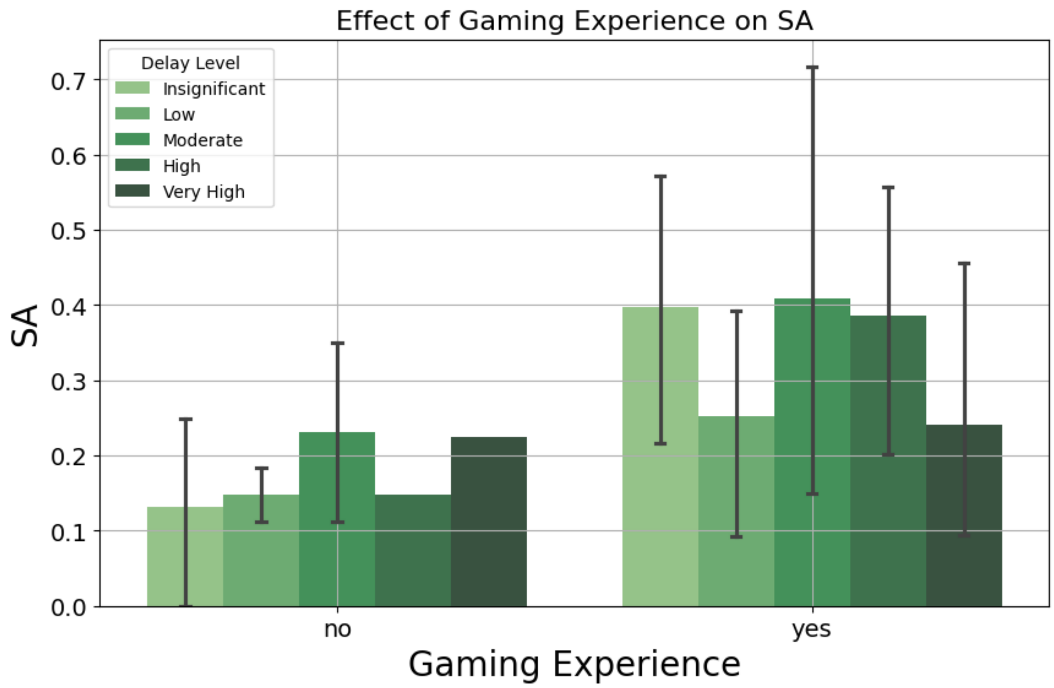


Figure 11: Comparison of SA between individuals with and without game experience and increasing delay conditions.

Figure 12 shows the different levels of perceived UW detected by participants with different game experience under increasing delay conditions. In both cases, the highest UW was recorded at the highest delay level. Participants with prior experience, recorded their lowest UW when delays were moderate, and the other group when the condition was in the low category. Against all expectations, game experienced participants recorded higher UW in most delay categories. Signaling that even with better objective performance in navigation and SA tests, the cognition load perceived from these individuals was more sensitive to increasing delays during teleoperation. For the other group, participants recorded lower and more variable UW results. This highlights the subjective and individual differences from the tested individuals.

In summary, results show that participants with gaming experience generally performed better in the objective tests. Task completion time (Figure 10) was lower for participants with gaming experience, indicating faster task completion and greater adaptability in teleoperation scenarios. Participants with gaming experience also achieved higher situational awareness (SA) scores (Figure 11), demonstrating improved spatial awareness and navigation capabilities. However, participants with gaming experience reported higher levels of subjective UW than the ones who do not (Figure12). This result could indicate high sensibility for more prepared operators than for the general population, highlighting the importance for mitigation practices based on perceived UW in delayed operations (Musicant et al., 2023).

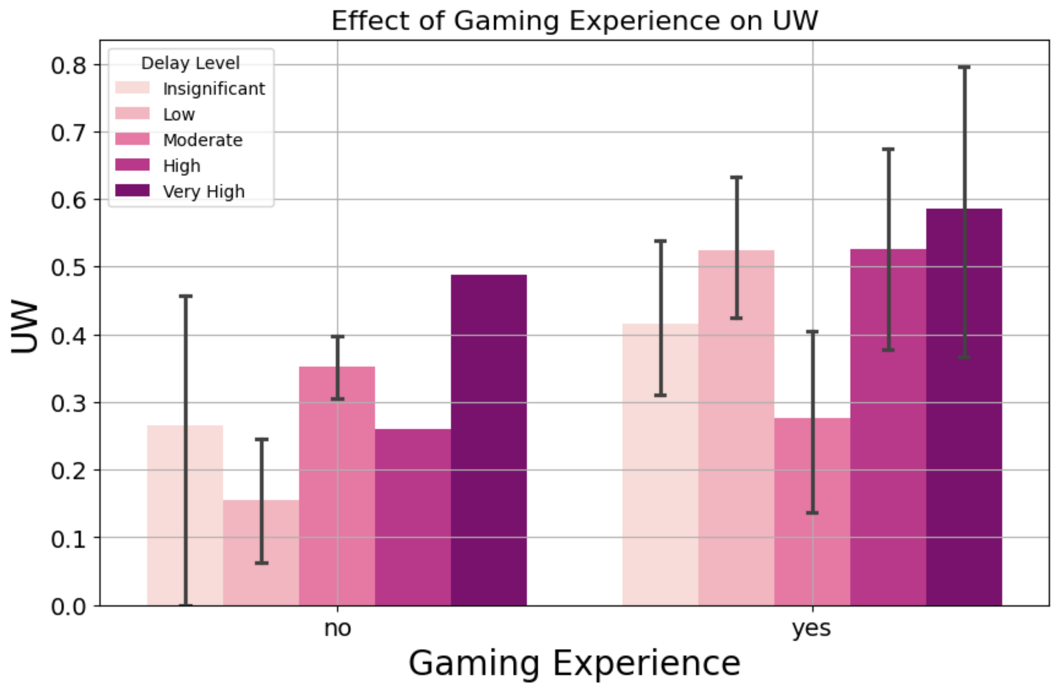


Figure 12: UW overall score from participants with and without prior game experience at different delay conditions.

4.5 Correlation Analysis

The correlation heatmap (Figure 13) provides a comprehensive view of the relationships between key variables measured in the experiment, including the dimensions for UW: time delays, mental demand, performance, temporal demand, effort, frustration, and overall UW score. Along with the objective metrics: navigation task completion time and SA score . The correlation values range from -1 (indicating a strong negative relationship) to +1 (indicating a strong positive relationship), with stronger correlations represented by darker shades.

Looking from the delays column, the highest positive correlation ($r = 0.45$) is correlated with the UW frustration, indicating that participants experienced higher frustration levels as time delays increased. This aligns with previous findings that prolonged time delays negatively impact user emotion and lead to higher frustration levels, as suggested by Yang and Dorneich (2015). And supports the hypothesis that mental workload increases under time-delayed conditions, as discussed in the study by Musicant et al. (2023).

The second highest positive relation between time delays and the rest of the variables was the Time Scores, or completion time of the task with a ($r = 0.28$). This shows that the completion time of the navigation task was moderately affected by time delays. Even though the relation was not as considerable as we expected, it is important to consider when we look at the results from higher delays. Especially if we take a look back at Figure 7a shows that delays beyond 1000 ms result in a small linear rise in time results. Even though participants produced the lowest results with a 1000 ms delay, this quickly changed as the delays increased to 1800 ms.

Overall UW and performance reported similar magnitudes of positive relation with delays ($r = 0.23$ and $r = 0.20$ respectively). This results suggests that there was a mild positive impact on overall workload and the UW performance dimension. This corresponds to participants rating their performance as less successful and reporting a higher work across every UW factor.

In the other hand, there is a significant negative relation between UW performance and SA results with ($r = -0.45$). Meaning that participants who did very well on the maze reconstruction task, reported a lower (better) score in their performance assessment during the NASA-TLX survey.

To visualize these two metrics better, a plot shown in Figure 14 was made to compare the results of UW performance (inverted results for easier comprehension) and SA scores. This figure shows that participants with higher maze results tend to report higher UW performance as well. Even more than with the completion time test. This aligns with the correlation map results and highlights the importance of the performance metric when looking at SA to measure delayed teleoperation results (Wojtusch et al., 2018).

Looking at the time scores column from the correlation map 13, the strongest relation in magnitude comes directly from

Figure 13: Correlation Heatmap of Time Delays, Task Performance, and NASA TLX Metrics

the SA (or maze score) variable with ($r = -0.34$). Meaning that participants with lowest navigation times also reported the highest SA scores. This is shown in Figure 15 where the normalized completion time was divided into 4 different categories for better comparison with the SA results. The plot also shows how participants with the poorest performance in the navigation task had relatively lower SA scores as well. The following results aligns with the claim that faster operators maintained better SAs, which has also been observed in prior studies on operator performance under time delay conditions (Sloan, 2005).

The overall score for UW situated on the bottom row from the correlation map, also shows interesting results. Evidently, there exists high correlations within the UW metrics since they are part of the overall score metric. However, mental demand showed the highest relation with ($r = 0.84$) making it the biggest predictor for UW compared to the other dimensions. And performance resulted the lowest indicator from the UW dimensions with a correlation of ($r = 0.31$). Interesting enough, performance was voted as one of the most important metric to consider according to (Wojtusch et al., 2018) when assessing delayed telerobotic systems.

For the objective metrics, the UW had slight positive and negative correlation with completion time ($r = 0.17$) and SA ($r = -0.16$). As show in Figure 8a and Figure 8b, the completion time increased when participants reported high UW (0.4 +). And the same goes for the SA results, where the lowest maze scores reported are aligned with the highest UW (0.8-1.0).

