

**The University of Birmingham**

**Enhancing Human-Robot Interaction in Telerobotics:  
Investigating the Impact of Cognitive and Information  
Processing on Human Operator's Situational Awareness,  
Attention and Cognitive Workload**

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## ABSTRACT

This research is motivated by the need to advance human-robot collaboration in high-stakes environments, where limited understanding and real-world research exist on the effects of information verbalization and goal-directed tasks in telerobotic systems, in doing so this thesis delves into the interdisciplinary field of Human-Robot Interaction (HRI). The research primarily focuses on telerobotics systems and their operator. The novelty of this research lies in its exploration of how cognitive factors such as IQ and information verbalisation impact human-robot collaboration in telerobotics, providing key insights into telerobotic operator's Situational Awareness (SA), attention allocation, performance, and cognitive workload. This research contributes to advancing the design of telerobotic systems and improving human-robot collaboration, offering new perspectives on how cognitive processing affects goal-directed tasks in complex, real-time environments. The study contribution extends the understanding of how a telerobotic operator's Situational Awareness (SA), attention allocation, performance, and cognitive workload can be affected by their cognitive and information processing approaches. To achieve this, the study employed an advanced robotic system from Boston Dynamics and simulated real-world scenarios, including a nuclear station investigation and a human search and rescue mission. Data were collected from thirty participants engaged in telerobotic exercises, analysed through the lens of advanced methodologies, including a Multi-Tools Measurement Structure, across varying levels of task difficulty. The results indicate that verbalisation facilitates the benefits of Multimodal Processing, Real-time Engagement, and Self-Auditory experience, optimising attention allocation and reducing mental workload. Information verbalisation also contributes to a more efficient allocation of cognitive resources, significantly improving the operators' ability to perceive and comprehend the meaning of task elements in a remote environment. Furthermore, the study reveals a crucial link between operators' Intelligence Quotient (IQ) and their ability to acquire and maintain SA in telerobotic operations. The positive correlation between individual SA levels and IQ, suggesting that IQ assessments can effectively predict an operator's situational awareness capabilities. This research is significant for its contribution in advancing telerobotic system design and improving human-robot collaboration, by integrating findings on cognitive processing and human factors, it offers practical insights that enhance system design to better support operator situational awareness, attention allocation, and workload management. These improvements can lead to more intuitive and efficient interfaces and controls, making telerobotic systems more responsive to operator needs. Additionally, it supports industrial recruitment processes, helping organisations select candidates with cognitive skills suited to telerobotic roles. The study also provides strategies for streamlining onboarding, enabling operators to achieve proficiency faster crucial for performance in high-stakes, real-time environments.



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## **LIST OF ABBREVIATIONS**

AI-Artificial intelligent

ANOVA - Analysis of Variance

AR - Augmented Reality

CARS - Crew Awareness Rating Scale

C-SAS - The Cranfield Situation Awareness Scale

DR - Data Recorder

EST - Event Segmentation Theory

HAI - Human-Automation Interaction

HCI - Human-Computer Interaction

HRI - Human-Robot Interaction

HTI - Human-Telerobotic Interaction

IQ - Intelligence Quotient

LOD - Level of Difficulty

LOA - Level of Automation

LOTD - Level of Task Difficulty

MANOVA - Multivariate Analysis of Variance

MARS - Mission Awareness Rating Scale

MR - Mixed Reality

NASA-TLX - National Aeronautical and Space Administration Task Load Index

PAPDR - Pen-and-Paper Data Recording

QUASA - The Quantitative Analysis of Situational Awareness

SAGAT - The Situation Awareness Global Assessment Technique

SARS - The Situation Awareness Rating Scales Technique

SART - Situation Awareness Rating Technique

SA - Situational Awareness

SD - Standard Deviation

SWAT - Workload Assessment Technique

TENG - Triboelectric Nanogenerator

TSAS - Tactile Situation Awareness Systems

VR - Virtual Reality

VRD - Verbal Data Recording

VWM - Verbal Working Memory

VDR - Verbal Data Processin



# Chapter 1 Introduction

## 1. Introduction

In an era characterised by the relentless advancement of robotics, automation, and artificial intelligence, the boundaries between humans and machines are becoming increasingly porous. This metamorphosis gives rise to a new paradigm of human-machine symbiosis, where the cognitive interplay between human operators and autonomous robotic entities takes centre stage.

The study of human-operator situational awareness in the realm of telerobotic systems is a crucial and significant endeavour. Enhancing situational awareness (SA) of operators in telerobotics has direct real-world applications, impacting industries and possibly improving quality of life for instance, through advanced remote medical procedures or safer handling of hazardous materials for human-in-the-loop systems, where the decision-making process involves human judgement. The operator uses the robot as an extension of themselves to perform tasks, often relying on the robot's sensors and mechanical capabilities to interact with the remote environment.

The motivation behind this research arose from a profound recognition of the multifaceted intricacies inherent to human-robotic interaction. It is situated at the confluence of diverse disciplines, echoing the ever-evolving technological innovation landscape.

Investigating operator situational awareness relative to their cognitive style within this context cannot be overstated. Endsley suggested that specific critical cognitive attributes are the primary factors influencing SA (Park, D., Yoon, W. C., & Lee, U. 2020). As telerobotic

systems become integral components of various domains, including manufacturing, healthcare, nuclear operations, human search and rescue, and space exploration, a nuanced understanding of how human operators perceive, interpret, and respond to remote environments becomes imperative. This dynamic interplay between the human-operator cognitive style and machine intelligence forms the focal point of our inquiry.

The gap that this PhD addresses lies in understanding how cognitive factors influence operator performance in telerobotic systems, particularly in high-stakes environments.

Looking in to the study's literature review advancements in technology have revolutionised the interaction between humans and machines, a deeper investigation into this two-way cognitive interaction has not been understood fully. The complexity and emergence of HRI underscore the need for an in-depth understanding of human-operator cognition and its impact on SA in telerobotic operations (Monje et al., 2008; Lee, 2022). While robotics and automation have seen substantial advancements (Siciliano & Khatib, 2016), there is limited real-world research on the effects of information verbalisation and goal-directed tasks on human-robot collaboration (Murphy, 2014). According to Salmon, P. M., and Stanton (2009), success in telerobotic operation lies not in progressing or owning the system, but in how well we use it.

Based on the study's literature review, the key aspects of operator performance, such as situational awareness (SA), attention allocation, and cognitive workload management, remains insufficiently explored (Endsley, 1995). Furthermore, limited situational awareness (SA) is a major challenge in implementing teleoperation systems (Fan J, Li X, and Su X, 2022), as it hinders an operator's ability to effectively manage and respond to remote tasks.

Despite the challenges inherent in evaluating the real-world impact of Human Factors

concepts, existing literature indicates that SA has not yet attained the same level of influence as other Human Factors (HF) safety-related concepts, such as 'human error' and 'mental workload' (Salmon et al., N. A. (2013). This observation highlights a disparity in the attention and application given to various facets of Human Factors within telerobotic and safety critical domains. The relatively limited impact of SA compared to more extensively studied areas like human error and mental workload suggests a potential gap in research focus and practical application. This gap underscores the need for a more balanced approach in HF research, where equal emphasis is placed on all critical components, including situational awareness, to enhance overall human-system efficiency.

Additionally, the role of individual cognitive abilities, such as Intelligence Quotient (IQ), in predicting and enhancing an operator's SA and their performance in telerobotics has not been thoroughly investigated. Many current telerobotic systems are designed with a focus on technical functionality but fail to address the nuanced interplay between cognitive processing and task complexity, leading to usability challenges and suboptimal human-robot interaction (Drury et al., 2003).

The importance of this research lies in addressing the identified significant gap in our understanding of the role of individual cognitive abilities, as well as the effects of information verbalisation and goal-directed tasks on human-robot collaboration. The novelty of this research goes further, focusing on how human cognitive modalities can be utilised to improve operators' SA, performance, and attentional allocation. By addressing these factors, the study contributes to creating systems that better support human decision-

making, reduce cognitive strain, and ultimately enhance the synergy between humans and robots.

This research is essential not only for optimising operator performance but also for ensuring safety, reliability, and efficiency in telerobotic operations across industries such as healthcare, nuclear operations, and search and rescue.

This study plays a critical role in designing interfaces, training programmes, and workflows tailored to support each individual's unique strengths and cognitive preferences. This helps build more adaptive systems that reduce cognitive strain and improve decision-making.

Given these considerations, this thesis aims to comprehensively expand the knowledge base in human-robot interaction by integrating findings from cognitive science and telerobotic research by exploring and elucidating the relationship between human cognitive styles, information processing, and their impact on an operator's situational awareness within telerobotic operation. This exploration is not just an academic pursuit but a crucial foundation for advancing the field, especially considering the unique challenges and complexities inherent in the remote operation of robotic systems due to the limited study in this specific field.

The novelty of the research also in this strategy of integrating cognitive human factors and the operator's information processing style, including visual-manual and visual-verbalisation approaches, into the heart of telerobotic research and development is imperative. Such integration will pave the way for empirical studies on human's SA in telerobotics, aiming to identify and analyse the underlying influential factors associated with these distinct information processing styles.

This research will significantly contribute to developing more adaptive, user-friendly, and efficient telerobotic systems, catering to a broader range of operator preferences and strengths. Ultimately, this will enhance operational performance, safety, workload management, and effective human-robot interaction, thereby contributing to telerobotic operations' overall success and efficiency (Endsley, 1995; Kaber et al., 2000; Ballantyne, 2007; Mehrdad et al., 2020; Oke et al., 2021; Weiss et al., 2021; Valner et al., 2018; Liu et al., 2022).

The research contributions and novel aspects of the study have been thoughtfully outlined as bullet points beside their areas of impact. This structured presentation highlights the key achievements and novel aspects of the study, providing a clear and concise overview of how the research advances understanding in Human-Robot Interaction (HRI) and Cognitive Science.

- **Industry-Relevant Insights:** Aims to optimise communication between operators and systems with direct applications in industries where telerobotics is critical, such as;

1. **Aviation**

2. **Healthcare**

3. **Industrial Automation**

4. **Military and Defence**

5. **Aerospace**

6. **Emergency Response and Disaster Management**

7. **Agriculture**

- **Practical Applications for System Design:** Contributes to improving control and command interfaces, and workflows to support operator SA, cognitive strengths, and reduce cognitive strain in these industries setting.
- **Recruitment Implications:** Offers insights for streamlining operator onboarding and recruitment, helping organisations select individuals with the cognitive skills and Intelligence Quotient level needed for telerobotic roles.
- **Improved Educational and Training Innovations:** Offers new strategies for educational and training frameworks that better support human-robot collaboration, focusing on cognitive factors. Further it contributes to develop more effective training programs tailored to individual cognitive strengths, helping operators achieve proficiency faster.
- **Better Error Detection and Recovery:** Enhances system capabilities in error detection and recovery, ensuring smoother human-robot collaboration in high-stakes environments.
- **Improving Decision-Making:** Focuses on cognitive approaches that aid in faster, more accurate decision-making in telerobotic operations, especially under pressure.
- **Reducing Cognitive Load:** Investigates strategies for reducing cognitive load on operators, leading to better task performance and improved safety outcomes.
- **Human-Robot Collaboration Enhancement:** Provides actionable insights into how cognitive processing affects operator performance in complex, real-time, goal-directed tasks, advancing the design of telerobotic systems.
- **Interdisciplinary Research Focus:** The study bridges human-robot interaction (HRI), cognitive science, and telerobotics, focusing on the operator's cognitive factors in high-stakes environments.

- **Novelty in Cognitive Exploration:** Investigates the impact of cognitive factors, such as IQ and information verbalization, on human-robot collaboration, offering new insights into situational awareness (SA), attention allocation, performance, and cognitive workload.
- **Significant Contribution to SA Understanding:** Deepens understanding of how individual cognitive abilities, especially IQ, affect situational awareness in telerobotic operations, establishing a link between IQ and SA for predicting operator performance.
- **Information Verbalisation Impact:** Demonstrates how verbalisation enhances multimodal processing, real-time engagement, and self-auditory experiences, optimising attention allocation and reducing mental workload.
- **Addressing Gaps in Existing Research:** Fills the gap in research on how cognitive abilities influence operator performance in telerobotics, especially in the context of information verbalization and goal-directed tasks, where previous studies have been limited.
- **Improving Performance and Safety:** Contributes to improving telerobotic system performance and safety by addressing cognitive factors that influence operator decision-making and task execution.

In summary, a PhD in this area can, not only push the boundaries of current knowledge but also have a tangible impact on various sectors and contribute to developing safer, more efficient telerobotic operation. These contributions and novel approaches align with the need for human-centred approaches in robotics (Goodrich & Schultz, 2007) and offer practical implications within industrial setting and add knowledge to science engineering.

## 1.2 Problem statement and Aim

The interdisciplinary field of Human-Robot Interaction (HRI) stands at the crossroads of diverse scientific disciplines, encompassing aspects of psychology, cognitive science, social sciences, engineering, and computer sciences (Adamides et al., 2014; Dautenhahn, 2007; Roesler et al., 2021). Despite its comprehensive nature, addressing both technological and social aspects of artificial intelligence, robotics, and human-computer interaction (Seibt et al., 2021), HRI continues to grapple with integrating human factors into the rapidly evolving sphere of telerobotics.

This thesis recognises the paramount importance of human factors in telerobotics, particularly in enhancing SA and operator performance. As the field delves into complex cognitive processes such as mental stress and safety awareness during human-robot collaboration (Lu et al., 2022), it becomes evident that there is a pressing need to focus on the human element of these interactions. This necessity becomes more apparent when considering the relative neglect of human factor issues in Human-Telerobotic Interaction (HTI), compared to other areas like aircraft piloting or human-computer interaction (Sheridan, 2016). The scattered nature of HRI research across various disciplines further exacerbates the challenge of synthesising a comprehensive understanding of teleoperation (Rawal et al., 2022).

Given these considerations, this thesis aims to comprehensively expand the knowledge base in human-robot interaction by integrating findings from cognitive science and telerobotic research by explore and elucidate the relationship between human cognitive styles, information processing, and their impact on an operator's situational awareness within



telerobotic operation.

## 1.3 Objectives of the Thesis

Based on the aim of the thesis, the study's objectives are outlined as follows:

### 1. Evaluate the Impact of Information Verbalising on SA and Performance

- **Specific:** Assess how verbalising information affects situational awareness (SA) and task performance in telerobotic systems.
- **Measurable:** Use quantitative metrics (e.g., SA rating scales, performance scores) to compare outcomes.
- **Actionable:** Design experiments where participants verbalise task-relevant information while operating telerobotic systems.
- **Realistic:** Focus on scenarios that mirror real-world telerobotic operations.
- Complete experimental data collection and analysis within the study timeline.

### 2. Analyse the Relationship between Task Difficulty and Situational Awareness (SA)

- **Specific:** Examine how varying task difficulty influences operators' SA in telerobotic environments.
- **Measurable:** Quantify changes in SA using validated tools and measure correlations between difficulty levels and SA scores.
- **Actionable:** Conduct controlled experiments adjusting task complexity in real-time.
- **Realistic:** Select task scenarios feasible for operators and measurable with existing instruments.
- **Time-bound:** Perform and analyse these experiments over a defined period.

### 3. Determine the Effects of Verbal Data Recording in Multitasking Environments

- **Specific:** Investigate how verbal data recording impacts attention, mental workload, and multitasking efficiency in telerobotics.
- **Measurable:** Use workload scales (e.g., NASA-TLX) and efficiency metrics (e.g., task completion time).
- **Actionable:** Compare verbal data recording to other recording methods during multitasking scenarios.
- **Realistic:** Focus on practical multitasking environments relevant to telerobotics.
- **Time-bound:** Conduct trials and analyses within the planned experimental phase.

### 4. Investigate the Influence of Cognitive Abilities on SA in Telerobotics

- **Specific:** Explore the role of individual cognitive abilities (e.g., IQ) in predicting SA proficiency in telerobotic tasks.
- **Measurable:** Analyse cognitive scores alongside SA metrics.
- **Actionable:** Design experiments that measure cognitive abilities and compare them with task performance outcomes.
- **Realistic:** Leverage standardised cognitive tests and operationally relevant SA tasks.
- **Time-bound:** Complete cognitive testing and data analysis within the research timeline.

### 5. Advance the Domain of Human-Robot Interaction (HRI)

- **Specific:** Synthesise empirical data and theoretical insights to improve understanding of human cognitive mechanisms and user interfaces in telerobotics.

- **Measurable:** Develop specific design recommendations based on data-driven insights.
- **Actionable:** Conduct experiments and literature reviews to derive evidence-based guidelines for ergonomic design.
- **Realistic:** Tailor recommendations to align with diverse cognitive profiles and operational constraints.
- **Time-bound:** Finalise the synthesis and design proposals within the study duration.

## 6. Bridge Identified Research Lacunae

- **Specific:** Conduct a systematic review and meta-analysis of human factors research gaps in telerobotics, focusing on SA, task complexity, and cognitive skills.
- **Measurable:** Identify key research gaps and propose integrative frameworks for addressing them.
- **Actionable:** Combine findings from existing cognitive science and telerobotic studies to create practical frameworks.
- **Realistic:** Focus on synthesising evidence from available studies while considering real-world applicability.
- **Time-bound:** Complete the review and framework development within the defined project timeline.

These objectives are specific, measurable, actionable, realistic, and time-bound (SMART), ensuring they can be systematically addressed within the scope of the thesis. These objectives are designed to systematically address the research questions and aim of the thesis, paving the way for advancements in the understanding and application of human factors in telerobotic operations.

## 1.4 Research Questions

### Research Question 1:

Does the use of an information verbalising approach in goal directed telerobotic task enhance human operators' Situational Awareness and improve their performance in telerobotic operation tasks, compared to the traditional Pen-and-Paper Data Recording (PAPDR) method?

This research question has been developed based on the concept focuses on the impact of different data recording approaches on human operators' situational awareness (SA) and performance in telerobotic operations. Specifically, it examines the 'information verbalising approach' as a method of data recording during task execution and its potential effects on cognitive processing and information retention. This approach posits that verbalising information, as opposed to traditional pen-and-paper methods, might enhance cognitive engagement with the task, thereby improving situational awareness and overall task performance.

Studies such as Ericsson and Simon (1984) on verbal protocols suggest that verbalising information while performing tasks enhances cognitive engagement and facilitates information processing and retention. Similarly, Endsley (1995) emphasises the critical role of situational awareness in dynamic and complex systems, highlighting how cognitive aids such as verbalisation can support better awareness and decision-making. Additionally, research by Wickens (2008) on cognitive load theory suggests that verbal interaction can reduce working memory overload, which is essential in high-stakes environments like telerobotic operations.

This concept explores how the mode of data recording, particularly verbalisation, influences the operator's ability to process and retain information, thereby impacting their situational awareness and performance in complex telerobotic tasks.

### **Research Question 2:**

How does the variation in the Level of Task Difficulty (LOTD) within a primary telerobotic task affect the SA levels of the subjects, and is there a quantifiable correlation where increased task difficulty leads to a decrease in SA levels, attention allocation and mental workload?

The concept revolves around this question is based on the dynamic relationship between the Level of Task Difficulty (LOTD) in telerobotic operations and its impact on the operator's situational awareness (SA). It posits that as the complexity or difficulty of a task within a telerobotic environment increases, greater cognitive demands are placed on the operator. These increased demands may result in a measurable decline in the operator's ability to maintain optimal situational awareness.

This concept draws on the principles of cognitive load theory and human factors engineering. Sweller's Cognitive Load Theory (Sweller, 1988) indicates that increased task complexity can overwhelm cognitive resources, resulting in diminished performance.

Endsley's (1995) model of situational awareness highlights that maintaining SA requires significant cognitive resources, which can be compromised under high task difficulty.

Additionally, Wickens' (2008) work on multiple resource theory emphasises the importance of managing task complexity to prevent cognitive overload, especially in environments where split attention and decision-making are critical.

Understanding the relationship between task difficulty and cognitive performance is vital for optimising task design, ensuring operator safety, and enhancing the overall effectiveness of telerobotic systems.

### **Research Question 3:**

Does the utilization of the Verbal Data Recording approach in a secondary task significantly affect participants' attention levels and reduce their mental workload during multitasking situations?

The research question 3 is based around the impact of different human verbalising information processing approaches on participants' cognitive load, as well as attention levels which is a subject of increasing interest in cognitive research. Specifically, the Verbal Data Processing (VDP) approach is theorised to interact with cognitive processes in a way that might influence attention and mental workload. This concept examines how the mode of data recording, particularly verbalisation, affects a participant's cognitive resources, potentially leading to changes in attention allocation and mental workload management during multitasking scenarios.

Research by Ericsson and Simon (1984) on verbal protocol analysis suggests that verbalisation can influence cognitive load by externalising internal cognitive processes, thereby affecting the allocation of attention. Kahneman's (1973) capacity theory of attention supports the idea that attentional resources are finite, and verbalisation may redistribute these resources during multitasking. Furthermore, Wickens (2008) highlights how task modality and cognitive load interact, suggesting that verbalisation as a mode of data processing may reduce overall mental workload by offloading some cognitive demands.

Understanding these interactions is critical for designing effective human-machine interfaces and improving cognitive performance in multitasking scenarios.

#### **Research Question 4:**

Do individual differences in cognitive abilities, as indicated by IQ scores, significantly influence the level of Situational Awareness in operators during telerobotic operations?

The exploration of how individual cognitive abilities, as reflected by Intelligence Quotient (IQ) scores, correlate with situational awareness (SA) in telerobotic operations forms the core of concept behind this research question.

This research area investigates whether cognitive capabilities, as quantified by IQ assessments, significantly influence an operator's ability to maintain and process SA in complex telerobotic environments.

Given the critical role of cognitive abilities in decision-making and problem-solving, this concept seeks to uncover the extent to which these abilities, as measured by IQ, can predict or influence an operator's proficiency in maintaining SA during telerobotic tasks. Research by Ackerman (1988) suggests that higher cognitive abilities enhance performance in complex and novel tasks. Endsley's (1995) model of SA emphasises the cognitive processes underlying effective SA maintenance, which aligns with findings that general intelligence correlates with task performance in dynamic systems (Fleishman & Mumford, 1989). Additionally, Salas et al. (1995) highlight the interplay between individual cognitive traits and team SA in high-stakes environments, further supporting the relationship between IQ and SA.

Understanding these connections is crucial for designing selection criteria and training programmes that optimise operator performance in telerobotic systems.

## **1.5 Organization of the Thesis: An Academic Overview**

### **Chapter 2: Comprehensive Literature Review**

Chapter 2 lays the foundation for this thesis, presenting an extensive literature review that delves into the multifaceted aspects of teleoperation, situational awareness, and human-robot interaction within telerobotics. Structured into several critical sections, each part of this chapter methodically explores interconnected research areas, offering a nuanced understanding of the field.

- Section 1 begins with a detailed examination of teleoperation and situational awareness, emphasizing the intricacies of human-robot interaction. This segment sets the stage for an in-depth understanding of telerobotic applications and their operational dynamics.
- Section 2 transitions into a critical analysis of the interplay between human factors and technological advancements in telerobotics. This insightful discourse scrutinizes the challenges faced by telerobotic operators, offering perspectives on human-centric interface design, system automation, and their impacts on operator situational awareness (SA). The technological landscape of telerobotics is also thoroughly reviewed.
- Section 3 shifts the focus to situational awareness within teleoperation. The chapter dissects human factors and ergonomic considerations, underscoring their pivotal role in addressing the unique challenges and opportunities in teleoperation and telerobotics.



- Section 4 introduces and explicates the theoretical frameworks and models that anchor this research. It delves into the cognitive processes of operators in teleoperation, probing their correlation with SA and examining cognitive processing and information verbalization.
- Section 5 explores the potential application of intelligence quotient assessments in evaluating individual variances in SA, opening new pathways to understand how cognitive abilities impact operator performance in telerobotics.
- The final section conducts an exhaustive review of human SA assessment instruments to pinpoint an effective method for evaluating telerobotic operators, thus enhancing operator performance and system efficiency.

Overall, Chapter 2 particularly amalgamates diverse research strands to present a comprehensive view of telerobotics, human factors, and situational awareness, providing critical insights to propel this dynamic field forward.

### **Chapter 3: Experimental Methodology**

Chapter 3 of this thesis transitions into a critical phase where the theoretical constructs and hypotheses delineated in the preceding chapters are translated into practical, empirical research. This chapter meticulously details the experimental methodology, serving as the cornerstone of the study's scientific rigour.

The chapter commences by articulating the experimental design. It delineates the specific experimental protocols and procedures, providing a blueprint of the study's operational framework. This section comprehensively describes the experimental setup, the variables under investigation, and the methods employed to manipulate and measure these variables.

The design is presented with an emphasis on how it aligns with the study's objectives and addresses the research questions and hypotheses.

The chapter delves into the participant selection process. This segment is crucial as it outlines participant inclusion and exclusion criteria, ensuring that the sample is representative and appropriate for the study's aim. Next, the chapter details the data collection methods. This chapter describes the instruments and tools used for data gathering, such as surveys, observation techniques, or technological devices. The validity and reliability of these instruments are discussed to establish their credibility. Additionally, the procedures for data collection are described, ensuring replicability and transparency in the research process.

#### **Subsequent Chapters: Data Analysis and Findings**

- **Chapter 4: Human Situational Awareness & Performance Assessment**

presents a thorough analysis of the collected data, focusing specifically on the measurement of subjects' SA and Performance variables. The primary objective was to address the research questions and test the study's hypotheses, to understand the relationships, patterns, and trends observed within the dataset.

- **Chapter 5: Assessment of participants' attention & Mental Workload level**

delves into the investigation of experimental data concerning participants' attention and mental workload levels. It also introduces sub-hypotheses pertinent to attentional and mental workload aspects.

- **Chapter 6: Investigating the Impact of IQ on Situational Awareness in Telerobotic Tasks**

embarks on an exploratory phase, examining the relationship between individual cognitive abilities and SA in telerobotic operations. This chapter evaluates the potential of IQ assessments as indicators of telerobotic operator situational awareness, given their link to cognitive abilities and decision-making.

- **Chapter 7: Synthesis, Conclusions, Limitations and Future Direction**

Finally, Chapter 7 synthesizes the discussions, findings, and conclusions drawn from the preceding technical chapters. It also critically addresses the research's limitations and experiments, paving the way for a detailed discussion on future research implications and potential directions for further exploration in this field.

This structured approach ensures that the thesis is not only academically rigorous but also clear, engaging, and systematically arranged to guide the reader through a comprehensive exploration of telerobotics and human factors.

Figure 1 offers a detailed schematic overview of the thesis's organizational structure. It outlines the specific topics and areas of emphasis covered in each chapter, providing a clear roadmap of the thesis's content and progression.

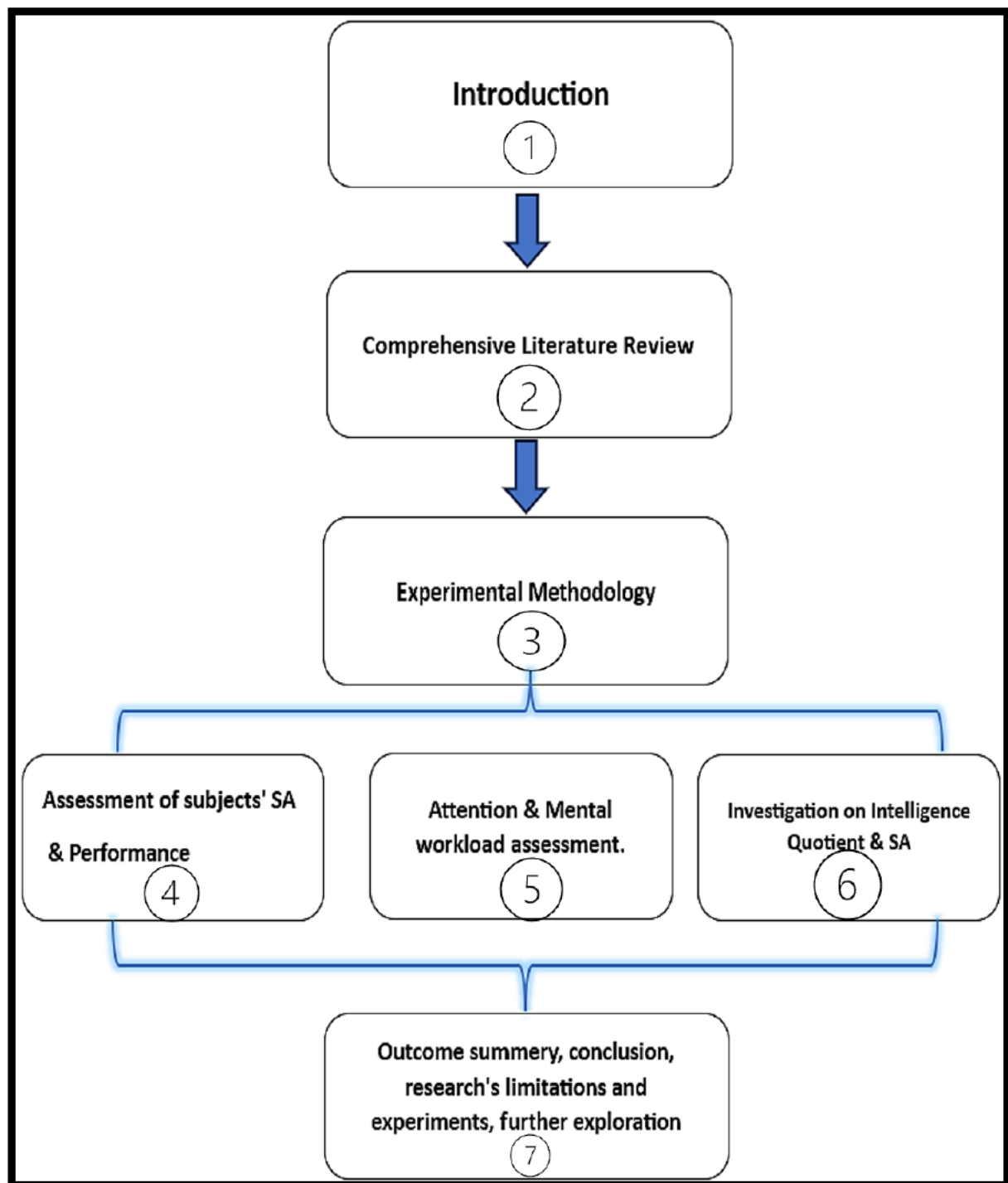


Figure 1 Structure of thesis

## **Chapter 2**

### **Literature Review**

#### **2.1 Introduction**

This chapter delves into the intricate relationship between human operator, tele-robotic and situational awareness, underlining the critical role of human-robot interaction (HRI) in augmenting the efficacy and safety of remote operations while investigating the effect of utilising different human-cognitive and information processing styles. The exploration begins with a focus on HRI, considering how multidisciplinary insights contribute to creating symbiotic man-machine systems and bringing the human and the machine engaging in two-way cognitive interaction. Following this, the discussion transitions to the specifics of telerobotics and teleoperation—the core domains where the human factor meets robotic precision.

Human-Operators in teleoperation are the fulcrum upon which the success of remote interventions turns; their cognitive abilities, workload management, and the use of technology profoundly impact their situational awareness and, consequently, operational outcomes. Human-centric interface design is central to optimising these interactions, which places the operator's experience at the forefront of technological innovation. This design philosophy aims to streamline the interaction between humans and machines and focuses on minimising operational complexity to enhance SA.

Automation is a double-edged sword; while it has the potential to reduce workload and elevate performance, it must be balanced to avoid eroding operator SA—especially with varying levels of automation. Furthermore, investigation of the integration of technology in teleoperation extends to sensory technologies, data fusion, augmented and virtual reality

(AR/VR), and haptic feedback, have been analysed where each of which promises to amplify human capabilities in remote settings.

With SA being paramount in teleoperation, the chapter examines theoretical frameworks that underpin the assessment and enhancement of operator cognition and SA. These frameworks offer models for understanding how operators process information and interact with robotic systems, shedding light on the cognitive underpinnings influencing SA. Further, investigation on information verbalising and its potential to affect operators SA has added even more value to this theoretical framework.

The chapter also critically considers individual differences, such as operator IQ, assessing its impact on the SA level. Complementing this cognitive approach, various methods of SA assessment are investigated, ranging from objective metrics to well-established subjective techniques, to capture the nuanced picture of operator awareness.

In sum, this chapter serves as a coherent structure by which the reader may navigate the diverse yet interconnected avenues of teleoperation and human-robot interaction. By dissecting the elements that form the foundation of teleoperation success, we aim to elucidate the path to enhanced situational awareness, improved performance, and, ultimately, seamless, and safe remote operations.

## **2.2 Teleoperation and Situational Awareness:**

### **2.2.1 Human-Robot Interaction**

In the past few decades, we have witnessed a surge in the deployment of robots and automation, accompanied by ongoing advancements in technical innovations within various

industrial sectors (International Federation of Robotics, 2019). Furthermore, the advancement of artificial intelligence and robotics has significantly affected humanity's lives (Bin et al., 2023).

Specifically, integrating robotics into human activities has become increasingly prominent, representing a significant technological evolution with multifaceted impacts. This matter has, even more, signified the attention to Human-robotic interaction to the extent that every year, The Institute of Electrical and Electronics Engineers (IEEE) holds a specialist's symposium on human–robotic interaction since 2006 (IEEE Robotics and Automation Society, 2015).

**Human-Robot Interaction (HRI)** involves the study, design, and assessment of robotic systems intended for use by or with humans, as defined by Goodrich & Schultz (2007). It is an interdisciplinary field combining human and robot factors, researched across diverse disciplines such as psychology, cognitive science, social sciences, engineering, and computer sciences (Adamides et al., 2014; Dautenhahn, 2007; Roesler et al., 2021). HRI addresses both the technological and social aspects of artificial intelligence, robotics, and human-computer interaction (Seibt et al., 2021).

HRI is a dynamic and evolving field aimed at creating effective and seamless interactions between humans and robots. It encompasses areas such as social signal recognition, augmented reality, and spatial dialogue to enable natural collaboration (Green et al., 2008). The field also examines robotic psychology, bridging gaps between humans and robots and offering insights into the nuances of interaction (Stock & Nguyen, 2019).

HRI emphasises evaluating operator well-being by studying cognitive psychology, mental stress, and safety awareness during human-robot collaboration (Lu et al., 2022). It also

explores robot learning through human demonstrations, focusing on knowledge adaptation when humans introduce environmental changes (Kyrarini et al., 2018).

Applications of HRI extend to healthcare, addressing challenges such as fear of caregiver displacement and the appropriateness of robot use (Olaronke et al., 2017). Additionally, HRI delves into emotion-based interaction, intent prediction, trajectory forecasting, and multi-agent human-robot collaboration in various environments (Berns & Zafar, 2018; Monfort et al., 2015; Abbasova & Nagy, 2017).

The historical trajectory of HRI also saw a focus on cognitive robotics, as demonstrated by (Monje et al., 2008), and the study of human intentions during collaborative tasks, as seen in the work of (Tlach et al., 2018). These efforts underscored the increasing attention to understanding human cognition and intentions in the context of HRI. Additionally, the increasing emphasis on personalized and adaptive interactions have been understood by the work of Hale et al. (2019) and Williams et al. (2017). Integrating advanced technologies, practical applications in industrial settings, and a deeper understanding of human cognition and cultural responsiveness reflects the field's multifaceted and dynamic nature.

In addition, the use of AI technologies to improve sociological analysis and the contributions of sociology to the social robot project have been explored, demonstrating the multifarious perspectives and applications of humanised or social robots as a medium of communication (Zhao, 2006). Moreover, developing human-like cognitive biases in robots for long-term companionship is a novel application in robotics, focusing on creating and maintaining relationships between robots and humans (Biswas & Murray, 2015).

Based on the role and structure of telerobotics, the aspects of HRI encompass a diverse range of topics, including social interaction, psychological effects, physical interaction, decision-



making support, trust, and safety considerations. The multidisciplinary domain of HRI has been rapidly advancing across various disciplines. However, the field remains notably fragmented, making it challenging to stay updated with the latest developments or to evaluate the comprehensive body of research related to teleoperation (Rawal, Niyati & Stock-Homburg, 2022). Specifically, technology advancement has restructured the human and the machine engaging in two-way cognitive interaction and the need for further understanding investigation within this field.

### **2.2.2 Telerobotic and Teleoperation**

Teleoperation and telerobotics generally describe conditions where humans can access remote locations through semiautonomous systems (Sheridan, T. B., & Parasuraman, R. (2005). Most human-robotic interactions can be considered telerobotic or teleoperation tasks due to the significant advances in mechatronics, control, and planning, which have made safe physical Human-Robot Interaction possible (Haddadin, 2015). In recent years, teleoperation has gained significant attention as it allows a human operator to control a robot in a remote environment (Macchini et al., 2021)

Telerobotics is the area of robotics concerned with controlling robots from a distance using wire and wireless communications (Kang et al., 2013). The human operator receives sensory data about a distant environment through an interface and acts by relaying instructions to machines located there. The telerobotic system serves two principal roles. Initially, it engages the operator's sensory faculties by projecting data of the distant environment onto a display system with various forms, like a computer monitor or virtual reality headsets. Subsequently, it processes the operator's commands, ensuring precise control over distant

apparatus such as automated machines. Various interfaces utilize different forms of input from the user, such as gestures, force, verbal commands, or symbolic cues (Wagner, Petra & Malisz, Zofia & Kopp, Stefan. (2014). The telerobot receives these diverse commands to execute tasks in a distant location accurately.

Human-robot collaboration is an essential application for integrating robots with advanced interaction capabilities (Ajoudani et al., 2017). The advent of telerobotic systems has revolutionized various aspects of industry and human life (Mehrdad et al., 2020).

Additionally, developing architectures for Internet telerobotic systems has expanded the reach of telerobotic operations, allowing robots to be remotely controlled and monitored through the Internet (Trilaksono, 2007). The utilisation of telerobotic systems is rapidly increasing, and their benefits have been well established in many areas, including health care, nuclear, human search and rescue, military and defence, and telepresence (Lichiardopol, 2007).

For instance, the da Vinci surgical system, which is currently one of the widely used telerobotic devices, which has been approved for clinical use in all abdominal operations in countries such as Australia, Japan and United Kingdom indicating the increasing role of telerobotic systems and operators in medical procedures (Ng et al., 2007). Furthermore, telerobotics or telesurgery has come closer to reality with the adaptation of robots to provide surgical assistance from a remote site if needed (Challacombe et al., 2005).

Telerobotic systems have also been found to be crucial in hazardous environments, where they enable remote robotic interventions, ensuring the safety of human operators (Lunghi et al., 2019).

Based on the role of teleoperation in industry and HRI structure, The role of operators in teleoperation tasks is crucial, as it involves a complex combination of cognitive, perceptual, and motor skills. Teleoperation requires operators to control robots or systems remotely, often in hazardous or inaccessible environments. The cognitive ability of operators is essential in teleoperation tasks, as it directly impacts their performance and the operation's overall success. Operators must possess spatial cognitive abilities to navigate and manipulate remote systems effectively.

Although there is a significant body of research in the field of telerobotic and HRI due to their multi-disciplinary nature, in comparison to activity on human-factor issues in human-automation interaction in piloting aircraft or human–computer interaction, the human factor issues related to Human-Robotic Interaction has been relatively neglected and still there is a massive gap in meeting the human factor issues related to human-robot interaction (Sheridan, 2016 – Hum. Factors). Both the complexity and emergence of human-robot interaction have provided an overview of the challenges and opportunities in telerobotic and teleoperation systems, emphasizing the need for a more comprehensive understanding of human factor issues in these contexts, explicitly increasing attention to understanding human cognition (Monje et al., 2008; Lee 2022).

### **2.2.3 Different application of Telerobotic**

**Telerobotics** refers to the remote operation of robotic systems through advanced technologies such as sensors, cameras, and haptic feedback, enabling precise and effective control in various domains. This field has significant applications, including:

#### **1. Healthcare**

Telerobotics has revolutionised the healthcare industry, particularly through robotic-assisted surgeries. Systems like the da Vinci Surgical System allow surgeons to perform minimally invasive procedures with greater precision and minimal patient recovery time (Yang et al., 2017). Telemedicine applications utilise telerobotic platforms to provide remote diagnosis and treatment in underserved areas (Cohen et al., 2018). Furthermore, telerobotic rehabilitation devices assist patients in physical therapy by remotely guiding movements, improving accessibility to quality care (Lu et al., 2012).

## **2. Space Exploration**

In space exploration, telerobotics enables remote operation in extreme environments. Robotic systems such as NASA's Robonaut assist astronauts in tasks aboard spacecraft (Diftler et al., 2011). Additionally, planetary exploration missions, including the Mars Curiosity Rover, rely on telerobotics to perform intricate surface explorations (Grotzinger et al., 2012).

## **3. Nuclear Industry**

The nuclear industry employs telerobotics for decommissioning and maintenance tasks in hazardous environments, ensuring worker safety. Remote robots perform tasks such as handling radioactive materials and inspecting reactors in high-radiation zones (Shimada et al., 2016).