In summary, the correlation map reveals that time delays are closely associated with increased frustration, while UW factors such as mental demand, effort, and temporal demand are strongly related with each other and not to the objective metrics like completion time and SA. SA scores are linked to both navigation and perceived task performance, with faster

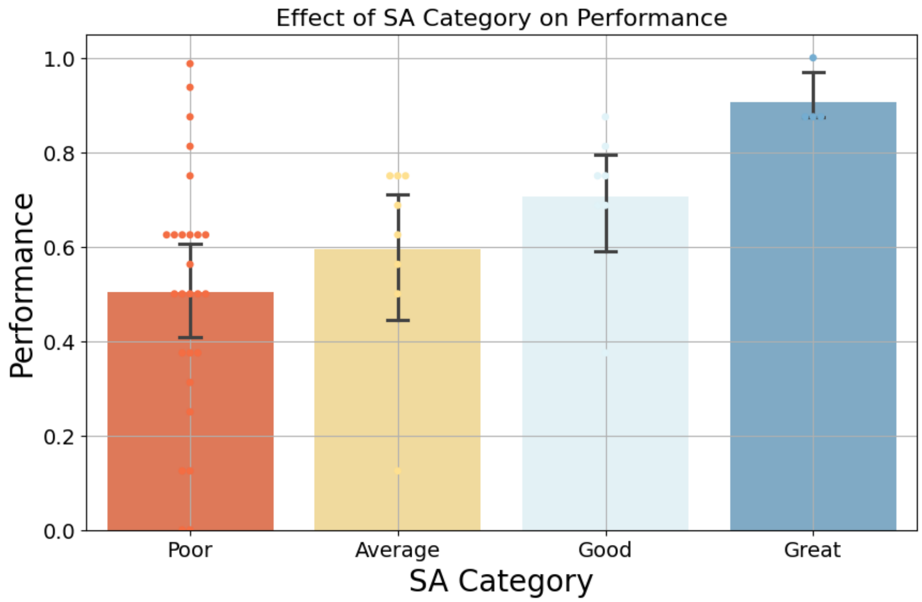


Figure 14: UW overall score vs SA results

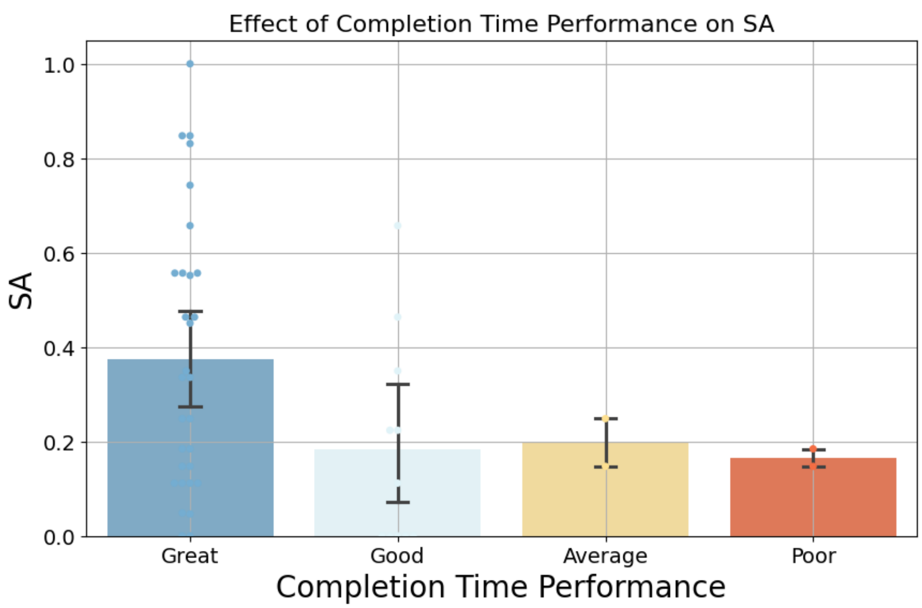


Figure 15: SA scores vs Completion Time

completion times generally correlating with better situational awareness and higher sense of task success. Delays proved to be insignificant to SA scores with a ($r = -0.05$). Nonetheless, they did had a modest relation with the navigation task and overall UW. As shown in Figure 7a, when delays surpassed 1000 ms the completion time followed a modest increase.

In order to have a better overview of the results and extract their statistical significance between each variable, there exist a variety of methods to make this analysis more robust. The correlation map is a great visual tool to see how each variable affect each other, but it it does not show if these correlations provide probabilistic importance. A number of studies from our literature review, one of them being Lu et al. (2019), performed statistical models (ANOVA test) to further analysis the importance of their results. For this motive, in the next section Section4.6 a statistical model (OLS regression model) is employed to check the impact of time delays faced with the objective and subjective variables.

4.6 Regression Analysis Results

A Regression analysis model was applied to explore the relationships between various dependent variables measured during the experiment, including all UW dimensions: mental demand, temporal demand, performance, effort, frustration, overall score. And the objective metrics: completion time and SA score. Ordinary Least Squares (OLS) regression was chosen to estimate the strength and significance of these relationships, providing insight into which variables were most affected by time delays.

The OLS regression results offer coefficients that quantify the magnitude and direction of the relationship between time delays (independent variable) and the dependent variables. Additionally, statistical measures such as the standard error, t-value, and p-value were used to assess the reliability of these estimates. The results below include a clear distinction between statistically significant and non-significant findings, allowing us to identify which factors were most impacted by time delays.

To determine the statistical significance of each connection between time delays (independent variable) and various dependent variables, we use two fundamental metrics: the t-value and the p-value.

A high t-value implies that the observed difference is less likely to be related to random chance, implying a stronger link between the independent and dependent variables. In the context of this research, a higher t-value indicates a greater connection between time delays and the dependent variable.

The p-value, on the other hand, shows the likelihood that the observed effect could occur by chance if there's no true relationship between the variables. A p-value ¡ 0.05 suggests statistical significance, implying that the observed connection is less than 5% chance. In this analysis, a low p-value indicates that time delays have a statistically significant influence on the dependent variable, whereas a higher p-value indicates that the effect is not statistically significant.

These parameters, taken together, contribute to the reliability of the observed correlations in the regression model. Only statistically significant results (low p-values and high t-values) are regarded strong evidence of an effect, allowing us to determine which factors are most affected by time delays.

Dependent Variable	**Coefficient**	**Standard Error**	**t-Value**	**P $>\|t\|$**	**Significance**
Time Scores	0.0066	0.0034	1.9392	0.0591	Marginal
SA Score	-0.0016	0.0044	-0.3578	0.7222	Not Significant
Mental Demand	-0.0027	0.0058	-0.4743	0.6377	Not Significant
Temporal Demand	0.0035	0.0060	0.5845	0.5619	Not Significant
Performance	0.0069	0.0051	1.3565	0.1820	Not Significant
Effort	0.0037	0.0063	0.5818	0.5638	Not Significant
Frustration	0.0184	0.0056	3.2593	0.0022	Significant
Overall Score	0.0050	0.0032	1.5658	0.1247	Not Significant

Table 9: OLS Regression Results

The OLS results in Table 9 present the coefficients, standard errors, t-values, p-values, and whether the results were statistically significant or not. Figure 16 shows the plots for each dimension against time delays from the regression analysis for better visualization.

For mental demand, the coefficient is -0.0027, suggesting a small negative relationship with time delays, but this result is not statistically significant ($p = 0.638$). Similarly, for temporal demand, the coefficient of 0.0035 reflects a minor positive association, but it is also statistically insignificant ($p = 0.562$).

The coefficient for performance is 0.0069, indicating a positive relationship, but this result is not significant ($p = 0.182$). Effort, with a coefficient of 0.0037, also shows a minor positive relationship, but it is not statistically significant ($p = 0.564$).

For overall NASA-TLX scores, the coefficient of 0.0050 suggests a positive relationship, but the result is not statistically significant ($p = 0.125$). Time scores have a coefficient of 0.0066 and are close to statistical significance ($p = 0.059$), indicating a marginal relationship between time delays and task completion time.

The SA score coefficient is -0.0016, and the result is statistically insignificant ($p = 0.722$), showing no meaningful effect of time delays on maze performance.

The time scores, or completion time, showed a positive coefficient of 0.0066, a standard error of 0.0034 and a t-Value of 1.9392. The significance was marked as "Marginal" since the P-value was very close to 5% (0.0591). So it is not meaningful according to our condition of 5% or below to be considered significant, but it was closer than any other metrics.

Frustration was the only result showing a statistically significant relationship with time delays (coefficient = 0.0184, t-value = 3.25930 and p-value = 0.0022). This suggests that higher time delays are a meaningful variable when it comes to users' frustration in delayed teleoperation.

In summary, frustration remains the only significant variable impacted by time delays, with higher delays consistently increasing frustration levels. Other variables such as mental demand, temporal demand, and performance were not significantly affected by time delays, though time scores were marginally affected. This suggests that among the various factors analyzed, frustration was the most strongly influenced by delays, aligning with Seo et al. (2023)'s results. These results could point to a key area for improving operator experiences under delayed conditions by considering frustration levels as a design element.