## **4. Defence and Military**

In the defence sector, telerobotics plays a vital role in bomb disposal through robots such as PackBot and TALON, which disarm explosives remotely (Murphy, 2014). It is also used in

surveillance and reconnaissance missions in inaccessible or hostile areas (Prassler et al., 2000).

## **5. Underwater Exploration**

Telerobotics facilitates deep-sea exploration, where Remotely Operated Vehicles (ROVs) like the Jason and Hercules systems operate at depths beyond human reach (Yoerger et al., 2007). These systems are also crucial for inspecting underwater pipelines and maintaining offshore structures (Marani et al., 2009).

## **6. Industrial Applications**

In the oil and gas industry, telerobots are deployed for pipeline inspections and handling hazardous materials (Wang et al., 2015). Manufacturing applications include precision assembly and quality control in environments unsafe for human operators (Tan et al., 2016).

## **7. Search and Rescue**

Telerobotics has become essential for disaster response, navigating through collapsed buildings or hazardous areas to locate victims (Murphy et al., 2008). Robots like CRASAR have demonstrated their utility in real-world search and rescue missions, such as post-earthquake operations (Casper & Murphy, 2003).

## **8. Agriculture**

In agriculture, telerobotics facilitates precision farming through tasks like targeted spraying and automated harvesting, improving yield and efficiency (Bechar & Vigneault, 2016).

Telerobots also assist in remote monitoring of crops and livestock, reducing labour demands (Shamshiri et al., 2018).

## **9. Education and Research**

Telerobotic systems are increasingly used in remote experimentation for research, enabling scientists to operate equipment in controlled or distant environments (Schmidt et al., 2014). In robotics education, students use telerobots to learn programming, mechanics, and real-world problem-solving techniques (Papert, 1993).

## **10. Commercial and Consumer Applications**

Telerobotics has made strides in telepresence, enabling remote participation in meetings, events, or social interactions through platforms like Beam (Tsui et al., 2011). In the consumer sector, home assistance robots support elderly or disabled individuals with daily tasks, enhancing their quality of life (Broadbent et al., 2009).

Telerobotics continues to expand its potential applications, driven by advancements in AI, 5G, and haptics, which promise to further enhance its efficiency and adaptability across industries. These applications form the foundation for studying how telerobotics can address critical challenges in human-robot collaboration.

## **2.3 Human Factors and Technology Integration**

### **2.3.1 Human-Centric Interface Design approaches**

Human-centric interface design in system control interfaces is critical to ensuring efficient and effective human-machine interaction. It emphasises the importance of considering human factors in the design of human-machine interfaces for process control systems (Nachreiner et al., 2006). This approach involves prioritising human capabilities, limitations,

and user-centred principles in the design and development of interfaces for controlling complex systems (Hou, 2011).

This design philosophy places the human operator at the forefront, aiming to create interfaces that facilitate efficient, intuitive, and safe interaction while accounting for the user's cognitive, physical, and perceptual characteristics. Human-centric interface design integrates human factors, cognitive psychology, and human-computer interaction principles to optimise complex systems' symbiotic relationship between the user and the control interface (Chignell, M., Wang, L., Zare, A., & Li, J. (2023)). This principle highlights the significance of considering human-centred design principles to create intuitive interfaces supporting operators' cognitive processes.

The academic underpinnings of human-centric interface design emphasise the following key principles:

1. **Cognitive Load Considerations:** Incorporating an understanding of human cognitive capabilities and limitations to minimise cognitive load, support effective decision-making, and task execution (Sweller, 1988; Wickens, 2002).
2. **User-Centred Design:** Emphasising iterative engagement with end-users to understand their needs, preferences, and workflows, informing the design process and ensuring interfaces are intuitive and aligned with user expectations (Norman, 1988; Gould & Lewis, 1985).
3. **Information Display and Visualisation:** Utilising visual perception and information processing principles to present system status, feedback, and control options

organised and interpretable to support situational awareness and decision-making (Tufte, 1990; Endsley, 1995).

4. **Task Compatibility:** Ensuring that the interface aligns with the user's mental models, preferences, and the nature of the tasks, thereby enhancing usability and reducing potential errors (Rasmussen, 1983; Vicente, 1999).
5. **Ergonomic Considerations:** Accounting for physical ergonomics and human comfort to design interfaces that support efficient and comfortable interaction, considering factors such as reach, visibility, and physical control (Shneiderman, 1992; Salvendy, 2012).
6. **Feedback and Error Management:** Providing informative feedback and effective error management mechanisms to guide users, bring attention to critical issues, and support error recovery (Norman, 1983; Nielsen, 1994).

By integrating these principles in the design of system control interfaces, human-centric approaches seek to optimise user performance, reduce the potential for human error, and enhance overall system effectiveness (Human Centered Design, 2021). From an academic perspective, human-centric interface design aims to bridge the gap between the cognitive and physical capabilities of the human operator and the complex demands of controlling intricate systems, with the overarching goal of creating interfaces that are intuitive, supportive, and aligned with the needs and capabilities of the user.



### 2.3.2 Automation

Due to the sensitivity of the task on remote-operation operators, one of the leading human factor issues is addressing the complex relationship between task workload and situational awareness (SA) in remote-operation environments, which requires a multi-faceted approach.

First, the design of remote-operation systems should minimize unnecessary cognitive load on operators by streamlining interfaces, providing relevant and timely information, and automating routine tasks. Additionally, training programs should focus on enhancing operators' cognitive skills, such as information processing, attention management, and decision-making under high workload conditions, Wickens et al. (2013) highlight that cognitive load can be significantly reduced by designing interfaces that simplify information processing and eliminate redundant elements. Additionally, Endsley (1995) emphasises the importance of presenting information in a way that supports situational awareness, ensuring operators can focus on critical tasks. Promoting situation awareness through effective communication, feedback mechanisms, and advanced monitoring tools can bolster operator performance and SA in remote-operation environments. However, while optimized automation design can manage routine tasks effectively, human operators excel in manoeuvring complex, non-routine situations that may fall outside the capabilities of the automated system (McBride, S 2013).

In the discourse of automation reliance, reliability emerges as a multifaceted determinant that exerts influence on the optimal engagement with automated systems. Automation also plays a crucial role, as Parasuraman et al. (2000) demonstrate, by handling routine functions and allowing operators to allocate cognitive resources to more demanding activities. The heterogeneity of automation reliability has discernible effects on user interactions, as

evidenced by empirical studies, for instance study by Wang, Pynadath, & Hill, (2015) found that when automation performance is inconsistent, it leads to fluctuations in trust and more frequent human intervention further, additionally, In settings where automation's reliability is perceived as low or variable, operators tend to override the automation more frequently, which can lead to cognitive overload and inefficiencies (Di Pasquale et al., 2023). It has been established that systems characterised by undependable automation precipitate adverse outcomes, including but not limited to, decrements in task performance, attenuation of trust, and a propensity toward the abdication of automated tools. Conversely, empirical instances reveal that a high degree of automation fidelity may be counterproductive, engendering a milieu of overdependence and subsequent complacency amongst users, such complacency often stems from a shift in operator trust towards the automation, leading to reduced vigilance and slower recovery when the system fails unexpectedly (Parasuraman & Manzey, 2010; Molloy & Parasuraman, 1996).

Beside that, effective training programs are essential for enhancing operators' cognitive skills, such as information processing, attention management, and decision-making under high workload conditions. Salas et al. (2012) stress that targeted training can improve operators' ability to manage stress and complexity in dynamic environments. Wickens (2008) adds that such training can mitigate the effects of mental workload by enabling operators to efficiently handle multiple tasks simultaneously. Finally, research by Oprins et al. (2010) shows that task-specific training significantly enhances performance, especially in high-pressure scenarios, by improving decision-making and cognitive resource allocation.

Furthermore, research has consistently shown the potential of adaptive automation in mitigating the adverse effects of high task workload on situation awareness (SA).

Parasuraman (2009) found that adaptive automation significantly improved change detection and SA in a high-workload reconnaissance mission. C. F. Rusnock (2017) further demonstrated that revoking strategies, particularly those based on a minimum duration, effectively reduced workload and increased SA. Fletcher, S (2020) highlighted the importance of applying adaptive automation to lower-level functions, such as information acquisition and action implementation, for better operator adaptation. Sauer (2011) emphasized the need to consider the impact of work-related stressors, with forced choice being the most effective form of explicit control of adaptive automation under high-stress (mental workload) conditions. These studies collectively underscore the potential of adaptive automation in enhancing SA under high task workloads.

Research in the human factors field has identified the direct cause of both mental workload and situational awareness, where reducing the operator's mental workload can significantly increase situational awareness during the execution of the task, specifically in remote control and remote operation. Various studies have shown that cognitive load impacts the ability to maintain SA, and strategies for managing workload are crucial for improving task execution and decision-making. Specifically, reducing unnecessary cognitive burden can help operators remain focused on critical information, improving their awareness of the system's state and their environment (Shao et al., 2019; Shao & Qianxiang, 2019; Fong et al., 2013). By dynamically allocating tasks between operators and automated systems, adaptive automation aims to balance workload while supporting operators in maintaining optimal SA. Research into human-automation interaction and developing adaptive systems tailored to remote operation environments can offer valuable insights into optimizing operator performance and SA.

On the other hand, it is natural that the automation studies are mostly focused on the technical capabilities of the machine system (Schaefer, K. E.; Chen, J. Y. C.; Szalma, J. L.; Hancock, P. A. (2016)), these dichotomous findings underscore the imperative for a calibrated approach to automation reliability within the broader context of human-automation interaction (HAI). It is thus incumbent upon designers and engineers to judiciously modulate the reliability of automation in a manner that harmonizes user performance optimization with the mitigation of trust-related pitfalls. In accordance with the principles articulated in Wright, J. L., Chen, J. Y. C., & Lakhmani, S. (2020), a meticulous amalgamation of agent transparency and reliability within the domain of human-robot interaction stands to buttress user confidence and enhance the perceived reliability of automated systems. The synergy of these elements is pivotal to the advancement of user-centric automation paradigms that align with the dynamic cognitive and affective contours of human operators.

### **2.3.3 Automation level and SA**

As the volume of information to be processed continues to grow, human information processing capabilities become increasingly overwhelmed; the benefit and services of automation in the reduction of human information overloading, which in turn increased operator's SA (Torkel Klingberg · 2009, Endsley 1995) demonstrates the increasing reliance on automation to perform tasks in complex systems, while the human operator plays a diminished role. However, the human operator remains responsible for comprehending the state of these systems in the event of malfunctions, necessitating human intervention (Parasuraman & Sheridan 2000).

Furthermore, in many cases, automation can change the operator's role to an unintended and unanticipated form, and it can be introduced into almost all aspect of systems (Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000)) Automated systems can also demonstrate proficiency in deductive reasoning, effectively processing a multitude of alternatives simultaneously. However, they exhibit limitations in inductive reasoning, which necessitates creativity. On the other hand, though humans may encounter challenges in managing multiple hypotheses concurrently, they exhibit proficiency in conducting inductive reasoning. Despite the high level of automation in systems, humans still play a crucial role in task execution (Richard Breton and Éloi Bossé 2003). Indeed, autonomous systems currently fall short in matching the cognitive capabilities of humans, particularly in their capacity to respond accurately and suitably to novel situations (Kirchner EA, Kim SK, Straube S, Seeland A, Wo"hrle H, et al. (2013). Therefore, it is crucial to measure the SA of the human automation team, including facets of shared and complementary SA, to determine the best effect of automation on SA (Cain et al., 2016).

The effect of automation on human situational awareness (SA) can vary depending on the context. In some cases, automation can improve human SA by providing real-time data, alerts, and reminders, enhancing decision-making and task performance. However, overreliance on automation can lead to complacency and a decreased ability to maintain SA during system failures or unexpected events (Qing et al., 2021). Automation can also lead to skill degradation and reduced ability to effectively manage complex tasks without technological support. Therefore, it must consider the potential consequences of automation regarding situation awareness and decision-making performance Out-of-the-loop performance problems.

Automation significantly impacts human SA, with various studies highlighting both positive and negative effects. Automation is introduced to maintain workload within acceptable limits, reduce human errors, and increase SA (Endsley, M. R. (2016).). However, it has been found that automation can lead to decreased SA, particularly in the event of automation failure (Qing et al., 2021). The impact of automation on SA is influenced by the level of automation (LOA), with higher LOAs enhancing performance during normal conditions but increasing the risk of human-system failure in the event of automation failure (Blanc et al., 2015). Additionally, automation can lead to complacency, skill degradation, and automation bias, negatively impacting SA (Cummings, 2004). The level of control in automation is crucial, as determining an appropriate level of automation can minimize adverse effects on operator SA (Endsley & Kiriş, 1995).

Furthermore, adaptive automation, which shifts the amount of work between the human and the system over time while maintaining a high level of SA, has been proposed as a solution to the overwhelmed operator (Greef & Arciszewski, 2007). It has also been observed that automation can reduce workload and improve monitoring efficiency, potentially enhancing SA (Bailey et al., 2006). However, it is essential to note that even when automation functions as expected, humans may still experience decreased SA due to mode awareness errors (Marquez & Cummings, 2008). The impact of automation on SA is a complex issue, as it is influenced by factors such as information processing and working memory abilities, the level of automation, and the nature of the task being automated (Jipp & Ackerman, 2016).

The impact of automation is further compounded by the cognitive burden placed on human operators by automation, as well as the heightened potential for performance problems to

impact system efficacy (Baird et al., 2022). While fully automated systems offer advantages, they also pose the risk of operators being unable to perform tasks manually following an automation failure, thereby exacerbating the out-of-the-loop performance problem (Sethumadhavan, 2009). This reduced ability of operators to take over manual control in the event of automation failure is a potential consequence of high levels of automation support (Sethumadhavan, 2011). The experimental findings by Meike Jipp and Phillip L. Ackerman (2016) revealed that as levels of automation increased, operator performance demonstrated improvement, juxtaposed with a decline in their situation awareness, which has highlighted the need for further investigation and consideration in the design and implementation of automated systems within various contexts.

The out-of-the-loop performance problem in system automation alludes to the diminished capacity of operators to effectively intervene and resume manual control in the event of automation failure (Endsley & Kırış, 1995). This challenge surfaces when operators are hindered in their ability to revert to manual operations due to an excessive reliance on automation (Kaber & Endsley, 2004). Potential repercussions of out-of-the-loop performance issues include operators' inability to intervene successfully or promptly during system failure (Parasuraman et al., 2000). Intermediary levels of automation have been observed to aid in sustaining operator involvement in system performance, enhancing situational awareness and curbing out-of-the-loop performance problems (Endsley & Kaber, 1999). Moreover, the level of automation (LOA) significantly influences operator situational awareness and engagement, thereby aiding in mitigating out-of-the-loop performance problems (Endsley, 2017).

Research has consistently shown that operators who are removed from control loops experience a range of negative consequences, including decreased vigilance, over-reliance on automation, and a decline in manual control skills (Kaber, 1997; Endsley, 1995). This out-of-loop can lead to longer system recovery times and poorer response accuracy, particularly in system failure (Endsley, M.& Kiriş, E., 1995). The shift from active to passive information processing is a critical factor in this decline (Endsley, 1995). To address the above issues, it is essential to consider the level of control given to operators in interacting with automation (Endsley, 1995). Therefore, it is essential to consider the potential consequences of automation, particularly regarding operator's SA and decision-making performance, while assessing and optimizing human-system interaction. Assessing the SA of the human automation team and understanding the effects of automation on SA are crucial steps in determining the overall impact of automation.

### **2.3.4 Technology Integration**

Technology integration in teleoperation and human-machine interaction is crucial in enhancing human situational awareness. It provides operators with the tools and systems to effectively perceive, comprehend, and anticipate changes in their operational environment. However, integrating multiple technologies has been highlighted as essential for advancing teleoperation beyond its current limits, emphasising the need to carefully integrate various technologies (Goodrich et al., 2013). The types of technology integrated in teleoperation and human-machine interaction that contribute to enhancing human situational awareness can be categorised as follows:

#### **1. Sensory Technologies:**



Advanced sensor technologies, such as cameras, LIDAR, radar, and other sensory input devices, provide real-time environmental data to operators, allowing them to perceive and understand the operating environment with a high degree of fidelity.

Integrating sensor technologies in teleoperation and human-machine interaction is a critical area of research and development. Wearable sensors significantly enhance interactive accuracy and user experience in human-machine interaction systems (Yin et al., 2020). These sensors enable the effective transfer of human intentions to machines and the collection of feedback information from the machine, thus facilitating bidirectional electronic systems connecting humans and machines (Lim et al., 2014). Developing noncontact humidity sensors with high sensitivity and rapid response is crucial for advanced noncontact human-machine interaction applications (Yang et al., 2019). Furthermore, tactile and force sensors in immersive human-machine interactions have gained prominence due to their ultra-thin, ultra-soft, and conformal characteristics (Xu et al., 2023).

Furthermore, triboelectric nanogenerator (TENG) technology has shown significant advantages in human-machine interaction and high-fidelity platforms, highlighting its potential application prospects (Luo et al., 2023). The development of highly stretchable capacitive-based strain sensors has shown promise for human motion monitoring, physiology monitoring, and human-machine interaction (Atalay et al., 2017). Additionally, the use of all-printed soft human-machine interfaces for robotic physicochemical sensing has introduced an artificial intelligence-powered multimodal robotic sensing system, emphasising the potential for advanced human-machine interaction applications (You et al., 2022) where the enhancement of human SA can be promising.

However, the utilisation of sensory technology in the hope of enhancing human situational awareness comes with its disadvantages and costs. For instance, integrating sensor technologies to increase human situational awareness with the use of tactile situation awareness systems (TSAS) to enhance human factors during flight can lead to increased workload and reduced situation awareness, potentially impacting the system's effectiveness (Rupert et al., 2016). Similarly, implementing bright integrated vests for K9 units to increase situational awareness and response time may introduce complexities in maintaining the balance of system autonomy with human interaction for optimal operator situation awareness and system performance (Krommyda et al., 2021).

## **2. Data Fusion and Visualisation:**

Integrating multiple sensor data sources through data fusion techniques enables the creation of comprehensive and easily interpretable visual representations of the operational environment. This sensory integration facilitates operators' comprehension of complex spatial and situational information. On the other hand, the computational complexity of sensor fusion algorithms can grow significantly as the number of sensors increases in human-system interaction, impacting the real-time performance and efficiency of the system, which can result in the reduction of the operator's Situational Awareness. Additionally, the need to reduce the computational complexity resulting from the complex dependence of sensor data poses a significant challenge, requiring the development of efficient and computationally light fusion algorithms (Castanedo, F. (2013).

## **3. Augmented Reality (AR) and Virtual Reality (VR):**

AR and VR technologies can offer immersive and interactive representations of the operating environment, enabling operators to visualize and interact with spatial and contextual

information more intuitively and engagingly. AR and VR technologies have shown potential in enhancing operator situational awareness in various domains. Studies have indicated that virtual reality can improve situational awareness without increasing operators' workload, highlighting its potential benefits in enhancing the perception of the operational environment (Roldán et al., 2017). Additionally, the application of augmented reality in combat decision support has contributed to developing situational awareness and supporting effective decision-making in tactical environments (Chmielewski et al., 2019). Furthermore, mixed reality visualization has demonstrated the potential to improve cyber situational awareness and communication in cyber teams, indicating the benefits of advanced visualization techniques in enhancing situational awareness (Ask et al., 2023). Moreover, the development of outdoor augmented reality systems has been explored to enhance situational awareness in outdoor environments, providing operators with enriched visual information to improve their awareness of the surroundings (Neuhöfer & Alexander, 2011). These findings collectively suggest that AR and VR technologies have the potential to positively impact operator situational awareness across various domains, from combat decision support to cyber team communication and outdoor environments.

However, the human factor issues with AR and VR encompass aspects related to immersion, interactivity, operator's performance efficiency, health and safety, and social impact (Chen & Wu, 2023; Stanney et al., 1998). These technologies have the potential to induce illusions and alter perceptions, leading to changes in implicit attitudes and behaviours (Peck et al., 2013; Banakou et al., 2013).

Furthermore, the embodiment in virtual bodies can impact implicit biases and influence behaviour (Peck et al., 2013; Slater et al., 2010). Additionally, AR and VR applications' appeal

and engagement factors are influenced by interaction and responsiveness models (Shen, 2019; Steed et al., 2018).

In terms of how AR and VR can effect human health it has been found that the prolonged use of AR and VR technologies can adversely affect eye health and vision where. VR-based technology has been linked to adverse effects such as blurred vision and disorientation (Zhao et al. 2020). These technologies often involve close visual proximity and eye strain due to the need for the eyes to converge and accommodate simultaneously. Moreover, the optics of AR and VR devices may cause discomfort, including double vision and headaches. If these factors are not addressed, they can lead to long-term eye conditions such as myopia, accommodative dysfunction, and binocular vision problems. Additionally, the use of AR in medical education has raised concerns about its impact on vision, particularly in individuals with low vision and conditions such as macular degeneration (Powell et al., 2020). Therefore, it is essential to be aware of the main potential risks associated with the extended use of AR and VR devices on operators and to take appropriate measures to mitigate them.

#### **4. Haptic Feedback and Tactile Interfaces:**

Incorporating haptic feedback and tactile interfaces allows operators to receive sensory input beyond visual and auditory cues, giving them a more comprehensive understanding of the operational environment and potential hazards.

Haptic feedback and tactile interfaces are integral to human-computer interaction, particularly in VR and teleoperation systems. Haptic feedback technology involves the recreation of the sense of touch by applying forces, vibrations, or motions to the user (Kikuchi et al., 2015). Tactile feedback is essential for enhancing user experience and interaction in various applications, such as above-device gesture interfaces (Freeman et al.,

2014), virtual reality environments (Jadhav et al., 2017), and wearable haptic interfaces (Trinitatova & Tsetserukou, 2019).

Using a haptic stylus with inertial and vibrotactile feedback has been shown to improve manipulability and enrich the interaction experience (Arasan et al., 2013), which can be the approach to increase the operator's Perception of the Elements in the environment.

Additionally, tactile/haptic user interfaces for tabletops and tablets offer different user experiences than visual and audible feedback (Weber, 2014). This also has been noted that, passive haptic learning facilitated by wearable computers has been explored to teach typing skills through tactile interfaces (Seim et al., 2014). Perception of ultrasonic haptic feedback on the hand has also been studied, highlighting the importance of realistic haptic rendering in surface textures (Wilson et al., 2014). Overall, haptic feedback and tactile interfaces are crucial in enhancing user experience, interaction, and immersion in virtual reality and teleoperation systems (Mihelj & Podobnik, 2012; Choi & Tan, 2005).

Using haptic feedback and tactile interfaces in operator systems can present several challenges and issues. While these technologies offer enhanced sensory experiences and interaction, they can also introduce potential drawbacks and limitations. For instance, wearable haptic interfaces may pose challenges in design, particularly in delivering vibrotactile sensations at the interface with the skin (Bilal et al., 2020). Beside this haptic interfaces, such as haptic pens, may need to address accessibility concerns for individuals with visual or motor impairments (Lee et al., 2004).

The realistic rendering of haptically simulated textures has been a common problem, as they may sometimes be perceived as behaving unrealistically, impacting the overall user experience (Choi & Tan, 2005). Moreover, integrating tactile stimulation into haptic training

simulations may present challenges related to veridical interactions and feedback, particularly in medical applications, highlighting the need for further progress and improvement in training simulations (Lelevé et al., 2020). Additionally, using haptic interfaces in virtual reality and teleoperation systems may require careful consideration of sensory substitution and the potential effects on human-scale virtual environments and product design (Richard et al., 2006).

On top of the mentioned issues, the associated high cost of implementing haptic feedback and tactile interfaces can be prohibitive for some companies, making adopting these technologies difficult. With this in mind, the inconsistency and unreliability of haptic feedback can confuse operators due to various factors. When there is a mismatch between efference copy (the internal representation of movement) and sensory feedback in a given movement context, the ability to predict the outcome of actions which is an essential aspect of sensorimotor control can be compromised (Danion et al., 2012). what's more, when depth cues become unreliable and have a reduced correlation with haptic feedback, the operators may experience errors, necessitating cue reweighting (Cesaneek & Domini, 2019).

In situations where visual and haptic feedback are out of sync and conflicted, users may ignore the haptic feedback, choosing to rely instead on continuous visual feedback, leading to confusion and potential errors (Jay et al., 2007). Moreover, the bidirectional properties of haptic feedback may be applied to prevent passivity of the subject, but inconsistent results may arise due to the design of performance-degrading haptic methods and feedback provided to control groups in non-haptic modalities (Sigrist et al., 2014; Basalp et al., 2021). Furthermore, when haptic feedback is always consistent with the physical slant of the surface, but the texture cue is sometimes unreliable, users may need clarification in judging

surface slant for placing objects (Louw et al., 2007). Additionally, haptic feedback is usually high-cost, noisy, and unreliable, introducing challenges and potential confusion for users due to low durability, low performance, high cost, and less compatibility with other sensors (Le et al., 2021). Not to mention the variations which exist between individuals in perceiving feedback effectiveness, their preferences, and the load the modalities place on different user groups may contribute to consistency in feedback effectiveness, leading to clarity (Nuamah et al., 2019). Inconsistencies among participants may also arise due to traffic control schemes that reduce the number of update packets, further contributing to confusion in haptic virtual environments (Schuwerk & Steinbach, 2013).

Conjointly the limitations of haptic feedback need to be addressed, especially when visual feedback is lost, unreliable, or inadequate, to ensure clarity soon (Hamid, 2018). Moreover, persistent errors can produce a novel adaptation on the operators that gradually reduces the relative influence of an unreliable depth cue, potentially leading to user confusion (Cesanek et al., 2019). In robotic systems, the lack of haptic feedback has been identified as a significant drawback, potentially leading to confusion and challenges in user interactions (Abiri et al., 2016). Furthermore, longer delays in haptic feedback can increase incorrect associations between objects and the feedback, potentially causing confusion among users (Kangas et al., 2014). The complexity structure of the underlying physiology of haptic processes, expense, complexity, and limited workspace also contribute to the inconsistency and unreliability of haptic feedback, potentially leading to user confusion (Aziz & Mousavi, 1970).

## **2.4 Situational Awareness in Teleoperation**

### **2.4.1 Teleoperation Operators**

The human factor issues related to teleoperation and telerobotic systems are multifaceted and have significant implications for human cognition and performance. Human factors and ergonomics are crucial in addressing significant challenges and opportunities in teleoperation and telerobotic systems. The relationship between human cognitive processes and the design and operation of these systems is a crucial area of focus in human factors research. More significantly, the restricted situational awareness of the system's operators remains a crucial obstacle to implementing teleoperation systems (Darvish et al., 2019).

Using teleoperation and telerobotic systems presents challenges related to human cognitive workload, decision-making, and situational awareness. The cognitive demands imposed on human operators during teleoperation tasks are influenced by system latency, sensory feedback, and the complexity of the control interface (Rogers et al, 2017, Rogers et al., 2013). These factors can significantly impact the cognitive load on human operators, affecting their decision-making processes and overall task performance.

In the same way, the design and evaluation of teleoperation interfaces are essential for human factors and ergonomics, as they can significantly affect the human operator's performance (Gholami et al., 2022; Valner et al., 2020). Transparency, control design, and situational awareness are critical in developing teleoperation interfaces to support human cognitive processes and decision-making (Tang et al., 2019; Azimifar et al., 2017).

Additionally, assessing human factors associated with telerobotic tasks requires a



comprehensive methodology to accurately evaluate human-robot interaction's cognitive and ergonomic aspects (Kumar et al., 2020).

The division of labour between robots and humans is another essential human factor in teleoperation and telerobotic systems (Parsons & Kearsley, 1982; Draper, 1995).

Understanding the optimal allocation of tasks between human operators and robots is essential for maximizing overall system performance and ensuring the well-being of human operators. This division of labour directly impacts the cognitive demands on human operators and their ability to interact with robotic systems effectively.

Moreover, the security and resilience of teleoperation systems are critical human factor considerations, as they directly impact human operators' trust and decision-making processes (Bonaci et al., 2015). Addressing denial-of-service attacks and ensuring the robustness of teleoperated systems are essential for maintaining human operators' confidence and cognitive well-being during teleoperation tasks.

Overall, human factors issues related to teleoperation and telerobotic systems are closely intertwined with human cognitive processes (Amirhossein & Ehsan, 2019). Investing in human factors issues related to teleoperation and telerobotic systems is crucial for ensuring the safety and effectiveness of these systems. Human factors such as user interface design, situational awareness, and communication between operators and robots can greatly impact the success of teleoperation and telerobotic systems. By investing in research and development to address these issues, the improvement of the overall performance and reliability of these systems ultimately leads to better outcomes in fields such as space exploration, hazardous materials handling, and disaster response.

## 2.4.2 Situation Awareness

As per Lowe, (2016), Oswald Boelke first recognised the notion of situational awareness in World War I. Boelke understood the crucial significance of becoming aware of the enemy's intentions before they could gain a similar awareness.

The fundamental concept of situational awareness, defined as the gap between a human operator's perception of system status and the actual system status, was articulated by Woods in 1988. Although this idea gained limited attention in technical and academic circles until the late 1980s, it has become a prominent subject of discussion, specifically in this teleoperation, telepresence, and automation era.

The delay in the widespread recognition of this concept is attributed to the perceived urgency of the problem. The impetus for research and development of Human's SA initially came from the aviation industry, driven by the pressing need for pilots and air traffic controllers to enhance their situational awareness (Orique 2017). This demand arose as it became increasingly evident that system design was no longer optimised for human operation and, in certain conditions, surpassed the human capacity to monitor effectively. This issue has caused decrement and even loss of operators SA. An aircraft accident review by Hartel, Smith & Prince, 1991 (Smith-Jentsch 2001), identified that over 200 disasters have been caused by operators' poor SA, which has intensified the importance of SA.

Although the evolution of situational awareness research correlates closely with the rise in automation levels in flight control, it has been evidenced that the concept of situational awareness extends beyond aviation and is equally relevant to human supervisory control in land-based industries Kaber, D. and Endsley, M. (2004).

In SA, scholars and professionals have endeavoured to clarify the multifaceted nature of its definition, often abbreviated as SA in the literature due to its multivariate nature. At its core, situational awareness involves a fitting comprehension of a given situation (Smith & Hancock, 1995). Three predominant definitions emerge: the first revolves around an information processing framework, the second underscores its reflective nature, and the third introduces an embedded worldview.

Due to the complex and multi-aspect nature of Human Situational Awareness, there are various views and interpretations of the SA concept at the academic level. It has made SA measurement an intricate task (Stanton, NA, Salmon 2017). One of the obvious reasons for this issue is the multi-dimensional structure of SA and theoretical contention and opinion disagreement of the Situational Awareness principle. Considering the above statements, (Cak et al. 2020, Jeon et al. 2014; Wanyan et al. 2018) Situational Awareness perspective is awareness in working memory and (Endsley, 1995a) interpreter AS information-processing product of operators, in contrast (Smith & Hancock, 1995) view Situational Awareness as a direct consciousness of external events.

Furthermore, looking deeper into SA literature, it can be noted that Situational Awareness models have been differentiated regarding the model's psychological manner. For instance, (Niesser, 2014) theory model approach is based on activity theory, whereas (Endsley, 1995a), which uses a level approach, is based on cognitive theory that is accomplished with information processing. Other modelling view argue that Situational Awareness should only be represented by a singular psychology form rather than a product of various human cognitive elements.

Apart from this, various point of view in describing human SA the most accepted form of SA description in literature can be defined as "the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future"(Green et al.2016). This definition underscores the SA process's interconnected nature of perception, comprehension, and projection. This SA definition was initially developed by Dr. Mica Endsley's view of situational awareness and centres around the understanding and process of monitoring, interpreting, and projecting critical information in dynamic environments. In her articles, Endsley combined and unified the research conducted in the preceding decade. Endsley, a recognised expert in human factors and situational awareness. Figure 1 indicates that how the Endsley’s three-level model can be integrating within dynamic goal directed tasks.

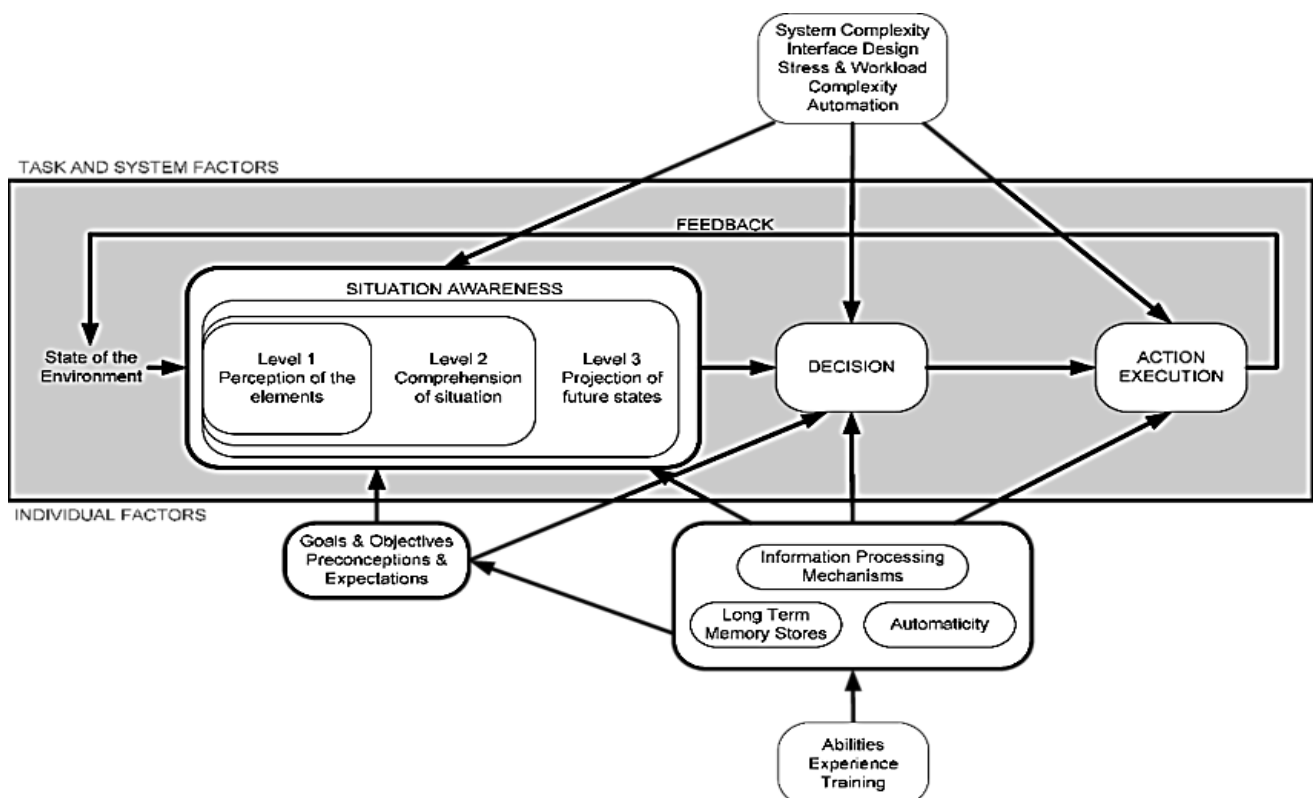


Figure 2The three-level model of SA (Source: Endsley 1995a).

Endsley's model breaks down situational awareness into three levels:

**1. Level 1: Perception of the Elements in the Environment**

The first level involves noticing critical information and cues pertinent to goals or activities in the environment. This step is foundational, as missing crucial data at this stage can impact subsequent levels of SA.

**2. Level 2: Comprehension of the Current Situation**

The gathered information is synthesised at this level to understand how it relates to the individual's goals. This level involves integrating multiple pieces of information to form a bigger picture, discerning relevance, and prioritising significance.

**3. Level 3: Projection of Future Status**

The final level involves anticipating future events or states based on the current situation. This is where one uses the understanding of the situation to predict what will happen next, critical to decision-making and taking effective action.

Endsley emphasises that situational awareness is vital across many domains, especially in complex, dynamic environments such as aviation, military operations, and, more recently, autonomous vehicle operation and human-robot interaction. It is important to note that situational awareness is a state of knowledge, not just the process of gaining information. Moreover, Endsley's model stresses that situational awareness precedes decision-making and performance in the human operator's process. Within human factors research, this situational awareness model is used to understand and improve human performance in complex systems and enhance system design to better support situational awareness among users. Wickens (2007) comprehensively reviewed Mica Endsley's work on situation

awareness, highlighting its applications in training, error analysis, design, selection, teamwork, and automation.

In the realm of teleoperation systems, where an operator's perceptual processing is intricately linked with remote locations without direct physical presence, there is a notable decrease in situational awareness. This reduced awareness heightens the risk of human errors and diminishes overall performance, as highlighted by Woods et al. in their study from 2004. Given these challenges, enhancing the operator's SA becomes particularly crucial in the field of teleoperation to mitigate the potential negative consequences associated with limited direct perception of the remote location.

#### **2.4.2.1 SA in Human-Robot**

For effective collaboration, it is essential for both humans and robots to have mutual knowledge of each other's presence and functions, a concept known as Human-Robot Interaction (HRI) Awareness. Drury et al (J.L. Drury, J. Scholtz, and H.A. Yanco 2015,11-119) define HRI awareness as the human's grasp of the robot's position, activities, condition, and environment, alongside the robot's comprehension of the human's commands or directives necessary for guiding its actions, as well as an awareness of the operational conditions and limitations within which the robot functions. Without this mutual awareness, the quality of interaction between humans and robots is significantly diminished, leading to a deterioration in the performance of tasks they are jointly executing ( G. Randelli 2011). J.L. Drury, J. Scholtz, and H.A. Yanco 2003 identify five distinct categories of HRI awareness.

The concept of awareness in human-robot collaboration can be categorized into five distinct types, vital for optimizing interactions and task performance:

1. **Human-Robot Awareness:** This involves humans possessing detailed awareness of the robots' locations, environments, identities, functions, and statuses.
2. **Human-Human Awareness:** This pertains to the comprehensive knowledge that human collaborators have of each other's locations, environments, identities, functions, and statuses.
3. **Robot-Human Awareness:** This refers to robots having a clear understanding of the instructions provided by humans that are necessary to execute specific tasks.
4. **Robot-Robot Awareness:** This relates to robots having awareness of the directives issued to them by other robots, enabling coordinated action.
5. **Human's Overall Mission Awareness:** This encompasses the understanding that human operator has of the collective objective of the activities being undertaken by both humans and robots.

Alongside these forms of awareness, there are five fundamental classifications of interactions between humans and robots (Steinfeld, A. Goodrich 2008,203-2075). These classifications include the level of autonomy, the nature of information transfer, team structure, mutual adaptation, the learning and training processes for individuals and robotics, as well as the configuration of the task at hand.

## **2.5 Theoretical Frameworks and Models:**

The relationship between verbal recording, information processing, and situational awareness (SA) is a critical area of study, particularly in contexts involving human-robot interaction (HRI) and remote operations. This section explores various theoretical

frameworks and models that provide insights into how verbalisation impacts cognitive processes and enhances SA. Cognitive theories, such as Cognitive Load Theory (Sweller, 1988) and Dual-Task Theory (Kahneman, 1973), explain how mental workload and information processing capacity are influenced by task demands. Additionally, Communication Models (Shannon & Weaver, 1949) and Information Integration Theory (Anderson, 1981) emphasise the role of verbal communication in integrating sensory and cognitive inputs, which is crucial for maintaining accurate SA in complex environments.

Verbal recording, as a method of information processing, is hypothesised to engage cognitive resources in a manner that enhances mental representation and improves operator awareness during task execution. The theories discussed in this section offer a foundation for understanding the impact of verbalisation on cognitive load, attention, and SA, supporting the hypothesis that verbal data processing can lead to more effective decision-making in remote operations.

### **2.5.1 Understanding Operator's Cognitive Processes in**

#### **Teleoperation**

Understanding the operator's cognitive processing is a critical factor in human and systems interaction, specifically in applications in which human Situational Awareness is critical. The complexity of the human cognitive process reflects the intricate nature of human factors in interacting with systems (Fan et al., 2022). Human cognitive processing encompasses many functions integral to human cognition and environmental interaction. These aspects include perception, attention, memory, language skills, visuospatial processing, executive



functioning, and affective aspects (Żyszkowska, 2015; Wilson, 2002; Murphy et al., 2020; Harmon et al., 2016; Gini et al., 2015; Adam & Krämer, 2021).

Human verbal skills are also central to human cognition, facilitating communication and information processing. Visuospatial processing is essential for spatial reasoning and visualisation, contributing to human-system interaction and cognitive burden reduction (Harmon et al., 2016). Cognitive processing studies have been applied to investigating cognitive control processes, the complexity of cognitive systems, and the processes occurring within those systems (Beran, 2015; Siew et al., 2018). The research also extends to studying cognitive info-communication, enhancing human-machine interaction systems, and understanding human cognitive behaviour in conversational settings (Hunyadi, 2014).

While significant progress has been made in understanding human cognitive processing, the existing literature highlights its multidimensional and interdisciplinary nature. Research underscores the complexities of cognition and its implications across various domains. However, there is a need for further exploration and empirical studies to bridge the gap in understanding operator cognitive processing, particularly in the context of teleoperation and telerobotics. Addressing this gap presents an opportunity to enhance human-system interaction quality and advance the design of intelligent systems that effectively accommodate and support human cognitive functioning in teleoperation and telerobotic applications.

One of the main human factor issues within telerobotic and teleoperation activity is that within such systems, operators are overloaded with the adoption of new technologies which dramatically transform their interaction with systems. In contrast, their natural cognitive processing or human factors have not been considered in depth during the system design

(Parker, 2014; Woherem, 1991), this is due to challenges such as limited understanding of human behaviour in applied settings, the dearth of attention paid to human factors in expert system design hinders the proper consideration of human factors in system design (Parker, 2014; Woherem, 1991) as well as the limitations and issues rise from the novel systems. Further, research emphasises the need to understand human operators' ability to interact with adaptive automation applied to complex systems information processing, highlighting the significance of human cognitive functions in such interactions (Kaber et al., 2005). For instance, introducing automation to the system can directly affect human activity, imposing new coordination demands on human operators and influencing their cognitive processing (Parasuraman et al., 2000).

Perception, the initial level of the operator's SA described by Endsley's model, also plays a crucial role in the human cognitive system, participating in higher-level cognitive processes and contributing to the processing of information (Żyszkowska, 2015). Attention is another fundamental aspect influencing the selection and processing of sensory information and is essential for various cognitive tasks (Wilson, 2002). Working Memory, both short-term and long-term, are also a key aspect of cognitive processing, enabling the retention and retrieval of information for decision-making and problem-solving (Murphy et al., 2020).

On the other hand, how an operator approaches or is directed to use a system can significantly influence their performance and the overall quality of human-system interaction, particularly in terms of cognitive processing. For instance, studies have shown the impact of an operator's physical activity on cognitive function (Colcombe & Kramer, 2003; Caserta & Abrams, 2007). Similarly, adjusting a system's display settings in a teleoperation task can notably affect the operator's Situational Awareness (Bledt et al.,

2019), which is closely linked to cognitive functions (Liu et al., 2014). Moreover, integrating human factors into the engineering of safety-critical systems requires consideration of cognitive aspects during human-system interaction (Dzaack & Urbas, 2009). Applying cognitive theory to engineering systems can also lead to system enhancements (Zhou & Qian, 2014).

Executive functioning, which includes cognitive processes such as problem-solving, decision-making, and planning, is critical for goal-directed behaviour and adaptation to various situations (Gini et al., 2015). When system operator engages in goal-directed behaviour, they focus on specific tasks and objectives, which can help streamline their cognitive efforts and improve overall attention. Additionally, verbal skills enable individuals to articulate thoughts, concepts, and strategies, providing a cognitive framework for organising and processing information. This linguistic processing can aid in the encoding and retrieval of information, contributing to improved working memory (Ptak & Schneider, 2005).

The organisation of information in natural information processing systems, including human cognition, governs the activities of natural entities, highlighting the central role of cognitive processing in human behaviour and interaction with systems (Sweller & Sweller, 2006). The synergy between goal-directed behaviour and human verbal effect on cognitive processing can bolster an operator's attention by channelling mental resources toward relevant tasks while minimising distractions. Furthermore, verbal skills can enhance working memory by providing a structured way to hold and manipulate information, facilitating efficient decision-making and problem-solving. As a result, it has been hypothesised that the combined utilisation of goal-directed behaviour and verbal skills offers a powerful

mechanism for optimising cognitive functioning, ultimately benefiting an operator's attention and working memory capacities.

### **2.5.2 SA and Cognitive Processes**

These constructs' interdependence and mutual influence characterise the relationship between human situational awareness (SA) and cognitive processing. SA encompasses the perception and comprehension of environmental elements within a specific context (Beck et al., 2015). It involves continuously monitoring the environment, understanding the meaning of information, and projecting future states, all of which are cognitive processes (Beck et al., 2015). The main aspects of mutual cognitive processes involved in SA include attention, memory, perception, and executive functions, which collectively contribute to the formation and maintenance of SA (Liu et al., 2014).

Also, SA is closely linked to cognitive workload, affecting attentional resources and cognitive processing capacity (Lyu et al., 2017). The cognitive state of individuals, including their attentional focus and cognitive workload, significantly influences their SA and subsequent decision-making (Lyu et al., 2017). Moreover, SA relies on cognitive abilities such as memory, reasoning, and problem-solving, which are essential components of cognitive processing (Doane, 2003).

The cognitive processes involved in SA are crucial for effective decision-making and performance across various domains, including healthcare, aviation, driving, and team collaboration (Schulz et al., 2013; Desvergez et al., 2019; Furuta et al., 2009). Additionally, the relationship between SA and cognitive processing is evident in the impact of physical activity on cognitive function, which in turn influences SA (Colcombe & Kramer, 2003;

Caserta & Abrams, 2007). The cognitive processes that underpin SA are also influenced by emotional, motivational, and cultural factors, highlighting the multifaceted nature of the relationship between SA and cognitive processing (Nielsen & Sarason, 1981).

This can be added that the measurement and analysis of SA involve cognitive models and cognitive workload assessment, emphasizing the intertwined nature of SA and cognitive processing (Endsley, 1995). The cognitive workload associated with SA tasks directly affects the cognitive resources available for processing situational information, thereby influencing SA levels (Lyu et al., 2017). Additionally, the cognitive processes involved in SA are crucial for team collaboration and communication, further highlighting the interconnectedness of SA and cognitive functioning (Furuta et al., 2009).

Findings from this literature review highlight the interdependence and mutual influence between human situational awareness (SA) and cognitive processing. Based on these insights, it is hypothesised that directing operators to employ different modes of information processing can directly impact their cognitive processing, subsequently influencing their SA.

Therefore, manipulating the sensory modalities through which operators process information, such as engaging them in verbal descriptions and visual or auditory prompts, can influence their cognitive processing directly. This possible effect, in turn, may impact their ability to monitor their environment, comprehend information, and project future states – all crucial components of situational awareness.

Furthermore, previous research has demonstrated the multifaceted relationship between SA and cognitive processing, highlighting the influence of emotional, motivational, and cultural factors on cognitive processes (Gorman & Cooke, 2003; Hutton et al., 2016). Thus, by directing operators to engage in different sensory modes, it is feasible that their cognitive

state and subsequent SA can be directly impacted, potentially affecting their decision-making, performance, and overall situational awareness in their respective domains.

In conclusion, this study hypothesizes that manipulating an operator's natural cognitive processing through engagement in different sensory modalities can directly influence their situational awareness. This hypothesis proposes a direct link between sensory processing, cognitive processing, and situational awareness, underlining the potential for interventions aimed at optimizing operators' cognitive functioning in various contexts and domains.

### **2.5.3 Cognitive processing and information verbalization**

The verbal description or verbal reporting of events in real-time is closely related to event perception, which depends on sensory cues and knowledge structures representing previously learned information about event parts and inferences about actors' goals and plans (Zacks et al., 2007). This process engages neuropsychological and cognitive mechanisms, including memory, prefrontal cortex functions, and perspective-taking, to construct a coherent verbal representation of the ongoing event.

By Mariën et al. 2013 Verbal working memory (VWM) is accountable for briefly storing verbalizable information, including letters, words, numbers, or nameable objects (Mariën et al. 2013). However, research on the neural basis of verbal working memory is one of the most challenging concepts when compared with visual or spatial working memory as it is a uniquely human phenomenon (Bradley R. Buchsbaum, 2016)

A fundamental challenge to the cognitive neuroscience of verbal working memory has been to integrate both empirical data and theoretical constructs that have emerged from different subfields—cognitive, neurological, neuropsychological—of enquiry in the brain and

behavioural sciences, however, more comprehensive research suggests that verbal working memory can be viewed as a functional adaptation of core neural substrates that enable the perception, comprehension, and production of speech (Bradley R. Buchsbaum, 2016).

In essence, information is believed to be stored in a phonological or sound-based code within a structure, resembling a tape loop, capable of retaining a limited amount of information for a brief period. However, the duration for which this information can be held is significantly extended when the individual engages in subvocal rehearsal of the phonological information, as highlighted in research by T. Drew and E.K. Vogel (2009).

Furthermore, research on the effects of loud or oral reading has yielded robust evidence in the benefits which has extend to various aspects, including enhanced phonological awareness, improved understanding of print concepts and increased comprehension as outlined in Merga's study (2017). Engaging in loud reading allows individuals to benefit from the self-auditory experience and the focused attention required for verbalization.

Recent investigations highlight that interactive read-aloud approaches, which actively involve students in the reading process, can lead to even greater educational advantages, as indicated by Young et al. (2023). Reading aloud has also been associated with memory advantages, particularly when dealing with mixed lists of words. Studies, such as Forrin et al. (2016), demonstrate increased hits and reduced false alarms for words read aloud in a mixed list, showcasing overall memorial benefits.

This memory advantage is particularly relevant for operators in telerobotic or teleoperation settings, where dealing with mixed data is common. Gionet et al. (2022) found that reading some words aloud during presentation, as opposed to silently, provides a substantial

memory advantage for the produced words. According to Clark and Andreasen (2014), read-aloud practices are considered a key factor in engaging cognitive processes.

The collective evidence from various studies strongly supports the positive impact of reading aloud on memory retention and cognitive engagement. These findings emphasize the significance of incorporating read-aloud interventions and interactive approaches in educational settings to extend similar benefits to operators.

Moreover, verbally describing an event in real-time involves the cognitive representation of perceived and to-be-produced events through integrated, task-tuned networks of feature codes, known as event codes (Hommel et al., 2001). These event codes are cognitive structures crucial in representing and processing real-time verbal descriptions of events. Furthermore, the verbal description of events in real-time is associated with the cognitive processes of event segmentation and action stream updating, as proposed by event segmentation theory (EST) (Loucks et al., 2016).

Additionally, verbal reporting has been found to mediate the impact of working memory on cognitive tasks (Zheng et al., 2005). According to EST, the segmentation of the action stream occurs automatically in real time, reflecting the continual updating of event models.

Verbalising an event in real-time engages cognitive processes related to language comprehension, working memory, and attention as individuals actively process and describe ongoing events (Zainal & Newman, 2020). The verbalization process also involves the interpretation of non-verbal cues and the coherent and meaningful representation of events, reflecting the integration of verbal and non-verbal cognitive processes (Evans & Evans, 2018).



In conclusion, the verbal description of events in real time significantly influences human cognitive processing, engaging various cognitive mechanisms such as memory, attention, problem-solving, and language comprehension. This process involves the integration of sensory cues, knowledge structures, and event codes, contributing to the construction of coherent verbal representations of ongoing events.

While extant research has underscored the significance of verbal communication in human–human interactions as an avenue to gauge the depth and efficacy of communications influencing situation awareness (Bleakley et al., 2012), as well as its instrumental role in the context of medical emergency care wherein frequent and contextually relevant verbal exchanges have been shown to augment situation awareness (Bourgeon et al., 2014), there exists a notable dearth of knowledge regarding the impact of operator verbal reporting on their situational awareness specifically within the domain of telerobotic and teleoperation.

## **2.6 IQ assessment as evaluating Individual differences**

Individual IQ assessment results can serve as a potential indicator of operators' situational awareness level differences. IQ, or intelligence quotient, measures an individual's cognitive abilities, including perception, analysis, and problem-solving (Murtza et al., 2020). Individual IQ assessment results hold promise as an indicator of telerobotic operator situational awareness due to their association with cognitive abilities, decision-making, and cognitive performance. However, careful consideration of IQ assessments' quality, context, and interpretation is crucial for effectively leveraging IQ as an indicator in the dynamic and demanding field of telerobotics.

The relevance of IQ in this context lies in its ability to assess an individual's general intelligence, which is crucial for understanding how operators perceive and respond to the dynamic and complex situations encountered in telerobotic operations (Floyd et al., 2008). Telerobotic operations, particularly in complex surgical procedures, demand high cognitive processing and decision-making levels from operators (Ballantyne, 2002; Ballantyne, 2007). As such, the operator's IQ can provide insights into their cognitive capacity and potential to handle the demands of telerobotic tasks.

Moreover, IQ has been linked to cognitive performance, indicating its potential relevance in assessing an operator's ability to comprehend and respond to the challenges inherent in telerobotic operations (Schneider & Niklas, 2017; Løhaugen et al., 2010). Additionally, IQ assessments have been associated with prioritising goals and decision-making, suggesting their potential influence on operator intent and response in varying telerobotic situations (Schneider et al., 2022). Furthermore, studies have shown a correlation between IQ assessments and cognitive performance, emphasising the potential of IQ as an indicator of the cognitive capabilities required for effective telerobotic operations (Belisle et al., 2018; Yasumura et al., 2016).

However, it is essential to consider the contextual factors and the quality of IQ assessments when utilising IQ as an indicator for telerobotic operator situational awareness (Fehrenbacher & Helfert, 2012). The quality and reliability of IQ assessments play a critical role in ensuring the validity of using IQ as an indicator in telerobotic operations (Lin et al., 2010; Fadahunsi et al., 2019). Additionally, the potential floor effects and distribution of scaled scores in IQ assessments must be considered to interpret and utilise IQ results accurately in telerobotic operations (Whitaker & Wood, 2007; Deary, 1995).

According to academic reports, an operator with high IQ scores may have advanced cognitive abilities, which could potentially correlate with improved decision-making, adaptability, and the capacity to manage complex and dynamic telerobotic tasks (Deary et al., 2010; Mackintosh, 2011). Conversely, lower IQ scores indicate potential challenges in processing information, problem-solving, and maintaining situational awareness, which could affect an operator's performance in telerobotic operations (Stankov & Roberts, 2017).

By considering individual IQ differences, we can account for operators' diverse cognitive abilities and information-processing styles. Higher IQ individuals may demonstrate faster information processing, superior problem-solving skills, and enhanced adaptability in dynamic environments, potentially leading to heightened situational awareness (Deary et al., 2010; Stankov & Roberts, 2017). Conversely, lower IQ individuals may exhibit different cognitive strategies and require tailored support to optimise their situational awareness (Sternberg, 2003; Mackintosh, 2011).

It allows for developing targeted training initiatives, adaptive interfaces, and support mechanisms tailored to individual cognitive profiles, ultimately enhancing overall situational awareness and system performance.

Therefore, incorporating assessments of individual IQ differences alongside other cognitive and domain-specific factors is integral to comprehensively evaluating and optimising situational awareness within complex systems like telerobotics.

## **2.7 Human Situational awareness assessment**

### **2.7.1 Objective Measures**

Objective measures are crucial in assessing human situational awareness in telerobotic and human interaction contexts. Endsley and Kiriş (1995) highlighted the significance of situation awareness in dynamic systems and emphasized the need for objective measures to evaluate and enhance situation awareness in varied settings. Furthermore, Kaber, D., Onal, E., & Endsley, M. (2000) pointed out that situation awareness may be enhanced with automated systems, which can provide superior, integrated information to operators, underscoring the potential benefits of objective measures in improving situational awareness in human-telerobotic interactions—the Situation Awareness Global Assessment. Additionally, the study by Loft et al. (2013) demonstrated the use of the Situation Present Assessment Method to measure situation awareness in simulated submarine track management, highlighting the relevance of objective measures in assessing situational awareness in complex operational environments. Moreover, assessing situation awareness in human-robot teams has been a subject of interest, with researchers emphasizing the need for objective measures to evaluate and enhance situational awareness in these collaborative settings. The study by Munasinghe et al. (2004) also highlighted the interactive learning performance of human teleoperators in telerobotic mini-golf, emphasizing the use of appropriate techniques to enhance the performance of human teleoperators, underscoring the potential benefits of objective measures in optimizing human-telerobotic interactions.

### **2.7.2 Review of established SA assessment**

Recent studies have made significant progressing in understanding and quantifying human situational awareness. Bhavsar, P et al (2017) proposed novel measures of situation awareness based on eye gaze dynamics, which were found to reliably identify participants' awareness during abnormal situation management. Tenney, Y. J. and Pew, R. W. (2006) discussed the operational definition of situational awareness and its measurement strategies, emphasising the need for attention, recall, and relevant actions.

On the other hand, (Stanton et al., 2009) have proposed that most established models have been correctly determined, but each may link to separate elements of Situational Awareness. Therefore, selecting an adequate SA measurement model is a complex and problematic, as most SA measurement tools are constructed based on different models.

The further complexity of selecting an appropriate SA measurement tool arises from the diversity of the developed tools, where (Stanton et al, 2005) revealed just over thirty Situational awareness measurements. However, these thirty measurement tools have been classified into five methods by (Salmon et al., 2006):

1. Supervised rating method
2. Freeze probe recall techniques.
3. Real-time probe
4. Post-trial subjective rating
5. Process indices

(P Salmon, N Stanton, G Walker, D Green., 2004) have confirmed the lack of reliable and valid measures of SA in command, control, communication, computers, and intelligence environments. In addition, the SA literature has confirmed that each measurement tool measures various aspects of Situational awareness. Additionally, the inadequacy of a Universal acceptance of an SA measurement tool has made it even more complex to select an individual assessment tool for Situational awareness (Stanton et al 2017). This diversity may occur due to the relation of each tool with their constructed models.

The SA assessment tool's reliability, validity, advantages, disadvantages, applicability, and analysis requirements have been scrutinised in the SA tool section process for the project—the evaluation of the existing measurement tools adopted from (Stanon et .2005). In addition, classification has been utilised to simplify and speed up the selection process (Salmon et al, 2006). This approach eliminates the need to look into over thirty Situational Awareness assessment tools for evaluation. In contrast, the overall structure of all existing assessment tools was examined against the project's requirements.

### **1. Supervised rating method**

The main advantage of the supervised rating technique is its non-intrusive approach. Some of the Situational Awareness Assessment tools have been constructed based on these Observer rating techniques, including The Situation Awareness Behavioural Rating Scale (Matthews et al. 2000; Matthews & Beal, 2002) has been used in infantry personnel SA within field training exercises. Due to the nature of this technique, the related tools need to be observed and assessed by domain experts. However, this requirement raises doubt on the outcome, as the result of the Situational Awareness assessment is only based on the observer's opinion and not on the view of the person or the team that performs the task

under examination (Salmon et al., 2006). Another disadvantage of this technique is its applicability in simulated or remote-controlled experiments (Salmon et al., 2006), as the assessment is only based on the participant's behavioural performance. In addition, the Observer rating technique relates SA and participant's performance, and this can be problematic as expert participants may perform a task well while lacking a high SA level or a subject with inadequate performance level while maintaining a prominent level of SA (Salmon et al., 2006). Therefore, utilising such a technique (Observer rating) does not meet the project requirements.

## **2. Real-time probe**

In this technique, the subject's SA is assessed in parallel with the task's performance in the same way as Observer rating techniques. However, the subjects are accountable for responding to the SA-related queries, which means the actual participant's SA level reflected the result rather than a third party's view (an Observer) on the subject's performance. In Real-time probes, subject matter experts must structure the SA-related queries according to the task's points of interest (Paul Salmon, et al, 2006). The subjects are questioned without interruption during task performance. Participants' SA levels are measured based on their response time and answer accuracy to the queries, which can directly reveal the intrusion of the participants' attention levels on the final SA result. Other drawbacks of this technique can be the generation of SA-related queries by subject matter experts due to high cost, availability, and their point of view on the AS matter related to the tasks. On top of these, due to the complexity and diversity of tasks in teleoperation and telerobotic operations, numerous experts are required to address queries generated related to each task. This is also why more time is required to develop SA queries (Endsley, M. R, 2019).

### **3. Post-trial subjective rating**

The self-rating technique is a subjective SA assessment provided by the subjects involved in the task under examination; the assessment is normally accomplished post-trial. The main benefit of this technique includes simplicity, its minimal cost, and its rapid processing nature. Additionally, the Self-rating technique has been classified as a non-intrusive method as they are administered post-trial and do not affect the subject's performance. It is worth mentioning that there is no need for subject matter experts due to their rating nature by the participants, and more importantly, the post-trial subjective rating method is one of the recommended techniques that can be used for SA assessment of team-operated tasks (Endsley et al, 2017).

On the other hand, as the subject's SA is assessed post-trial, they may not remember well when and at what point of the task they possessed an inadequate or superior Situational Awareness level (Endsley, 1995b). more to this matter, Endsley (1995b) has recorded that participants may suffer from reporting detailed data regarding past mental events. This issue has raised doubt about the accuracy of the subject's rating on their SA level at the end of the trials.

The applicability of the SA measurements based on post-trial subjective rating has been assessed by looking into various established post-trial self-rating methods, including the situation awareness rating technique (SART). The mission awareness rating scale (MARS) (Matthews & Beal, 2002) technique, The Crew awareness rating scale (CARS) (McGuinness B., Foy L. (2000) technique, The situation awareness rating scales technique (SARS) (Waag & Houck, 1994), the quantitative analysis of situational awareness (QUASA) technique (McGuinness, 2004), and the Cranfield situation awareness scale (C-SAS) (Dennehy, 1997).



Based on this assessment, The Situation Awareness Rating Technique (SART) has been identified as one of the models that meets the project requirements despite the disadvantages of the Self-rating technique. The popularity of this model is another factor that has been considered as it proves its validity and reliability in Situational Awareness assessment fields (Paul Salmon, et al, 2006).

#### **4. Process indices**

Recording participants' progress while executing the task under analysis is process indices models, similar to real-time probe and supervised rating methods. The Process indices' main benefit is eliminating limitations associated with post-trial subjective rating, addressed in the previous section.

It is worth mentioning that this method directly correlates with participants' attention levels (Stanton, N.A, PM Salmon · 2009). In studies (e.g., Smolensky, 1996), the approach includes using an eye movement tracker to record the participant's eye movement while tasks are executed. In this way, it was possible to determine how and on what activities the subject's attention was allocated during the performance. In addition (Janette Rose, Chris Bearman, Anjum Naweed, and Jillian Dorrian, 2019) have used a separate method that involves Concurrent verbal protocol analysis; in this model, the participants are required to think aloud to generate a written transcript from the participant thinking and behavioural actions. Psychologically, looking at the human mental thinking process, it can be concluded that people mostly think about issues they pay more attention to (Cherry, 1953); therefore, concurrent verbal protocol analysis also generates a significant correlation with the operator's attention allocation and not performance. However, subjects' task performance is

one of the main aspects or inputs to SA outcomes that need to be considered when situational awareness measurement is the point of interest.

Examining the Process indices relevancy has shown negligible suitability in the project's points of interest, and this method generates a good understanding of the participant's attentional allocation rather than capturing an overall subject's Situational Awareness level (Paul Salmon, et al, 2006).

## **5. Freeze probe recall techniques**

The Freeze probe recall techniques is close to a Real-time probe but with the difference of randomly stopping (freezing) the task under analysis to measure the participant's SA at the task's freeze time using a set of SA queries. This method provides a more accurate SA assessment due to its real-time assessment and elimination of reporting detailed data regarding past mental events in post-trial. Importantly, most freeze probe recall techniques are designed to measure an individual's SA, which is one of the project's main requirements.

The screening process has been done on the SA assessment techniques based on Freeze probe recall techniques such as Situation Awareness of en-route air traffic controllers in the context of automation (SALSA) (Hauss & Eyferth 14 2003), The situation awareness control room inventory and the situation Awareness Global Assessment Technique (SAGAT) (Endsley, 1995a). In this analysis procedure, the SAGAT technique's applicability, validity, and reliability by Endsley was the most promising method. The situation awareness global assessment technique, one of the unique methods that directly measure the subject's SA; even more, evidenced-based data proposes its direct correlation with the SA metric. Due to the SAGAT technique's high popularity, its validity and reliability have been scrutinised by numerous studies, such as the high-reliability suggestion from Endsley (2000), Zhang, T., et al 2020)

and. There is a claim that the SAGAT is the most widely validated of all SA techniques (Paul Salmon,et al, 2006).

Although the Freeze probe recall technique benefits from numerous advantages over other SA assessment methods (Paul Salmon,et al, 2006), there needs to be more clarity about the complexity of the Freeze probe recall implementation in real-world acting or in-the-field tasks. Additionally, there is the possibility that the intervention of the main task under analysis may have a negative effect on the participant's performance level (Paul Salmon,et al, 2006). It is worth mentioning that some studies, including Paul Salmon,et al, 2006, have suggested some approaches that can make it possible to reduce the effects of these problems within the Freeze Probe Recall technique. The suggested methods include: first, instead of halting (freezing) the main task, the operator could complete the SA queries during the task's lower difficulty phases; second, the freeze time can be designed to align with the natural flow of the main task, allowing the SA queries to be completed with minimal impact on the operator's performance.

## **Chapter 3**

### **Technical Methodology**

#### **3.1 Methodology**

This methodology chapter outlines the research approach and methods employed in this project, which were designed to meet established academic standards and ensure the robustness and reliability of the research findings.

Using telerobotic task provides a unique opportunity to examine situational awareness in a complex and dynamic environment, yielding a rich source of data for analysis (Bodner, D., & Cohen, B. (2019). The chapter also addresses the ethical considerations associated with the research methodology and the data collection structure. The primary goal of this chapter is to describe the research methodology employed to evaluate the validity and reliability of the study outcomes. A top-down view has been generated to illustrate the overall structure of this chapter, as depicted in Figure 3. This visual representation provides a clear and comprehensive overview of the chapter's layout and content, facilitating a better understanding of its thematic progression and key elements.

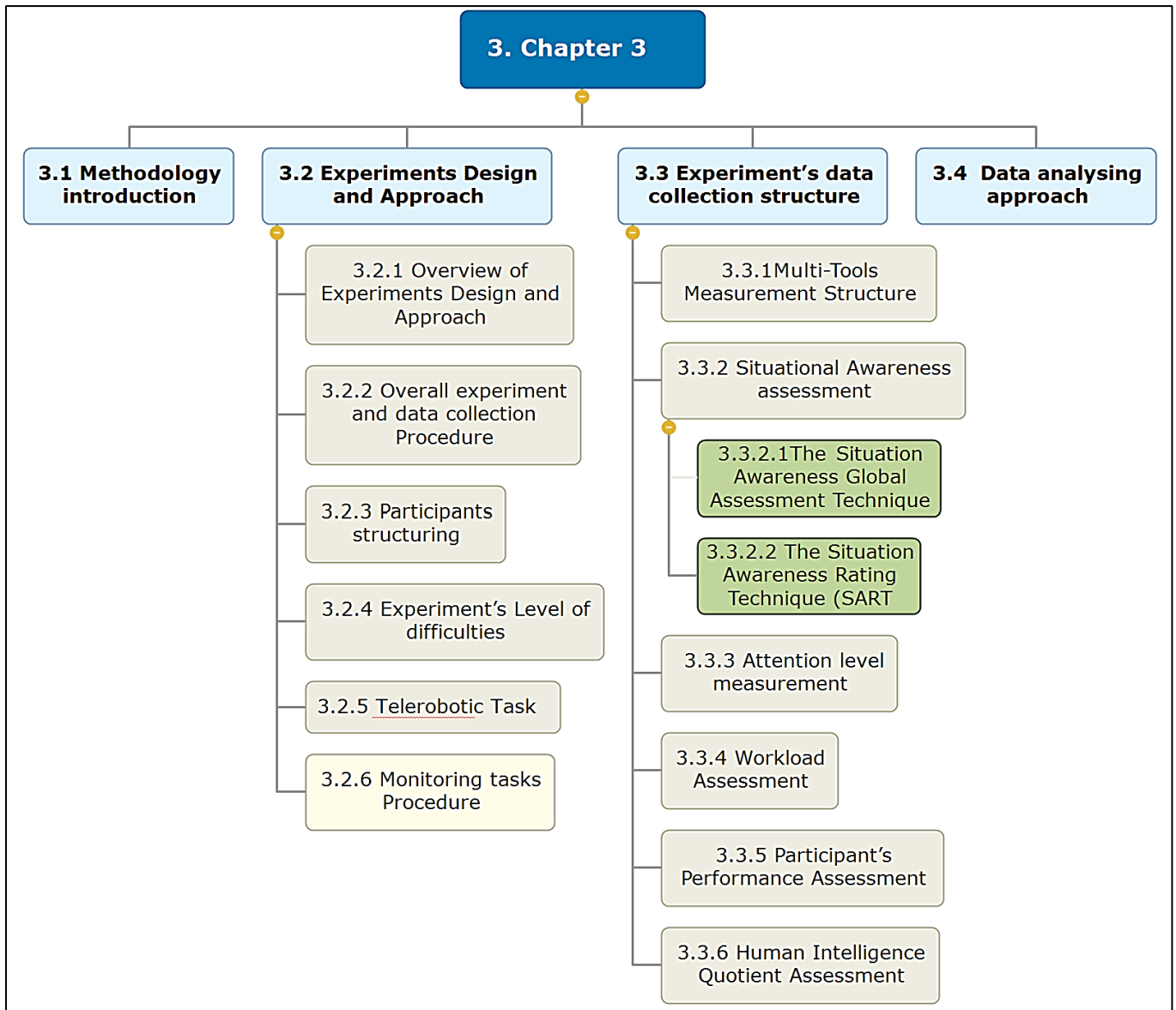


Figure 3 Methodology section structuring.

## 3.2 Experiments Design and Approach

### 3.2.1 Overview of Experiments Design and Approach

The primary task in this project simulated a real-world telerobotic scenario in which a nuclear station environment was investigated, while conducting human search and rescue mission. This approach not only mimicked a real-world scenario but also allowed for the collection of valuable data using the most relevant and reliable data collection instruments

for analysis and interpretation (Endsley, 2016). The main experiment involved a telerobotic exercise, in which subjects performed tasks at three different levels of difficulty, generating three-dimensional output data for analysis.

Moreover this approach is particularly suitable for the project due to its emphasis on realism, relevance, and analytical depth:

1. **Real-World Relevance:** Simulating a telerobotic operation in a nuclear environment replicates the high-stakes and complex dynamics encountered in real-world search and rescue missions. This ensures the study's findings are applicable to practical scenarios, aligning with Endsley's (2016) emphasis on ecological validity in human factors research. Additionally, the method resonates with the principles of human-centred design for mission-critical systems (Vicente, 2004).
2. **Data Collection Precision:** By employing reliable and context-appropriate instruments, the experiment captures nuanced insights into operator performance and situational awareness across different task complexities. This aligns with recommendations in the field for robust data collection methods that address both quantitative and qualitative aspects of operator behaviour (Stanton et al., 2017).
3. **Controlled Variation in Difficulty:** The use of tasks at three distinct levels of difficulty offers a structured framework for evaluating how varying cognitive and physical demands affect operator performance. This experimental design supports an iterative approach to understanding the interplay between task complexity, cognitive load, and situational awareness, critical in teleoperation research (Wickens, 2008).

4. **Three-Dimensional Output Data:** Generating three-dimensional data enhances the ability to conduct in-depth analyses, such as spatial awareness and decision-making under varying conditions. This approach has been recognised as essential for advancing the understanding of dynamic human-machine interaction (Parasuraman & Riley, 1997).

An advanced robotic dog called "Spot" (illustrated in figure 4) from Boston Dynamics was used for this teleoperation task (Boston Dynamics, n.d.). Operators were required to control the robot's movement within a designated area, while simultaneously monitoring its state and investigating the environment to collect and record data from associated instruments. The use of such advanced robotic systems in telerobotic tasks has been shown to be effective in a variety of domains, including manufacturing and search and rescue operations (Mahmoudi et al., 2019).



Figure 4 experiment's Robot Spot

A secondary task was included in the experiment to measure the operators' attention levels during the main experiment, due to the relevance of secondary tasks in understanding attention allocation in real-world scenarios (Reimer, B. 2009). This data monitoring exercise was performed concurrently with the main experiment and was intentionally designed for this purpose.

The present study utilised a Data Recorder (DR), an individual responsible for documenting the data verbally communicated by the main operator (subjects). The Oral Data Recording (ODR) was designated as the primary experimental intervention, and the experimental design allowed for its incorporation of a DR without disrupting the single-person operator telerobotic tasks.

It is important to note that strategic measures including Standardising Communication Protocols, Role Delineation and Isolating Operator SA were taken into account in this study to minimise data analysis complexity, enhance project outcome clarity, and mitigate the potential disadvantages associated with teamwork and avoiding the effects of human's communication variation on operator's SA (Leonard, M. 2004). Moreover, efforts were made to prevent the degradation of participants' efficiency commonly associated with joint operations in teleoperation systems (Kaber, D. B., & Riley, J. M. 1999., George, J. M. 2000).

The communication between the main operators and the DR was restricted to insure that the DR was solely responsible for documenting data, although the main operator was allowed to review recorded data to ensure its validity.



By clearly assigning data documentation responsibility to the DR, clear accountability and a well-defined process were ensured for accurate and reliable data. At the same time, allowing the main operator to review the recorded data ensured a level of quality control during the project's task execution.

This methodology approach also facilitated the classification of the experiment tasks as single-person operations rather than a teamwork operation. Moreover, it enabled the preservation of the experimental intervention as an independent variable within the experiment, facilitating observation of its effects on the project's dependent variable. These outcomes significantly enhanced the methodological rigour of the study and strengthened the validity of the findings.

A total of thirty participants were recruited to perform the experiment exercise, The selection of 30 participants for the experiment was influenced by established practices in previous studies of similar scope and design. Notably, Endsley's (2000) foundational framework for assessing situational awareness (SA) provided critical guidance in determining the experimental setup and participant structure. Endsley's work emphasises the importance of a well-structured participant pool to ensure robust data collection and analysis of SA in controlled environments. Moreover, this number aligns with a common range used in cognitive and SA-focused research, balancing statistical power and logistical feasibility while accommodating the practicalities of telerobotic task simulations. The participants were divided into three groups, with each group consisting of ten individuals, following the experimental framework outlined in Endsley (2000). This division was designed to assess task performance and situational awareness (SA) under conditions of varying complexity.

Group 1 completed tasks with low difficulties, simulating basic operational challenges often used as baselines in SA studies (Endsley, 1995; Durso & Gronlund, 1999). Group 2 undertook moderate difficulty tasks, incorporating increased cognitive demands and workload to analyse intermediate levels of performance and SA. Group 3 faced elevated difficulty tasks, characterised by higher decision-making requirements and problem-solving complexities. These tasks were chosen to examine cognitive strain and SA degradation under stress, consistent with prior findings in cognitive and SA research (Patrick et al., 2006; Gorman et al., 2006). This experimental stratification mirrors validated methodologies in SA research, enabling comprehensive analysis of cognitive load, performance, and SA maintenance in telerobotic operations. By implementing this structure, the study aligns with best practices in assessing human performance across a spectrum of operational complexities (Endsley, 2000; Stanton et al., 2017).

Notably, main operators underwent a comprehensive initial training program prior to the actual experiment. The training program aimed to familiarise the operators with the tasks, procedures, and data recording structures involved in the experiment, ensuring their competence in effectively performing the required tasks. The importance of this training program in enhancing the reliability and validity of the study cannot be overstated.

In addition to the initial training program, participants also underwent an online, web-based human intelligence quotient (IQ) assessment. This assessment measured the participants' cognitive abilities, including memory, concentration, logic, visual, and verbal skills. The IQ assessment established a baseline measure of the participants' cognitive abilities that could be used to evaluate the potential impact on other key human factors considered in the project, including attention, performance, and human situational awareness.

The inclusion of the IQ assessment aligns with established academic standards and adds an additional layer of rigour to the research design. By facilitating the interpretation of study results, the assessment enhances the overall quality and credibility of the research outcomes. This approach is supported by Gottfredson (1997), who emphasised the role of intelligence measures in capturing individual differences, thereby aiding in the analysis of complex tasks and their outcomes (*Intelligence*, 24(1), 79–132).

In designing the experiment's tasks, careful consideration was given to the requirements for the tools necessary for data measurements and collection. This involved a thorough evaluation of the selected data collection instruments to ensure their validity, reliability, and compatibility with the project. The chosen instruments for data collection include the Situation Awareness Global Assessment Technique (SAGAT) and the Situation Awareness Rating Technique (SART). These tools were specifically utilized to measure situational awareness, a concept comprehensively detailed in Section 3.3.2 of this document. Both methodologies play a crucial role in evaluating the depth and accuracy of operator awareness in dynamic environments, providing a robust framework for analysing the impact of situational awareness on performance.

Additionally, the NASA Task Load Index (NASA TLX) was used for workload assessment, while The Measure of Time to Task Completion was used for performance measurement.

### **3.2.2 Overall experiment's procedure**

The experimental procedure consisted of the following steps: First, participants were recruited, and their demographic information was recorded including their age, gender and

Physical Ability/Disability. Next, they were provided with an introduction to the experiment, including a description of the overall purpose and the data collection procedures.

The experiment commenced with an assessment of participants' intelligence quotient (IQ). Following this, the main tasks of the experiment were initiated, which involved performing a telerobotic task concurrently with a secondary task. Participants' performance on the tasks, as well as their attention levels, were assessed throughout the experiment.

At random intervals, the experiment and all ongoing assessments were temporarily paused in order to assess participants' SA using the Situation Awareness Global Assessment Technique (SAGAT), a question-based assessment. Once the SAGAT assessment was completed by the participants, the experiment and ongoing assessments were resumed.

Upon completion of the telerobotic task, participants were asked to complete the Situation Awareness Rating Technique (SART), a post-trial SA assessment instrument. Finally, participants' mental workload was assessed using the NASA Task Load Index (NASA-TLX) app.

### **3.2.3 Participants structuring**

The experiment participants were mostly members of The University of Birmingham, and they were invited to take part in the experiment through face-to-face or Flyers/posters around the campus. More importantly, the research undertaken as part of this study adhered to ethical guidelines established by the University of Birmingham. The ethical approval process, a standard requirement for conducting research involving human participants, was completed to ensure that the study met the highest ethical standards. This process included a comprehensive review of the study's methodology, participant consent protocols, and measures for safeguarding participant welfare. Confirmation of this approval

has been documented and is included in figure 5, ensuring transparency and compliance with institutional and ethical research norms.

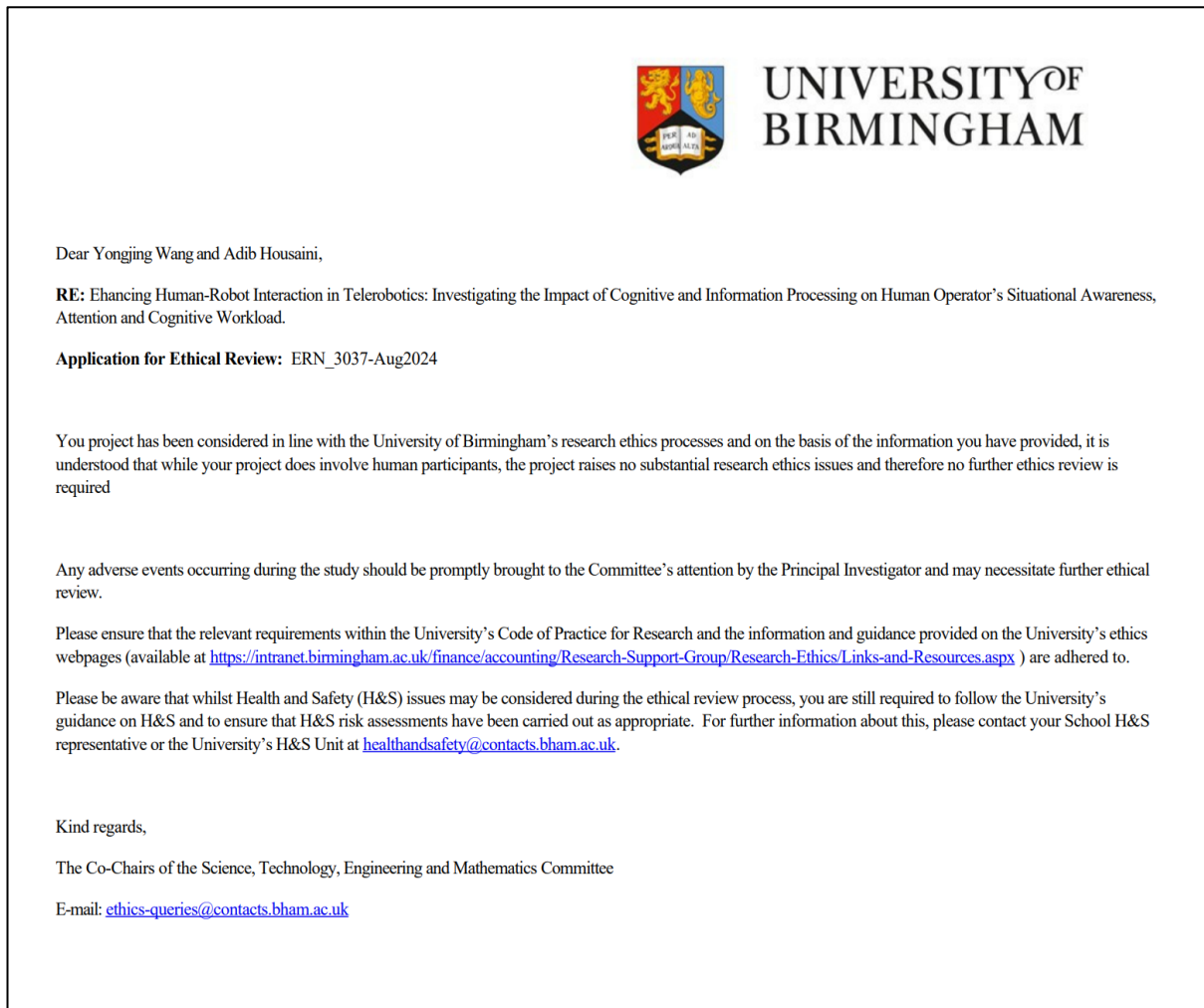


Figure 5 the Ethics review confirmation

The main operators were allocated among three distinct teams, each assigned with the completion of the experiment at a different Level of Difficulty (LOD). Specifically, team 1 completed tasks with low difficulties, team 2 with moderate difficulties, and team 3 with elevated difficulties. Moreover, each team's participants were divided into two sub-groups, labelled as group A and group B. In group A, the tasks were completed by the main operator only. In contrast, group B undertook the same tasks but with the experimental intervention (Data Recorder) added, and their outcomes were recorded for comparison with group A's

results. The sub-groups in team 1 were denoted as A1 and B1, those in team 2 were named A2 and B2, and the final sub-groups in team 3 were identified as A3 and B3.