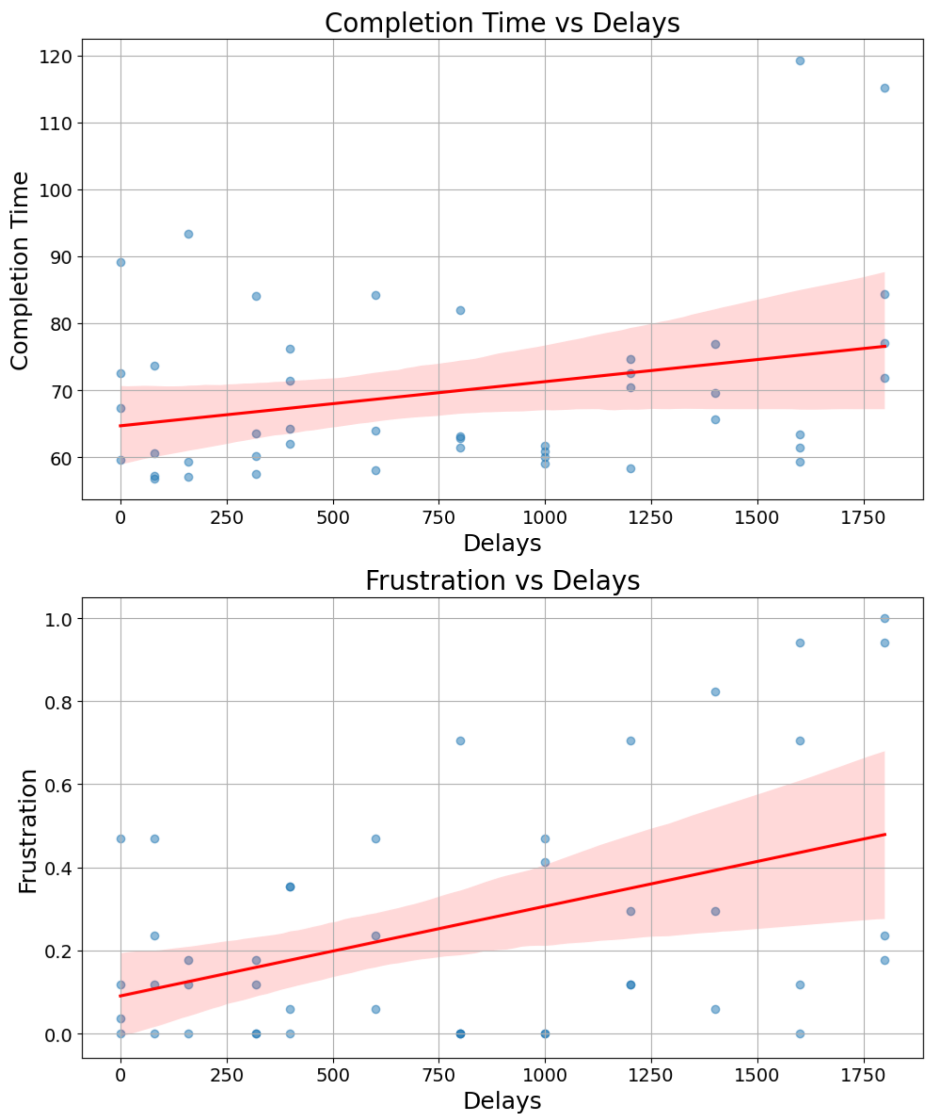


Figure 16: Regression plots: Completion Time and Frustration metrics against delays

4.7 Regression Analysis for Delays Surpassing 1000 ms

Based on the previous section, we noticed that the navigation scores where very close to be statistically relevant to the increased time delays. That is why a second regression analysis was made, this time only considering delays from 1000 ms up to 1800 ms. This results will help us confirm hypothesis 2.3.2 where we hypothesized that after 1000 ms, there would be a significant increase in completion time. Due to the participants' change in their control strategy (Chen et al., 2007).

The table bellow (Table 10) shows the complete regression analysis between the independent variable (Delays) and the previous studied metrics, including SA and UW dimensions.

Dependent Variable	Coefficient	Standard Error	t-Value	P>—t—	Significant
Completion Time	0.000482	0.000193	2.495	0.023	Yes
SA score	-0.000308	0.000235	-1.312	0.207	No
UW Overall Score	0.000348	0.000205	1.693	0.109	No
Mental Demand	0.000222	0.000245	0.904	0.379	No
Temporal Demand	0.000266	0.000244	1.087	0.292	No
Performance	0.000328	0.000226	1.454	0.164	No
Effort	0.000164	0.000273	0.602	0.555	No
Frustration	0.000434	0.000268	1.620	0.124	No
Overall Score	0.000348	0.000205	1.693	0.109	No

Table 10: OLS Regression Results: Larger Delays from 1000 ms up to 1800 ms)

Effectively, the results in the table show that the completion time of the navigation task is more sensitive to higher delays. The table outputs a t-value of 2.495 and a p-value of 0.023, suggesting that now time delays posses a greater statistical importance in the context driving performance. This result is illustrated by Figure 17. However, the table also shows that Delays above 1000 ms lost their statistical importance to all the other variables, including Frustration which was the highest in previous analysis.

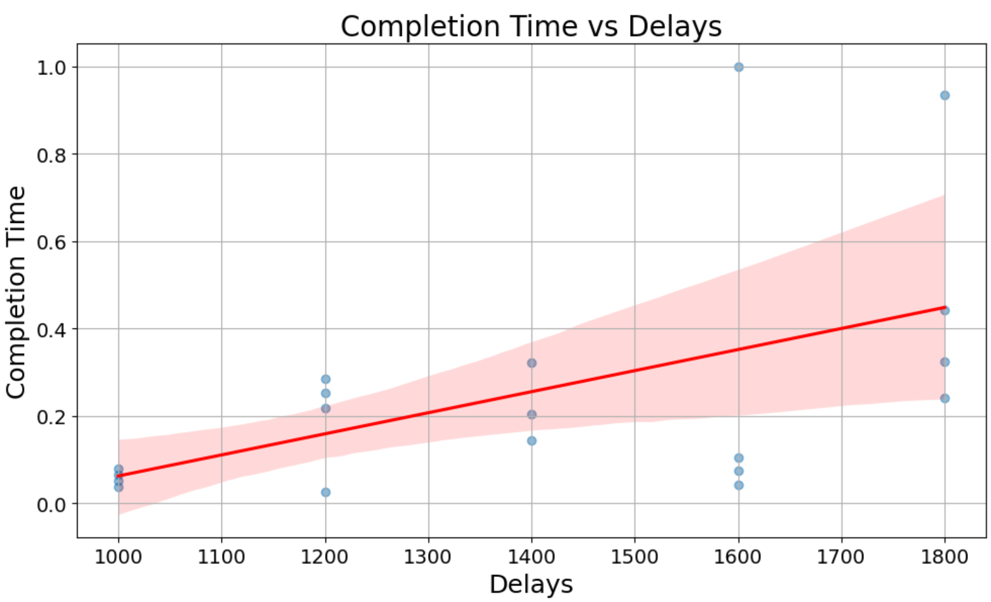


Figure 17: Regression plots: Completion time scores against Delays from 1000 ms to 1800 ms

5 Conclusion

The goal of this study was to investigate the effects of time delays on teleoperated robotic platforms, particularly operators performance, situational awareness, and user workload in simulated reconnaissance mission. This study tried to better understand the impact of delays on operators' abilities to navigate, make judgments, and maintain control in teleoperated systems with delayed feedback by introducing delays ranging from 0 to 1800 ms.

5.1 Synthesis of Findings and Hypotheses Evaluation

Through this study, several hypotheses (Section 2.3.2) were developed and tested to study the impact of time delays on teleoperation performance, resulting in a mix of confirmed discoveries and unforeseen results. These findings offer new perspectives on the adaptive capabilities of operators under delay conditions, and the influence of individual factors like prior experience.

The first hypothesis, predicted that delays of 300 ms up to 900 ms would significantly impair task performance and situational awareness (SA), was not supported by our results. Objective performance metrics, such as completion time and SA scores, showed minimal impact across delay conditions, even at delays as long as 1800 ms. This stability in performance, suggests that operators could have employed compensatory strategies to counterbalance the delay effects. For instance, operators would often resort to reconstruct the maze starting from the starting and ending positions of the grid, and then proceed to fill up the gaps. It was also observed that people would often go for the move and wait strategy mentioned in literature (Chen et al., 2007). According to the regression analysis made, while delays did increase frustration, they did not degrade SA or task completion time, underscoring an adaptive capacity in operators and challenging our initial assumptions for H1.

The second hypothesis predicted a linear association between delay duration and task completion time when delays surpassed 1000 ms, as prior research observed a change to "move and wait" methods in high-delay environments (Chen et al., 2007). While completion times increased with larger delays, the increase was not truly linear. Instead, operators appeared to change their navigational tactics to account for these delays, implying that slower speeds allowed for more adaptability in managing delayed feedback. This subtle delay-completion time relationship, especially at lower speeds, partially confirms H2 but reveals a more intricate interaction than previously thought. The additional trials reported in the appendix back up these findings, demonstrating that lower speeds may reduce mental workload while navigating with delayed feedback.

Our third hypothesis, which proposed that time delays would increase user workload, particularly frustration and mental demand, was partially supported by the results. As delay durations increased, participants consistently reported heightened frustration. This aligns with findings from Yang and Dorneich (2015) and Seo et al. (2023), who similarly observed increased cognitive load under delay in teleoperated environments. The significant frustration results imply that while task performance may remain stable, the experienced user workload from the operator is a primary effect of delayed feedback. This is especially true, when considering the results from more experienced operators in the main set of experiments over the rest of the population. This supports H3 and suggests that future systems could benefit from frustration-managing systems to help operators control their emotional stress and effort in high-delay situations.

Finally, the final hypothesis predicted that smaller delays between 170 ms and 400 ms would have little effect on performance due to the task's moderate speeds (2 m/s) and simplicity. However, while SA scores and task completion times were consistent during the modest delays, annoyance levels increased. This study underscores the importance of user-centered delay management, even at reduced delay thresholds (Yang and Dorneich, 2017). These results are consistent with our study's primary findings, as depicted in Figure 16, showing that even moderate delays can affect operator experience. This partially challenges H4, suggesting that low delays may not be as negligible as initially anticipated, particularly in terms of the emotional response of users.

5.2 Linking Findings to the Appendix and Experimental Insights

The additional analysis in the Appendix (Section A) provided further insight into how variations in speed and delay influence operator performance. Higher velocities (up to 6 m/s) resulted in significant increases in completion time and workload, validating earlier research indicating that speed can amplify the negative impact of delays (Musicant et al., 2023). These supplementary findings reinforce the primary experiment, emphasizing the practical importance of adaptive control factors that can manage speed and delays, especially in high-stakes teleoperated missions.

Additionally, the lack of significant SA impact across varying delay and velocity conditions (Figure 19b) aligns with the idea that situational awareness may be maintained through compensatory techniques even as mental demand or effort increases (Endsley, 1995). This insight emphasizes the importance of designing teleoperation interfaces that not only address performance with respect to objective metrics (navigation and SA results) but also subjective metrics such as UW to assess emotional responses to delay.

5.3 Theoretical and Practical Implications

The findings expand teleoperation research by emphasizing the complex interaction of emotional responses and cognitive load in delayed situations. While much of the literature has focused on performance degradation as a direct result of time delays, our findings indicate that frustration may be a more pressing worry, particularly for low-speed teleoperation. This supports Seo et al. (2023), who recognized the vulnerability of frustration and mental demand during delay, and proposes that mental resilience techniques could be useful.

The steady performance measures (SA and completion time) even under delayed conditions suggest that slower speeds could be used as a mitigating approach. This is a very useful factor for teleoperation in reconnaissance or mapping, when high accuracy is required but pace can be regulated to facilitate decision-making during delays (Zhu et al., 2011). Integrating adaptive speed controls, predictive displays, and other visual aids, such as sliding-and-zooming interfaces, VR or AR(Davis et al., 2010; Moniruzzaman et al., 2022), can enhance control and minimize UW, improving operator performance in delay-prone conditions.

5.4 Limitations and Future Directions

The study's narrow speed range (2 m/s in the main experiment) may have influenced the low impact of delays on task performance, as prior studies indicate more significant delay effects at greater speeds (Moniruzzaman et al., 2022). Future study should incorporate greater diversity of velocities and more advanced task designs to adequately represent the problems of teleoperation under different settings, as demonstrated in the Appendix experiments.

The use of the same maze layout for SA assessment might have severely limited the results for this metric. The decision for using the same maze design for every run was heavily influenced by Yang and Dorneich (2017) results, which suggested that maze complexity and changes on the navigation task can affect the overall results; even the subjective measures. However, at the moment of starting experimentation, it was evident that some of the participants would rely mostly on their memory from previous attempts, creating a learning effect, making SA assessment more complicated. Additionally, some of the participants took significantly longer periods of time to complete the SA in comparison with others. Controlling this metric by incorporating a time limit or measure, can provide valuable insights for SA assessment and also for User Workload measurement.

Applying User Experience surveys, as mentioned by Wojtusch et al. (2018), could be greater beneficial for future iterations. For our specific case, where no mitigation technique or novel design system was implemented to mitigate this delays, UE was not considered to take part of the experimental design subjective metrics. However, looking back at our results and data, it could have been a nice addition for grading the experimental assignment and to rate our approaches for future work. Asking about the type of delay introduced, the maze layout, the vehicle's dimension, or just general feedback. Even adding time components on the maze or driving task could have been more insightful, especially for UW assessment.

The relatively small sample size of 15 participants, following data exclusion, restricts generalization, and additional studies with larger, more diverse samples could validate these findings. Simulated environments, while controlled, may also lack certain real-world complexities encountered in teleoperation, such as sensory limitations or variable network conditions, as highlighted in studies of fire reconnaissance (Dyrks et al., 2008). In accordance to this, our delays implementation based on Unreal Engine Spring Arm Component, might not fully cover the idea of a realistic variable time delay due to connectivity issues. We also explored the possibility of Emulating Network retard-ness into the system, but the chose was made for the former option in hopes to get more valuable insight and to avoid inconclusive results that could not be compared with the literature research.

5.5 Final Remarks

In conclusion, time delays did not markedly degrade SA or task completion times but they did significantly increase frustration, supporting the idea that user workload's dimensions from delayed feedback is a key area for improvement. Teleoperated systems, like those in Rots in de Brand, have more problems with communication delays as they resort to cutting-edge technologies like SLAM, thermal imaging, and virtual reality. This is especially true in emergency situations where delays are inevitable and while streaming and operating at long-range distances. Based on this, addressing frustration and speed control through adaptive interfaces and lag compensation strategies could be essential for long-term operator well-being and efficiency. The study advances the understanding of teleoperation under delay conditions, emphasizing the need for better system designs that address both performance and emotional load in teleoperated environments.

A Appendix: Additional Experiment on Time Delays with Varying Velocities

This appendix provides supplementary analysis conducted with four different velocities and five types of time delays. This experiment was designed to explore the relationship between varying delay conditions, operator workload, and performance across different velocities. The velocity ranges were carefully chosen based on based on reported speed rates on reviewed literature (Musicant et al., 2023).

A number of 7 participants were recruited to take part of this additional experiment. Each one of them, like in the main tests, would take 3 different tests with varying independent conditions. In contrast with the previous iteration, we included different velocities (4 in total) and time delays (5 in total). The steps in delays was reduced to simplify the testing and analysis of the results, but the threshold range was kept almost identical, starting from no delay to 2000 ms.

In light that previous experiments showed that low to moderate delays did not have significant impact on any of the task outcomes, we decided to showcase what effects does varying velocity brings to the table. Musicant et al. (2023) offers an analytical table with multiple studies involving teleoperation in delay conditions. The goal of this table, however, was to compare different techniques to mitigate time delays (e.g., Predictive Displays, AR,..). The authors also made remarks about specific time delay thresholds based on their experimental results, suggesting that delays between 300 ms to 600 ms already have a significant impact on UW and navigation performance (Musicant et al., 2023). Nevertheless, in contrast to our experiments, the speed of their simulated vehicle (around 19 km/h = 6.0 m/s) was considerably higher than the ones simulated by us (2 m/s). For this reason, the extra set of experiments for velocities ranging from 2 m/s to 6 m/s was consider ideal for testing our hypothesis.

Below is a summary of the findings along with the relevant figures and tables.

Measure	Count	Mean	Std	Min	25%	50%	75%	Max
Velocity(m/s)	21	4.29	1.49	2.20	3.60	5.00	6.00	6.00
Delay(ms)	21	690.48	741.22	0.00	0.00	500.00	1000.00	2000.00
Completion Time (seconds)	21	48.21	18.98	22.88	31.78	42.55	62.25	88.29
SA score	21	73.81	21.49	35.89	50.15	78.02	89.47	100.00
Mental Demand	21	45.48	24.95	10.00	20.00	50.00	70.00	80.00
Temporal Demand	21	38.81	28.76	0.00	15.00	40.00	60.00	90.00
Performance	21	31.67	20.88	5.00	20.00	20.00	50.00	70.00
Effort	21	48.57	29.16	10.00	20.00	50.00	75.00	100.00
Frustration	21	22.86	26.86	0.00	5.00	10.00	40.00	100.00
Overall Score	21	31.23	16.49	7.50	20.00	31.67	37.50	71.67

Table 11: Descriptive Statistics of Task Metrics: the teleoperated task was conducted with velocities of 2.2 m/s, 3.6 m/s, 5.0 m/s, and 6.0 m/s, and time delays of 0 ms, 250 ms, 500 ms, 1000 ms, and 2000 ms. The tests aimed to observe how increasing time delays affect completion time, cognitive workload, and performance at different speeds. Key workload metrics such as mental demand, temporal demand, performance, effort, frustration, and overall NASA-TLX scores were evaluated.