The design of this participant structure has several advantages. Firstly, it facilitates the generation of three distinct sets of experiment outcomes at varying levels of difficulty, thereby increasing the reliability of the results. Secondly, by segregating the task completion with and without experimental intervention across the three levels of difficulty, the validity of the outcomes can be significantly enhanced. Figure 6 in this study provides a visual representation of the project participant structuring setup.

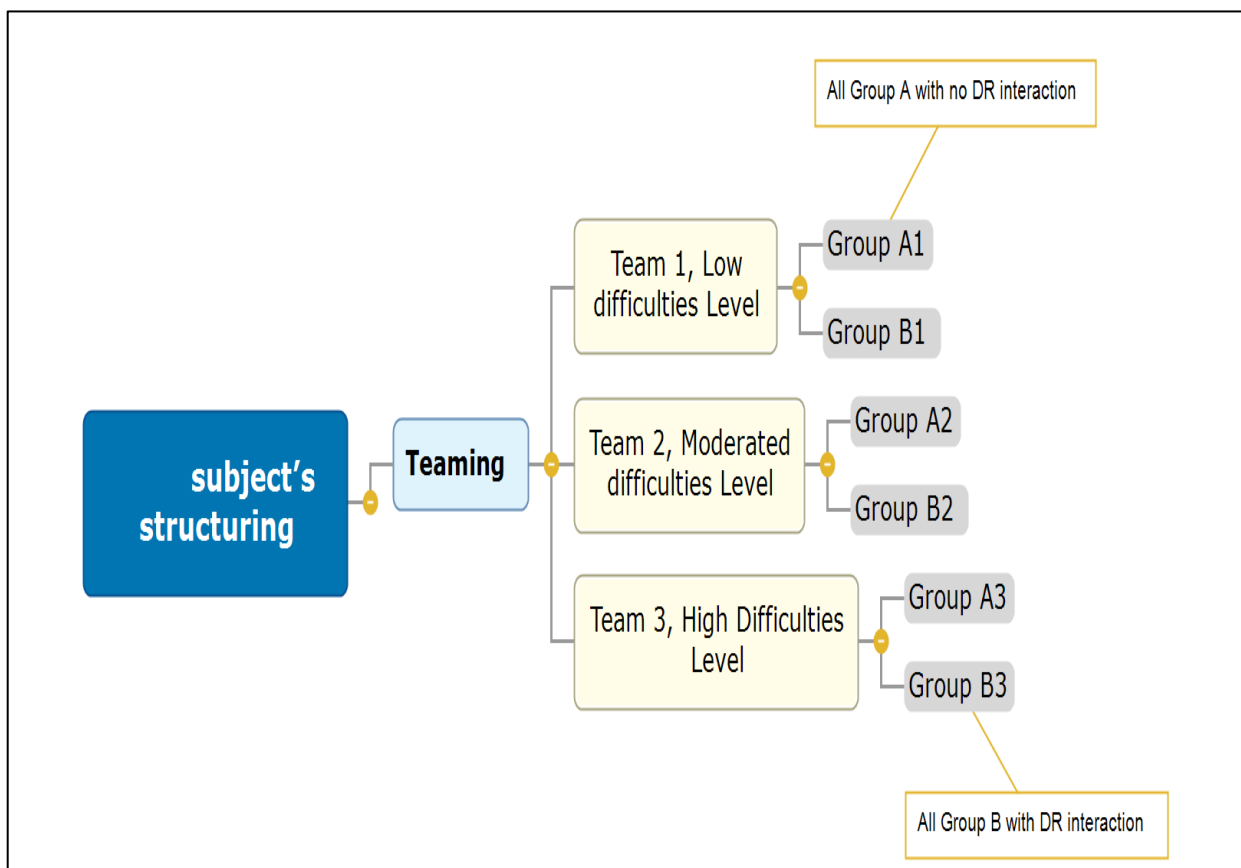
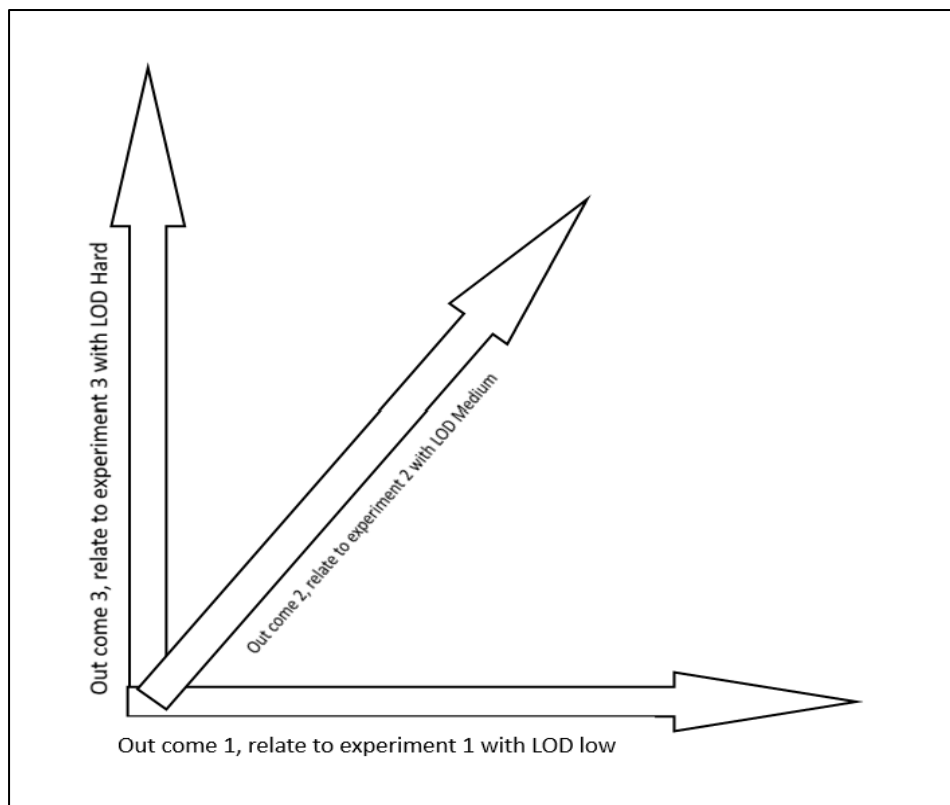


Figure 6 visual representation of the project participant structuring setup.

### 3.2.4 Overall Experiment's Level of difficulties

This section is an overall structure of the experiment's level of difficulty and more detailed explanation on the experiment's level of difficulties presented within 3.2.5 section

(Telerobotic Task). In this research, the Level of Difficulty of the task was treated as an independent variable. The primary objective of categorising the difficulty level was to confirm the reliability of the findings. This approach resulted in the creation of a three-dimensional data extraction structure. Specifically, three level of difficulties in the experiment's were conducted to evaluate human factors, namely the operator's Situational Awareness (SA), Performance, and Attention level which generates a three dimensional research output. The outcomes of these experiments were then analysed and combined to generate an individual outcome on each dimension. A visual representation of the experiment's Level of Difficulty and measurement factor's structure is presented in Figure 7.



*Figure 7 experiment's Level of Difficulty and measurement factor's structure*

### 3.2.5 Telerobotic Task

The study is concerned with investigating the efficacy of a telerobotic task in a challenging and safety-critical environment, namely a nuclear station, with a dual purpose of data collection and human search and rescue. The chosen scenario was selected based on the research aims and objectives of the study, and the availability of the necessary equipment from the University of Birmingham. The task was conducted in a controlled environment in an engineering building within the University premises.

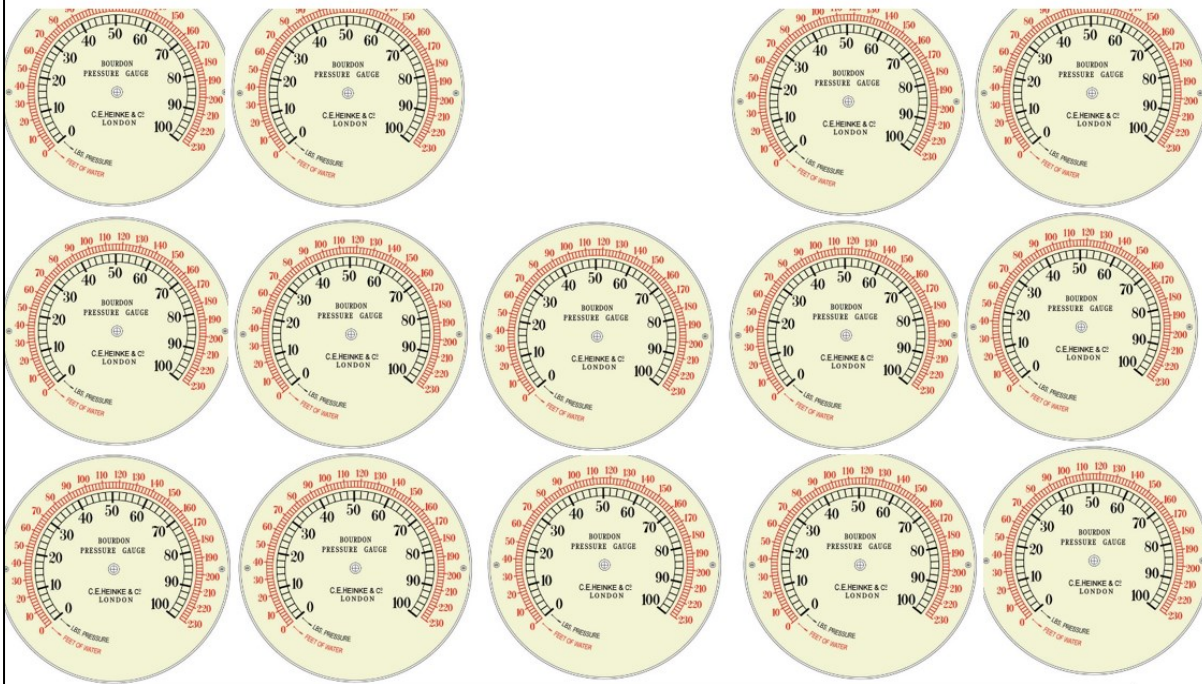
The chosen scenario for this study, conducted in a controlled environment at the University of Birmingham, closely aligns with the research aims and objectives. Controlled settings are typically utilised in this research to minimise external variables, thereby ensuring that observed effects or behaviours can be attributed to the experimental conditions (Robinson et al., 2016). While this approach guarantees reliable and accurate data and the scenario in this study replicates the fundamental requirements of the task, it may lack the dynamic challenges and environmental factors present in real-world settings, and it may not 100% reflect the variability and unpredictability of real-world environments such as nuclear plants or remote search-and-rescue operations (Endsley, 2016; Draper & Pashler, 2008).

The telerobotic tasks consisted of navigating the robot within the building, with the objective of investigating the area and collecting data through onboard sensors and cameras. Two groups of participants were assigned to the task, with Group A being tasked with manually recording the data, while Group B read the data aloud, which was recorded by a Data Recorder. Standardised data recording sheets were developed and utilised to ensure uniformity in data collection, as exemplified in Figure 8. The experiment's data were presented in three distinct formats: pressure gauges levels, radioactive detector states, and



human conditions (survivors) within the building as they have been shown in figure 9. Three levels of difficulty were implemented in the telerobotic task, namely hard, medium, and low levels. At each level, the primary operator was tasked with reading and recording the data, as well as taking appropriate action.

### Pressure gauges levels



### Radioactive Detector

| Conditions | Safe | Low level | High level | Dangerous |
|------------|------|-----------|------------|-----------|
| 1          |      |           |            |           |
| 2          |      |           |            |           |
| 3          |      |           |            |           |
| 4          |      |           |            |           |
| 5          |      |           |            |           |
| 6          |      |           |            |           |
| 7          |      |           |            |           |
| 8          |      |           |            |           |
| 9          |      |           |            |           |
| 10         |      |           |            |           |

### Human Interaction

|    | Need help | Not require help | Note |
|----|-----------|------------------|------|
| 1  |           |                  |      |
| 2  |           |                  |      |
| 3  |           |                  |      |
| 4  |           |                  |      |
| 5  |           |                  |      |
| 6  |           |                  |      |
| 7  |           |                  |      |
| 8  |           |                  |      |
| 9  |           |                  |      |
| 10 |           |                  |      |

Figure 8 Data Recording sheets.

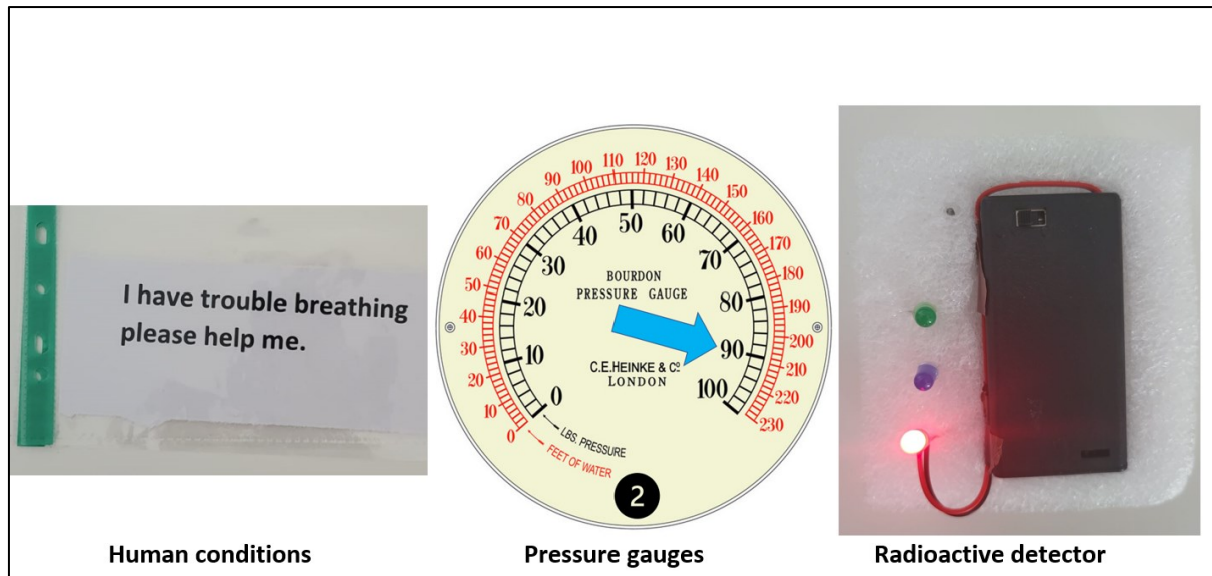


Figure 9 Experiment's data representation outlook.

The selected difficulty level configuration was determined based on the need to prolong task completion time, increase the complexity of data collection, and expand the range of the robot's mobility within the experiment area. To extend the task completion time, additional indicators were added, which required the operator to read and record more data. The complexity of data collection was increased by strategically positioning indicators in locations that were more challenging to locate and read. To expand the robot's mobility, operators were required to return the robot to its starting point in the hard and medium difficulty levels. The hard difficulty level included 8 pressure gauges and 4 radioactive detectors that were located in areas that were not easily visible. In the medium difficulty level, the number of items was reduced to 4 pressure gauges and 4 radioactive detectors located in more visible locations than the hard level. Finally, the low level of difficulty had 3 pressure gauges and 3 light indicators that were positioned at a distance of 2 meters and in more visible locations to the robot's points of view. The participants were informed how

many indicators they needed to collect during the experiment, and they were operating the robot separated from the robot.

The pressure gauge levels were categorised based on the nuclear equipment's conditions. High pressure was considered dangerous, low pressure was abnormal, and mid-range pressure indicated a normal system condition. The pressure range was numerically differentiated, with the low level representing pressure from 0° to 10 degrees, and 11° to 20 degrees indicating that the system is transitioning from a normal state to a low level. The gauges' states from 21° to 50 degrees were considered a normal condition. Reading from 51° to 70 degrees indicated that the system's condition was moving towards high pressure, and states from 71° to 100 degrees were set as high pressure.

Radioactive detector states were represented using LED lights, each combined with three LED lights: green for normal, blue for contaminated areas, and red for dangerous zones.

To replicate the scenario of human search and rescue and remaining people in the building, a set of four sentence signs was spread throughout the area. Operators were required to read the sentence, understand the content, record the survivor's condition, and take appropriate action. Survivor conditions were classified into two cases: those that did not require rescue and those that required rescue action. Upon spotting a rescue need sign, the operator was required to record the survivor's condition and return the robot to the base to bring the survivor to safety.

The experiment with the low difficulty level did not require any case of returning the survivor to safety. There was one return to the base case for the medium level and two cases for the high level.

The data collected during the experiment consisted of information on Pressure gauges levels, Radioactive detector states, and human search and rescue operations. These data were captured by the onboard cameras and projected onto a separate screen from the robot control system, enabling efficient data management. The robot employed in the experiment was a Spot robot from Boston Dynamics, which has been specifically designed for environmental investigation and data recording operations (Boston Dynamics, 2023). Its exceptional mobility capabilities, including climbing up and down stairs and obstacle avoidance, coupled with its 14 kg payload capacity made it an optimal choice for this project. The robot was remotely controlled by the main operator using a specific program from Boston Dynamics on a touch screen tablet controller. The use of digital joysticks on the tablet enabled the subjects to navigate the robot within a controlled area of the building. Figure 10 illustrates the control unit used to operate the robot.



Figure 10 the control unit used to operate the robot ([intuitive-robots.com](http://intuitive-robots.com))

Subjects were able to move the robot into all four directions, forward, backward, left, and right, on top of this movements they were able to move the robot up and down from building stairs. They were also able to go to complete stop of the robot at any given time just by not touching the controller, during the complete stop the robot remained at the same location and the same position. By utilising this feature, the experiment was able to randomly halt task performance, which constituted one of the major advantages of the robot employed. Although other robots available at the University of Birmingham were considered for the project, the Spot robot from Boston Dynamics was ultimately selected due to its alignment with the study's aims and objectives. The Spot robot was particularly suitable for the environmental investigation and data recording tasks required for the study, offering robust mobility and sensor capabilities ideal for the remote-operation scenario. Additionally, its availability at the university made it a practical choice for the research, ensuring that it could be easily integrated into the controlled environment setup for the experiment. This feature enabled the use of The Situation Awareness Global Assessment Technique (SAGAT) tool in a real-world experiment, rather than in simulated tasks, thereby fulfilling one of the principal objectives of the study. This approach allowed for the collection of first-hand data on the performance and reliability of SAGAT in real-world experiments, thus providing a more accurate evaluation of its utility in practical applications.

### **3.2.6 Monitoring tasks Procedure**

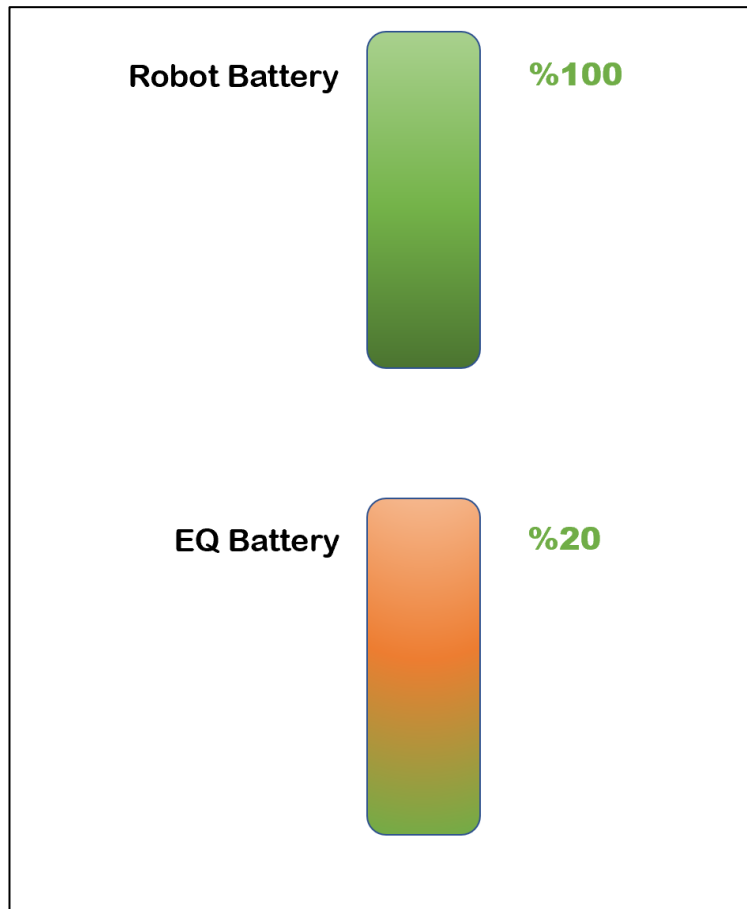
An additional supervisory activity was implemented in order to gauge the operators' level of attention beyond their primary task of controlling the robot and collecting data. This secondary task required operators to continuously monitor the state of the robot and its onboard equipment. The purpose of this visual signal monitoring task was to measure the

level of excess attention required by the operators. To this end, the visual signals were presented on a separate monitor from the robot controller, ensuring that the secondary task did not interfere with the primary task.

For this monitoring task, two distinct battery charging level signals were presented to the operators, with one signal corresponding to the actual robot battery and the other signal pertaining to the battery levels of the onboard equipment. The charging levels of these batteries were randomly altered between 100% and 10% levels. The presentation of these battery levels on the screen was optimised in accordance with the recommendations put forth in previous literature (Jennifer M. Riley in 2001). Specifically, the signals were displayed within the operator's vertical field of view spanning from 130 to 135 degrees and located on the lower left side of the monitor.

The battery charging levels were visually conveyed to the operators using both colour and numerical indicators. Specifically, a rectangular box was used to represent the battery level, with fully green boxes indicating a fully charged state, and the corresponding numerical indicator showing 100%. The battery levels were presented on the lower left side of the monitor, within the operator's vertical field of view of 130 to 135 degrees, as recommended

in previous studies (Jennifer M. Riley in 2001). A detailed demonstration of the battery level presentation is provided in Figure 11.



*Figure 11 Battery level presentation.*

The monitoring task was typified by its psychomotor nature, which encompassed monitoring, diagnosis, and appropriate action. Specifically, the operators were tasked with monitoring the charging levels of the robot's batteries and equipment, diagnosing their states, and taking action accordingly. In the event that one or both of the batteries were fully charged (reaching 100% charging level), the operator was required to acknowledge this by utilising a corresponding counter application, which was presented on the secondary monitor. The counter application allowed the operator to record and tally the number of times that each battery was recharged. The application consisted of two distinct categories, one for the robot's battery and the other for the onboard equipment's battery. Whenever a



battery was recharged, the operator was required to press the corresponding addition symbol in the appropriate category, after which the application was updated to record the operator's response. Figure 12 depicts the configuration of the counter application.

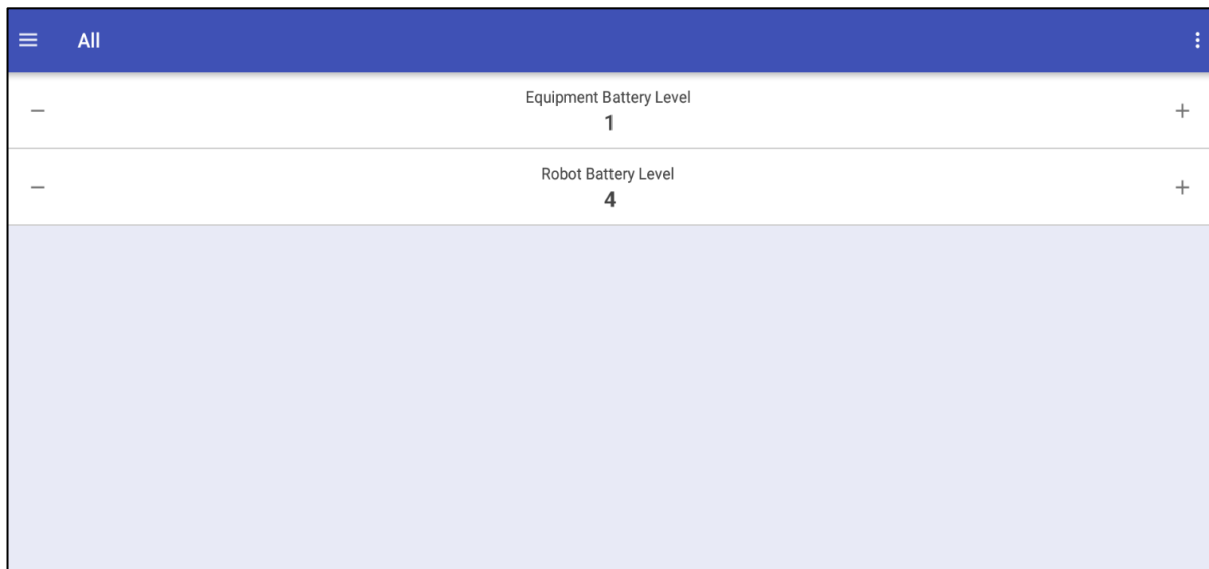


Figure12 Counter App presentation

### 3.3 Experiment's data collection structure

This section provides a comprehensive overview of the methods used for data collection and the instruments employed to gather the research variables. These methods have been systematically evaluated to ensure alignment with the study's hypothesis and experimental design.

#### 3.3.1 Multi-Tools Measurement Structure

Although integrating data collection from multiple platforms remains challenging due to inherent differences in the data, the use of a Multi-Tools Measurement Structure has proven advantageous in research methodology. This structure allows for the development of customisable analysis flows and tools that address these challenges effectively.

This approach brings several significant benefits to research. Firstly, it facilitates the gathering of diverse types of data through various instruments, which enriches the overall comprehension of the research topic. Secondly, by employing multiple sources and methodologies for data collection, it enhances both the reliability and validity of the findings. Thirdly, the approach is effective in mitigating the impact of potential confounding variables by simultaneously measuring various dependent and independent variables. Fourthly, it opens avenues for uncovering potential relationships and interactions among the variables, leading to deeper insights into the research topic. Ultimately, the Multi-Tools Measurement Structure stands out as a robust research strategy, offering a comprehensive and nuanced analysis of complex subjects.

The experiment necessitated the gathering of six separate data collections points for each of the three levels of difficulty in the telerobotic task. This indicates that a total of eighteen comprehensive data evaluations were obtained. Within these six required data some were collected prior to the task, others in real-time during task execution, and the remainder were collected post-trial. These data sets included two separate SA assessments, Mental Workload, Attention level, Performance, and human IQ. It is noteworthy that the human IQ was also independent variable, while the rest were considered dependent variables of the study.

To structure an effective Multi-Tools Measurement Structure, a top-down flowchart was created, as shown in Figure 13. This flowchart illustrates how the measurement instruments

were organised within the experiment and the order in which each instrument was employed and completed by the subjects.

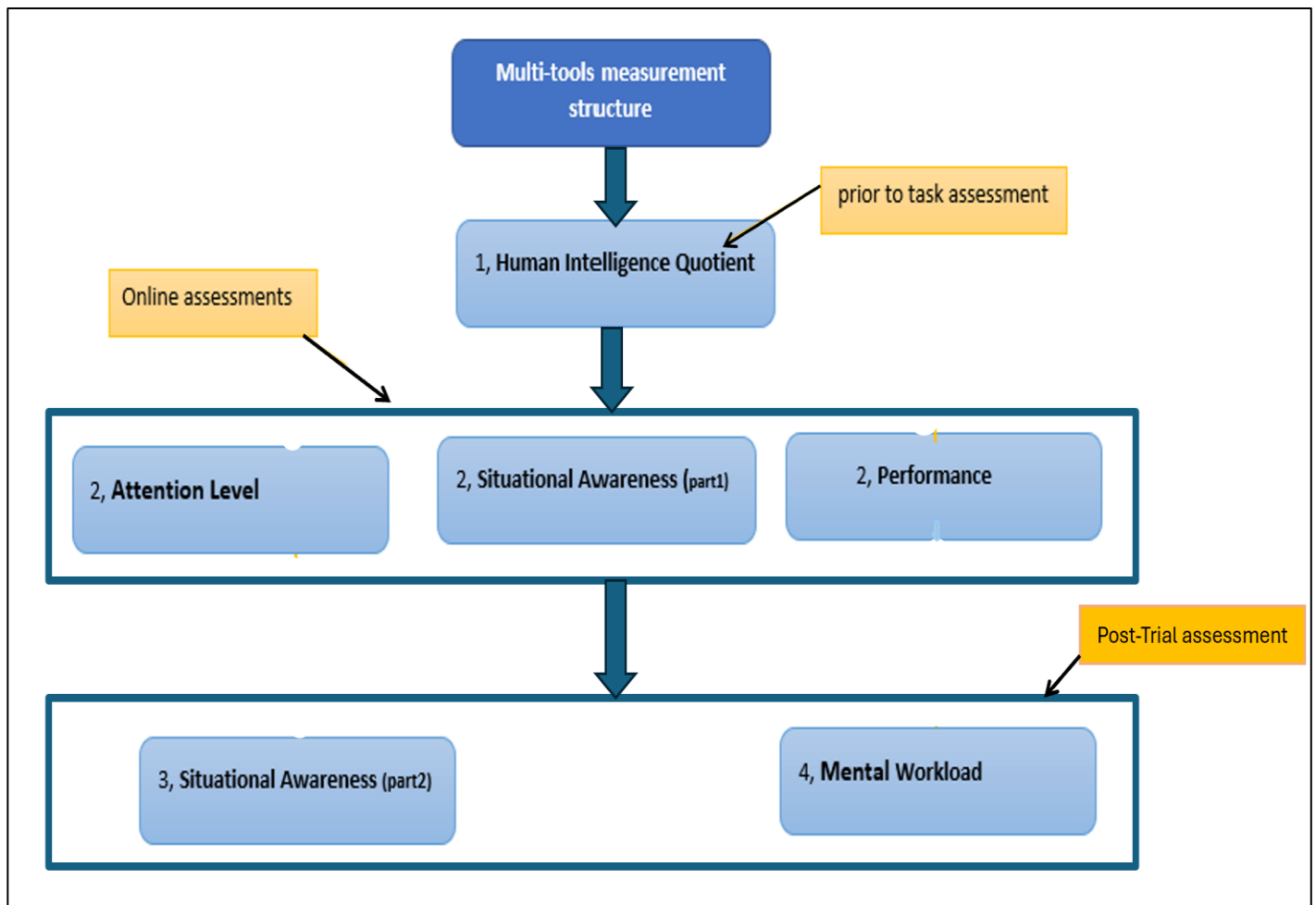


Figure 13 multi-tools measurement structure a top-down flowchart.

The selected data collection instruments for this study were including.

1. The situation Awareness Global Assessment Technique (SAGAT)(part1).
2. The Situation Awareness Rating Technique (SART)(part2).
3. Participant's IQ in terms of memory, concentration, logic, visual, and verbal.
4. Observation of Performance accuracy on a secondary task (Attention level).
5. NASA's Task Load Index (TLX) (Metal workload)
6. Non-intrusive Time-to-task completion (performance assessment).

To ensure a thorough comprehension of the research methodology, an in-depth analysis of each selected data collection tool is given in the following sections. This is imperative to establish a clear understanding of how the methods used to collect data and what are the respective strengths and limitations of each tool. Furthermore, an explanation is provided on how any associated limitations have been addressed, thus enhancing the validity and reliability of the research findings.

### **3.3.2 Situational Awareness assessment**

To measure one the primary dependent variable of the study, namely Human SA, a three-stage data collection tool assessment process was employed in this study to ensure a comprehensive and effective SA assessment.

The first stage involved analysing the human factors issues related to operators in telerobotic fields, which included examining the various categories of their SA to determine the relevant SA aspects in this field.

In the second stage, a comprehensive review of various SA assessment instruments was conducted to determine their relevance and potential benefits for this study.

Finally, in the third and final stage, the relevant methods were studied in order to determine how utilise and benefit from most advantages of the selected data collection tools in Situational Awareness assessment.

#### **3.3.2.1 The Situation Awareness Global Assessment Technique**

Due to the specific requirements of each SA tool and the experiment's structure, each instrument needed to be used at a different time during the experiment. The Situation

Awareness Global Assessment Technique (SAGAT), this assessment method has been developed based on the freeze and probe assessment approaches and it was used in real-time during the study's experiment. Therefore, during the execution of the main tasks, all tasks were randomly put on hold, and the SAGAT questionnaire was presented to the main operator to be completed during the freeze time while operators turned back from the task seen.

It is worth noting that the SAGAT questionnaire was an essential part of ensuring measurement accuracy, to develop a strong and valid questionnaire, the SAGAT assessment questionnaire was generated based on a detailed approach outlined by Mica R. Endsley in 2000, which provides guidance on how the SAGAT questionnaire should be structured. According to (Endsley,2000) the key elements of the SAGAT questionnaire include several important aspects. Firstly, it is completed only by the main operators, and during the freeze time. Secondly, the questions in the questionnaire are directly related to the subject's SA and do not address any other factors. Thirdly, while the questions are formulated in a similar manner, the questionnaire covers all three levels of SAGAT: 1, perception of data, 2, comprehension of meaning, and 3, projection of the near future. Considering these features during the SAGAT questionnaire development make this instrument an effective tool for assessing human SA for this study.

The flowing figure 14 illustrate the questioner that has been developed for the SAGAT assessment.

Queries on SA, potential responses, and the Level of SA targeted by each query.

| <b>SAGAT QUERY</b>                                            | <b>POSIBLE RESPONSES</b>                                               | <b>Participant's Answer</b> | <b>SA LEVEL</b> |
|---------------------------------------------------------------|------------------------------------------------------------------------|-----------------------------|-----------------|
| <b>What was the current task activity?</b>                    | (a) Searching<br>(b) Recording data<br>(c) Rescuing human              |                             | 1               |
| <b>What type of indicator was being recorded?</b>             | (a) Pressure gauge<br>(b) Radioactive<br>(c) Survivors<br>(d) Non      |                             | 1               |
| <b>Is the robot in a contaminated area?</b>                   | (a) Yeas<br>(b) No                                                     |                             | 1               |
| <b>What was the current situation of both battery levels?</b> | (a) Both full<br>(b) Both low<br>(c) One need charging<br>(d) Not sure |                             | 1               |
| <b>How many Pressures gage have been recorded so far?</b>     | (a) 1-3<br>(b) 3-5<br>(c) 5-7<br>(d) 7-9<br>(e) 10-15<br>(f) 15-20     |                             | 2               |
| <b>Which batty needed more recharging?</b>                    | (a) The Robot<br>(b) The equipment's                                   |                             | 2               |
| <b>Has any human detected?</b>                                | (a) Yeas<br>(b) No                                                     |                             | 2               |
| <b>What was the last indicator recorded?</b>                  | (a) Pressure gauge<br>(b) Radioactive<br>(c) Survivors<br>(d) Non      |                             | 2               |
| <b>Which batty need recharging next?</b>                      | (c) The Robot<br>(d) The equipment's                                   |                             | 3               |
| <b>What will be the radioactive indicator condition?</b>      | (a) Safe<br>(b) Danger<br>(c) Neutral                                  |                             | 3               |
| <b>What was the very next task activity?</b>                  | (a) Searching<br>(b) Recording data<br>(c) Rescuing human              |                             | 3               |
| <b>Is there any indicator close to the robot?</b>             | (a) Pressure gauge<br>(b) Radioactive<br>(c) Survivors<br>(d) Non      |                             | 3               |

Figure 14 Developed SAGAT questionnaire Assessment.

### 3.3.2.2 The Situation Awareness Rating Technique (SART)

The Situation Awareness Rating Technique (SART) is a self-rating SA model where participants subjectively rated their SA through a comprehensive rating scale. This SA assessment was utilized in a post-trial Situational Awareness manner. Although this instrument could be used based on 3D aspect measurement, it provides a more general outcome, therefore, in this study the ten dimensional 10D assessment version has been used. In this way the SART tool measures ten dimensions of SA, including concentration of attention, spare mental capacity, variability of the situation, instability of the situation, arousal, familiarity of the situation, focusing of attention, information quality, and information quantity. It should be mentioned that these 10D aspects have been categorised into three main sections including Demand (D), Supply (S) and Understanding (U). the developed questionnaire by Taylor in 1990 and was used in this study and the overall SA score through SART was calculated as  $SA = U - (D - S)$ . The selected questions layout used to assess the subject's SA utilizing the SART is shown in the figure 15.

In the final stage of the experiment, participants were asked to rate each dimension of the SART assessment on a seven-point rating scale, ranging from one (indicating low SA) to seven (indicating high SA). These individual ratings were then aggregated to generate an overall SA level for each participant.

| Construct                | Definition                                                              |
|--------------------------|-------------------------------------------------------------------------|
| Instability of situation | Likelihood of situation to change suddenly                              |
| Variability of situation | Number of variables which require one's attention                       |
| Complexity of situation  | Degree of complication (number of closely connected parts) of situation |
| Arousal                  | Degree to which one is ready for activity (sensory excitability)        |
| Spare mental capacity    | Amount of mental ability available to apply to new variables            |
| Concentration            | Degree to which one's thoughts are brought to bear on the situation     |
| Division of attention    | Amount of division of attention in the situation                        |
| Information quantity     | Amount of knowledge received and understood                             |
| Information quality      | Degree of goodness or value of knowledge communicated                   |
| Familiarity              | Degree of acquaintance with situation experience                        |

## SART construct & 10-D SART

### 10-D SART

|               |                          | Low High |   |   |   |   |   |   |
|---------------|--------------------------|----------|---|---|---|---|---|---|
|               |                          | 1        | 2 | 3 | 4 | 5 | 6 | 7 |
| DEMAND        | Instability of situation |          |   |   |   |   |   |   |
|               | Variability of situation |          |   |   |   |   |   |   |
|               | Complexity of situation  |          |   |   |   |   |   |   |
| SUPPLY        | Arousal                  |          |   |   |   |   |   |   |
|               | Spare mental capacity    |          |   |   |   |   |   |   |
|               | Concentration            |          |   |   |   |   |   |   |
|               | Division of attention    |          |   |   |   |   |   |   |
| UNDERSTANDING | Information quantity     |          |   |   |   |   |   |   |
|               | Information quality      |          |   |   |   |   |   |   |
|               | Familiarity              |          |   |   |   |   |   |   |

Figure 15 SART construction and questionnaire.

### 3.3.3 Attention level measurement

This section describes the methodology used to measure the participants' attentional allocation during the experiment's secondary task. A signal detection task was employed on two distinct battery levels to measure the operator's attentional resources. This approach was designed to determine the operator's level of attention during the telerobotic task under two different conditions, with and without the presence of a Data Recorder. The aim is to identify the amount of attention allocated to the telerobotic task in each condition by assessing the operator's signal detection performance. A higher signal detection score indicates that the operator allocates less attention to the telerobotic task, whereas a lower score indicates greater attention to the primary task. The procedure for completing the



secondary task and recording the outcome is detailed in section 3.1.5. Figure 16 illustrates the manner in which the secondary task and video feed from the onboard equipment were presented to the operators on the additional monitor. The use of this approach aligns with the Single Resource Theory of human attention, and previous studies have established the Hit-to-Signal Ratio in Signal Detection paradigm as a reliable means of evaluating attentional resource allocation (Broeker et al., 2021; Kaber, D. B. and Riley, J. M. 1999)

To ensure the instruments used were suitable for the study, several data collection methods were chosen and evaluated based on their consistency with the study's hypotheses. Notably, observation of performance accuracy on a secondary task has been established as a reliable means of measuring human attention resources (Broeker et al., 2021). Assessing a participant's attentional allocation is a commonly employed technique and measuring their performance on a secondary task while concurrently performing the primary task is a widely accepted approach (Chen, S. 2017).