A.1 Correlation Analysis

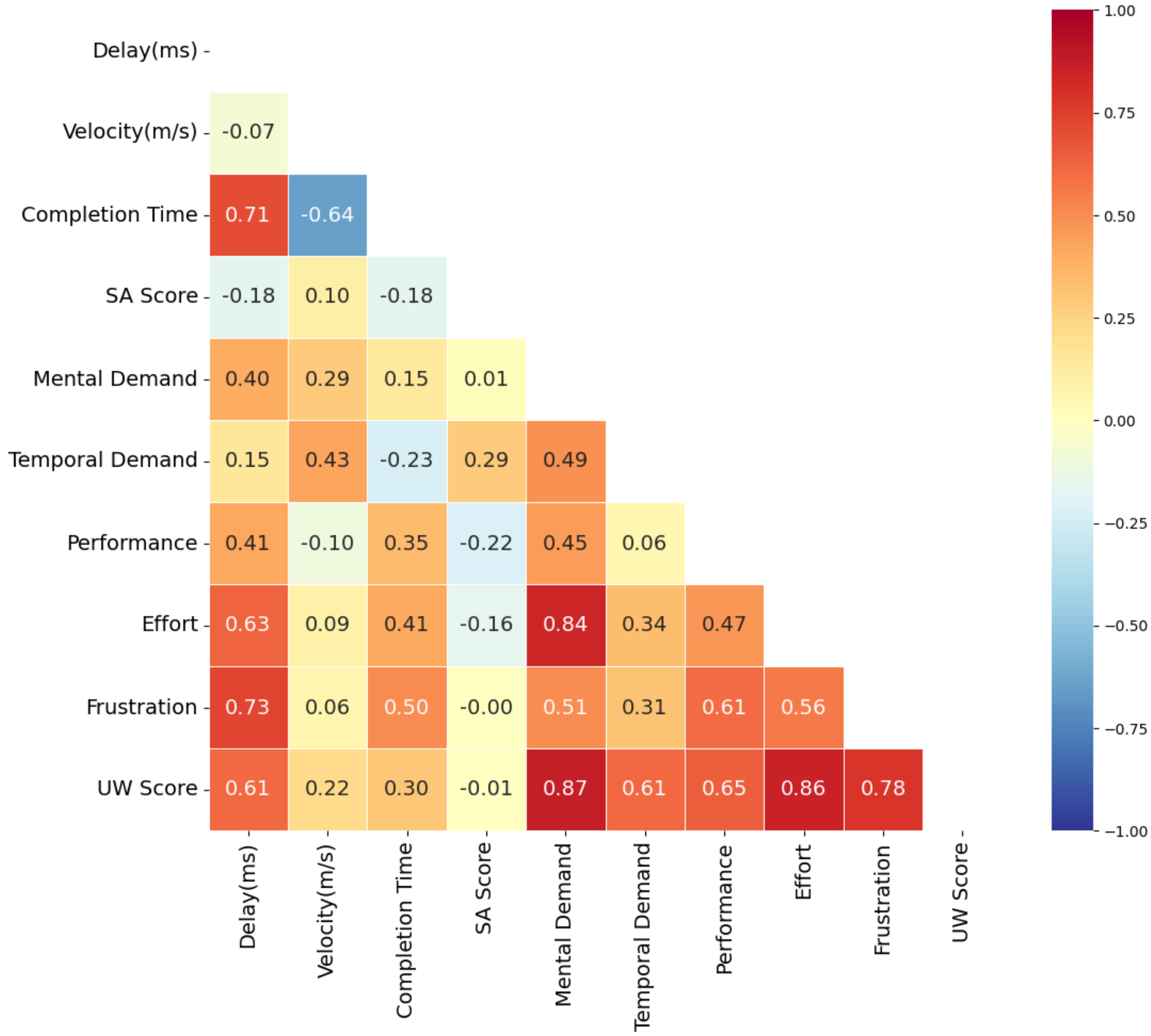
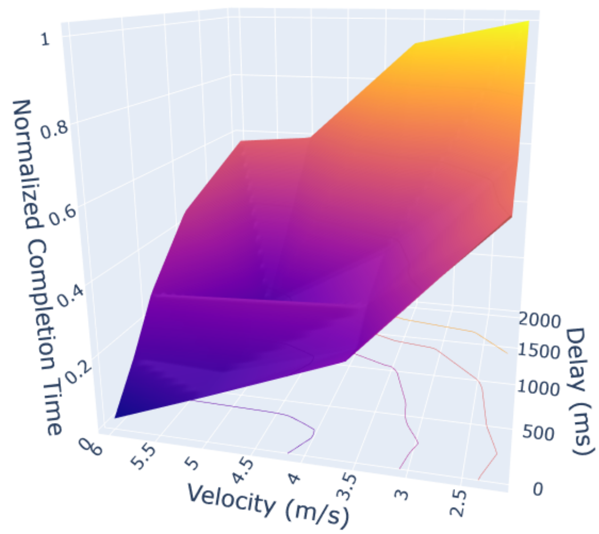
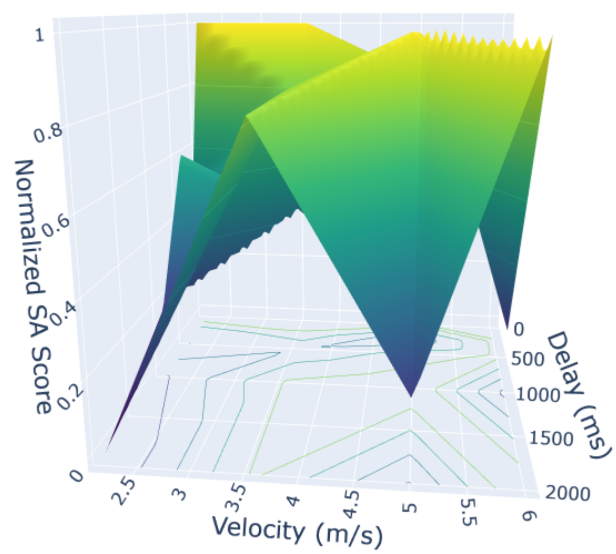


Figure 18: Correlation Heatmap of all metrics with delays and velocity included as variables. In this set of experiments, Delays demonstrated a significant positive relation ($r = 0.71$) with the completion time of the task. Frustration, effort and overall workload were also greatly affected by this condition. Velocity had a significant negative impact ($r = -0.64$) with the navigation task a modest positive relation with temporal demand. Both of these results suggest that as speed increased the completion time was lower and the temporal demand experienced by participants was higher.

A.2 3D Surface Plots for Completion Time and SA vs Delays and Velocity



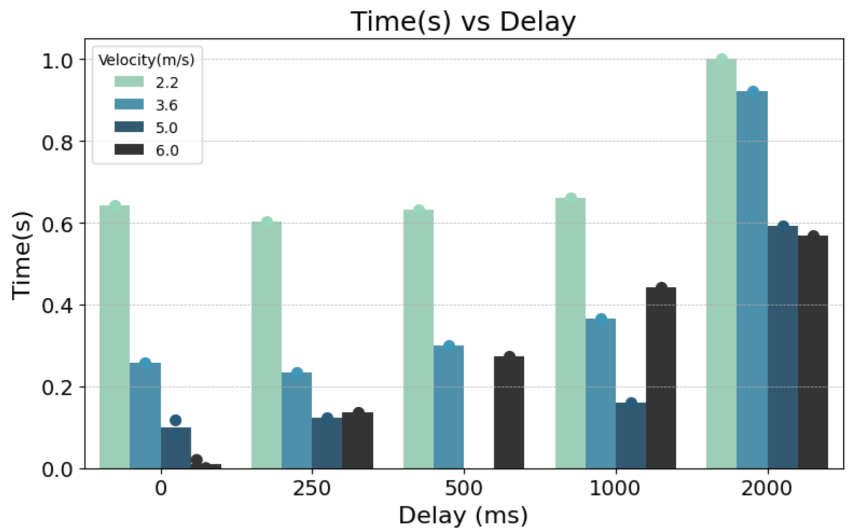
(a) 3D Surface Plot of Completion Time vs. Delay and Velocity: the completion time of the driving task incremented as time delays got closer to 2000 ms and velocity diminished.



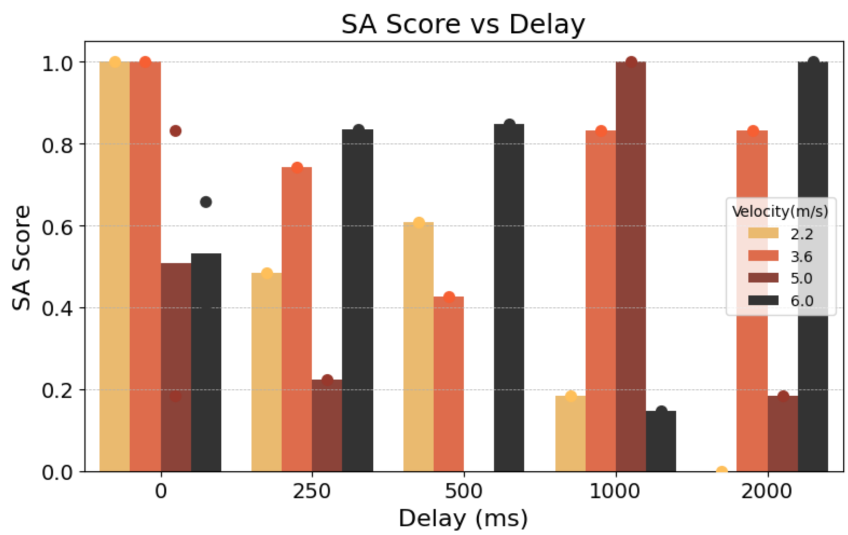
(b) 3D Surface Plot of SA score vs. Delay and Velocity: the SA score fluctuates without any indication of co linearity with any of the independent variables.

Figure 19: Comparison of 3D Surface Plots: (a) Completion Time vs. Delay and Velocity, (b) SA Score vs. Delay and Velocity

A.3 Bar Plots: Completion Time and SA vs Delays and Velocity



(a) Impact of Delay on Task Completion Time: This plot shows how task completion time varies with increasing time delays for different robot velocities. Higher delays generally lead to longer completion times, particularly at slower velocities.



(b) Effect of Delay on Maze Navigation Score: This plot illustrates the effect of increasing delay on maze navigation scores across different velocities. SA scores fluctuations are observed across all delays and speeds, so there is no indication of reduced navigation performance just by observing this graph.

Figure 20: Comparison of Delay Effects on Task Completion Time and Navigation Accuracy: These subfigures highlight how varying levels of delay impact task performance across different velocities in a teleoperated navigation task.

A.4 User Workload (UW) vs Time Delays and Different Velocities

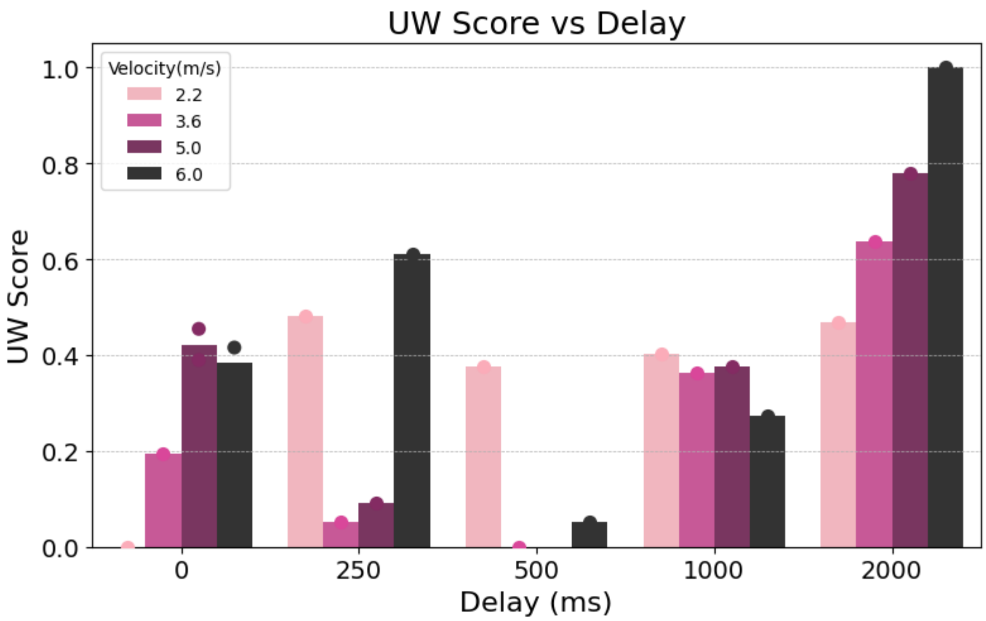
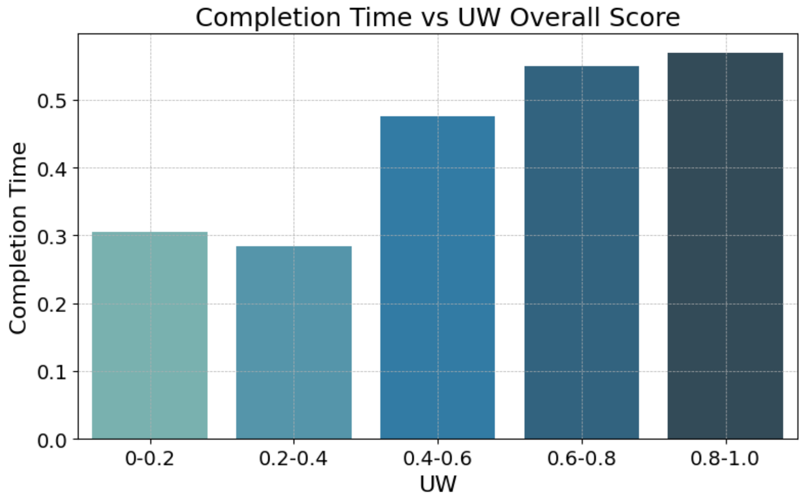
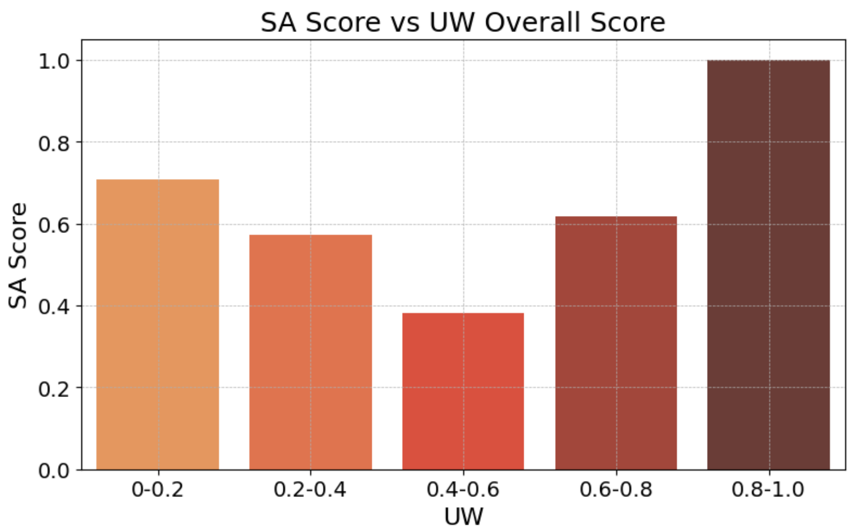


Figure 21: Effect of time delays with varying velocities in perceived User Workload (UW) overall score. The analysis was made to corroborate previous findings that stated that with increasing delay conditions UW increases. For this experiment in particular, we put that theory into test with augmenting velocities to investigate the changes that this variable provides to operator's cognitive strain.

A.5 Completion Time and SA vs Different Levels of UW



(a) Relationship between Normalized Completion Time and Overall UW Scores.



(b) Relationship between SA score and Overall UW Scores.

Figure 22: Comparative analysis of SA score and normalized completion time in relation to Overall UW. (a) shows the normalized completion time from the driving task and (b) shows the normalized SA scores, both compared to the perceived UW.

A.6 Regression Analysis Summary

In this section, we summarize the findings from the Ordinary Least Squares (OLS) regression analysis conducted to evaluate the effects of delay (ms) and velocity (m/s) on task completion time, SA score, and NASA-TLX workload dimensions (mental demand, temporal demand, performance, effort, frustration, and overall score).

A.6.1 Regression Results with Time Delays as the independent variable

Dependent Variable	Coefficient	Standard Error	t-Value	P > —t—	Significance
Time (s)	0.0171	0.0023	7.4750	0.0000	Significant
SA Score	-0.0001	0.0001	-0.7277	0.4762	Not Significant
UW Overall Score	0.0141	0.0039	3.6148	0.0020	Significant
Mental Demand	0.0143	0.0068	2.0866	0.0514	Borderline Significant
Temporal Demand	0.0071	0.0081	0.8677	0.3970	Not Significant
Performance	0.0115	0.0060	1.9089	0.0723	Marginally Significant
Effort	0.0250	0.0071	3.5077	0.0025	Significant
Frustration	0.0268	0.0058	4.6580	0.0002	Significant

Table 12: OLS Regression results with delays as independent variable

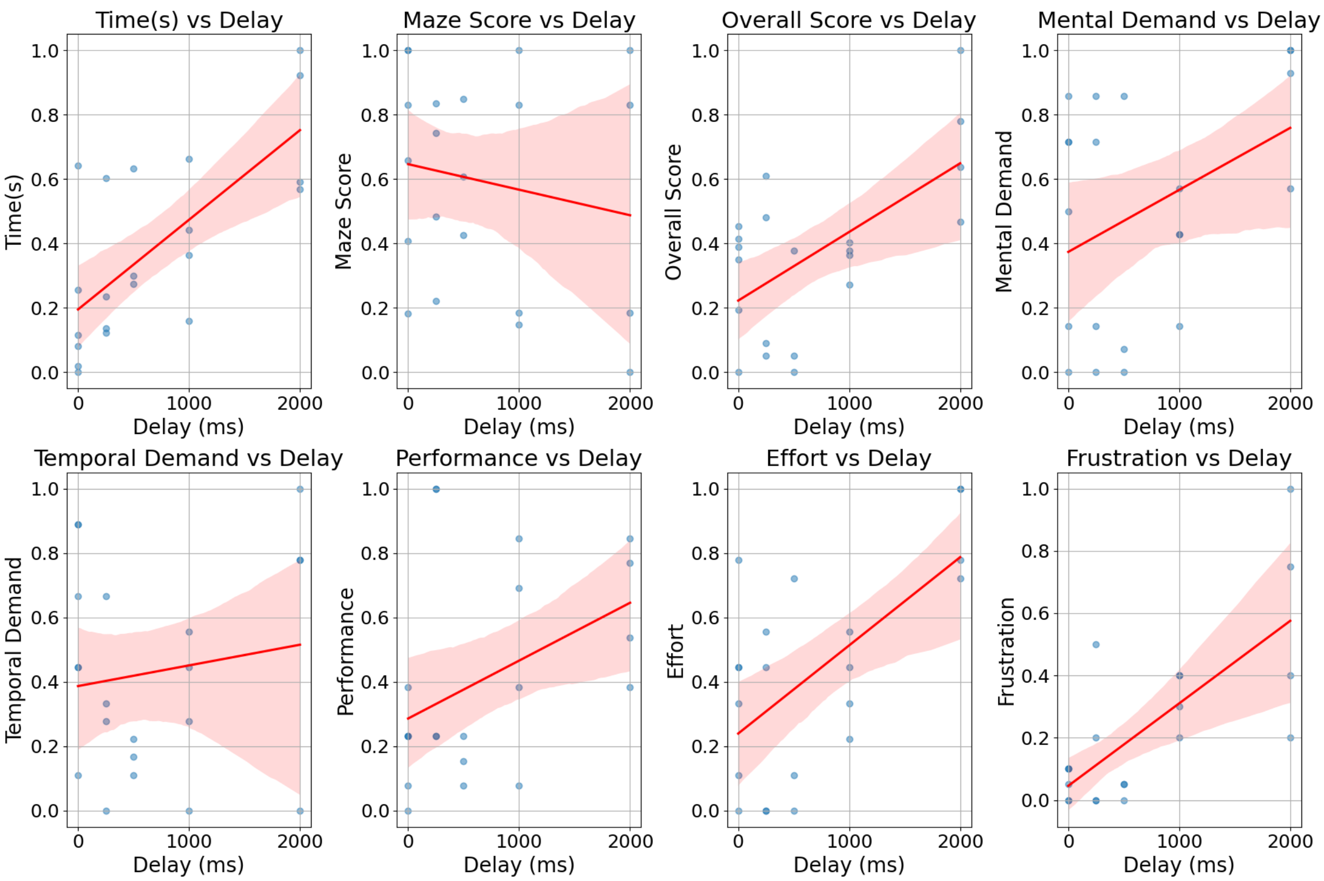


Figure 23: Plots of regression analysis of all dependent variables across delays

A.6.2 Regression Analysis of Delays at different fixed velocities

This section presents the Ordinary Least Squares (OLS) regression results for various dependent variables with delay as the independent variable, conducted at fixed velocities. The tables below summarize the results for each velocity.