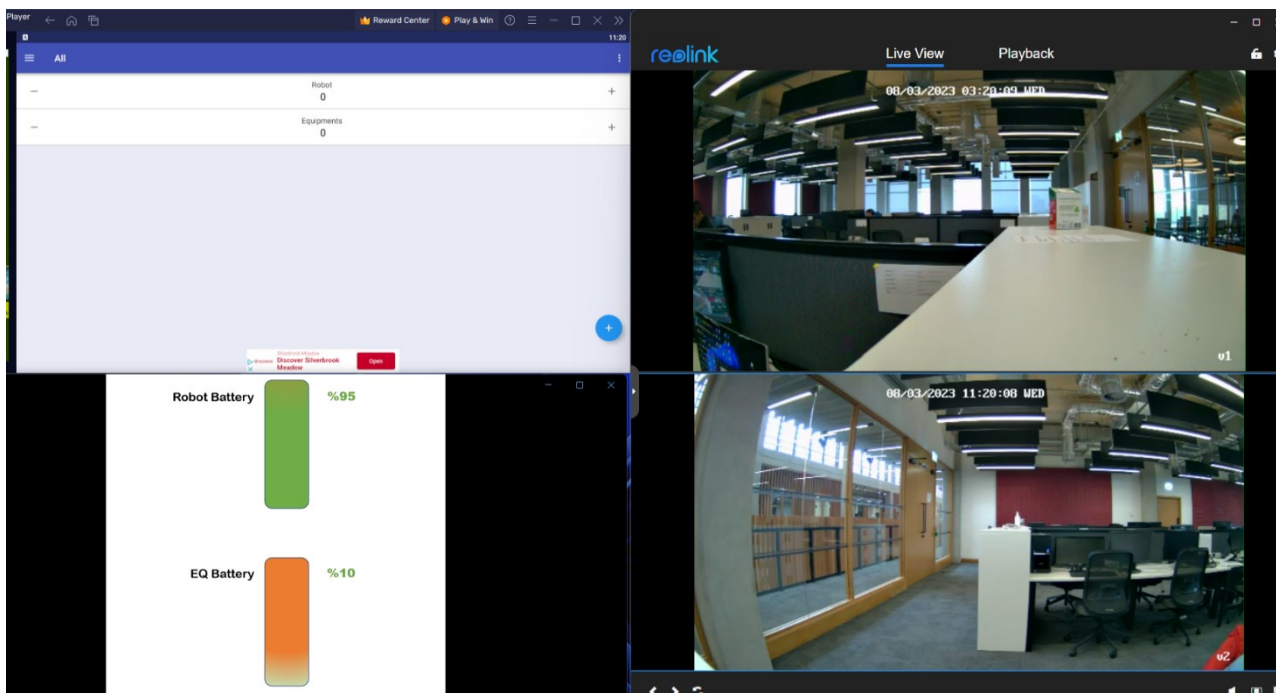


Figure 16 Secondary task implementation

### 3.3.4 Workload Assessment

This section clarifies the technical approach used to select the appropriate workload assessment tool for the study and how it was utilised in the data collection process.

Although there are numerous developed tools that have been validated for human workload assessment, these tools have been structured based on a variety of situations so each method meets requirements for various conditions. Therefore, selecting the most suitable workload assessment tool was a challenging task in human factors studies.

It is important to mention that due to the characteristic of telerobotic systems operation, the human mental workload assessment is the main consideration and not human physical workload. Looking back to the project's literature review on workload, there are two methods that have promising characteristics to be used in the project's assessment part. The two workload assessments include Task Load Index (TLX) and the Subjective Workload Assessment Technique (SWAT). These two workload measurement tools have been assessed based on their sensitivity, applicability, validity, reliability, operator's acceptances, intrusiveness, ease of use and procedure in multi-tool assessment approach.

Although both workload assessment tools lay into multi-dimensional subjective measurement approaches, the selected workload assessments were NASA's Task Load Index (TLX). Comparing Subjective Workload Assessment Technique (SWAT) with TLX, the SWAT only uses three-dimensional aspect approaches, including 1) time load, 2) mental effort load, and 3) psychological stress load. Each of these dimensions has been levelled to three levels first, low level, medium, and high.

Due to the non-intrusive nature of TLX, this instrument has no effect on the actual task under analysis and more importantly, in terms of operator's acceptance or willingness to complete the workload assessment,

The NASA Task Load Index (TLX) has been structured based on a six-dimensional approach to assess the operator's mental workload, including 1) mental demand, 2) physical demand, 3) temporal demand, 4) performance, 5) effort, and 6) frustration. The rating for these six-dimensional indexes is obtained with the help of a twenty-step bipolar scale (Hart & Staveland, 1988). The tool uses a score rating approach from 0 to 100 for each scale, which is rounded to the nearest 5.

Additionally, the six TLX's aspects are paired, which generate 15 individual pairs. These pairs are weighed by the subjects in terms of their relevance to the task under analysis. Using these two data scores rating from 0 to 100 and the weighed process, the final workload level is calculated. The values obtained from the score rating in each dimension are multiplied by the number of times that the same dimension has been selected in the weighing process. All scales have been summed and then divided by 15 (individual pairs), in which the final workload is obtained. The following table shows the TLX dimensional structure.

| TITLE                    | ENDPOINTS | DESCRIPTIONS                                                                                                                                                                                                  |
|--------------------------|-----------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>MENTAL DEMAND</b>     | Low/High  | How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving? |
| <b>PHYSICAL DEMAND</b>   | Low/High  | How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?             |
| <b>TEMPORAL DEMAND</b>   | Low/High  | How much time pressure did you feel due to the rate or pace at which the task or task elements occurred? Was the pace slow and leisurely or rapid and frantic?                                                |
| <b>PERFORMANCE</b>       | Good/Poor | How successful do you think you were in accomplishing the goals of the task set by the experimenter? How satisfied were you with your performance in accomplishing these goals?                               |
| <b>EFFORT</b>            | Low/High  | How hard did you have to work (mentally and physically) to accomplish your level of performance?                                                                                                              |
| <b>FRUSTRATION LEVEL</b> | Low/High  | How insecure, discouraged, irritated, stressed, and annoyed versus secure, gratified, content, relaxed, and complacent did you feel during the task?                                                          |

Table 1 the TLX dimensional structure.

The card sorting process in SWAT is one of the factors that negatively affect the subject's acceptance and willingness to complete the workload assessment correctly (Kantowitz, 1992), which, in fact, can affect the actual workload assessment results. Although SWAT has been used in numerous studies, and it has an acceptable applicability, its sensitivity is not as strong as TLX. In the same comparison with TLX, SWAT is not the participants' preferred method (Kantowitz, 1992).

Due to the sensitivity in assessing operator workload, the instrument's applicability, participant acceptance, validity, reliability, and ease of use were thoroughly evaluated. After careful consideration, the NASA-TLX workload assessment tool was selected as part of the multi-tools assessment framework.

Due to high demand of the NASATLX workload assessment the official NASA has developed a mobile app that has reduced both the processing assessment's complexity and time

required to assess the operator's workload, therefore this experiment has taken advantages of utilising this app at the mental workload data collection stage.

After completing both the experimental task and the SART assessment, participants were asked to complete the NASA Task Load Index (NASA-TLX) workload assessment through its mobile app. The app followed the exact structure of the NASA-TLX, which consisted of two separate sections. In the initial stage, participants rated their subjective experience on six dimensions using a scale ranging from 0 to 100 with 5-point intervals. This process is illustrated in Figure 17. Once this first section was completed, participants were presented with the weighing process, which involved selecting one option from 15 individual pairs that were derived from the six dimensions of the TLX workload assessment, based on their experience. More detailed documents have been provided within the appendix section. The findings of this TLX evaluation were computed automatically and tabulated in an Excel spreadsheet, as depicted in Figure 18. This mode of data collection considerably improved the precision and dependability of the results.

Rate task experience

NAME

Participant 1

TASK

Read the user guide  
Select "User Guide" in menu and read instructions and tips for using the application.

DATE

2023-05-03 13:15

Mental Demand

How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

Very LowVery High

Physical Demand

How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

Very LowVery High

Temporal Demand

How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

Very LowVery High

Performance

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

PerfectFailure

Effort

How hard did you have to work (mentally and physically) to accomplish your level of performance?

Very LowVery High

Frustration

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Very LowVery High

CONTINUE

Figure 17 the NASATLX workload assessment the official App configuration section 1.

|    | A              | B          | C     | D        | E               | F |
|----|----------------|------------|-------|----------|-----------------|---|
| 1  | Subject name   | Jonathon   |       |          |                 |   |
| 2  | Task text:     | Read the   |       |          |                 |   |
| 3  | Date/Time:     | #####      |       |          |                 |   |
| 4  |                |            |       |          |                 |   |
| 5  | Scale name     | Raw Rating | Tally | Weight   | Adjusted Rating |   |
| 6  | Mental Dem     | 60         | 4     | 0.266667 | 16              |   |
| 7  | Physical De    | 15         | 0     | 0        | 0               |   |
| 8  | Temporal D     | 75         | 3     | 0.2      | 15              |   |
| 9  | Performance    | 20         | 5     | 0.333333 | 6.666667        |   |
| 10 | Effort         | 65         | 2     | 0.133333 | 8.666667        |   |
| 11 | Frustration    | 25         | 1     | 0.066667 | 1.666667        |   |
| 12 |                |            |       |          |                 |   |
| 13 | Overall rating | 48         |       |          |                 |   |

Figure 18 TLX data capturing & calculation procedure.

Apart from the overall workload assessment score, the NASATLX assessment also provides in depth measure of each associated dimensions including Subjects' mental demand, performance, temporal demand, effort and frustration. These obtained data have been utilised in the study to define any possible correlations as well as evaluation.

### **3.3.5 Participant's Performance Assessment**

The operator's performance level is influenced by various factors such as situation awareness, attention level, decision-making ability, workload, and other human factor issues like experience, systematic and environmental effects. Hence, it is essential to assess the operator's performance to gain an overall understanding of the system's cause and effect relationship, particularly with respect to the project's primary variable, which is the detection rate.

Several studies have highlighted the importance of assessing operator performance in telerobotic systems. For example, a study by Chen et al. (2007) demonstrated that monitoring the operator's performance level is crucial for improving the overall efficiency of telerobotic systems. Similarly, another study by Wang et al. (2018) emphasised the need to evaluate the operator's performance level to enhance the reliability and safety of the system. Understanding the subject's performance level has helped in gaining an overall understanding of the system's cause and effect relationship with respect to the detection rate (DR), which is the primary variable of the project.

The time-to-task completion approach is a non-intrusive method for measuring operator performance that is particularly applicable to the project's task and multi-tool assessment structure. It has been suggested that the time-to-task completion approach is effective in

capturing the performance of operators as they approach task completion (Steel, P. (2007). In this method, the operator's time was recorded from the start of the project's experiment until it is completed, with time recording paused when the experiment is interrupted for the SAGAT queries (Endsley & Garland, 2000). The total time for each operator was then summed at the end of the experiment to obtain their time-to-task completion. A lower time-to-task completion is considered indicative of better performance, while longer times are indicative of lower performance levels (Endsley & Garland, 2000).

After recording the time-to-task completion for all participants, the recorded times were averaged for both experiment conditions, with and without the Data Recorder, and then compared to determine the effect of the Data Recorder on the operator's performance level (Stanton et al., 2003).

### **3.3.6 Human Intelligence Quotient Assessment**

The integration of measuring participants' IQ in terms of memory, concentration, logic, visual, and verbal skills into the study's multi-tool assessment structure was motivated by two main reasons. Firstly, previous research has suggested a possible relationship between human IQ and SA (Endsley, 1995; Sternberg, R.J, 1985). Secondly, the limited research on this relationship in SA literature has prompted the need for further investigation.

Both human situational awareness and IQ are crucial components of human psychology (Endsley, 1995; Sternberg, R.J, 1985). While SA's logical structure is related to memory, concentration, logic, and visual abilities, the potential correlation between IQ and SA is not well understood. Although IQ assessment has no direct impact on the primary task under



analysis, it can provide valuable insight into the participant's psychology and enable the construction of a relationship between SA and human IQ (Endsley, 2017; Reeve et al., 2018).

To assess participants' IQ, a web-based software called MentalUP, which specialises in cognitive assessments, was used before the actual project's experiment. The assessment was divided into five distinct categories, including memory, attention, logic, visual, and verbal tasks. Participants were given a brief explanation of each task's concepts and structure before each exercise. Once all five activities were completed, the results were presented as numerical values for each task (Cole, L. (2020, September 30). *IQ test*). The flowing figure 19 demonstrate that how the outcome of this test presented.

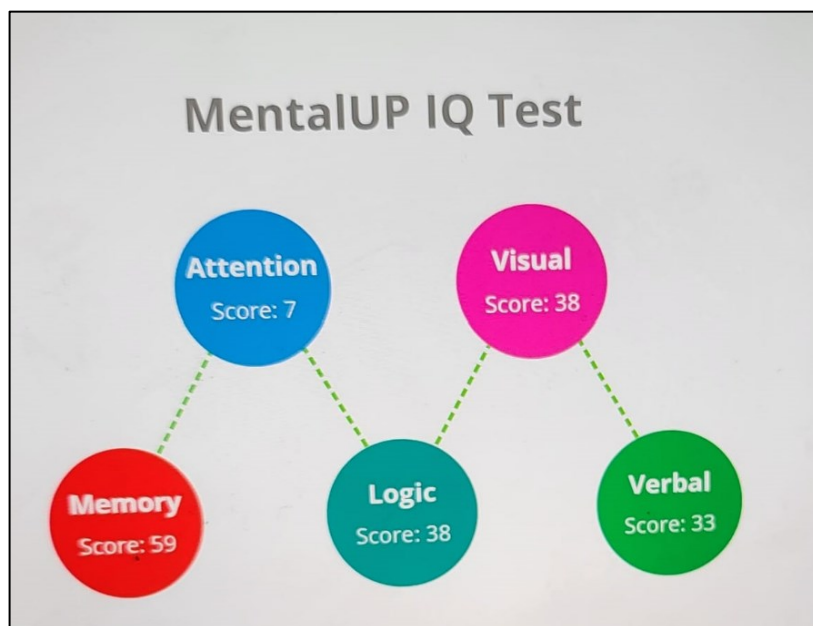


Figure 19 web-based software MentalUp outcome.

### 3.4 Data Analysis Techniques

This study analysed the impact of a Data Recorder's (DR) presence on participant performance across three difficulty levels (Easy, Medium, and Hard) by measuring 10 different variables. In each difficulty level, 10 participants were divided into two groups: one

with the DR present and one without. This resulted in a total of 30 participants and 300 variables assessed across all levels.

The independent variables were the three levels of difficulty and the presence or absence of the DR, along with the participants' Human Intelligence Quotient. The dependent variables, or Study's Obtained Variables (SOV), included workload, performance (objective and subjective), situational awareness (SAGAT and SART methods), attention level, temporal demand, effort demand, and frustration level.

The project research experiment's data which used within the data analysis process have been categorised between independent variables and obtained quantitative dependent variables that has been listed as:

The Qualitative variables. Which are independent variables.

- |                                     |   |   |
|-------------------------------------|---|---|
| 1. Level of difficulties easy       | } | 1 |
| 2. Level of difficulties medium     |   |   |
| 3. Level of difficulties hard       |   |   |
| 4. Absence of DR (circumstances 1)  | } | 2 |
| 5. Presents of DR (circumstances 2) |   |   |
| 6. Human Intelligence Quotient      |   |   |

The research's obtained quantitative variables. (These set of data called Study's Obtained Variables, SOV)

1. Workload NASATLX
2. Performance 1(Objective assessment, task completion time)
3. Performance 2(Subjective assessment, self-assessment)

4. Situational Awareness 1 (SAGAT assessment, on-line assessment)
5. Situational Awareness 2(SART method, post-trial assessment)
6. Attention level measurement (operator's signal detection performance on secondary assessment)
7. Temporal demand,
8. Effort demand
9. Frustration level.

The analysis began with Descriptive Statistics to summarize the data, followed by inferential statistics using Analysis of Variance (ANOVA) or T-Test to compare means between groups (with and without DR) for each variable. This approach aimed to determine if the DR's presence significantly affected the measured variables, providing insights into how environmental factors might influence performance outcomes. The methodology was consistent across all difficulty levels, offering a comprehensive view of the DR's influence across a spectrum of task complexities.

The analytical framework of the research is structured into three distinct sections, each focusing on different aspects of the study. Chapter Four delves into the analysis of data related to Situational Awareness (SA) and Performance metrics. This chapter aims to evaluate how participants perceive and manage information in their environment and how this awareness influences their performance outcomes.

Chapter Five shifts the focus towards examining participants' Attention levels and Mental Workload. This section is dedicated to assessing cognitive load and how participants allocate their attentional resources during tasks, providing insights into the cognitive demands placed on them.

Finally, Chapter Six explores the relationship between participants' Intelligence Quotient (IQ) and their Situational Awareness (SA). This chapter aims to identify any significant correlations between cognitive abilities, as indicated by IQ scores, and the capacity to maintain situational awareness in dynamic environments. This structure allows for a comprehensive analysis of the interplay between cognitive factors and performance in situational contexts.

## **Chapter 4**

### **Human Situational Awareness & Performance Assessment**

#### **4.1 Introduction.**

In this chapter, a thorough analysis of the collected data was conducted, focusing specifically on the measurement of subjects' Situational Awareness (SA) and Performance variables. The primary objective was to address the research questions and test the study's hypotheses, to understand the relationships, patterns, and trends observed within the dataset.

The measurement instruments and procedures used to obtain the subjects' SA and Performance data were described in detail within chapter 3. Furthermore, the reliability and validity of the measurement tools were considered to ensure that they accurately captured the desired variables. Potential challenges and limitations associated with the measurement process were acknowledged, and appropriate strategies were implemented to mitigate these issues.

The experiment's data in this chapter were subjected to a range of statistical analyses, beginning with descriptive statistics then statistical assumption and Inferential statistical tests. These analysis approaches were employed to provide a comprehensive overview of the subjects' performance levels and SA scores, allowing for the identification of key patterns and significant differences between the subject's SA and performance.

The design of the study allowed for the utilization of two independent Situational Awareness (SA) instruments: the Situation Awareness Global Assessment Technique (SAGAT) and the Situation Awareness Rating Technique (SART). While both instruments assess subjects' SA,

they focus on different aspects of SA through distinct analytical and psychological approaches (M. Salmon\*, Neville A. 2008). SAGAT primarily concentrates on information and data processing related to the experiment, while SART assesses an individual's subjective SA during task performance (P.M. Salmon et al. 39 (2009) 490–500). Consequently, each SA assessment was separately analysed, and the findings from each assessment were presented individually.

The implications of the findings related to SA and performance has been discussed in relation to the research questions and hypotheses, highlighting their significance. The strengths and limitations of the finding and statistical analyses have been addressed, and suggestions for future research to enhance the measurement of SA and performance in telerobotic-human interaction and similar concept have been provided.

Figure 20 illustrates the structural organisation of Chapter 4, outlining the key sections and their interconnections. It provides a clear overview of the chapter's progression, starting from the introduction and hypotheses, followed by the data analysis approach, and culminating in the detailed assessment of human situational awareness (SA) and performance. The figure highlights the logical flow of content, including the results and discussions for SAGAT and SART assessments, the evaluation of participant performance, and the chapter's conclusions and hypotheses discussion.

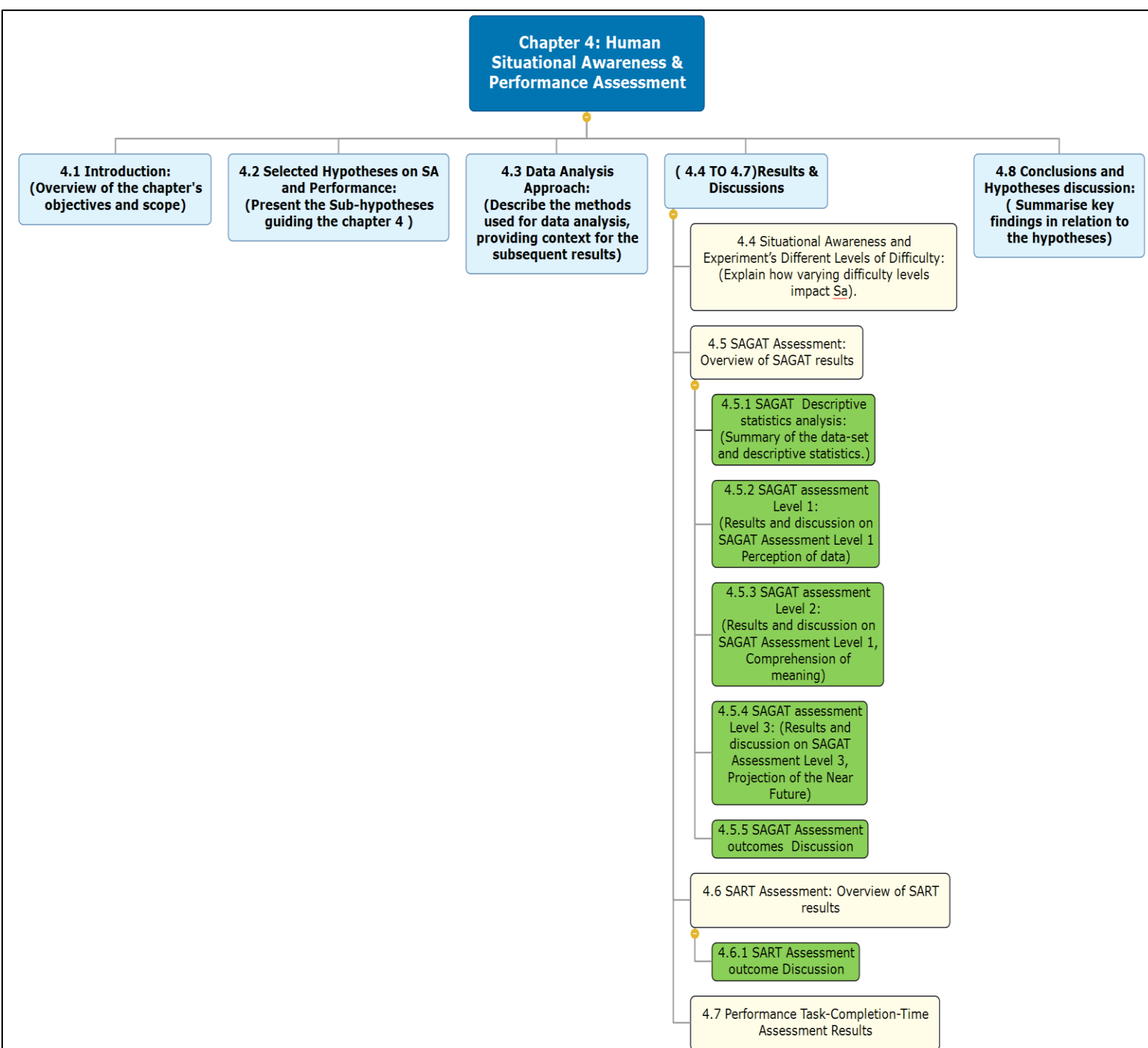


Figure 20 the structural organisation of Chapter 4

## 4.2 Selected Sub-Hypotheses on SA and Performance.

The hypotheses presented in this study establish a theoretical framework for examining and analysing the relationships between various variables. Here's a breakdown of each hypothesis:

### 1. Hypothesis 1:

- This hypothesis proposes that the use of the information verbalizing approach can significantly enhance subjects' Situational Awareness (SA) and potentially improve their performance in data collection tasks in a tele-robotic context. It suggests that employing VDR during task execution influences cognitive processing and information retention, thereby impacting SA and performance. The study aims to investigate whether verbal data recording leads to substantial differences in SA and performance when compared to Pen-and-Paper Data Recording.

### 2. Hypothesis 2:

- This hypothesis suggests that variations in the Levels of Difficulty (LOD) within the experiment can significantly affect subjects' performance, particularly in terms of Time-to-Task completion. It builds upon prior research by Jennifer M. Riley in 2001, which emphasizes the influence of LOD on performance outcomes.

### 3. Hypothesis 3:

- It is essential to note that changes in LOD within the primary experiment's task (Telerobotic task) should not significantly influence subjects' Situational



Awareness. This hypothesis focuses on the separation of LOD effects on SA from performance.

**4. Hypothesis 4:**

- Anticipated is a significant positive correlation between subjects' performance and SA results during the Telerobotic operation task within the experiment. This hypothesis aligns with previous works by Paul Salmon, Riley & Kaber, and Kaber et al., suggesting a positive relationship between performance and SA within similar contexts.

**5. Hypothesis 5:**

- Drawing from prior research by Mica R. Endsley, this hypothesis posits that scores obtained from the Situation Awareness Global Assessment Technique (SAGAT) and Situation Awareness Rating Technique (SART) assessments will not exhibit a significant correlation with each other. This is based on Endsley's findings regarding the distinct nature of these two assessment tools and their ability to capture different facets of situational awareness. SAGAT assesses the operator's awareness of task-related elements, while SART assesses the subjective level of awareness during task performance.

These hypotheses provide a theoretical framework for the investigation and analysis of the relationships between variables in the current study. They guide the interpretation of research findings and serve as a foundation for exploring the complex dynamics of situational awareness, performance, data recording methods, and levels of task difficulty in a tele-robotic context.

### 4.3 Data analysis approach

The experiment involved data collection from two controlled teams: Team One employed a Verbal Data Recording (VDR) method, while Team Two utilized a Pen-and-Paper Data Recording (PAPDR) approach. These teams participated in experiments under three different conditions, each designed with varying levels of difficulty. Experiment one was set at a high Level of Difficulty, experiment two at a medium Level of Difficulty, and experiment three at a low Level of Difficulty.

Crucially, recognizing the high sensitivity of human Situational Awareness (SA) to changes in task goals, system control and display methods (Endsley, 2000), as well as data collection techniques, no alterations were made to the task goals, system control methods, or objectives across all three experiments. This approach ensured that no additional variables or system-related factors would influence the participants' SA. The sole research intervention remained the different data collection methods employed by the operators.

This methodological consistency preserved the integrity of the experiments, allowing for a focused examination of the impact of data collection methods on SA while controlling for potential confounding factors related to task objectives and system operation.

To formally analyse the impact of the experiment's level of difficulty on participants' Situational Awareness (SA), a Multivariate Analysis of Variance (MANOVA) was conducted. The purpose of this analysis was to determine whether the combination of three independent variables, representing different levels of difficulty, had a significant effect on two dependent variables, namely, Situation Awareness Global Assessment Technique (SAGAT) and Situation Awareness Rating Technique (SART).

In this analysis, the experiments with varying levels of difficulty (Hard, Medium, and Low) served as categorical independent variables, and the results obtained from both situational awareness instruments (SAGAT and SART) were treated as continuous dependent variables. MANOVA was chosen as the statistical test to assess how these independent variables collectively influenced the dependent variables.

This approach allowed for a comprehensive examination of how changes in the experiment's level of difficulty affected participants' situational awareness, taking into account the information provided by both the SAGAT and SART instruments.

ANOVA (Analysis of Variance) is an appropriate choice for your data analysis for several reasons:

1. **Comparison Across Multiple Groups:** ANOVA is specifically designed to compare means across multiple groups or conditions. Since your study involves analysing the effects of different levels of difficulty on performance or other dependent variables, ANOVA is well-suited to determine whether statistically significant differences exist between these groups.
2. **Assumptions of Normality and Homogeneity of Variances:** The robustness of ANOVA is grounded in its assumptions of normality and homogeneity of variances. As you have rigorously tested these assumptions and applied transformations when necessary, you have ensured the method's validity for your dataset (Field, 2013).
3. **Handling Complex Experimental Designs:** ANOVA is versatile and can accommodate more complex experimental designs, such as repeated measures or factorial designs,

which are often used in studies involving human performance and workload assessments (Tabachnick & Fidell, 2019).

4. **Power and Efficiency:** Compared to non-parametric methods, ANOVA is more powerful when assumptions are met, as it uses all available data to assess differences. This makes it an efficient choice for studies requiring detailed analysis across conditions (Howell, 2010).
5. **Interpretability and Extensions:** ANOVA results are interpretable through post-hoc tests, which allow you to pinpoint which specific groups differ. Moreover, it is easily extendable to ANCOVA or mixed models if covariates or interactions need to be considered.

Both the assumptions of normality and homogeneity of variances for the ANOVA were thoroughly examined across all recorded data. In cases where the data did not meet the required assumptions, appropriate data transformation techniques were applied.

Specifically:

1. **Logarithm Transformation:** For variables that did not meet the assumptions of constant variance (homoscedasticity) and normality, a logarithm transformation was implemented. This transformation is known to stabilize variances and make data conform more closely to a normal distribution.
2. **Arcsine Transformation ( $Y=\arcsin(Y)$ ):** In instances where the data was binomial in nature, an arcsine transformation ( $Y=\arcsin(Y)$ ) was applied. This transformation is often used to normalize binomial data, which may have unequal variances or non-normal distributions.

3. **Binomial T-Test:** For further validation of the binomial data, a binomial t-test, such as the one available on the website [statology.org/effect-size](http://statology.org/effect-size), was conducted. This test helps ensure that the data is appropriately analysed and that the statistical inferences drawn are valid.

These data transformation and validation procedures were essential for meeting the underlying assumptions of the ANOVA analysis, ultimately ensuring the accuracy and reliability of the statistical results.

After confirming the impact of the experiment's level of difficulty on subjects' Situational Awareness (SA), the next step was to explore potential significant differences between the two independent teams participating in Verbal Data Recording (VDR) and Pen-and-Paper Data Recording (PAPDR). This preliminary phase of data analysis involved the following steps:

1. **Standardization of Raw Data:** The raw data sets collected from each experiment condition were standardized. This standardization process ensures that the data from different experiments and conditions can be meaningfully compared. It involves transforming the data to have a common scale, often with a mean of 0 and a standard deviation of 1.
2. **Descriptive Statistics:** Descriptive statistics were applied to the standardized data. This included calculating measures of central tendency, such as the Mean (average), Median (middle value), and Standard Deviation (a measure of data spread).
3. **Quantitative Summary and Analysis:** The standardized data were subjected to a quantitative summary and analysis. This process involved a thorough examination of the data to identify patterns, trends, and differences between the VDR and PAPDR teams.

4. **Tabular and Graphical Presentation:** The results of the analysis were presented in both tabular and graphical forms. Tabular formats offer a structured presentation of data, while graphical representations, such as charts and plots, provide visual insights into the findings.
5. **Adherence to Best Practices:** Throughout this phase, best practices in data analysis, as established by experts like G. Geoffrey Vining and Scott M. Kowalski, 2011, were followed to ensure the integrity and rigor of the analysis.

This meticulous data analysis process allowed for a comprehensive exploration of potential differences between the two independent teams, shedding light on how data recording methods (VDR and PAPDR) may influence subjects' SA under varying levels of experiment difficulty.

The selection of appropriate statistical methods for data analysis involved a systematic and rigorous approach. The standardized data, obtained from both scenarios (Verbal Data Recording - VDR and Pen-and-Paper Data Recording - PAPDR), underwent a thorough examination to assess their suitability for the chosen inferential statistical tests, such as Analysis of Variance (ANOVA) and t-tests. Here's a breakdown of the process:

1. **Data Screening:**

- The standardized data were carefully screened to evaluate their appropriateness for statistical analysis.

2. **Assumption Testing:**

- The sample data from each scenario (VDR and PAPDR) were subjected to various assumption tests. These tests assessed:
  - Normality: Ensuring that the data followed a normal distribution.

- Homoscedasticity: Checking for consistent variance of residuals across data points.
- Equality of Variances: Verifying that variances were comparable between scenarios.

### 3. Addressing Limitations:

- This rigorous testing was conducted to address potential limitations and sensitivity issues associated with standard inferential analysis, particularly regarding factors such as data sample size, measurement errors, and assumptions violations in t-tests.

### 4. Final Stage:

- The final stage of the analysis encompassed a comprehensive discussion and conclusion of the data outcomes. This phase also involved an examination of correlations within the data.

The systematic and sequential approach to data analysis aimed at achieving a comprehensive understanding of the study's intervention, specifically focusing on operators' Situational Awareness and Performance. It ensured that the selected statistical methods were applied to data that met the necessary assumptions, enhancing the reliability and validity of the research findings.

## Results & Discussions

### 4.4 Situational Awareness and Experiment's Different Level of difficulties

The study employed one-way Multivariate Analysis of Variance (MANOVA) to thoroughly investigate the impact of three distinct levels of experimental difficulty (Hard, Medium, and Low) on two specific situational awareness assessment tools, namely the Situation Awareness Global Assessment Technique (SAGAT) and the Situation Awareness Rating Technique (SART). These assessments were conducted using both Oral Data Recording (ODR) and Pen-and-Paper Data Recording (PPDR). the **Independent Variables (IVs)** and **Dependent Variables (DVs)** can be identified as follows:

#### **Independent Variables (IVs):**

- **Levels of Experimental Difficulty:** Hard, Medium, and Low.
- **Data Recording Methods:** Oral Data Recording (ODR) and Pen-and-Paper Data Recording (PPDR).

#### **Dependent Variables (DVs):**

- **Situational Awareness Assessment Tools:** Scores or outcomes from the Situation Awareness Global Assessment Technique (SAGAT) and the Situation Awareness Rating Technique (SART).

The results of this rigorous analysis revealed that variations in the levels of difficulty in the experiments did not have a statistically significant impact on the participants' Situational



Awareness. The statistical data indicated a lack of significance, with  $F(2, 28) = 1.5965$  and  $p = 0.1267$ , as determined using Wilk's Lambda.

Wilks' Lambda is a statistical measure used in Multivariate Analysis of Variance (MANOVA) to assess the overall effect of one or more independent qualitative variables (in this case, levels of task difficulty) on multiple dependent quantitative variables simultaneously.

The absence of significant effects in the levels of task difficulty can be attributed to two primary factors. First, meticulous attention was given to experiment design to minimize the influence of extraneous variables on the operator's Situational Awareness. Consequently, variations in the task's Level of Difficulty (LOD) were carefully controlled to maintain consistency in the task's objectives across all levels. Only the distance and the number of data collection points were manipulated to adjust the task difficulty while preserving the task's core objectives. Additionally, there were no changes in the format of the data presentation to operators, and the system's display remained constant throughout task execution in all three levels of Difficulty.

Secondly, the outcome may be attributed to the absence of a significant correlation between participants' Situational Awareness and the experiment's Levels of Difficulty. It is crucial to emphasize that the results strongly suggest that participants maintained a consistent level of attention and Situational Awareness throughout all three experiments, irrespective of the variations in task difficulty. This indicates the robustness of operator SA across different task complexities in the tele-robotic context.

## 4.5 SAGAT Assessment

The present section focuses on the analysis of the initial recorded data obtained from the Situation Awareness Global Assessment Technique (SAGAT) assessment. The objective of this analysis is to examine the outcome scores for each of the three levels of the SAGAT assessment: Level 1 (perception of data), Level 2 (comprehension of meaning), and Level 3 (projection of the near future).

The computation of SAGAT scores traditionally involves assessing participants' responses to relevant questionnaires and assigning a value of 1 for correct answers and 0 for incorrect ones (Salmon, Paul M. Stanton, Neville A. Walker 2009). However, this approach generates binomial results, which can pose challenges for analysis of variance. In the present study, a similar methodology was adopted, but with a modification. Correct responses were assigned ten (10) credits, while total incorrect responses received 0 credits. If the operator's answer fell within an acceptable tolerance of the correct answer but was not 100% correct, 5 credits were assigned to that particular question. This approach was chosen to ensure consistency across different assessment tools used in data analysis and to reduce the complexity of dealing with absolute errors. This alignment aimed to enhance the interpretability and comparability of the data, simplify the analytical process, reduce the effects of sample size, handle outliers, and facilitate correlation analysis (Hair, J.F et al, 2019).

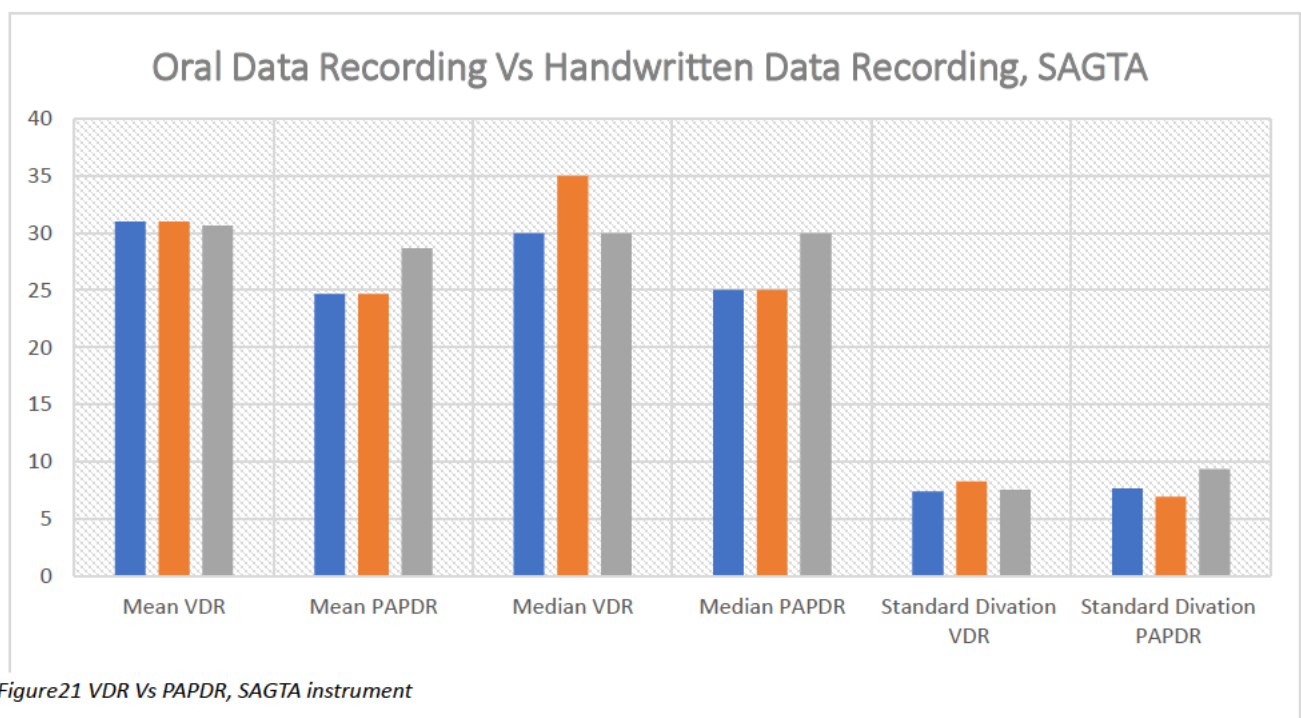
The accuracy of participants' responses on the SAGAT questionnaire was determined by comparing their answers with the predefined tasks and signals presented during the tele-robotic tasks across varying levels of difficulty within each experiment. This method of computation allowed for the assessment of the congruence between participants' responses

and the anticipated outcomes of the tele-robotic tasks, providing a quantifiable measure of the alignment between their perceived situational awareness and the actual task demands.

### 4.5.1 SAGAT Descriptive statistics analysis

Descriptive statistics were separately conducted for two data recording methods: Verbal Data Recording (VDR) and Pen-and-Paper Data Recording (PAPDR). Figure 21 provides a comparison of scores across SAGAT's Level 1, Level 2, and Level 3 for both data recording methods. This visual representation emphasizes the differences in median, mean, and standard deviation scores between VDR and PAPDR. Furthermore, this analysis of the data in both experimental conditions offers valuable insights into patterns, trends, and variations between the two methods.

Notably, the initial multivariate comparative analysis of the experimental data suggests that Verbal Data Recording has a positive influence on participants' Situational Awareness, particularly in relation to human Situational Awareness as measured by SAGAT.



Upon closer examination of the data values, it becomes evident that participants in the Oral Data Recording experiment achieved better outcomes compared to those in the Pen-and-Paper Data Recording experiment. This observation underscores the potential advantages of using the Verbal Data Recording approach in enhancing participants' Situational Awareness.

#### **4.5.2 SAGAT assessment Level 1, (Perception of data)**

To choose the appropriate data analysis method for the SAGAT Level 1 assessment data from both experimental groups, Verbal Data Recording (VDR) and Pen-and-Paper Data Recording (PAPDR), the data was standardized through Descriptive Statistics and central tendency statistics. This standardization process aimed to provide insights into the distribution of scores data for analysis.

As part of this data analysis, the median score was determined, representing the middle value of the data distribution. The median score for all subjects in the Pen-and-Paper Data Recording experiment was 25, while a median score of 30 was recorded from the Oral Data Recording (ODR) dataset.

In addition to the median score, the mean score was computed, which further offers insights into the central tendencies of the Situational Awareness (SA) scores under the two different conditions. The computed mean values are 31 for Oral Data Recording (ODR) and 24.67 for Pen-and-Paper Data Recording (PAPDR). These mean scores provide a measure of the average SA performance for participants using each data recording method and facilitate a comparison between the two approaches.

Furthermore, the analysis also took into account the dispersion or spread of the data, known as the standard deviation (SD). The standard deviation provides insights into the average

amount of deviation of individual scores from the mean values, reflecting the variability in the data.

The computed standard deviation for Oral Data Recording (ODR) was 7.36, while for Pen-and-Paper Data Recording (PAPDR), it was 7.67. These standard deviation values indicate the extent of variability in SA scores for each data recording method. A lower standard deviation typically suggests that the scores are closely clustered around the mean, while a higher standard deviation indicates greater variability or spread in the data.

To ensure the selection of an appropriate statistical data analysis method, tests for data normality and homoscedasticity of the residuals were conducted. The results revealed that the data from Oral Data Recording (ODR) does not follow a normal distribution based on the Shapiro-Wilk test shown in table 2. In contrast, the data set obtained from Pen-and-Paper Data Recording (PAPDR) is normally distributed.

Table 2 Normality test SAGAT L1

| Shapiro-Wilk test           | SAGTA L1, Verbal Data<br>Recording | SAGTA L1, Pen-And-Paper<br>data recording |
|-----------------------------|------------------------------------|-------------------------------------------|
| <b>W</b>                    | <b>0.878</b>                       | 0.968                                     |
| <b>p-value (Two-tailed)</b> | <b>0.044</b>                       | 0.828                                     |
| <b>alpha</b>                | 0.05                               | 0.05                                      |

The results from the Shapiro-Wilk tests are shown in the data tables above. According to the outcome of the Shapiro-Wilk test for the data from SAGAT Level 1, Verbal Data Recording (VDR), it is evident that the sample data deviates from a normal distribution. The primary outcome of the Shapiro-Wilk test, specifically the test statistic (W), was not sufficiently close

to the value of 1, and its associated p-value was found to be 0.044. These results led to the rejection of the null hypothesis, indicating that the data is not normally distributed.

Given the non-normal distribution and the observed right-skewness in the data, a Log Transformation was chosen and applied to the VDR dataset. This transformation was carried out to normalize the data and ensure that it meets the assumptions required for the selected statistical analysis.

The statistical Levene's test was employed to assess the equality of variances between the two groups. The results from this test were used as a preliminary analysis before conducting and selecting the inferential statistical tests. The test results are presented in Table 3, where the calculated f-ratio value is 0.0065, and the p-value is 0.936296. The non-significant p-value, which is greater than 0.05, indicates that there is no significant difference in variances between the two groups.

Therefore, based on the results of Levene's test, the assumption of homogeneity of variances is met for these data sets. This was an important consideration when selecting and conducting inferential statistical tests, as it ensured that the variances of the groups being compared are approximately equal.

*Table 3 Homogeneity test SAGAT L1*

| Result Details     |          |    |        |              |
|--------------------|----------|----|--------|--------------|
| Source             | SS       | df | MS     |              |
| Between-treatments | 0.1333   | 1  | 0.1333 | $F = 0.0065$ |
| Within-treatments  | 574      | 28 | 20.5   |              |
| Total              | 574.1333 | 29 |        |              |

As per the nature of the experiment's data and the research objectives, a two-sample T-Test was chosen to analyse the data from SAGAT assessment Level 1. This method was selected due to its suitability for small sample sizes, wide acceptance, and simplicity (please provide the reference).

The independent samples t-test compared the test scores between the Oral Data Recording method (mean = 31) and the Pen-and-Paper Data Recording approach (mean = 24.67). The t-statistic was found to be significant at  $t(28) = 2.30$ , with a p-value of 0.029.

This significant result suggests that there is a statistically significant difference in test scores between the two data recording methods, with Oral Data Recording yielding higher scores on average compared to Pen-and-Paper Data Recording. This confirmed that the participants who utilized the Oral Data Recording method exhibited a significant improvement in Level 1 (perception of data) compared to those who employed the PAPDR approach. This finding highlights a substantial enhancement in participants' ability to perceive and interpret data while executing the study's experiment (SAGAT Level 1).

#### **4.5.3 SAGAT assessment Level 2, (Comprehension of meaning)**

A similar data analysis approach was applied to SAGAT assessment Level 2 to identify differences between the experiment's groups. Initially, the raw data was standardized through descriptive statistics, which included computing essential elements such as the mean, median, and standard deviation. The summary of the descriptive statistics for SAGAT assessment Level 2 data is presented in Table 4.

Table 4 Data summery SAGAT L2

| Variable        | Observation<br>s | Obs.<br>with<br>missin<br>g data | Obs.<br>withou<br>t<br>missing<br>data | Minimu<br>m | Maximu<br>m | Mean  | Std.<br>deviatio<br>n |
|-----------------|------------------|----------------------------------|----------------------------------------|-------------|-------------|-------|-----------------------|
| SAGTA L2<br>ODR | 15               | 0                                | 15                                     | 15.00       | 40.00       | 31.00 | 8.28                  |
| SAGTA L2<br>HDR | 15               | 0                                | 15                                     | 15.00       | 40.00       | 24.67 | 6.94                  |

Table 5 SAGAT L2 Normality test

| Shapiro-Wilk test    | SAGTA L1, Verbal Data<br>Recording | SAGTA L1, Pen-And-Paper<br>data recording |
|----------------------|------------------------------------|-------------------------------------------|
| W                    | 0.894                              | 0.927                                     |
| p-value (Two-tailed) | 0.078                              | 0.243                                     |
| alpha                | 0.05                               | 0.05                                      |
| p-value (Two-tailed) | 0.078                              | 0.243                                     |
| alpha                | 0.05                               | 0.05                                      |

The data normalization test was conducted using the Shapiro-Wilk test, which was applied to data from both groups, the VDR and PAPDR. The results of the Shapiro-Wilk test are presented in Table 5. The computed Shapiro-Wilk test p-values for both groups are greater than the selected significance level alpha (0.05). This outcome leads to the conclusion that both sets of residuals follow a normal distribution.

Homoscedasticity tests of the residuals were conducted using Levene's tests for all the dependent variables. This test confirmed the homoscedasticity of the residuals in the obtained data sets, with a significant p-value of 0.248666 and an f-ratio value of 1.38796.

The result is not significant at  $p < 0.05$ , which confirms that the requirement of homogeneity



for the data from SAGAT assessment Level 2 is met. The Levene's test summary is presented in Table 6.

Table 6 Homoscedasticity tests SAGTA L2

| Levene's test Result Details |          |    |         |               |
|------------------------------|----------|----|---------|---------------|
| Source                       | SS       | df | MS      |               |
| Between-treatments           | 26.1333  | 1  | 26.1333 | $F = 1.38796$ |
| Within-treatments            | 527.2    | 28 | 18.8286 |               |
| Total                        | 553.3333 | 29 |         |               |

After conducting a comprehensive analysis of the data, it has been established that the experiment results exhibit a parametric structure, satisfying the assumptions of normality and homoscedasticity. This confirmation of parametricity supports the use of the two independent samples t-test with a selected significance level ( $\alpha=0.05$ ).

The results from the two-sample t-test between the two experiment groups indicated a significant difference, with the Oral Data Recording methods (mean = 31) and the Pen-and-Paper Data recording approach (mean = 24.67). The t-statistic was found to be  $t(28) = 2.27$ , with a p-value of 0.031.

The significant difference of the T-test has confirmed that the participant's Data Comprehension of meaning can significantly improve through Oral Data Recording method compared to Pen-And-Paper Data Recording approach.

#### 4.5.4 SAGAT assessment Level 3 (projection of the near future)

Similarly, the same data analysis approach used for SAGAT L1 and L2 was applied to analyses SAGAT L3 in both telerobotic experimental conditions. The initial descriptive data summary, including essential data elements for the raw data from SAGAT L3, has been recorded in Table 7.

Table 7 Summary statistics SAGAT L3

| Summary statistics SAGAT L3 |              |                        |                           |         |         |        |                |
|-----------------------------|--------------|------------------------|---------------------------|---------|---------|--------|----------------|
| Variable                    | Observations | Obs. with missing data | Obs. without missing data | Minimum | Maximum | Mean   | Std. deviation |
| SAGTA L3 ODR                | 15           | 0                      | 15                        | 20.000  | 40.000  | 30.667 | 7.528          |
| SAGTA L3 HDTR               | 15           | 0                      | 15                        | 10.000  | 40.000  | 28.667 | 9.348          |

Table 8 SAGAT L3 Normality test

| Shapiro-Wilk test    | SAGTA L3, Oral Data<br>Recording | SAGTA L3, Pen-And-Paper<br>data recording |
|----------------------|----------------------------------|-------------------------------------------|
| W                    | 0.886                            | 0.932                                     |
| p-value (Two-tailed) | 0.058                            | 0.287                                     |
| alpha                | 0.05                             | 0.05                                      |

In addition, the normality of both data sets has been tested using the Shapiro-Wilk test, which confirmed that both data sets from ODR and PAPDR are normally distributed. The summary of the Shapiro-Wilk test results is recorded in Table 9. The test outcomes show

that the p-values (Two-tailed) are greater than the selected significance level  $\alpha=0.05$ , indicating that both data sets follow a normal distribution.

The Levene's test was conducted to assess the homoscedasticity of the residuals for SAGAT assessment (Level 3). The test revealed that the homoscedasticity of data for both groups met the requirement, as indicated by an f-ratio value of 0.77088 and a p-value of 0.387418, which is not significant at  $p < 0.05$ . This confirms that the assumption of homogeneity is met for the data.

*Table 9 Homoscedasticity test ASGAT L3*

| The Levene's test Result Details |          |    |         |               |
|----------------------------------|----------|----|---------|---------------|
| Source                           | SS       | df | MS      |               |
| Between-treatments               | 16.1333  | 1  | 16.1333 | $F = 0.77088$ |
| Within-treatments                | 586      | 28 | 20.9286 |               |
| Total                            | 602.1333 | 29 |         |               |

Based on the preliminary statistical tests that substantiated the underlying assumptions for the two-sample T-Test and the adopted data analysis framework within this research, the findings reveal that there exists no statistically significant disparity between the outcomes achieved by participants employing the Oral Data Recording (ODR) method, characterized by a mean score of 30.667, and those using the Pen-and-Paper Data Recording (PAPDR) approach, with a corresponding mean score of 28.667. This conclusion is supported by the t-statistic result,  $t(28) = 2.08$ , and a p-value of 0.524.

The results derived from the statistical analysis of SAGAT assessment Level 3 offer a pivotal insight. Despite the observable enhancement in participants' Data Comprehension, particularly their interpretation of the conveyed information, with the utilization of Verbal

Data Recording (VDR), this data recording modality has not elicited any significant alteration in subjects' Situational Awareness, particularly in terms of their ability to foresee and project future events within the domain of the telerobotic task.

#### **4.5.5 SAGAT Assessment outcomes Discussion**

The outcomes of the SAGAT assessments provide substantial support for the hypothesis 1 positing that the practice of Oral Data Recording yields a noteworthy enhancement in Situational Awareness (SA). Interestingly, this significant effect was consistently observed in both SAGAT Level 1, pertaining to the perception of data, and SAGAT Level 2, focused on the comprehension of data meaning. However, when examining SAGAT Level 3, which delves into the projection of future events, the results indicate no substantial improvement or significant effect.

Several factors may contribute to this observed disparity in participants' ability to project the near future (SAGAT Level 3). Primarily, it is likely that participants needed to concentrate more attentively to identify relevant data indicators and monitor the actual robot's manoeuvres during the execution of the telerobotic task. Additionally, the inherent complexity of the telerobotic task and the concurrent secondary monitoring task may have constrained participants' capacity to adapt and discern patterns within the data indicators, thereby impeding their ability to project future events effectively.

In summary, it is imperative to recognize that this study primarily sought to investigate the impact of Oral Data Recording when compared to Pen-And-Paper Data Recording. While the findings suggest a significant influence on the perception and comprehension of data, further investigations are warranted to delve into the specific mechanisms underlying the

absence of a comparable effect on participants' ability to project the near future in similar context.

## 4.6 SART Assessment

The preliminary phase of data analysis entailed the standardization of raw data acquired from the Situational Awareness assessment, employing the Situation Awareness Rating Technique (SART). This analysis was focused on data collected within the two distinct experimental conditions, namely Oral Data Recording and Pen-And-Paper Data Recording.

The process commenced with the standardization of the raw SART data, wherein the appropriate equation ( $SA = U - (D - S)$ ) was applied to formalize the data. Subsequently, this formalized data underwent a comprehensive statistical analysis. SART scores for the participants were computed using the methodology proposed by Taylor (1990). In this approach, the participants' scores from the SART questionnaire were derived using the formula  $SA = U - (D - S)$ , where:

- SA represents the numerical value of the participant's Situational Awareness.
- U corresponds to the sum of scores from questions related to Understanding.
- D signifies the aggregated scores of questions related to Demand.
- S denotes the accumulated scores of questions concerning Supply.

This scoring method was selected for its alignment with established practices and its facilitation of the quantification and evaluation of participants' Situational Awareness levels based on their responses to the SART questionnaire.

This analysis followed a sequential approach that encompassed initial descriptive statistics, a rigorous examination for data normality, and an assessment of homoscedasticity. The objective was to ascertain the data's conformance to the required assumptions and, subsequently, to determine the suitability of an inferential statistical test for further analysis.

#### **4.6.1 Descriptive statistics analysis on SART**

These descriptive statistics, which encompass measures of central tendency such as the median and mean, along with measures of variability like variance and standard deviation, provide a comprehensive overview of the SART assessment scores. They offer valuable insights into the distribution of scores, the typical performance level, and the extent of variability among the participants.

The descriptive data analysis uncovered that the median score for Situational Awareness (SA) was 50, signifying the central value of the data distribution. The mean score slightly exceeded 47.27, representing the average SA assessment score for data obtained from the Oral Data Recording method. In contrast, the median and mean values acquired from Pen-And-Paper Data Recording were recorded as 42 and 40.73, respectively. These statistics reflect the central tendencies and performance levels of the participants in each data recording condition. Table 10 covers the summary of the SART statistics for both experiment's circumstances ORDR and PAPDR.

Table 10 Summery of Descriptive statistic, SART

| Summary statistics SART |                  |                           |                              |         |             |       |                   |
|-------------------------|------------------|---------------------------|------------------------------|---------|-------------|-------|-------------------|
| Variable                | Observation<br>s | Obs. with<br>missing data | Obs. without<br>missing data | Minimum | Maximu<br>m | Mean  | Std.<br>deviation |
| VDR                     | 15               | 0                         | 15                           | 30.00   | 59.00       | 47.27 | 8.39              |
| PAPDR                   | 15               | 0                         | 15                           | 30.00   | 50.00       | 40.73 | 6.49              |

To evaluate the data's variability, an analysis of variance was performed, yielding a variance of 14.160. This statistic provides valuable insights into the spread or dispersion of the Situational Awareness (SA) scores. Additionally, the standard deviation was meticulously calculated, resulting in a value of 8.388 for the Oral Data Recording group and 6.486 for the Pen-and-Paper Data Recording group. These standard deviations serve as indicators of the average deviation of individual SA scores from their respective means, further illustrating the variability within the data.

Furthermore, the dataset was subjected to a range analysis, disclosing that SA scores ranged from a minimum of 30 to a maximum of 59. This extensive range emphasizes the breadth of SA assessment scores captured within the Situation Awareness Rating Technique (SART) assessment.

In a concerted effort to ensure the data met the essential statistical assumptions, tests were conducted for normality and homoscedasticity of the residuals. These assessments were carried out employing the Shapiro-Wilk test and the Levene's test, respectively. The outcomes of these evaluations revealed that the data derived from both experimental conditions exhibited normal distribution characteristics. Moreover, the tests affirmed the

fulfilment of the homogeneity requirement, with an f-ratio value of 0.32636 and a non-significant p-value of 0.572368, thereby meeting the predefined significance level of  $p < 0.05$ .

In light of the confirmation of normality and homoscedasticity of the residuals, it can be reasonably deduced that the prerequisite conditions for executing a two-independent-samples T-test have been met. The selection of this inferential statistical test, renowned for its applicability and benefits, was warranted to assess the significant effect of Oral Data Recording on participants' Situational Awareness. The test outcomes conclusively established that Oral Data Recording had a substantial impact, as evidenced by a  $t(28)$  value of 2.27 and a statistically significant p-value of 0.024.

#### **4.6.2 SART Assessment outcome Discussion**

The statistical significance observed in the Situation Awareness Rating Technique (SART) was further substantiated by the conclusive outcomes obtained from the Situation Awareness Global Assessment Technique (SAGAT), particularly concerning the results acquired at Level 1 of the SAGAT assessment. This robust correlation between the SART results and the Level 1 assessment in the SAGAT serves to reinforce the credibility and reliability of the findings from the SART assessment.

As articulated by Endsley (1995b) with strong empirical support, there exists a substantial connection between participants' performance and their SART outcomes. This intricate relationship between the SART outcome and participants' performance levels has been thoroughly examined in our extensive analysis of subjects' performance. It is worth noting, however, that such a correlation between the SART and participants' performance levels



may present certain intricacies. The individual participants' susceptibility to the experimental conditions can engender a scenario where their assessment of the SART evaluation mirrors their actual task performance. In simpler terms, those who perform well may assign higher ratings to the SART assessment, while those who perform sub optimally may assign lower ratings.

To elucidate this relationship and address concerns about the potential influence of task performance on participants' SART assessments, a comprehensive correlation analysis between the SART and the SAGAT methods was executed. The aim was to ascertain whether participants' SART assessments are exclusively swayed by their task performance or if they genuinely reflect their SA. Nevertheless, it is imperative to acknowledge that due to the intrinsic nature of the SART assessment, it may not be entirely feasible to disentangle the SART outcome from the subjects' task performance. However, establishing a discernible connection with the SAGAT assessment Level 1 can be perceived as a valuable indicator of the SART instrument's enhanced accuracy in measuring SA.

## **4.7 Performance Task-Completion-Time Assessment Results**

Participants' performance was rigorously evaluated using a measure known as Task-Completion-Time, which entailed recording the time taken by each individual to successfully complete the telerobotic task in both experimental conditions, specifically Oral Data Recording (ODR) and Pen-and-Paper Data Recording (PAPDR), across various levels of experimental difficulty.

The primary objective in this phase was to investigate whether variations in the experiment's Level of Difficulty (LOD) exerted a statistically significant impact on the participants'

performance. To address this, the three distinct levels of experimental difficulty were selected as independent variables, while the participants' performance was designated as the dependent variable under scrutiny.

The chosen statistical technique for this assessment was the Multivariate Analysis of Variance (MANOVA), a robust method that facilitates the examination of how a dependent variable (performance) is influenced by several independent variables (LOD). To ensure the validity of the MANOVA, critical assumptions, such as the homogeneity of variances, were rigorously tested prior to conducting this statistical analysis.

The outcomes stemming from the Multivariate Analysis of Variance (MANOVA) conducted in this study unveiled a statistically significant difference among the experimental groups. The observed result was evident in the Wilks' Lambda statistic, which yielded a value of 0.85, along with an associated F-statistic of  $F(1, 28) = 4.15$ , and a p-value of less than 0.05. Furthermore, the effect size, as denoted by the partial eta squared ( $\eta^2 = 0.15$ ), revealed a noteworthy impact.

This statistical discovery suggests that the variations in the experiment's different levels of difficulty indeed had a substantial influence on the participants' task performance. In essence, while adhering to the fundamental teleoperator task concept, the manipulation of the number of indicators and their spatial distribution directly affected the cognitive abilities and task execution of the participants.

In scenarios where participants were tasked with acquiring additional data, particularly in the more challenging experiment levels, it required the robots to engage in more extensive manipulation. Nonetheless, a thorough examination of participants' Situational Awareness (SA) in conjunction with the levels of experiment difficulty (LOD) revealed a consistent

pattern. Irrespective of the fluctuations in experiment difficulty levels, there was no observable impact on participants' SA.

These findings offer valuable insights into the intricate interplay between task complexity, robot manipulation, and cognitive performance. They enhance our comprehension of how modifications in experimental conditions can affect participants' task performance while leaving their Situational Awareness unaffected. Consequently, these insights contribute to a deeper understanding of the dynamics involved in human-robot interaction across various levels of task complexity.

## **4.8 Conclusions and Hypotheses discussion**

This section encapsulates the research's concluding remarks in line with the initial hypotheses set forth in Chapter 4, focusing on participants' Situational Awareness (SA) and performance.

After evaluating subjects' SA in two distinct experimental conditions, namely Verbal Data Recording (VDR) and Pen-and-Paper Data Recording (PAPDR), several key conclusions have emerged. Firstly, it has been determined that participants' Situational Awareness remained unaffected by variations in the experiment's Level of Difficulty, in accordance with the third hypothesis outlined in Chapter 4. This observation can be primarily attributed to the consistency maintained in the experimental goals, subgoals, and telerobotic control strategies across different levels of difficulty.

Moreover, the statistical analysis has revealed a significant enhancement in subjects' SA when comparing VDR to PAPDR, indicating that Oral Data Recording can augment participants' cognitive abilities. However, it is worth noting that, as per the Situation

Awareness Global Assessment Technique (SAGAT) Level 3 assessment, there was no significant disparity between the participants' ability to project the near future in both experimental conditions.

The SA assessment results corroborate the initial hypothesis suggesting that Verbal Data Recording can indeed enhance participants' Situational Awareness. It is essential to acknowledge that, due to the nature of the participant grouping in the experiment and the significant influence of the experiment's Level of Difficulty on participants' performance, a formal assessment of the effect of Oral Data Recording on participants' performance based on Task Completion Time was not feasible. Nonetheless, this outcome aligns with the second hypothesis, indicating that the experiment's Level of Difficulty significantly impacts participants' performance. Further research will be required to comprehensively evaluate the influence of Oral Data Recording in comparison to other data recording methods.

Lastly, concerning the fifth hypothesis, it is evident that the outcomes of the Situation Awareness Global Assessment Technique did not exhibit a significant correlation with the Situation Awareness Rating Technique assessment SART. Notably, the close correlation observed between SART and SAGAT Level 1 may be attributed to the nature of the SART instrument, which assesses subjective levels of awareness during task performance and demonstrates an outcome that corresponds to participants' task performance during the execution of the telerobotic task. These findings underscore the unique characteristics of these two assessment tools, emphasizing their capacity to capture different facets of situational awareness within the experimental context (Paul M. Salmon\*, Neville A. 2008).

## **Chapter 5**

### **Assessment of participants' attention & Mental Workload level**

#### **5.1 Introduction**

Chapter five is dedicated to the evaluation of participants' attention levels and mental workload under two distinct experimental conditions: Verbal Data Recording (VDR) and Pen-And-Paper Data Recording (PAPDR). Participants in these experimental conditions engaged in a telerobotic task, navigating through three levels of difficulty. Furthermore, the chapter aims to assess the impact of the task's level of difficulty on participants' attentional levels and mental workload.

The evaluation of participants' attention levels in the primary experimental task (the telerobotic task) was conducted by analysing the operators' signal detection performance in a secondary assessment. This secondary task, designed concurrently with the main experiment, served the specific purpose of gauging participants' attention levels. A comprehensive delineation of the entire procedure related to the secondary task, employed to measure subjects' attention levels, is provided in Chapter 3, Section 3.3.3.

Concerning the evaluation of participants' mental workload, the NASA Task Load Index (NASA TLX) was employed, representing a multi-dimensional subjective measurement tool. This non-distributive instrument underwent scrutiny for its appropriateness and validity in alignment with the overall project's experiment. A comprehensive elucidation of the NASA TLX's procedural details and data collection approach is available in Chapter 3, Section 3.3.4.

The data in this chapter underwent a series of statistical analyses. Initial steps included descriptive statistics, followed by tests assessing statistical assumptions, and subsequently, the application of inferential statistical tests. These analyses were conducted to furnish a thorough portrayal of participants' Attention Levels and mental workload scores, allowing for the discernment of crucial patterns and noteworthy distinctions between experimental conditions.

Moreover, the outcomes of Chapter 5 were leveraged to address research questions and test hypotheses pertinent to the assessment of participants' attention levels and mental workload. This process facilitated a nuanced understanding of the relationships, patterns, and trends inherent in the dataset and across various experimental conditions.

Figure 22 outlines the structure of Chapter 5, providing a detailed overview of its key sections and their organisation. It begins with an introduction explaining the chapter's objectives and scope, followed by the selected hypotheses and data analysis approach. The central portion focuses on results and discussions, including assessments of attention allocation, descriptive statistics, operator attention and Levels of Difficulty (LOD), and variations in data recording procedures. Finally, the chapter concludes with a discussion of the findings in relation to the hypotheses.

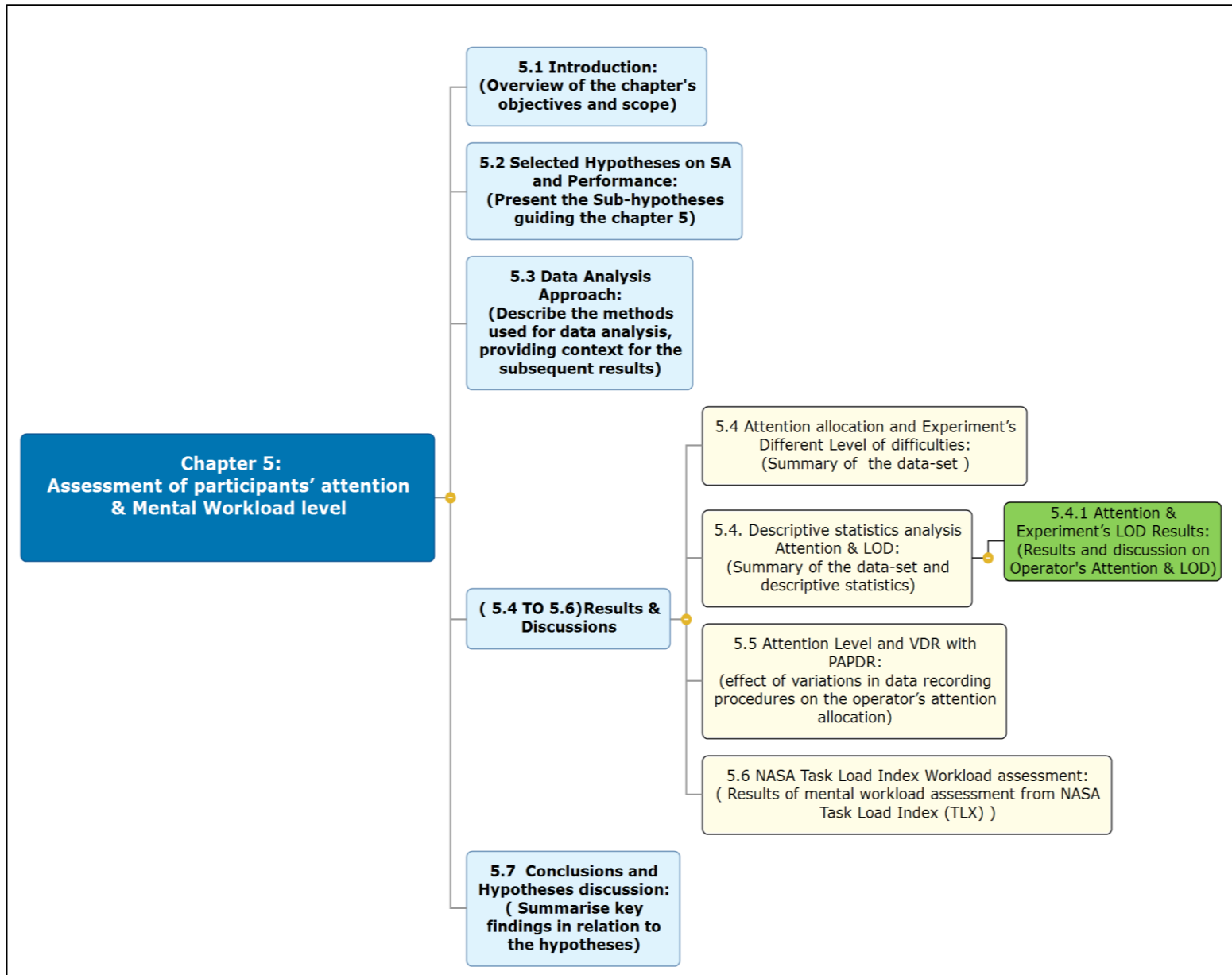


Figure 22 outlines the structure of Chapter 5

## 5.2 Selected Sub-Hypotheses on Attentional and mental workload levels

The hypotheses articulated in Chapter Five have established a theoretical framework for the systematic examination and analysis of relationships among various variables, including

attentional levels concerning the research intervention and participants' mental workload.

The breakdown of each hypothesis is as follows:

**1. Hypothesis 1:**

- This hypothesis posits that the utilization of the VDR approach can significantly diminish participants' attentional levels in the secondary task and potentially alleviate their mental workload.

**2. Hypothesis 2:**

- A higher signal detection score in the secondary task signifies that the operator allocates less attention to the telerobotic task, while a lower score indicates greater attention to the primary task. This hypothesis explores the relationship between signal detection scores and the distribution of attention.

**3. Hypothesis 3:**

- This hypothesis suggests that variations in the Levels of Difficulty (LOD) within the experiment can exert a significant impact on subjects' mental workload. It probes the correlation between task difficulty levels and the cognitive demand experienced by participants.

These hypotheses collectively provide a structured framework for investigating and understanding the complex interplay between attentional levels, the chosen intervention method (Verbal Data Recording), signal detection scores, and the influence of task difficulty on participants' mental workload. The subsequent analysis and interpretation of these hypotheses aim to contribute valuable insights to the overarching objectives of the study.



## 5.3 Data analysis approach

The experiment encompassed data collection from two meticulously controlled teams: Team One, employing a Verbal Data Recording (VDR) method, and Team Two, utilizing a Pen-and-Paper Data Recording (PAPDR) approach. These teams actively participated in three distinct experiments, each meticulously designed with varying levels of difficulty. Experiment one was structured at a Level of Difficulty Hard, experiment two at a Level of Difficulty Medium, and experiment three at Level of Difficulty Low. A comprehensive breakdown of the structural nuances of these experimental levels of difficulty can be found in chapter 3, section “3.2.4 Experiment’s Level of Difficulties.”

Notably, given the heightened sensitivity of human attentional and mental workload levels to shifts in task goals, system control and display methods, as well as data collection techniques, a deliberate decision was made to maintain uniformity. No modifications were introduced to the task goals, system control methods, or objectives across all three experiments. This meticulous approach aimed to preclude any additional variables or system-related factors from influencing participants' attention and mental workload. The singular research intervention pertained solely to the diverse data collection methods employed by the operators, alongside the deliberate variation in the experiment’s level of difficulty.

This methodological uniformity served to uphold the experiments' integrity, facilitating a focused investigation into the impact of data collection methods on participants' attentional and mental workload levels. Simultaneously, it mitigated potential confounding factors associated with task objectives and system operation.

To rigorously examine the impact of the experiment's level of difficulty on participants' attentional and mental workload, Analysis of Variance (ANOVA) was systematically executed. The primary aim of this analysis was to ascertain whether the amalgamation of three independent variables, representing distinct levels of difficulty, exerted a significant influence on two dependent variables: attentional and mental workload levels.

Stringent assessments of the assumptions underlying ANOVA, encompassing normality and homogeneity of variances, were meticulously conducted across the entire dataset. Instances where the data deviated from these requisite assumptions prompted the application of judicious data transformation techniques. Specifically:

1. **Logarithm Transformation:** Applied to variables exhibiting non-constant variance (heteroscedasticity) and deviation from normality, the logarithm transformation was employed. Renowned for stabilizing variances and aligning data more closely with a normal distribution, this transformation was instrumental in enhancing the robustness of the analysis.
2. **Box-Cox Transformation:** Employing a family of power transformations that subsumes the logarithmic transformation, the Box-Cox method optimally normalizes data by identifying the power ( $\lambda$ ) that maximizes normality. Distinguished by its versatility in accommodating various data distributions, this transformation contributed to the refinement of the dataset.

The meticulous execution of data transformation and validation procedures was imperative to uphold the foundational assumptions of the ANOVA analysis. This not only bolstered the accuracy of the statistical outcomes but also underscored the reliability of the results.

An essential phase of the data analysis entailed a comprehensive exploration of potential significant differences between the two independent teams involved in Verbal Data Recording (VDR) and Pen-and-Paper Data Recording (PAPDR).

following steps were taken to complete this preliminary phase of data analysis.

6. **Standardization of Raw Data:** The raw data sets collected from each experiment condition were standardized. This standardization process ensures that the data from different experiments and conditions can be meaningfully compared.
7. **Descriptive Statistics:** Descriptive statistics were applied to the standardized data. This included calculating measures of central tendency, such as the Mean (average), Median (middle value), and Standard Deviation (a measure of data spread).
8. **Quantitative Summary and Analysis:** The standardized data were subjected to a quantitative summary and analysis. This process involved a thorough examination of the data to identify patterns, trends, and differences between the VDR and PAPDR teams.
9. **Tabular and Graphical Presentation:** The results of the analysis were presented in both tabular and graphical forms. Tabular formats offer a structured presentation of data, while graphical representations, such as charts and plots, provide visual insights into the findings.

This meticulous data analysis process allowed for a comprehensive exploration of potential differences between the two independent teams, shedding light on how data recording methods (VDR and PAPDR) may influence subjects' SA under varying levels of experiment difficulty.

The selection of appropriate statistical methods for data analysis involved a systematic and

rigorous approach. The standardized data, obtained from both scenarios (Verbal Data Recording - VDR and Pen-and-Paper Data Recording - PAPDR), underwent a thorough examination to assess their suitability for the chosen inferential statistical tests, such as Analysis of Variance (ANOVA) and t-tests. Here's a breakdown of the process:

#### **5. Data Screening:**

- The standardized data were carefully screened to evaluate their appropriateness for statistical analysis.

#### **6. Assumption Testing:**

- The sample data from each scenario (VDR and PAPDR) were subjected to various assumption tests. These tests assessed:
  - Normality: Ensuring that the data followed a normal distribution.
  - Homoscedasticity: Checking for consistent variance of residuals across data points.
  - Equality of Variances: Verifying that variances were comparable between scenarios.

#### **7. Addressing Limitations:**

- This rigorous testing was conducted to address potential limitations and sensitivity issues associated with standard inferential analysis, particularly regarding factors such as data sample size, measurement errors, and assumptions violations in t-tests.

#### **8. Final Stage:**

- The final stage of the analysis encompassed a comprehensive discussion and conclusion of the data outcomes. This phase also involved an examination of correlations within the data.

The systematic and sequential approach to data analysis aimed at achieving a comprehensive understanding of the study's intervention, specifically focusing on operators' Situational Awareness and Performance. It ensured that the selected statistical methods were applied to data that met the necessary assumptions, enhancing the reliability and validity of the research findings.

## **Results & Discussions**

### **5.4 Attentional allocation and Experiment's Different Level of difficulties**

All participants were assigned the secondary task of monitoring battery signal levels to evaluate the degree of attention directed toward the primary telerobotic task. In this ancillary task, participants were presented with two battery signal levels: one signifying the real-time status of the robot's battery and the other denoting the battery level for onboard equipment. Both battery levels underwent random fluctuations, with the potential to descend to a low charge level set at 20%. Upon detecting a low signal for either battery, participants were mandated to acknowledge it by utilizing a corresponding counter application displayed on the secondary monitor. The cumulative count of signals detected was computed at the conclusion of each experiment.

The objective was to gauge the attention devoted to the telerobotic task in each condition by evaluating the operator's signal detection performance. A higher signal detection score suggests that the operator allocates less attention to the telerobotic task, whereas a lower score implies greater attention to the primary task. This methodology aligns with the Single Resource Theory of human attention, and its efficacy in measuring human attention resources has been established and validated in prior research (Broeker et al., 2021; "Mental Workload," 2021). The detailed procedure for executing the secondary task and recording its outcomes is elucidated in Chapter 3, Section 3.1.5.

Throughout the three levels of difficulty in the experiments, there were no alterations to the procedure and recording approach of the secondary task. This task remained consistent in both experimental conditions: Verbal Data Recording and Pen-and-Paper Data Recording.

To ascertain the impact of the experiment's levels of difficulty on the subjects' Attentional Level, a One-Way Analysis of Variance (ANOVA) was employed. ANOVA was chosen to investigate the influence of three distinct categorical independent variables (the qualitative experiment levels or LOD) on a single quantitative variable (Attention Level).

#### **5.4.1 Descriptive statistics analysis Attention & LOD**

Central tendency statistics were separately conducted for two data recording methods, Oral Data Recording (VDR), and Handwriting Data Recording (PAPDR). This computation has been repeated for all three experiment's levels of difficulties: Low, Medium, and Hard. The raw data were standardized using Descriptive Statistics and central tendency statistics, revealing crucial insights into the distribution of scores during data analysis. This process involved

determining the middle value of the data distribution, with the median score and standard deviation recorded for the PAPDR experiment and VDR.

The following table (Table 11) summarizes the computed values for PAPDR in all three experiment's levels of difficulty. Similarly, Table 12 includes the data summary for Verbal data recording.

*Table 11 Pen-and-Paper Data Recording attentional allocation data.*

| Descriptive statistics analysis Pen-and-Paper Data Recording attentional allocation data |          |      |        |
|------------------------------------------------------------------------------------------|----------|------|--------|
|                                                                                          | SD       | Mean | Middel |
| Hard Difficulty                                                                          | 1.140175 | 7.6  | 8      |
| Medium Difficulty                                                                        | 1.140175 | 9.4  | 9      |
| Low Difficulty                                                                           | 1.341641 | 11.6 | 11     |

*Table 12 Verbal Data Recording Descriptive analysis.*

| Attentional Descriptive statistics analysis Verbal Data Recording |          |      |        |
|-------------------------------------------------------------------|----------|------|--------|
|                                                                   | SD       | Mean | Middel |
| Hard Difficulty                                                   | 1.140175 | 5.6  | 6      |
| Medium Difficulty                                                 | 1.140175 | 8.4  | 8      |
| Low Difficulty                                                    | 1.140175 | 10.4 | 10     |

Numerically comparing the mean scores across all three levels of difficulties, it has been indicated that, on average, participants engaged in Verbal Data Recording had lower scores in the secondary task compared to the subjects from PAPDR. This, in turn, indicates that they

pay more attention to the main telerobotic task. Furthermore, data normality was assessed through the Shapiro-Wilk test, and homoscedasticity of the residuals was examined using Levene's test.

### 5.4.2 Attention & Experiment's LOD Results

To ensure adherence to the assumptions required for ANOVA (Analysis of Variance), both datasets obtained from Verbal Data Recording and Pen-and-Paper Data Recording were rigorously analysed to detect any significant effects. To identify the effect of the experiment's Level of Difficulties on the subject's Attentional Level, a One-way Analysis of Variance (ANOVA) was utilized. ANOVA was employed to detect the effect of three different categorical independent variables (the qualitative experiment levels (LOD)) on a single quantitative variable (Attention Level). This approach was implemented separately for both experimental conditions, Verbal Data Recording and Pen-and-Paper Data Recording. In this manner, the recorded scores from subjects participating in VDR in each different level of difficulty were assessed independently from subjects who took part in PAPDR. This analytical approach allowed for a focused examination of the results, concentrating solely on the effect of the experiment's Level Of Difficulties. The formula of the utilised ANOVA in this section can be written as

$$Y_{ij} = \mu + LOD_i + e_j \quad (1)$$

Where;

*$Y_{ij}$  = the response variable (Attention Level);*

*$\mu$  = the grand mean*



***LOD<sub>i</sub>** = the fixed effect of the *i* th level of difficulty*

***e<sub>j</sub>** = error within each LOD*

After performing a one-way ANOVA to assess the impact of experiment levels (Low, Medium, High) on participants' Attentional level for data from VDR team, the following results has been obtained:

- 1. F-statistic:** 22.46 was calculated as F-statistic which measures the ratio of the variance between groups to the variance within groups.
- 2. P-value:** The associated p-value for the F-statistic was 0.00024.

The obtained results, particularly the p-value indicating statistical significance, provide sufficient evidence to reject the null hypothesis. This confirms that there are significant differences among the participants' attention levels across the variations in the experiment's Level Of Difficulty when the experiment data were recorded verbally.

To further explore these differences, a Post Hoc Tukey procedure was employed to facilitate pairwise comparisons within the ANOVA data. Tukey's HSD test identified significant differences between various pairs of means, shedding light on specific levels of difficulty that contributed to the observed variations in attention levels among participants.