Dependent Variable	Coefficient	Standard Error	t-Value	P > —t—	95% Confidence Interval	Significant
Time (s)	0.0124	0.0032	3.8240	0.0315	[0.002, 0.023]	Yes
SA score	-0.0281	0.0081	-3.4762	0.0402	[-0.054, -0.002]	Yes
Mental Demand	0.0050	0.0187	0.2676	0.8063	[-0.054, 0.064]	No
Temporal Demand	-0.0010	0.0122	-0.0819	0.9399	[-0.040, 0.038]	No
Performance	0.0150	0.0175	0.8589	0.4535	[-0.041, 0.071]	No
Effort	0.0345	0.0142	2.4360	0.0928	[-0.011, 0.080]	No
Frustration	0.0005	0.0141	0.0354	0.9740	[-0.044, 0.045]	No
UW Overall Score	0.0090	0.0077	1.1713	0.3260	[-0.015, 0.033]	No

Table 13: OLS Regression Results for Velocity = 2.2 m/s

Dependent Variable	Coefficient	Standard Error	t-Value	P > —t—	95% Confidence Interval	Significant
Time(s)	0.022492	0.004499	4.999401	0.015397	[0.008, 0.037]	Yes
SA score	0.000478	0.009921	0.048179	0.964602	[-0.031, 0.032]	No
Mental Demand	0.032500	0.007112	4.569615	0.019661	[0.010, 0.055]	Yes
Temporal Demand	0.013500	0.017027	0.792861	0.485775	[-0.041, 0.068]	No
Performance	0.012500	0.012593	0.992616	0.394067	[-0.028, 0.053]	No
Effort	0.031500	0.007654	4.115509	0.025991	[0.007, 0.056]	Yes
Frustration	0.020000	0.006532	3.061862	0.054913	[-0.001, 0.041]	No
UW Overall Score	0.018333	0.005875	3.120437	0.052454	[-0.000, 0.037]	No

Table 14: OLS Regression Results for Velocity = 3.6 m/s

Dependent Variable	Coefficient	Standard Error	t-Value	P > —t—	95% Confidence Interval	Significant
Time (s)	0.0150	0.0035	4.2584	0.0237	[0.004, 0.026]	Yes
SA score	-0.0032	0.0171	-0.1891	0.8621	[-0.058, 0.051]	No
Mental Demand	0.0167	0.0111	1.4990	0.2308	[-0.019, 0.052]	No
Temporal Demand	-0.0014	0.0146	-0.0932	0.9316	[-0.048, 0.045]	No
Performance	0.0058	0.0069	0.8345	0.4652	[-0.016, 0.028]	No
Effort	0.0225	0.0116	1.9515	0.1461	[-0.014, 0.059]	No
Frustration	0.0345	0.0068	5.0645	0.0149	[0.013, 0.056]	Yes
UW Overall Score	0.0130	0.0075	1.7442	0.1795	[-0.011, 0.037]	No

Table 15: OLS Regression Results for Velocity = 5.0 m/s

Dependent Variable	Coefficient	Standard Error	t-Value	P > —t—	95% Confidence Interval	Significant
Time (s)	0.0187	0.0029	6.4300	0.0030	[0.011, 0.027]	Yes
SA score	0.0075	0.0127	0.5865	0.5890	[-0.028, 0.043]	No
Mental Demand	0.0053	0.0155	0.3404	0.7507	[-0.038, 0.048]	No
Temporal Demand	0.0166	0.0190	0.8740	0.4314	[-0.036, 0.069]	No
Performance	0.0139	0.0141	0.9821	0.3816	[-0.025, 0.053]	No
Effort	0.0156	0.0168	0.9258	0.4070	[-0.031, 0.062]	No
Frustration	0.0476	0.0066	7.2403	0.0019	[0.029, 0.066]	Yes
UW Overall Score	0.0165	0.0107	1.5346	0.1997	[-0.013, 0.046]	No

Table 16: OLS Regression Results for Velocity = 6.0 m/s

A.6.3 Regression Results with Velocity (m/s) as Independent variable

Dependent Variable	Coefficient	Standard Error	t-Value	P > —t—	Significance
Time (s)	-7.5939	1.1376	-6.6756	0.0000	Significant
SA score	0.0765	0.1943	0.3937	0.6984	Not Significant
UW Overall Score	2.9387	1.9453	1.5107	0.1482	Not Significant
Mental Demand	5.3198	3.4072	1.5613	0.1359	Not Significant
Temporal Demand	8.5068	4.0482	2.1014	0.0500	Borderline Significant
Performance	-1.0175	3.0079	-0.3383	0.7391	Not Significant
Effort	2.6804	3.5555	0.7539	0.4607	Not Significant
Frustration	2.1430	2.8670	0.7475	0.4644	Not Significant

Table 17: OLS Regression Results with Velocity as independent variable: Velocity had a significant effect on completion time (p > 0.001), with higher speeds resulting in faster task completion. However, velocity did not significantly impact SA score, mental demand, frustration, or overall workload.

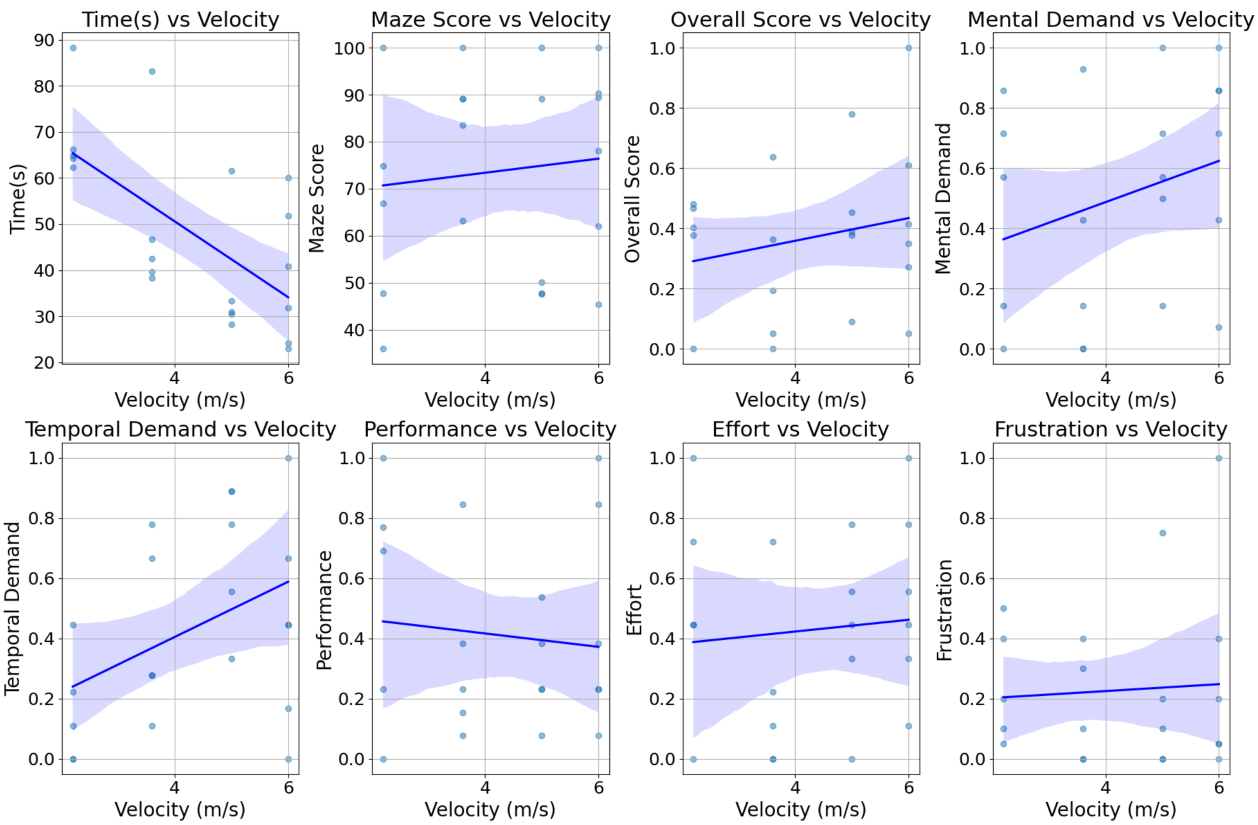


Figure 24: Regression lines figures from OLS analysis with velocity as independent variable

A.7 Discussion of the Appendix

This appendix explores how different time delays and velocities affect task completion time, situational awareness (SA), and user workload (UW) during teleoperation scenarios. By adjusting the delay from 0 ms to 2000 ms and velocity rate from 2.2 m/s to 6.0 m/s, this experiment simulated real-world conditions where network latency and control speed often fluctuate. The following discussion analyzes significant data from the tables and figures, with a focus on understanding the consequences for remote operations in challenging scenarios.

Table 11 provides an overview of core performance metrics. The average task completion time was 48.21 seconds, but ranged from 22.88 to 88.29 seconds, suggesting high sensibility to the independent variables (delays & velocities). SA scores appeared to be high overall (mean = 73.81), but the repetition of the task invites the user to remember their previous missteps disregarding the navigation task to remember the layout of the maze and using only their memory to succeed in this task. Increased mental demand and effort at lower velocities and higher delays also point to a rise in cognitive load under these conditions, implying that slower speeds combined with greater delays introduce more mental strain.

Figure 18, which displays a correlation-map, reveals strong correlations between delay and completion time ($r = 0.71$), as well as notable correlation with frustration, effort, and overall UW score. These findings indicate that increased delays can lead to extended task times and higher cognitive demands, while greater speeds generally reduce task completion time ($r = -0.64$). Interestingly, velocity's correlation with temporal demand ($r = 0.43$) suggests that faster rates could raise experienced urgency, emphasizing the necessity to balance regulate velocities for better teleoperation experiences.