Table 13 provides a summary of the pairwise comparisons for the data from three separate experiment levels of difficulty. The test results reveal notable differences in attentional allocation scores. The most substantial difference is observed between the experiment levels of difficulty low and hard ( $Q = 9.41$ ,  $p = 0.00006$ ), indicating a significant distinction in attentional allocation. On the other hand, the smallest significant difference is observed

between experiment levels of difficulty low and medium ( $Q = 3.92$ ,  $p = 0.04150$ ). These findings highlight the varying impact of different levels of difficulty on participants' attentional allocation.

Table 13 summary of the Pairwise Comparisons VDR (attentional allocation)

| <b>Pairwise Comparisons</b>        |                                                 | <b>HSD<sub>.05</sub> = 1.9238</b> | <b>Q<sub>.05</sub> = 3.7729</b> | <b>Q<sub>.01</sub> = 5.0459</b> |
|------------------------------------|-------------------------------------------------|-----------------------------------|---------------------------------|---------------------------------|
|                                    |                                                 | <b>HSD<sub>.01</sub> = 2.5729</b> |                                 |                                 |
| <b>L<sub>1</sub>:L<sub>2</sub></b> | M <sub>1</sub> = 5.60<br>M <sub>2</sub> = 8.40  | 2.80                              | Q = 5.49 ( $p = .00570$ )       |                                 |
| <b>L<sub>1</sub>:L<sub>3</sub></b> | M <sub>1</sub> = 5.60<br>M <sub>3</sub> = 10.40 | 4.80                              | Q = 9.41 ( $p = .00006$ )       |                                 |
| <b>L<sub>2</sub>:L<sub>3</sub></b> | M <sub>2</sub> = 8.40<br>M <sub>3</sub> = 10.40 | 2.00                              | Q = 3.92 ( $p = .04150$ )       |                                 |

Additionally, the obtained F-statistic of 13.68 and the p-value of 0.009 recorded for the dataset from subjects participating in Pen-and-Paper Data Recording. Similarly, these results indicate significant differences in subjects' attentional allocation within the three experiment levels of difficulties.

Furthermore, the ANOVA result was further investigated to identify pairwise differences using the Post Hoc Tukey test. The results indicate that there is no significant difference in the subjects' attentional allocation between experiments with a hard and medium level of difficulty ( $Q = 3.32$ ,  $p = 0.08669$ ). However, significant differences were identified across the low level of difficulty with both hard and medium levels of difficulties. These findings provide insights into the nuanced impact of different levels of difficulty on participants' attentional

allocation when the experiment data were recorded through Pen-And-Paper, with specific distinctions highlighted by the Tukey test.

Table 14 summary of the Pairwise Comparisons PAPDR (attentional allocation)

| <b>Pairwise Comparisons</b>        |                                                 | <b>HSD<sub>.05</sub> = 2.0434</b> | <b>Q<sub>.05</sub> = 3.7729    Q<sub>.01</sub> = 5.0459</b> |
|------------------------------------|-------------------------------------------------|-----------------------------------|-------------------------------------------------------------|
|                                    |                                                 | <b>HSD<sub>.01</sub> = 2.7329</b> |                                                             |
| <b>T<sub>1</sub>:T<sub>2</sub></b> | M <sub>1</sub> = 7.60<br>M <sub>2</sub> = 9.40  | 1.80                              | Q = 3.32 ( <i>p</i> = .08669)                               |
| <b>T<sub>1</sub>:T<sub>3</sub></b> | M <sub>1</sub> = 7.60<br>M <sub>3</sub> = 11.60 | 4.00                              | Q = 7.39 ( <i>p</i> = .00058)                               |
| <b>T<sub>2</sub>:T<sub>3</sub></b> | M <sub>2</sub> = 9.40<br>M <sub>3</sub> = 11.60 | 2.20                              | Q = 4.06 ( <i>p</i> = .03482)                               |

According to the separate statistical results from each experimental circumstance test (VDR and PAPADR), there is evidence that the variation in the experimental levels of difficulty indeed had a significant effect on operators' attentional allocation to the main telerobotic task.

The significant effects of the task's level of difficulty on subjects' attentional allocation involve considering various cognitive and perceptual factors. A breakdown of the key aspects that may have influenced this outcome includes:

### 1. Cognitive Load Theory:

- The cognitive load theory plays a crucial role; as the task difficulty increases, the cognitive load on the participants is likely to increase. Cognitive load refers to the mental effort required for information processing and problem-solving.
- With higher task difficulty, individuals may need to allocate more cognitive resources to manage the complexity of the task. This increased cognitive load can impact attentional resources available for other aspects of the task. This issue is more evident in the analysis of the subject's attentional allocation for Pen-And-Paper Data Recording, where the higher (Hard) experiment level of difficulty had a significant effect on participants' attentional allocation, and their scores on the secondary task were significantly reduced.

## **2. Attentional Resources and Allocation:**

- These results also align with the concept of attentional resources reviewed within study's literature . As attention is a limited resource, individuals need to allocate it effectively based on task demands.
- As the task becomes more challenging, participants might need to focus more on the robot manoeuvring and data collection elements of the task, diverting attention from other aspects. In this case, the reallocation of attentional resources from the secondary task to the main task becomes necessary.

## **3. Perceptual Demands:**

- The perceptual demands of the task. Tasks with higher difficulty might require more careful and detailed observation, affecting how individuals distribute their attention across the secondary task.

- Perceptual demands interact with cognitive demands, influencing how subjects prioritize information processing.

#### **4. Individual Differences:**

- it is essential to acknowledge that individuals may vary in their ability to handle tasks of different difficulty levels. Factors such as expertise, experience, and cognitive abilities can influence how individuals (subjects) distribute attention under varying task demands.

#### **5. Implications for Human-Machine Interaction:**

The practical implications of these findings for human-machine interaction are noteworthy. For example, understanding how attention is allocated under different task difficulties can inform the design of interfaces and systems to support human performance in this case the effect of the Verbal Data Recording.

In this section of participant attention allocation assessment, it is important to note that the analysis was conducted separately for each experimental circumstance: Verbal Data Recording and Pen-And-Paper Data Recording. This implies that the effect of changes within the data recording procedure was not considered in this data analysis section. However, the next section (5.5) has been specifically designated to identify the effect of this research variable.

To address this issue and in relation to the insignificant effect of the experiment's Level of Difficulty on participants' attention allocation, further research may need to refine the experimental design, specifically based on the assessment of the operator's attentional allocation. This could include considerations such as increasing the sample size or using specific or combined measures of human attention assessment. It is also crucial to analyze

the results in the context of existing literature on attention and task difficulty to gain a deeper understanding of the findings.

## **5.5 Attention Level and VDR with PAPDR**

This section is dedicated to understanding the effect of variations in data recording procedures on the operator's attention allocation. Considering the impact of the experiment's difficulty level on participants' attentional allocation, the data assessment for Verbal Data Recording in each of the three experiment's Levels of Difficulty was compared as a single dataset with the dataset from Pen-And-Paper Data Recording in each experiment's level of difficulty. This was done due to the insignificant effect of the experiment's level of difficulty on the participant's attention level assessment.

Initially, statistical assumption tests were separately conducted for two data recording methods: Verbal Data Recording (VDR) and Pen-and-Paper Data Recording (PAPDR) in section 5.4.1. The computed mean values are compared within Figure 23 for Pen-and-Paper Data Recording (PAPDR). The comparison of mean values across each level of difficulty shows that the subjects scored lower values in Verbal Data Recording compared to PAPDR. As the mean value of VDR shows a smaller value compared to PAPDR mean, this can be an indicator that the subjects recorded fewer hit signals on the secondary task, showing greater attention allocation to the actual telerobotic task.

A pairwise mean value was compared across the two different data recording approaches; however, the only significant difference was detected only across the Hard Level of Difficulty, where the f-ratio value is 7.69231 with the p-value = 0.024166.

The absence of significant differences across the medium level and low LOD for both experiment circumstances (VDR and PAPADR) computed with an f-ratio value of 1.92308 and a p-value of 0.202934 for medium LOD. In addition, for low LOD, the f-ratio value is 2.32258 with a p-value of 0.166013. The detection of attentional allocation significant difference only for the Hard Level of difficulty between Verbal and Pen-And-Paper Data Recording can be attributed to the extensive time that subjects spent on the experiment, as well as the complexity of the telerobotic task in the Hard level, which could have increased the sensitivity of the assessment. A detailed discussion and conclusion on this outcome have been presented within section 5.7.

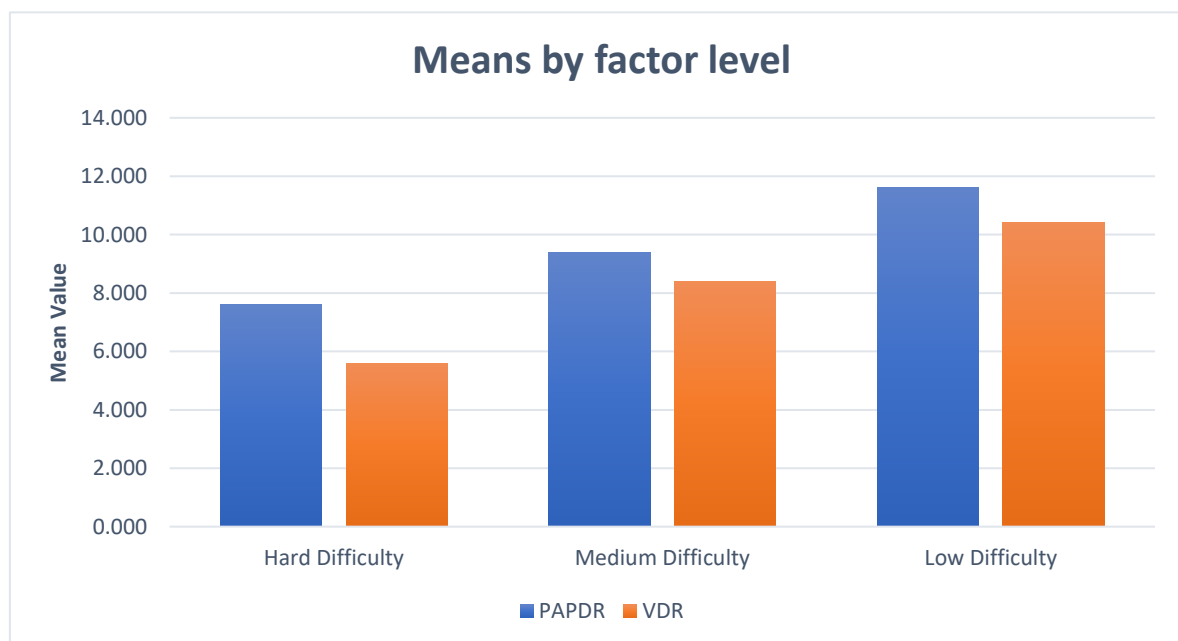


Figure 23 mean values comparison for Pen-and-Paper Data Recording (PAPDR).

## 5.6 NASA Task Load Index Workload assessment

Participant's mental workload was evaluated post-experiment using the NASA Task Load Index (NASA-TLX) approach. The selection of NASA-TLX for this study was based on its

sensitivity, applicability, validity, reliability, operator acceptance, non-intrusiveness, ease of use, and its multi-dimensional assessment approach.

The NASA Task Load Index assesses the participant's cognitive workload across six dimensions: 1) mental demand, 2) physical demand, 3) temporal demand, 4) performance, 5) effort, and 6) frustration. Ratings for these dimensions are obtained using a twenty-step bipolar scale. The tool employs a score rating approach ranging from 0 to 100 for each scale, rounded to the nearest 5.

The questionnaire was completed through the official NASA Task Load Index (TLX) app, simplifying the workload assessment process for operators, and enhancing their willingness to complete the questionnaire after each experiment.

The task's workload was manipulated by altering the overall difficulty level of the experiment. Difficulty levels were determined based on the need to extend task completion time, increase the complexity of data collection, and expand the robot's mobility within the experiment area. To achieve this, additional indicators were introduced, requiring operators to read and record more data. The complexity of data collection was heightened by strategically placing indicators in locations that were more challenging to locate and read. Additionally, in the hard and medium difficulty levels, operators were required to return the robot to its starting point, expanding its mobility.

A single overall mental workload score, computed through the NASA Task Load Index, indicated the experiment's improved validity (Bustamante and Spain, 2008). Any workload scores below 50 was considered acceptable (Endsley, 1988).



Upon assessing all participant's results, it was determined that the workload associated with the three experiment levels of difficulty fell within the acceptable range. The average single overall mental scores were 36.56, 45.19, and 48.23 for low, medium, and high levels of difficulty, respectively. Consequently, the associated overall workload for all experiment variations was graded as "acceptable."

In addition, the data sets were tested for their normality and the equality of variances within groups, also appropriate adjustments were made to the data where the normality was not met.

The MANOVA outcome reveals significant differences between experiments with different levels of difficulty, where  $F(2,28) = 2.54$ ,  $P = 0.039$ . However, pairwise comparisons indicate differences only between the Hard and Low levels of difficulty ( $Z = 10.24$ ,  $P = 0.23$ ). This raises the possibility of combining scores from the Medium and Hard levels of difficulty to analyse the effect of Verbal Data Recording.

An independent-sample T-test was employed to analyse the single overall mean workload from NASA-TLX between the two experimental conditions: Verbal Data Recording and Pen-And-Paper Data Recording. The T-test results with statistical significance ( $t(18) = 2.18$ ,  $P = 0.027$ ) indicate that the VDR condition has a lower overall mental workload.

Additionally, in addition to analysing the overall mental workload, the six related sub-scales of the TLX test were individually tested for each experimental condition. These six sub-scales include Temporal, Effort, Frustration, Physical, Mental, and Performance.

The average scores for all individual sub-scales are listed within Figure 24, comparing both experimental circumstances, VDR and PAPDR. According to the initial overall mental

workload assessment results, the VDR exhibited lower requirements in all six sub-scale variations. Notably, physical and mental sub-aspects showed the largest differences among other sub-scales. These results can be attributed to the transition from using the robot tablet controller to writing down experiment data in a specified table. It should be noted that visible frustration was observed during the Pen-And-Paper Data Recording experiment, particularly during the hand-changing process from the controller to the data recording table and back to the controller.

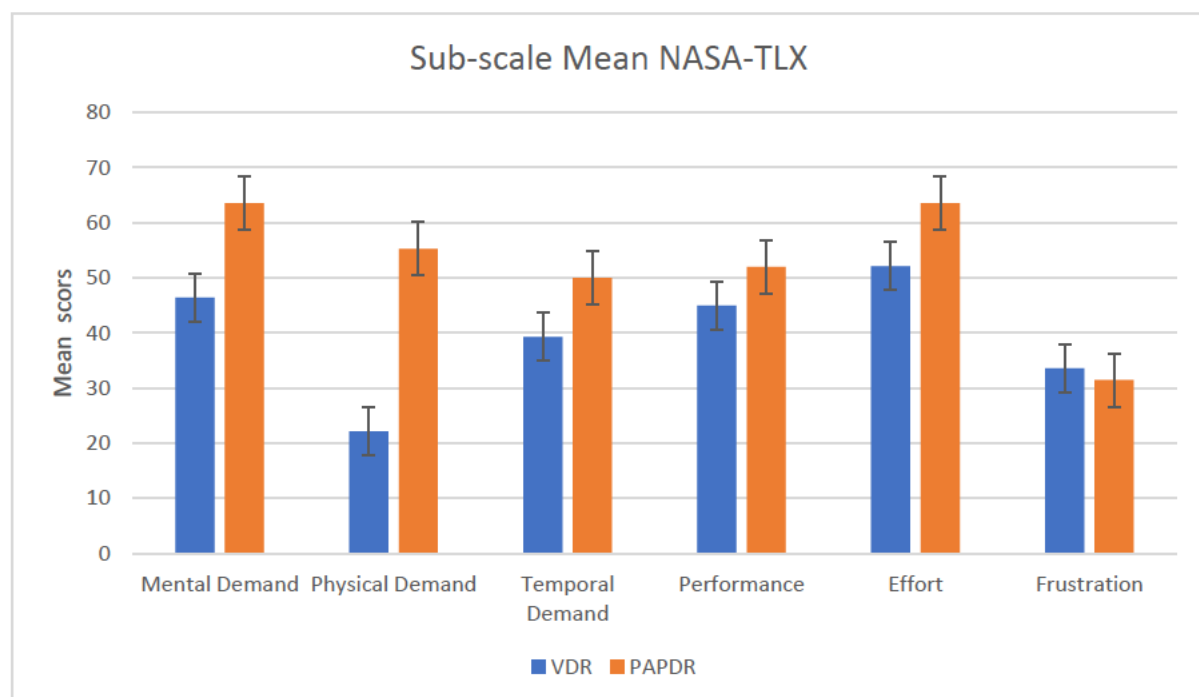


Figure 24 mean comparison of Sub-scale Mean NASA-TLX

## 5.7 Conclusions and Hypotheses Discussion

This section encapsulates the concluding remarks of the research, focusing on both the operator's attentional allocation and their mental workload, in line with the initial hypotheses set forth in Chapter 5 as well as the analyses outcomes. It's essential to note that the primary consideration of the study is how to improve and assess the operator's situational assessment in remote locations, rather than evaluating the usability of the

experiment's robot systems or analysing specific hardware or software. However, the concepts explored can be applied more broadly to assess or enhance operators' cognitive performance in both remote and onsite locations.

The significant effect of Verbal Data Recording (VDR) on the subject's task attentional orientation and mental workload compared to pen-and-paper data recording has been influenced by several factors:

- 1. Real-time Engagement:** VDR involves expressing thoughts and observations verbally in real-time. This immediate engagement can keep the subject actively involved in the task, leading to enhanced attention.
- 2. Reduced Cognitive Load:** Speaking out loud may reduce cognitive load compared to the cognitive processes involved in writing. This reduction in cognitive load can contribute to a lower mental workload, allowing subjects to allocate more mental resources to the telerobotic task.
- 3. Multimodal Processing:** Verbal communication engages both auditory and cognitive processes. The multimodal nature of verbalization may enhance information processing and comprehension, leading to a more efficient cognitive workflow.
- 4. Continuous Interaction:** Verbal communication allows for continuous interaction with the task. The ongoing verbal dialogue may create a dynamic and interactive environment, maintaining the subject's interest and facilitating sustained attention.
- 5. Natural Communication Mode:** Verbal communication is a natural and intuitive mode of expression. Subjects may find it more comfortable and familiar to verbalize thoughts, potentially reducing the perceived mental workload.

**6. Adaptability:** Verbal communication allows for adaptability in expressing thoughts.

Subjects can adjust their verbalizations based on the task's demands, providing a flexible means of communication that aligns with the dynamic nature of telerobotic operations.

**7. Social Interaction:** Verbalization often involves communication with others, such as

experimenters or team members. The social aspect of verbal communication may enhance collaboration and reduce feelings of isolation, positively influencing mental workload.

**8. Feedback Loop:** Verbal communication creates a feedback loop where subjects receive

immediate feedback on their verbalizations. This feedback loop can contribute to a sense of control and mastery, potentially reducing the perceived mental workload.

**9. Task Integration:** Verbal Data Recording integrates seamlessly with the ongoing task. The

act of speaking about the task becomes an integral part of the overall process, potentially reducing the cognitive separation between recording data and performing the task.

**10. Subjective Experience:** The subjective experience of participants is crucial. Conducting

post-task interviews or surveys can provide insights into their experiences, perceived workload, and preferences regarding the data recording method.

The statistical analysis conducted in Chapter 5 reveals that the utilization of Verbal Data

Recording has a positive impact on subjects' mental workload with statistical significance ( $t(18) = 2.18, P = 0.027$ ) indicate that the VDR condition has a lower overall mental workload.

This outcome aligns with the first hypothesis proposed in Chapter 5. Moreover, the lower scores recorded on the secondary task by the subjects suggest a higher degree of attention

directed towards the primary telerobotic task. Examining the correlation between subjects' mental workload indicates that variations in the Levels of Difficulty (LOD) within the experiment significantly influence subjects' mental workload.

It is crucial to acknowledge that the observed effects may vary depending on the specific characteristics of this study, the nature of the telerobotic task, and the participants involved. Throughout this study, a combination of quantitative and qualitative data was meticulously collected to comprehensively understand the impact of Verbal Data Recording on attention and mental workload during both data collection and statistical analysis.

## **Chapter 6**

### **Investigating the Impact of IQ on Situational Awareness in Telerobotic Tasks**

#### **6.1 Introduction**

In the preceding chapters, the study delved into the intricacies of telerobotic experiments, exploring the effects of data recording methods on human Situational Awareness, performance, attention and mental workload. Chapter 6 focusing on the interplay between individual cognitive abilities and situational awareness (SA) during telerobotic operations.

This chapter constitutes a detailed analysis of data collected from two distinct groups of participants: those engaged in Verbal Data Recording and those employing Pen-and-Paper Data Recording methods. Beyond the telerobotic task itself, an extend scrutiny to the participants' cognitive capacities, specifically their Intelligence Quotient (IQ) which measured prior to the experiments through a specified application.

A pivotal component of this investigation is the evaluation of participants' situational awareness through the Situational Awareness Global Assessment technique during the course of the telerobotic experiments. Chapter 4's analysis revealed that the variation in task difficulty levels had no discernible impact on participants' situational awareness, serving as a crucial foundation for the subsequent exploration.

In the dynamic and complex field of telerobotics, the proficiency of human operators in maintaining SA is critical for the successful operation and management of remote robotic systems. This proficiency is not merely a function of training and experience but is also closely linked to the inherent cognitive abilities of the individual. As such, exploring the

relationship between individual cognitive abilities, as indicated by IQ scores, and SA in telerobotics becomes not only relevant but essential.

The significance of this exploration lies in the recognition that cognitive abilities, often quantified through IQ assessments, play a fundamental role in how operators perceive, process, and understand the information within a telerobotic environment. Cognitive abilities encompass various aspects like problem-solving skills, memory, attention, and processing speed, all of which are crucial components in maintaining effective situational awareness. Understanding how these abilities impact SA can provide invaluable insights into optimizing telerobotic operations.

Specifically, the need to investigate this relationship arises from several key considerations:

1. **Predictive Analysis:** If cognitive abilities could predict SA proficiency, it would enable the development of more targeted training and selection processes for telerobotic operators. This could lead to enhanced operational effectiveness and safety, as operators with higher SA are likely to make more informed and accurate decisions.
2. **Customised Training and Support:** Identifying how different levels of cognitive abilities influence SA can guide the creation of customized training programs. Operators with varying cognitive strengths might benefit from tailored training that addresses specific areas needing enhancement, leading to more effective skill development.
3. **Technological Adaptation:** Understanding the impact of cognitive abilities on SA can inform the design of telerobotic systems. Systems could be adapted or augmented to complement the operator's cognitive profile, thereby improving overall system usability and effectiveness.

4. **Human-Centric Approach:** This exploration emphasizes the human-centric aspect of telerobotics. By focusing on the human operator's cognitive abilities, the research aligns with the goal of developing telerobotic systems that are not only technologically advanced but also attuned to the needs and capabilities of the human user.
5. **Advancement in HRI Research:** This study contributes to the broader field of Human-Robot Interaction (HRI) by providing empirical evidence on the cognitive aspects of human-robot collaboration. It extends the existing body of knowledge and opens new avenues for research in cognitive ergonomics within telerobotics.

The aim of this study, therefore, is to determine whether and to what extent individual cognitive abilities, as reflected in IQ scores, predict or influence an operator's proficiency in maintaining situational awareness in telerobotic operations. Such an investigation is not only academically significant but also has practical implications in enhancing the efficiency, safety, and user-friendliness of telerobotic systems.

Chapter 6 consists of detailed overview of the data analysis approach flowed by the selected hypotheses related to human's Situational Awareness and their Intelligence Quotient, then an overview of the Intelligence Quotient assessment. The flowing sections include the detailed statical analysis of participants' SA and their IQ. In addition, the results of the statical analysis have been discussed and the outcomes of Chapter six were leveraged to address research questions and test hypotheses pertinent to the assessment of participants' Situational Awareness and their IQ assessment.

This figure 24 illustrates the structure of Chapter 6, which focuses on investigating the impact of IQ on situational awareness in telerobotic tasks. It provides an overview of the chapter's key components, beginning with the Introduction in Section 6.1, followed by the



Selected Hypotheses on SA and Performance in Section 6.2. Section 6.3 outlines the Data Analysis Approach, offering methodological context for the results.

The Results & Discussions span Sections 6.4 to 6.6, detailing the assessment of human intelligence quotient, a discussion of IQ data, and its relationship to situational awareness.

Finally, Section 6.7 presents the Conclusions and Hypotheses Discussion, summarising the findings in relation to the hypotheses. This figure provides a visual roadmap for navigating the chapter's content.

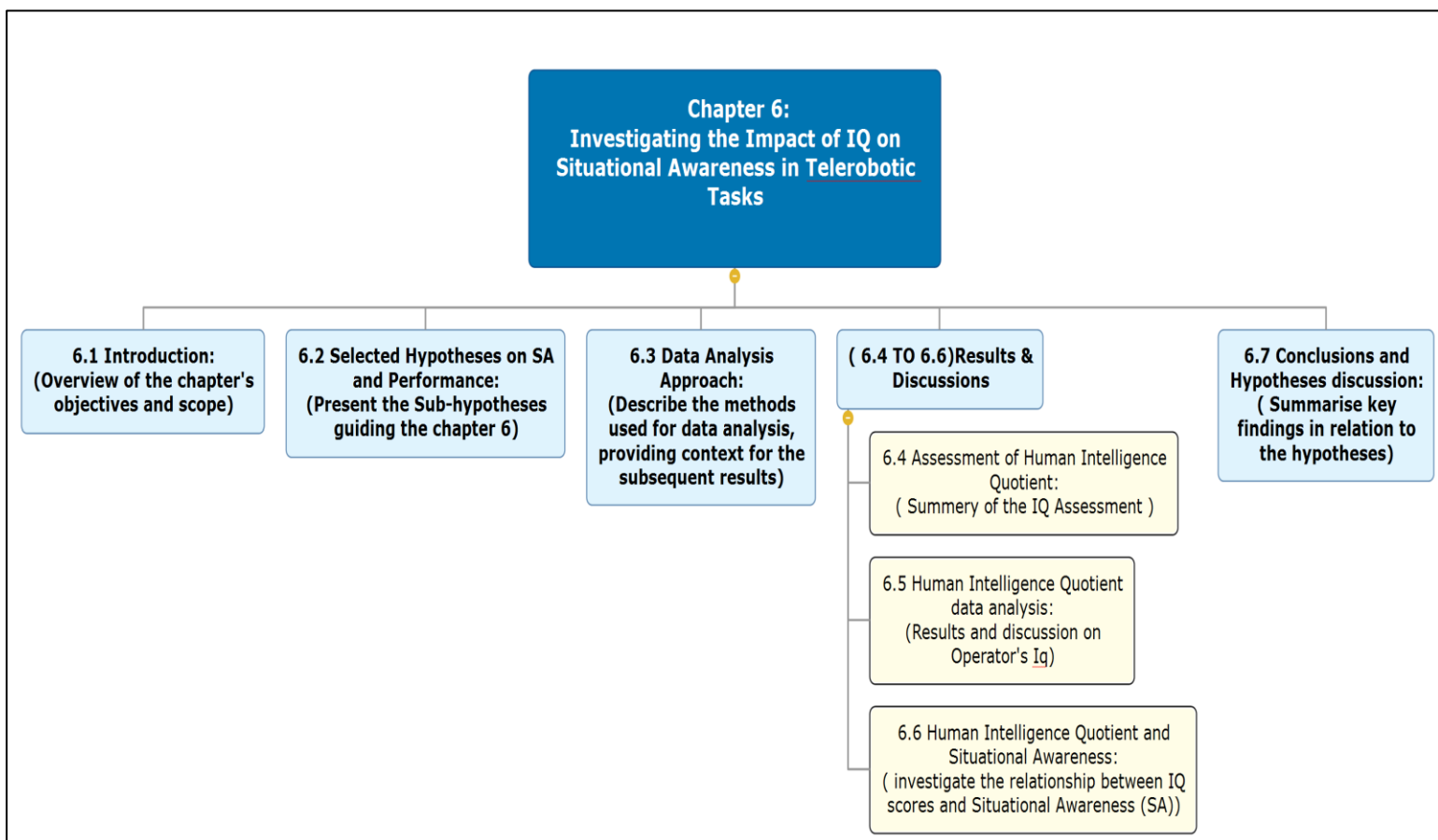


Figure 25 the structure of Chapter 6

## 6.2 Selected Sub-Hypotheses

In Chapter 6, the formulate hypotheses that address this specific research question the focus shifts to the analysis of the relationship between participants' intelligence (measured through IQ) and situational awareness (SA) during telerobotic tasks, the considered hypotheses in this chapter are as follow:

### 1. Main Hypothesis:

- H0 (Null Hypothesis): There is no significant relationship between participants' intelligence (IQ) and their situational awareness during telerobotic tasks.
- H1 (Alternative Hypothesis): There is a significant positive/negative relationship between participants' intelligence (IQ) and their situational awareness during telerobotic tasks.

### 2. Directional Hypotheses:

- H0: Intelligence has no directional impact on situational awareness during telerobotic tasks.
- H1 (Positive Direction): Higher intelligence is positively associated with enhanced situational awareness during telerobotic tasks.
- H1 (Negative Direction): Higher intelligence is negatively associated with situational awareness during telerobotic tasks.

### 3. Group-Specific Hypotheses:

- H0: There is no difference in the relationship between intelligence and situational awareness between participants using Verbal Data Recording and Pen-and-Paper Data Recording.
- H1: The relationship between intelligence and situational awareness differs significantly between participants using Verbal Data Recording and Pen-and-Paper Data Recording.

#### **4. Interaction Hypothesis:**

- H0: The relationship between intelligence and situational awareness is not moderated by the difficulty level of telerobotic tasks.
- H1: The relationship between intelligence and situational awareness is moderated by the difficulty level of telerobotic tasks.

## **6.3 Data analysis approach**

The journey into Chapter 6 marks a pivotal juncture in our exploration of the intricate relationship between individual cognitive attributes and situational awareness (SA) within the realm of telerobotic tasks. Building upon the findings from Chapter 4, where the absence of a significant effect of varying task difficulty levels on SA was established, now the research delves into the nuanced realm of subject's IQ and its potential impact on SA during telerobotic- Data-Monitoring task.

**1. Standardization of IQ Data:** the initial data analysis step involves the meticulous standardization of raw data gleaned from participants' IQ assessments tool. Leveraging descriptive statistics embark on a journey of quantitative explanation. Through the use of

tables and graphical presentations to elucidate the distribution of IQ scores within the two specified participant groups VDR and PAPADR. This process was essential for laying the foundation of research subsequent statistical analyses, enabling the interpretation to discern patterns, central tendencies, and variations within the IQ data.

- 2. Quantifying the diversity of IQ scores:** this is instrumental in comprehending the range of cognitive abilities present in the participant pool. The aim is not only to unravel the central tendencies but also to visually represent the dispersion of intelligence levels across both the Verbal Data Recording and Pen-and-Paper Data Recording groups. This step provides a crucial contextual backdrop for overarching inquiry into the potential link between IQ and SA.
- 3. Data Screening and Assumption Testing:** With our standardized IQ data in hand, it was possible to transition of the data into the realm of data screening and assumption testing. The robustness of our subsequent statistical analyses' hinges on the fulfilment of key assumptions, namely normality and homoscedasticity.
- 4. Normality:** The normality of our data distribution is scrutinized through statistical tests, such as the Shapiro-Wilk test. Should the assumption of normality be violated, corrective measures, including data transformations such as log transformations, will be considered. This iterative process is vital to ensure the validity and reliability of subsequent inferential analyses.
- 5. Homoscedasticity:** Homoscedasticity, the assumption of equal variance across groups, is equally pivotal. The Levene's test is deployed to assess this assumption. Should the assumption be compromised, additional corrective measures will be applied to fortify the robustness of our analyses.

In weaving through these stages of data analysis, not only unravelling the potential impact of intelligence on SA but also adhering to the rigorous standards of statistical inquiry. This methodology is designed not only to scrutinize the nuances of individual cognitive capacities but also to uphold the integrity and validity of the research outcomes. Through this multifaceted approach, this has been striven to illuminate the complex interplay between intelligence and situational awareness in the dynamic landscape of telerobotic tasks specifically where live data collection is essential.

## **6.4 Assessment of Human Intelligence Quotient**

Participants' Intelligence Quotient was assessed in terms of memory, concentration, logic, visual, and verbal skills. This IQ assessment treated as a basic individual's differences in information-processing and working-memory capability to understanding the effect of individual's abilities on development of huma's Situational Awareness within telerobotic goal directed tasks and effect of data collection approach variation (Verbal Data Recording and Pen-And-Paper Data Recording). An Intelligence Quotient assessment was constructed into the study's multi-tool assessment structure, and it was completed by the participants prior to the actual study experiment. This Intelligence Quotient assessment was independent from both telerobotic and the secondary tasks implementation.

To assess participants' IQ, a web-based software called MentalUP, which specialises in cognitive assessments, according to their official information these online tests designed by licensed psychologists or renowned institutions with addition of five million participant. Through this assessment the subject's basic cognitive capability performance was scored

through five simulated tasks in terms of distinct categories, including memory, attention, logic, visual, and verbal assessment tasks.

## **6.5 Human Intelligence Quotient data analysis**

Descriptive static was the initial step to standardise the obtained raw data from the participant's IQ assessment. This descriptive static has been divided into two separate analyses due to the flowing consideration.

1. The experiment encompassed data collection from two meticulously controlled teams:  
Team One, employing a Verbal Data Recording (VDR) method, and Team Two, utilizing a Pen-and-Paper Data Recording (PAPDR) approach.
2. The positive significant effect of Verbal Data collection approach on participant SA, declared within chapter 4.
3. The independent of subject's cognitive capability from the project's experiment's assessment.

Within the first data examination, the mean, median and Standard deviation of IQ assessment's elements from the subjects who participated within the Verbal Data Recording experiment, the second data analysis completed based on the obtained data.

The IQ scores from the participants were also categorised based on well-known IQ Bell Curve.

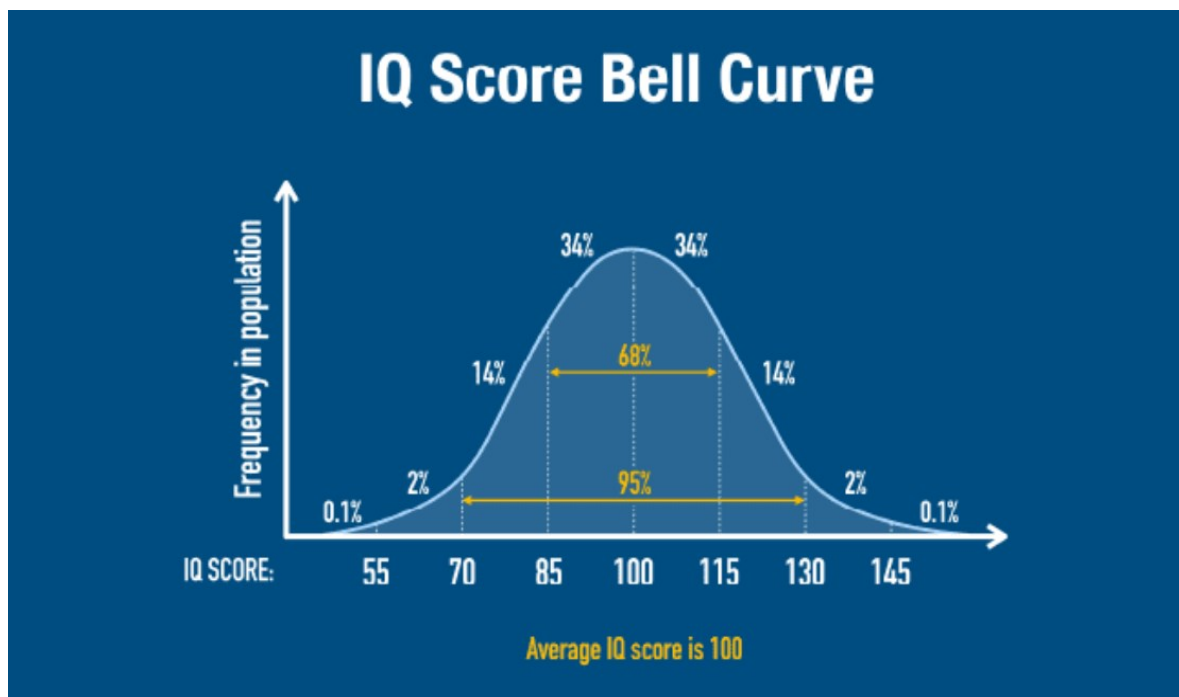


Figure26 IQ Bell Curve Ranges (MentalUp.com)

Martinez M. Future Bright: A Transforming Vision of Human Intelligence. Oxford University Press. 2013) where the peak of the “bell” shape indicates the majority of the subject’s scores lie and both side of the slope indicate the lower and above average recorded IQ results.

The subject’s IQ score subjects has been categorised as follow.

145 – 160 Very gifted or highly advanced

130 – 144 Gifted or very advanced

120 – 129 Superior

110 – 119 High average

90 – 109 Average

80 – 89 Low average,

This classification is based on IQ test-guide official (Dave Evangelisti, 2024) After computing all participants' IQ mean scores, the outcomes show 16 scores within the average range, 5 low average scores, 8 subjects with high average and only 1 subject at Superior who scores just over 120.

## **6.6 Human Intelligence Quotient and Situational Awareness**

To investigate the relationship between IQ scores and Situational Awareness (SA) scores and determine if an increase or decrease in IQ corresponds to changes in operator's SA, correlation analysis has been used. Specifically, Pearson's correlation coefficient.

As SAGTA tool consist of three levels, Level 1 (perception of data), Level 2 (comprehension of meaning), and Level 3 (projection of the near future). The correlation analysis of each Level has been computed according to the associated subject's IQ results which means according to each recorded IQ score there is a SA results which consists of three independent levels.

The steps taken in this correlation analysis are as follow:

### **1. Data Preparation:**

- Ensuring that there is pairs of IQ scores and corresponding SA scores for each participant in each experiment circumstances.
- Considering the assumptions associated with Pearson's correlation including Bivariate Normality, No Perfect Relationships and No Confounding Variables

### **2. Perform Pearson's Correlation:**



- Use Excel as statistical software to calculate Pearson's correlation coefficient between overall IQ scores and SA scores in each level. As well as considering the Sub-elements of IQ assessment correlation with all three levels of SAGTA levels.
- Pearson's correlation coefficient ranges from -1 to 1, where:
  - 1 indicates a perfect positive linear relationship,
  - -1 indicates a perfect negative linear relationship, and
  - 0 indicates no linear relationship.

### **3. Interpretation:**

- A positive correlation coefficient suggests that as IQ scores increase, SA scores also tend to increase.
- A negative correlation coefficient suggests that as IQ scores increase, SA scores tend to decrease.
- The magnitude of the correlation coefficient indicates the strength of the relationship.

### **4. Statistical Significance:**

- Assess the statistical significance of the correlation. This is usually done by performing a hypothesis test where the null hypothesis is that the correlation is zero (no relationship). The p-value associated with the correlation coefficient has been calculated according to the Pearson's R value and the number of the sample, this P value indicate whether the observed correlation is statistically significant.

## 5. Consider Other Factors:

- In addition, as correlation by itself does not imply causation, other factors that might influence both IQ and SA have been analysed including the IQ individual Sub-Elements (Memory, Concentration, Logic, Visual, and Verbal skills) so main causation can be established through correlation and their associated elements.

Initially the correlation coefficients between overall IQ score and each SA levels for participants of Verbal Data recording have been computed followed their associated significant level.

1. Correlation between SAGTA Level 1 (perception of data), and IQ R scores: 0.76 (Strong positive correlation) with computed P Value  $<0.001^{**}$ .
2. Correlation between SAGTA Level 2 (comprehension of meaning and IQ scores with R value of 0.70 which indicate a moderate positive correlation, the computed P value= 0.0033
3. Correlation between SAGTA Level 3 (projection of the near future) and IQ scores with R value of 0.30 which indicate a weak positive correlation the computed P value of 0.1337 as an insignificant correlation.

Similarly, the correlation analysis on data obtained from the subjects who participated in the Pen-and-Paper Data Recording has been computed. The outcome of the correlation analysis indicates a similar association analysis but with difference within the correlation strengths.

1. Pearson's correlation coefficient which has been calculated between SAGTA Level 1 (perception of data), and associated IQ score is R value of 0.72 and computed  $P=0.0024$ .

2. The calculated R value and P-Value was 0.53 and 0.44 for SAGTA Level 2 (comprehension of meaning) and participant's IQ scores.
3. Correlation between SAGTA Level 3 (projection of the near future) and IQ scores with R value of 0.084 indicate a weak positive correlation the computed P value of 0.77 as an Non-statistically significant correlation.

In order to consider the other relayed elements within this analysis the correlation of IQ sub-elements with the subject's SA has been computed in order to identify which Sub-element play a more crucial effect compared to other elements. This analysis has been recorded in table 15 for the subject's team associated with VDR and table 16 for participants took part within the PAPDR.