Figures 19a and 19b further illustrate how delay and velocity interact with completion time and SA scores. As delay increases and speed decreases, task completion time rises (Figure 19a), highlighting how these factors together affect task duration. In contrast, SA scores (Figure 19b) do not show a clear correlation with either of these variables, suggesting that SA may be less affected by changes in delay or speed than task completion time, possibly due to compensatory strategies adopted by operators. This statement aligns with findings from Endsley (1995) and Yang and Dorneich (2017), who discussed how SA can be maintained even with higher delays and task complexity.

In Figure 20, the effect of delay on task completion time and SA scores is further investigated. Completion time consistently increases with higher delays across all velocities, with slower speeds amplifying this effect (Figure 20a). However, SA scores, as shown in Figure 20b, do not exhibit a straightforward relationship with delay, indicating that navigation accuracy does not necessarily suffer with increased delay—underscoring that while delay impacts efficiency, it may not directly impair SA.

Figure 21, shows the results of experienced workload against different delay and velocity conditions. In this image we can see how as delays reach their highest value of 2000 ms, the perceived UW increases proportionally with the velocity condition. Suggesting that participants felt the most annoyed during the teleoperation experiment with higher control complexity and delays condition (Yang and Dorneich, 2017). This also suggests that excessive speed can cause difficulties when working with teleoperated platforms. Finally, if we look at the 0 ms delay, it shows that the perceived UW was greater with velocities of 5 m/s and 6 m/s.

Finally, Figure 22a and Figure22b examine the relationship between workload (measured from NASA-TLX) and the objective performance metrics (navigation and maze tasks). Notably, completion time (Figure 22a) correlates positively with perceived workload, especially at moderate rates (+ 0.2). This indicates that participants who took more time completing the maze reported higher degrees of UW. However, SA scores (Figure 22b) show no consistent trend with workload, suggesting that a high cognitive load does not inherently diminish situational awareness, a finding consistent with previous studies on the resilience of SA in teleoperation tasks (Yang and Dorneich, 2017; Endsley, 1995).

The regression analyses further illustrate these relationships. Table 12 shows that delay significantly impacts task completion time (p-value = 0.000, t-value = 7.475), workload (p-value = 0.002, t-value = 3.615), effort (p-value = 0.0025, t-value = 3.508) and frustration (p-value = 0.0002, t-value = 4.658). Interestingly, SA scores revealed no significant relationship with delay, replicating the observations from Figures 19b and 20b. When focusing on fixed velocities (Tables 13 - 16), delays showed a greater impact with higher velocities by looking how p and t values decrease and increase, respectively, suggesting that managing delays is crucial in teleoperated control at higher speeds.

Overall, this analysis highlights the need for teleoperation interfaces that prioritize efficiency and User workload mitigation techniques, especially under high-delay conditions. To address these issues, several strategies identified in our literature research, such as predictive displays (Davis et al., 2010; Musicant et al., 2023) and sliding-and-zooming interfaces (Moniruzzaman et al., 2022), where considered. However, these strategies may have limited applications in scenarios specific to our study, such as dangerous fire situations, where limited visibility caused by smoke complicates the visual feedback channel. This is a challenge where Rots in de Brand aims to make important improvements.

These findings provide useful information to develop teleoperated systems' interfaces, pointing out the significance of controlling speed and delay to improve operator performance and workload management. Integrating alternative mitigation approaches, focusing on the operator's response rather than only focusing on task performance, can make room for major improvements and raise the technology readiness level (TRL) for teleoperated control of locomotion with time delays for reconnaissance in dangerous fire situations.

References

Balen, J., Damjanovic, D., Maric, P., Vdovjak, K., Arlovic, M., and Martinovic, G. (2023). Firebot-an autonomous surveillance robot for fire prevention, early detection and extinguishing. In *2023 15th International Conference on Computer and Automation Engineering (ICCAE)*, pages 400–405. IEEE.

Chacón, C. (2020). *S. Methods, Strategies and Application Cases for Robotic Telemanipulation in Hazardous Environments*. PhD thesis, Ph. D. Thesis, Universidad Politécnica de Madrid, Madrid, Spain.

Chen, J. Y., Haas, E. C., and Barnes, M. J. (2007). Human performance issues and user interface design for teleoperated robots. *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*, 37:1231–1245.

Claypool, M. and Claypool, K. (2010). Latency can kill: precision and deadline in online games. In *Proceedings of the first annual ACM SIGMM conference on Multimedia systems*, pages 215–222.

Davis, J., Smyth, C., and McDowell, K. (2010). The effects of time lag on driving performance and a possible mitigation. *IEEE Transactions on Robotics*, 26:590–593.

Dyrks, T., Denef, S., and Ramirez, L. (2008). An empirical study of firefighting sensemaking practices to inform the design of ubicomp technology. In *Sensemaking Workshop of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2008). Retrieved from http://dmrussell. googlepages. com/Dryks-final. pdf.*

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human factors*, 37(1):32–64.

Farajiparvar, P., Ying, H., and Pandya, A. (2020). A brief survey of telerobotic time delay mitigation. *Frontiers in Robotics and AI*, 7:578805.

Ferrell, W. R. (1966). Delayed force feedback. *Human factors*, 8(5):449–455.

Gatsoulis, Y., Virk, G. S., and Dehghani-Sanij, A. A. (2010). On the measurement of situation awareness for effective human-robot interaction in teleoperated systems. *Journal of cognitive engineering and decision making*, 4(1):69–98.

Hart, S. (1988). Development of nasa-tlx (task load index): Results of empirical and theoretical research. *Human mental workload/Elsevier*.

Hu, H., Perez, C., Sun, H.-X., and Jagersand, M. (2016). Performance of predictive display teleoperation under different delays with different degree of freedoms. In *2016 International Conference on Information System and Artificial Intelligence (ISAI)*, pages 380–384. IEEE.

Kohrs, C., Angenstein, N., and Brechmann, A. (2016). Delays in human-computer interaction and their effects on brain activity. *PloS one*, 11(1):e0146250.

Korte, C., Nair, S. S., Nistor, V., Low, T. P., Doarn, C. R., and Schaffner, G. (2014). Determining the threshold of time-delay for teleoperation accuracy and efficiency in relation to telesurgery. *Telemedicine and e-Health*, 20:1078–1086.

Lu, S., Zhang, M. Y., Ersal, T., and Yang, X. J. (2019). Workload management in teleoperation of unmanned ground vehicles: Effects of a delay compensation aid on human operators' workload and teleoperation performance. *International Journal of Human–Computer Interaction*, 35(19):1820–1830.

Moniruzzaman, M., Rassau, A., Chai, D., and Islam, S. M. S. (2022). High latency unmanned ground vehicle teleoperation enhancement by presentation of estimated future through video transformation. *Journal of Intelligent and Robotic Systems: Theory and Applications*, 106.

Musicant, O., Botzer, A., and Shoval, S. (2023). Effects of simulated time delay on teleoperators' performance in inter-urban conditions. *Transportation Research Part F: Traffic Psychology and Behaviour*, 92:220–237.

Nivera, K. (2023). House fires in the netherlands: What you need to know. *DutchReview*. Accessed: 2023-10-30.

Penin, L. F. (2002). Teleoperation with time delay-a survey and its use in space robotics. *Technical Report of National Aerospace Laboratory*.

Rahman, B. (2020). Time-delay systems: An overview. *Nonlinear Phenomena in Complex Systems*, 23(07).

Ricks, B., Nielsen, C. W., and Goodrich, M. A. (2004). Ecological displays for robot interaction: A new perspective. In *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)(IEEE Cat. No. 04CH37566)*, volume 3, pages 2855–2860. IEEE.

Seo, M., Gupta, S., and Ham, Y. (2023). Evaluation of performance and mental workload during time delayed teleoperation for the lunar surface construction. *IEEE Transactions on Visualization and Computer Graphics*.

Sloan, J. (2005). *The Effects Of Video Frame Delay And Spatial Ability On The Operation Of Multiple Semiautonomous And Tele-operated Robots.* Phd thesis, University of Central Florida. Electronic Theses and Dissertations, 393.

Stark, L. W., Kim, W. S., and Tendick, F. (1988). Cooperative control in telerobotics. In *Proceedings. 1988 IEEE International Conference on Robotics and Automation*, pages 593–595. IEEE.

Tener, F. and Lanir, J. (2022). Driving from a distance: challenges and guidelines for autonomous vehicle teleoperation interfaces. In *Proceedings of the 2022 CHI conference on human factors in computing systems*, pages 1–13.

Unreal Engine Documentation (2023). *Camera Lag and the Spring Arm Component.* Accessed: 2023-11-04.

Wojtusch, J., Taubert, D., Graber, T., and Nergaard, K. (2018). Evaluation of human factors for assessing human-robot interaction in delayed teleoperation. In *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 3787–3792. Institute of Electrical and Electronics Engineers Inc.

Woodward, J. and Ruiz, J. (2022). Analytic review of using augmented reality for situational awareness. *IEEE Transactions on Visualization and Computer Graphics*, 29(4):2166–2183.

Yang, E. and Dorneich, M. C. (2015). The effect of time delay on emotion, arousal, and satisfaction in human-robot interaction. *Proceedings of the Human Factors and Ergonomics Society*, 2015-January:443–447.

Yang, E. and Dorneich, M. C. (2017). The emotional, cognitive, physiological, and performance effects of variable time delay in robotic teleoperation. *International Journal of Social Robotics*, 9:491–508.

Zheng, Y., Brudnak, M. J., Jayakumar, P., Stein, J. L., and Ersal, T. (2018). A predictor-based framework for delay compensation in networked closed-loop systems. *IEEE/ASME Transactions on Mechatronics*, 23(5):2482–2493.

Zhu, J., He, X., and Gueaieb, W. (2011). Trends in the control schemes for bilateral teleoperation with time delay. In *Autonomous and Intelligent Systems: Second International Conference, AIS 2011, Burnaby, BC, Canada, June 22-24, 2011. Proceedings 2*, pages 146–155. Springer.