*Table 15 correlation of IQ sub-elements with the subject's SA for team VDR*

| Measures                   | SAGTA Level 1 |        | SAGTA Level 2 |        | SAGTA Level3 |      |
|----------------------------|---------------|--------|---------------|--------|--------------|------|
| Pearson's (R) and P values | R             | P      | R             | P      | R            | P    |
| Memory                     | 0.89          | <0.001 | 0.65,         | 0.0087 | 0.2          | 0.45 |
| Concentration              | 0.76          | 0.0036 | 0.50          | 0.57   | 0.25         | 0.37 |
| Logic                      | 0.49          | 0.16   | 0.58          | 0.023  | 0.49         | 0.63 |
| Visual                     | 0.55          | 0.033  | 0.34          | 0.21   | 0.15         | 0.59 |
| Verbal                     | 0.43          | 0.11   | 0.26          | 0.35   | 0.10         | 0.72 |

Table 16 Correlation of IQ sub-elements with the subject's SA for team PAPDR

| Measures                 | SAGTA Level 1 |        | SAGTA Level 2 |        | SAGTA Level3 |      |
|--------------------------|---------------|--------|---------------|--------|--------------|------|
|                          | R             | P      | R             | P      | R            | P    |
| Pearson (R) and P values |               |        |               |        |              |      |
| Memory                   | 0.80          | 0.009  | 0.65          | 0.0087 | 0.20         | 0.45 |
| Concentration            | 0.70          | 0.0035 | 0.50          | 0.057  | 0.25         | 0.37 |
| Logic                    | 0.38          | 0.016  | 0.58          | 0.023  | 0.30         | 0.28 |
| Visual                   | 0.50          | 0.058  | 0.34          | 0.21   | 0.15         | 0.59 |
| Verbal                   | 0.43          | 0.11   | 0.26          | 0.35   | 0.10         | 0.72 |

## 6.7 Conclusions & Discussions

Perception of data is a fundamental cognitive skill. Individuals with a high level of data perception are likely to process information more efficiently and accurately, which aligns with the requirements of the IQ test that includes visual tasks related to pattern recognition and data interpretation. The strong positive correlation between the perception of data in all participants results and IQ scores suggests that individuals who excel in perceiving and recognizing data, patterns, and information in their IQ test tend to have higher SA specifically in terms of Perception of Data (SAGTA Level 1).

The moderate positive correlation between Comprehension of Meaning (SAGTA Level 2) and IQ scores indicates that individuals who can understand and derive meaning from the information they perceive tend to have moderately higher IQ scores test at the logic sub-element of IQ test.

Comprehension of meaning involves not only recognizing data but also interpreting information. This ability is crucial for problem-solving, which is a significant component of IQ tests that are included within the logic tasks.

Non-statistically significant correlation of participant's IQ scores and Projection of the Near Future (SAGTA Level 3) indicate that, in the context of this experiment, the ability to project the near future

doesn't strongly influence IQ scores. The main reason is limited relevance to IQ test as projection of the near future involves skills related to anticipation and prediction, the experiment's IQ test that did not heavily rely on future projection skills, so it has not been directly assessed.

Moreover, this correlation aligns with the general intelligence factor (g factor) theory in psychology, Information processing efficiency and association of working memory with operator's SA. where g factor) theory suggests that various cognitive abilities are interrelated, and a high g factor often corresponds to high performance in a wide range of cognitive tasks. Information processing efficiency refers to the ability to process and comprehend information with optimal use of resources. It encompasses the speed and accuracy with which individuals can perceive, interpret, and respond to incoming information.

Furthermore, correlation factors of Verbal IQ, Full Scale IQ, and Verbal Comprehension of Wechsler Adult Intelligence Scale - Third Edition (WAIS-III) have been found to have strong correlations with memory function (Murayama et al., 2013).

## **Chapter 7**

### **Synthesis, Conclusions, Limitations and Future Directions**

#### **7.1 Introduction**

This thesis aimed to comprehensively expand the knowledge base in human-robot interaction by merging insights from cognitive science with empirical findings in telerobotic. The central focus was to explore and clarify how human cognitive styles and information processing dynamics influence operators' situational awareness within the realm of telerobotics. The conducted study culminated in the development of evidence-based recommendations aimed at optimizing telerobotic-operator Situational Awareness. These recommendations are rooted in an exhaustive analysis encompassing a diverse array of tasks and contexts.

The experimental component of this research was meticulously designed to assess key parameters such as operators' situational awareness, performance, attention allocation, cognitive workload, and human intelligence quotient. The experiments were set in a real-world telerobotic framework, simulating a nuclear station environment to study intricate aspects of human-robot interaction in high-stakes scenarios. Additionally, a human search and rescue mission was replicated to further test the applicability of these findings in critical, real-life situations.

Within this telerobotic exercise, subjects were engaged in tasks characterized by three distinct levels of difficulty. This stratification allowed for a nuanced examination of how varying task complexities impact operator performance and cognitive engagement. The data

collected from these tasks were three-dimensional, providing a rich, multifaceted dataset for in-depth analysis.

## 7.2 Synthesis of Findings

The study presented in this thesis is structured around six distinct yet interconnected objectives, each aiming to deepen our understanding of human-robot interaction in the context of telerobotics. Which is illustrated in figure 27, these objectives are methodically designed to address various facets of the field, combining theoretical insights with empirical research.

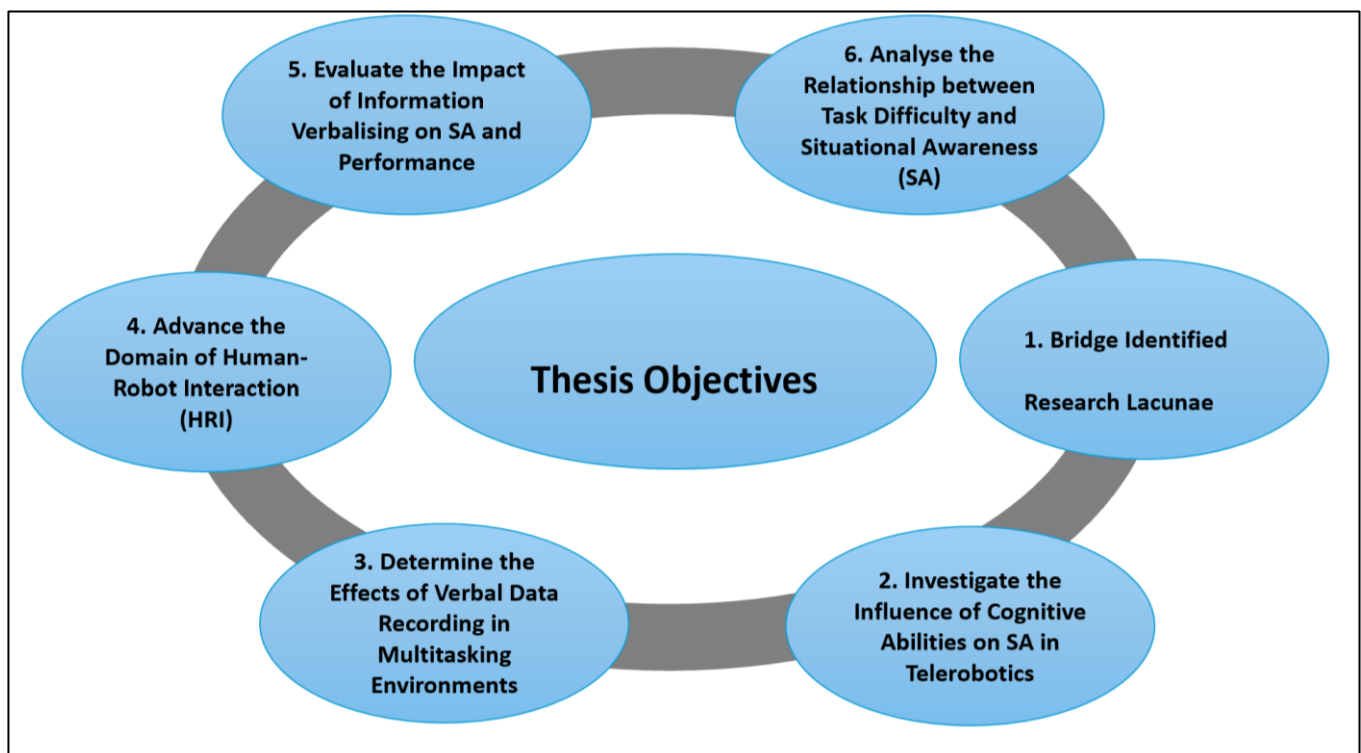


Figure 27 Thesis objectives

The inaugural objective of this research was to conduct a methodical investigation into the prevailing gaps within the existing literature on human factors in telerobotics, particularly focusing on Situational Awareness and cognitive abilities. This investigation was driven by the recognition that human factor considerations in Human-Telerobotic Interaction (HTI) have not received adequate

attention compared to other domains. This oversight is significant, considering that inadequate SA among telerobotic operators is a notable hindrance to the efficient functioning of these systems. Moreover, this objective acknowledges the critical need in the current robotics revolution not just for advanced technological development but for mastery in its practical application, especially concerning the interaction and control dynamics between operators and robotic systems.

This necessity stems from the intricate and multidisciplinary essence of HRI, which has undergone transformative shifts due to rapid technological advancements. These developments have significantly altered the landscape of human-machine interaction, demanding a thorough exploration into the complex, reciprocal cognitive interactions between humans and robots.

In bridging insights from cognitive science and telerobotic research, the study hypothesizes that real-time verbal reporting, particularly in goal-directed telerobotic operations, can substantially enhance an operator's SA. This proposed enhancement is grounded in the direct interplay between human cognitive processing and the act of information verbalization. The process of human information processing, especially during event perception, heavily depends on sensory cues and engages a range of neuropsychological and cognitive mechanisms. These mechanisms include memory retention, the functioning of the prefrontal cortex, and the ability for perspective-taking, all of which are instrumental in constructing a coherent verbal representation of unfolding events.

However, the research also uncovers a significant gap in the current understanding of verbal working memory, especially when contrasted with visual or spatial working memory. Verbal working memory is a distinctively human trait and holds considerable importance in the realms of telerobotics and teleoperation. Despite its critical role, there is a noticeable



deficiency in research regarding how operator verbal reporting impacts their SA in these specific fields. Addressing this lacuna is a pivotal aspect of this research, carrying substantial implications for improving the effectiveness of operators and the overall operational efficiency of telerobotic systems.

The second research objective of this thesis was centered on assessing the impact of information processing methods on operator Situational Awareness (SA) in telerobotic operations. This objective sought to delve into the influence of varying cognitive styles on how operators perceive, understand, and anticipate information within a telerobotic environment. A significant focus was placed on evaluating the effect of the Information Verbalizing approach on SA and performance during telerobotic tasks.

To facilitate this investigation, a comprehensive system and technology assessment was conducted on the robotic systems available at the University of Birmingham. This assessment included the development and integration of modular software and hardware, tailored to suit the environmental conditions where the experimental tasks were executed.

Chapter 4 of the thesis is specifically dedicated to a statistical analysis aimed at determining the impact of information or data verbalization by operators on their SA and performance.

This analysis was crucial in addressing Research Question 1: "Does the use of an information verbalizing approach in goal-directed telerobotic tasks enhance human operators' Situational Awareness and improve their performance in telerobotic operation tasks, compared to the traditional Pen-and-Paper Data Recording method?"

The study's results show that when operators reported verbally during telerobotic tasks, their Situational Awareness (SA) improved significantly. Specifically, the statistical analysis indicates that there was a meaningful enhancement in the operators' ability to both

perceive the elements of the task ( $t(28) = 2.30$ ,  $p\text{-value} = 0.029$ ) and understand their significance ( $t(28) = 2.27$ ,  $p\text{-value} = 0.031$ ) within a remote environment. These  $p\text{-values}$ , being less than 0.05, suggest that the improvements observed are statistically significant and not due to random chance. However, according to the Situational Awareness Global Assessment Technique (SAGAT) Level 3 assessment, there was no significant difference in the participants' ability to project the near future under the experimental conditions.

Additionally, a complementary SA assessment instrument, the Situation Awareness Rating Technique (SART), was also employed to further investigate the impact of verbal information processing on operator SA. The results from SART indicated a positive and significant effect of verbal information processing on operators' SA with significant of  $t(28)=2.27$ ,  $p=0.024$ .

In summary, the outcomes of this objective demonstrated that the Information Verbalizing approach positively influences operators' situational awareness, particularly in enhancing their perception and comprehension during telerobotic operations. However, it is important to note that this enhancement did not extend to the operators' ability to project future states in the given experimental setup. These insights contribute significantly to our understanding of the role of cognitive and information processing methods in shaping operator SA in telerobotics.

The third objective of this study was to assess the impact of verbal data recording on operators' attention allocation and mental workload during goal-directed telerobotic tasks. To address this objective, Chapter 5 focused on analysing the collected data to elucidate the effects of verbal information processing. This analysis was pivotal in responding to Research Question 3, which asked, "Does the utilization of the Verbal Data Recording approach in a

goal-directed telerobotic task significantly affect participants' attention levels and reduce their mental workload during multitasking situations?"

The results of the research indicate that when operators engage in verbal information processing while performing targeted tasks with telerobots, there is a significant increase in their ability to concentrate on the main task. This is evidenced by a substantial F-statistic value of 22.46 and a significant p-value of 0.00024. Additionally, this process of verbalization appears to lower the mental workload for the operators. One of the key factors contributing to this outcome is benefits of Multimodal Processing and Real-time Engagement where operators also benefit from the self-auditory experience and the focused attention required for verbalization. These benefits combination is taken into account as the main source of cognitive load reduction associated with speaking out loud. This reduction in cognitive burden, compared to other cognitive processes, is attributed to the benefits of Multimodal Processing and Real-time Engagement, which verbalization facilitates.

Furthermore, the results offer substantial insights into the interplay between mental workload and attention allocation in human operators. Specifically, the study found that a reduction in cognitive load, achieved through verbal data recording, leads to a decreased mental workload. This, in turn, allows subjects to devote more mental resources to the primary telerobotic task. In essence, verbal data recording not only aids in focusing attention more effectively on the task at hand but also contributes to a more efficient allocation of cognitive resources, enhancing overall task performance.

In summary, the outcomes of this objective provide valuable contributions to our understanding of how task's data verbalization impacts cognitive processes in telerobotics. The findings underscore the efficacy of verbal information processing in optimizing attention

allocation and reducing mental workload, thereby facilitating more effective and efficient human-operator interaction in telerobotic operations.

The fourth objective of this thesis was focused on exploring the influence of operators' inherent cognitive abilities on their ability to acquire and maintain Situational Awareness (SA) in the context of telerobotic operations. This exploration was directly aligned with addressing Research Question 4, which posits, "Do individual differences in cognitive abilities, as indicated by IQ scores, significantly influence the level of Situational Awareness in operators during telerobotic operations?"

To investigate this, the study conducted a detailed analysis of data correlations, drawing from two separate experimental setups. Each experiment was meticulously designed to reveal the impact of operators' intrinsic Intelligence Quotient (IQ) on their SA in a telerobotic environment. The results derived from these experiments are pivotal in illuminating the relationship between cognitive abilities and SA.

The findings disclosed in this part of the thesis demonstrate a clear and substantial correlation between the subjects' IQ levels and their SA during telerobotic operations. Notably, this correlation was most evident in the realms of data perception and comprehension by the operators. The analysis, utilizing the Situational Awareness Global Assessment Technique (SAGAT), especially at Level 1 (perception) and Level 2 (comprehension), significantly correlated these aspects of SA with the subjects' IQ scores, thus validating the proposed relationship.

Further in-depth analysis of the data revealed that specific cognitive faculties, namely Cognitive Processing Speed, Working Memory, and Attention, have a more pronounced impact on operator's SA in telerobotic operations. The speed at which cognitive processing

occurs is fundamental for the quick assimilation and processing of environmental information, which is crucial for maintaining SA in dynamic telerobotic scenarios. Similarly, Working Memory is critical for holding and manipulating situational information, facilitating effective decision-making processes. Attention, particularly in its capacity to selectively focus on pertinent stimuli while filtering out irrelevant information, is essential to prevent SA from being compromised by information overload or environmental complexities.

In conclusion, the results from this investigation significantly enhance our understanding of how intrinsic cognitive abilities, particularly as quantified by IQ, intertwine with and influence SA in telerobotics. This profound connection between IQ and essential components of SA has far-reaching implications for the processes of selecting, training, and supporting telerobotic operators. It opens the door for developing more targeted, effective, and human-centered approaches in telerobotics, ensuring that operators are not only technically proficient but also cognitively well-equipped to handle the complexities of telerobotic operations.

The fifth objective of this thesis was to establish and analyses the relationship between the Level Of Difficulty and Situational Awareness (SA), attention allocation, and mental workload, aligning with Research Question 2: "How does the variation in LOD within a primary telerobotic task affect the SA levels of the subjects, and is there a quantifiable correlation where increased task difficulty leads to a decrease in SA levels, attention allocation, and mental workload?"

The findings, as elucidated in Chapter 4, revealed that participants' SA remained largely consistent despite variations in the experiment's LOD. This outcome aligns with the third

hypothesis of the thesis, suggesting that task difficulty does not significantly impair SA. Two main factors contribute to this observation:

1. **Controlled Experimental Design:** The experimental design was meticulously crafted to minimize the influence of extraneous variables on the operators' SA. Variations in LOD were carefully regulated to ensure that the objectives of the task remained constant across all levels. This consistency in experimental goals, subgoals, and telerobotic control strategies across different levels of difficulty was instrumental in maintaining stable SA among participants.
2. **Cognitive Acceptance Level:** The absence of a significant correlation between SA and LOD may also be attributed to the task difficulties being within the cognitive acceptance threshold of the participants. This suggests that the LOD were not excessively demanding, thus not overloading the participants' cognitive capabilities.

Chapter 5 further substantiates that significant differences were observed in participants' attention levels with variations in LOD, particularly when data were recorded verbally. The most pronounced difference was noted between low and high levels of difficulty, while the least significant difference occurred between low and medium levels. These findings imply that the task's LOD substantially affects attentional allocation, necessitating consideration of various cognitive and perceptual factors, including Cognitive Load Theory, Perceptual Demands, and Attentional Resources and Allocation.

In conclusion, these results highlight the robustness of operator SA in telerobotic contexts across different task complexities and the connection to studies and theoretical frameworks from Chapter 2, the Literature Review.. They also underscore the significant impact of LOD

on attentional allocation, especially when coupled with verbal data recording, offering valuable insights into the cognitive dynamics at play in complex telerobotic operations.

### **7.3 Overall Research Limitations and Future Directions**

In summary, the limitations identified in this research, particularly those influenced by limited funding resources, have shaped the scope and depth of the investigations conducted. The constrained budget impacted the range of technologies employed. On top of this, the diversity of participant groups was effected due to the limited funding because to persuade participants to take part in this project, they were provided with Amazon vouchers as a token of appreciation for their time and effort. However, due to the limited budget allocated to the study, it was not feasible to include a larger number of participants., and the extensiveness of data collection, potentially affecting the comprehensiveness of the findings.

Moreover, the restricted ability to probe verbal information processing in varied telerobotic environments limits the generalizability of the findings related to its impact on SA. Future research would benefit from exploring these aspects in more diverse settings to validate and expand upon the current understanding of verbal information processing in telerobotics.

The correlation between IQ and SA, a significant finding of this study, is based on the specific experimental conditions utilized. This relationship may exhibit variations in different operational contexts, particularly with the increasing integration of virtual reality (VR), augmented reality (AR), and mixed reality (MR) in telerobotic operations. Investigating the interplay between IQ and SA in these technologically advanced environments could yield valuable insights, contributing to the advancement of telerobotics and human-telerobotic interaction.

One notable limitation in the current research pertains to the methods used for assessing operator IQ. While the study employed certain tools to measure Intelligence Quotient (IQ) as a proxy for cognitive abilities, there exists an opportunity to utilize more formal, comprehensive, and potentially more accurate tools for IQ assessment.

The tools used in this research, although effective to a degree, may not encompass the full spectrum of cognitive abilities encapsulated within an individual's IQ. More robust and standardized IQ testing instruments, which are designed to provide a deeper and multifaceted understanding of cognitive capabilities, could yield more precise and nuanced insights.

Using such formal tools can lead to outcomes that are not only more robust but also more reflective of the complex nature of human intelligence. These tools often include a broader range of cognitive tasks and measures. Incorporating more comprehensive assessments would allow for a more detailed evaluation of how different cognitive dimensions specifically influence situational awareness in telerobotic operations.

The meticulous control of experimental variables, while essential for minimizing extraneous influences, resulted in a limited assessment of variability in task difficulty. This aspect may restrict the understanding of SA in less controlled or more variable telerobotic environments. Future studies should aim to examine SA in more dynamic and unpredictable settings to gain a fuller understanding of its nuances.

Looking ahead, several directions for future research emerge, taking into consideration the effects of information or data verbalization:



1. **Utilizing Emerging Technologies:** Future research should leverage evolving technologies in telerobotics. This includes evaluating verbal information processing in conjunction with AI, AR, and machine learning technologies, to assess their collective impact on operator performance and SA.
2. **Expanding the Experimental Framework:** There is an opportunity to broaden the experimental framework in future studies. This expansion could encompass a range of operational settings, incorporate a wider array of cognitive assessments, and enable a deeper exploration of human factors in telerobotics.
3. **Diverse Participant Recruitment:** Securing additional funding could facilitate the inclusion of a more diverse group of participants. This diversity would not only enhance the representativeness of the research but also contribute to the robustness and generalizability of the findings.

In closing, this research has laid a foundation for further exploration in the field of human-robot interaction, specifically in telerobotics. The identified limitations and proposed future directions offer a roadmap for subsequent studies to build upon the insights gained, driving forward the advancement of telerobotic systems and their alignment with human cognitive processes.

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# **APPENDIX**

Appendix A Experimental Information Sheet

Appendix B Experimental Health & Safety Guidelines

Appendix C Experiment Consent Form

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Appendix F Situational Awareness Global Assessment Technique Questionnaire

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.

## Appendix A Experimental Information Sheet



### Experimental Information Sheet for Participants

**Experiment Title:** Utilization of Spot the Dog Robot in Real-World Scenarios

**Introduction:** Welcome to our research experiment! We appreciate your participation in this study, which involves using the Spot the Dog robot from Boston Dynamics. In this experiment, you will engage in simulated real-world scenarios, specifically a nuclear station investigation and a human search and rescue mission. The purpose of this study is to analyse your situational awareness, attention allocation, mental workload, performance, and your IQ.

### Experiment Description:

- **Robot Utilization:** During the experiment, you will interact with the Spot the Dog robot, controlled by our team. This robot will be an integral part of the scenarios you will navigate.
- **Scenarios:** You will participate in a simulated scenario: a nuclear station investigation and a human search and rescue mission. These scenarios are designed to be engaging and realistic.
- **Data Collection:** We will collect data at various times throughout, before, and after the experiment to understand your cognitive and behavioural responses. This includes data on situational awareness, attention allocation, mental workload, performance, and your IQ.

### Data Privacy:

- **Withdrawal:** If at any point during the experiment, you decide to withdraw, all data collected up to that point will be destroyed, ensuring your privacy and confidentiality.
- **Data Handling:** All collected data will be anonymized and securely stored on the University's IT system. Your identity will remain confidential, and the data will only be used for the purposes of this PhD research experiment.
- **Publication:** The anonymized data may be used in academic journals or conferences to contribute to scientific research. However, rest assured that your personal information will remain confidential in any publications.

**Contact and Further Information:** If you have any questions, concerns, or would like more details about the experiment or its results, please feel free to contact us. We are here to provide any additional information or clarification you may require.

Thank you for participating in this valuable research. Your involvement is crucial in advancing our understanding of human-robot interactions and enhancing the field of robotics and cognitive science.

**Contact Information.**

**Name;** Adib Housaini

**Email.** [REDACTED]

## **Appendix B      Experimental Health & Safety Guidelines**



Experimental Health & Safety Guidelines should be read by participants prior to any research experiment and training.

### **1. Robot Familiarization and Training:**

- Before using the Spot robot, you'll receive training on how to operate it safely and efficiently.

### **2. Emergency Procedures:**

- We have clear plans in case of robot malfunctions or emergencies. Our team knows how to stop the robot and respond to unexpected situations.

### **3. Protective Gear:**

- You may be required to wear safety gear like goggles or gloves, depending on the experiment's needs. We'll provide these if necessary.

### **4. Robot Inspection:**

- We regularly check the robot for any issues to ensure it's safe for operation. If we find any problems, we'll fix them immediately.

### **5. Workspace Safety:**

- We've marked the robot's operating area to prevent accidental contact. Please stay within designated areas to stay safe.

### **6. Risk Assessment:**

- We've identified and minimized potential risks associated with the robot's use to ensure everyone's safety.

### **7. Remote Control:**

- If the robot is controlled remotely, we'll ensure operators have a clear view of the robot through the dedicated control display.

### **8. Battery Management:**

- We'll manage the robot's batteries to ensure they are always in good condition and operational.

### **9. Communication:**

- Our team will use clear signals and verbal commands to coordinate safe robot operations.

### **11. Supervision:**

. A responsible supervisor will oversee the entire experiment to ensure safety guidelines are followed.

Name.....

Signature..... Date .....

## Appendix C Experiment Consent Form



### Consent Form

ID #\_\_\_\_

#### PhD Research Experiment

|                                                                                        | Please tick to confirm |
|----------------------------------------------------------------------------------------|------------------------|
| I am over 18                                                                           |                        |
| I have read and understood the information sheet                                       |                        |
| I have been given the opportunity to ask questions about the study                     |                        |
| I understand that I have the right to withdraw from the experiment at any time         |                        |
| I agree to report any discomfort that might arise from using the system                |                        |
| I agree to the anonymous data being collected from me to be used for research purposes |                        |
| I understand that all data recorded will be anonymised and will not be linked to me    |                        |
| I agree to take part in the above-mentioned experiment                                 |                        |

Name.....

Signature..... Date .....

## Appendix D Participant Recruitment sheet

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**Play with Spot The Dog Robot & get Amazon Voucher**

If you would like to hands on one of the advanced robot on plant earth for 1 hour.

1. Get involved in our Robot server study.
2. Get your time slot & Play with Spot
3. Get your Amazon voucher.

Hi, my name is Adilb, I am a Ph.D. student from School of Engineering, my project is based on enhancing **Human & Robot interaction**. Part of my research is getting survey using one of the most advanced robot from Boston Dynamic (USA). If you would like to take a part in this survey, please contact me via my email address. I will send you the timing slot and you can select your suitable slot.

[axh419@student.bham.ac.uk](mailto:axh419@student.bham.ac.uk)

## Many thanks

[illegible]



## Appendix E Participant Recruitment sheet



Candidate application form for Situational Awareness project experiment.

Date;                      time;                      Experiment number ;

Candidate number; -----

Candidate Name; -----

Gender: F ☐ M ☐

Email address; -----

-----  
Experiment variable;    A                      B

Candidate assigned team; -----

Candidate assigned group; -----

Experiment's difficulty level; -----

An intelligence quotient test number; -----

Experiment Starting time; -----

Experiment completion duration; -----

Monitoring task score; Robot battery -----    Equipment Battery-----    total score; -----

-----  
Candidate signature; -----



## Appendix F Situational Awareness Global Assessment

### Technique Questionnaire

Queries on SA, potential responses, and the Level of SA targeted by each query.

| SAGAT QUERY                                            | POSIBLE RESPONSES                                                      | Participant's Answer | SA LEVEL |
|--------------------------------------------------------|------------------------------------------------------------------------|----------------------|----------|
| What was the current task activity?                    | (a) Searching<br>(b) Recording data<br>(c) Rescuing human              |                      | 1        |
| What type of indicator was being recorded?             | (a) Pressure gauge<br>(b) Radioactive<br>(c) Survivors<br>(d) Non      |                      | 1        |
| Is the robot in a contaminated area?                   | (a) Yeas<br>(b) No                                                     |                      | 1        |
| What was the current situation of both battery levels? | (a) Both full<br>(b) Both low<br>(c) One need charging<br>(d) Not sure |                      | 1        |
| How many Pressures gage have been recorded so far?     | (a) 1-3<br>(b) 3-5<br>(c) 5-7<br>(d) 7-9<br>(e) 10-15<br>(f) 15-20     |                      | 2        |
| Which batty needed more recharging?                    | (a) The Robot<br>(b) The equipment's                                   |                      | 2        |
| Has any human detected?                                | (a) Yeas<br>(b) No                                                     |                      | 2        |
| What was the last indicator recorded?                  | (a) Pressure gauge<br>(b) Radioactive<br>(c) Survivors<br>(d) Non      |                      | 2        |
| Which batty need recharging next?                      | (c) The Robot<br>(d) The equipment's                                   |                      | 3        |
| What will be the radioactive indicator condition?      | (a) Safe<br>(b) Danger<br>(c) Neutral                                  |                      | 3        |
| What was the very next task activity?                  | (a) Searching<br>(b) Recording data<br>(c) Rescuing human              |                      | 3        |
| Is there any indicator close to the robot?             | (a) Pressure gauge<br>(b) Radioactive<br>(c) Survivors<br>(d) Non      |                      | 3        |



## Appendix G Situation Awareness Rating Technique (SART),

### Questionnaire

| Construct                | Definition                                                              |
|--------------------------|-------------------------------------------------------------------------|
| Instability of situation | Likelihood of situation to change suddenly                              |
| Variability of situation | Number of variables which require one's attention                       |
| Complexity of situation  | Degree of complication (number of closely connected parts) of situation |
| Arousal                  | Degree to which one is ready for activity (sensory excitability)        |
| Spare mental capacity    | Amount of mental ability available to apply to new variables            |
| Concentration            | Degree to which one's thoughts are brought to bear on the situation     |
| Division of attention    | Amount of division of attention in the situation                        |
| Information quantity     | Amount of knowledge received and understood                             |
| Information quality      | Degree of goodness or value of knowledge communicated                   |
| Familiarity              | Degree of acquaintance with situation experience                        |

### 10-D SART

|               |                          | Low High |   |   |   |   |   |   |
|---------------|--------------------------|----------|---|---|---|---|---|---|
|               |                          | 1        | 2 | 3 | 4 | 5 | 6 | 7 |
| DEMAND        | Instability of situation |          |   |   |   |   |   |   |
|               | Variability of situation |          |   |   |   |   |   |   |
|               | Complexity of situation  |          |   |   |   |   |   |   |
| SUPPLY        | Arousal                  |          |   |   |   |   |   |   |
|               | Spare mental capacity    |          |   |   |   |   |   |   |
|               | Concentration            |          |   |   |   |   |   |   |
|               | Division of attention    |          |   |   |   |   |   |   |
| UNDERSTANDING | Information quantity     |          |   |   |   |   |   |   |
|               | Information quality      |          |   |   |   |   |   |   |
|               | Familiarity              |          |   |   |   | 9 |   |   |

# Appendix H    Workload Questionnaire



 NASA TLX

1:12

NAME

Please enter your name

Task #1

**Read the user guide**  
Select "User Guide" in menu and read instructions and tips for using the application.

>

Task #2

**Add your own tasks**  
Open the "Settings" menu to select and create you own questionnaires.

>

Task #3

**Customize**  
Modify CSV exporter options in the "Settings" menu.

>

Task #4

**Contribute!**  
Go to "About" menu to read how can you support development of this application.

>

# Appendix H Workload Questionnaire



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← Rate task experience

1:21

NAME

Please enter your name

TASK

Read the user guide

Select "User Guide" in menu and read instructions and tips for using the application.

DATE

2024-01-06 13:13

Mental Demand

How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

Very Low

Very High

Physical Demand

How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

Very Low

Very High

Temporal Demand

How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

Very Low

Very High

Performance

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

Perfect

Failure

Effort

How hard did you have to work (mentally and physically) to accomplish your level of performance?

Very Low

Very High

Frustration

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Very Low

Very High

CONTINUE

# Appendix H Workload Questionnaire



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1:26

← Rate workload sources

SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 1 of 15

PERFORMANCE

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

OR

FRUSTRATION

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 2 of 15

TEMPORAL DEMAND

How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

OR

MENTAL DEMAND

How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 3 of 15

TEMPORAL DEMAND

How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

OR

FRUSTRATION

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 4 of 15

PHYSICAL DEMAND

How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

OR

FRUSTRATION

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

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## Appendix H Workload Questionnaire

### SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 5 of 15

#### PERFORMANCE

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

OR

#### MENTAL DEMAND

How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

### SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 6 of 15

#### TEMPORAL DEMAND

How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

OR

#### EFFORT

How hard did you have to work (mentally and physically) to accomplish your level of performance?

### SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 7 of 15

#### FRUSTRATION

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

OR

#### EFFORT

How hard did you have to work (mentally and physically) to accomplish your level of performance?

### SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 8 of 15

#### FRUSTRATION

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

OR

#### MENTAL DEMAND

How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

### SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 9 of 15

#### PHYSICAL DEMAND

How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

OR

#### TEMPORAL DEMAND

How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

# Appendix H Workload Questionnaire



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## SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 10 of 15

EFFORT

How hard did you have to work (mentally and physically) to accomplish your level of performance?

OR

PHYSICAL DEMAND

How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

## SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 11 of 15

MENTAL DEMAND

How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

OR

PHYSICAL DEMAND

How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

## SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 12 of 15

PHYSICAL DEMAND

How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

OR

PERFORMANCE

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

## SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 13 of 15

MENTAL DEMAND

How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

OR

EFFORT

How hard did you have to work (mentally and physically) to accomplish your level of performance?

## SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 14 of 15

PERFORMANCE

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

OR

TEMPORAL DEMAND

## SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 15 of 15

EFFORT

How hard did you have to work (mentally and physically) to accomplish your level of performance?

OR

PERFORMANCE

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?





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## Appendix I Workload results calculated.

Subject name: -----

Task text: "Read the user guide.

Select User Guide"" in menu and read instructions and tips for using the application.""

Date/Time: 13/03/2023 11:57

| Scale name      | Raw Rating | Tally       | Weight      | Adjusted Rating |
|-----------------|------------|-------------|-------------|-----------------|
| Mental Demand   | 10 2       | 0.133333333 | 1.333333333 |                 |
| Physical Demand | 50 2       | 0.133333333 | 6.666666667 |                 |
| Temporal Demand | 40 2       | 0.133333333 | 5.333333333 |                 |
| Performance     | 55 3       | 0.2 11      |             |                 |
| Effort          | 55 2       | 0.133333333 | 7.333333333 |                 |
| Frustration     | 60 4       | 0.266666667 | 16          |                 |

Overall rating 47.66666667

## Appendix J Intelligence Quotient (IQ), Questionnaire.



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Name:

Daniel

Age:

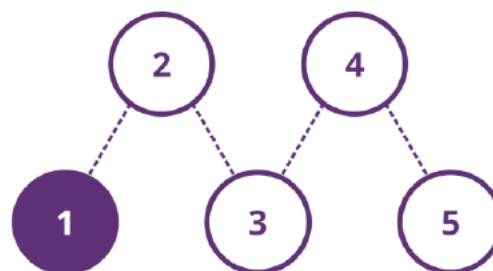
28

Start Test

- During the test, the question is at the top and the choices are at the bottom in each step.  
You need to find the relationship between them.
- Don't forget that your test completion time will affect your test results.

### MentalUP IQ Test

Test your mental skills in 5 steps and discover your potential!



Start Now

# IQ Test



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## 1. Question

If you rearrange the letters "CARACTTIN" you have the name of a(n):

☐ a. Continent

☐ b. City

☐ c. Ocean

☐ d. Animal

## 2. Question

What is the next number in the series:

7, 10, 16, 28, 52, \_\_

☒ a. 88

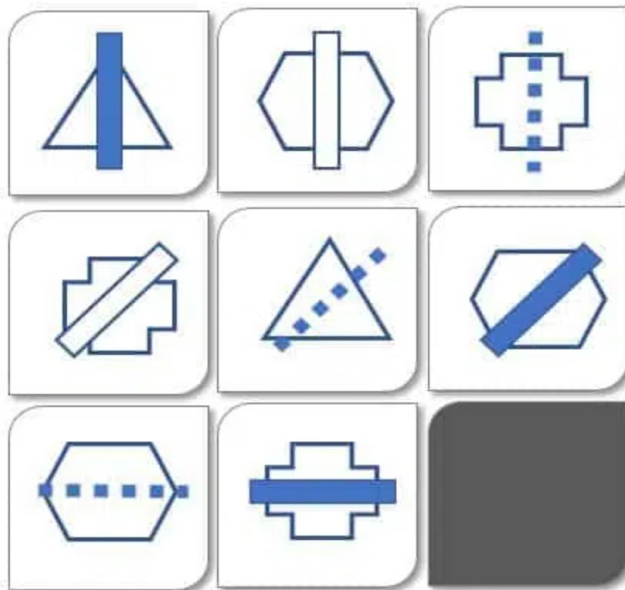
☐ b. 100

☐ c. 66

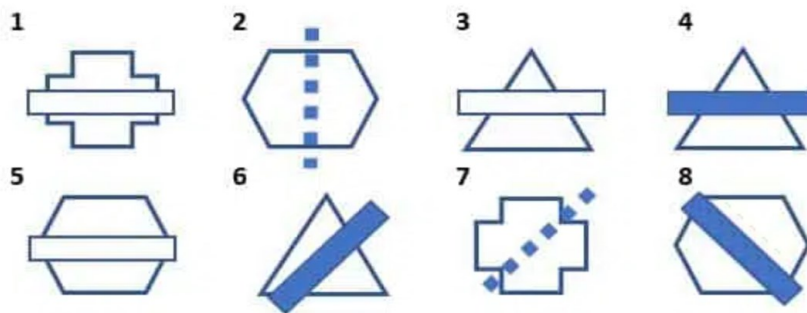
☐ d. 76

### 3. Question

Which figure belongs in the empty spot?



TEST-GUIDE www.test-guide.com



### 4. Question

Which conclusion follows from the statements with absolute certainty?

1. None of the runners is a teacher.
2. All of the attendees are runners.

☐ a. some drones are teachers

☐ b. no runners are attendees

☐ c. teachers are not attendees

☐ d. all runners are teachers



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**6. Question**

Afraid is to scared as brave is to \_\_\_\_\_.

☐ a. courageous

☐ b. cowardly

☐ c. timid

☐ d. trustworthy

**7. Question**

An organization hosts monthly meals for families in the community. In March, 70 people attended the meal. In April, 60 attended. Their highest attendance was in May, with 20 more than April. What is their average monthly attendance?

☐ a. 75

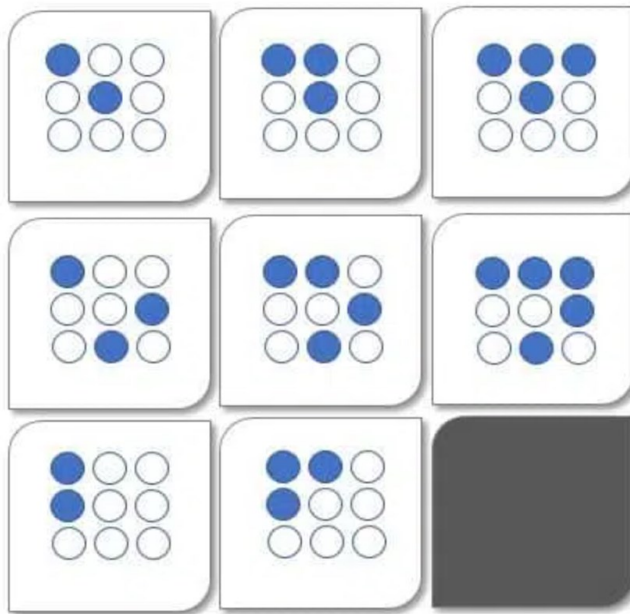
☐ b. 50

☐ c. 80

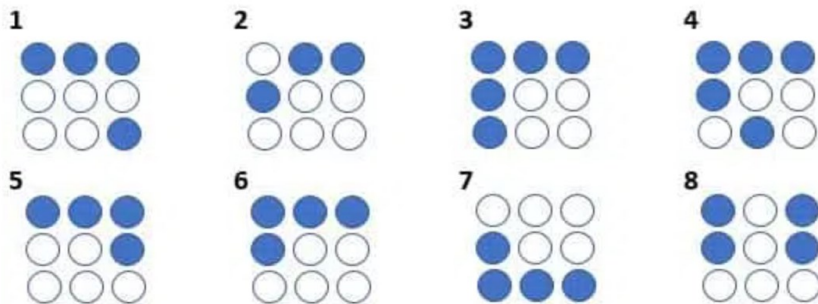
☐ d. 70

### 8. Question

Which figure belongs in the empty spot?



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### 9. Question

If the first two statements are true, is the final statement true?

1. Mrs. Jones is responsible for collecting all of the fifth grade classes' money for the school fundraiser.
2. Sally attends Mrs. Jones' school.
3. Mrs. Jones is responsible for collecting Sally's money for the fundraiser.

☐ a. Yes

☐ b. No

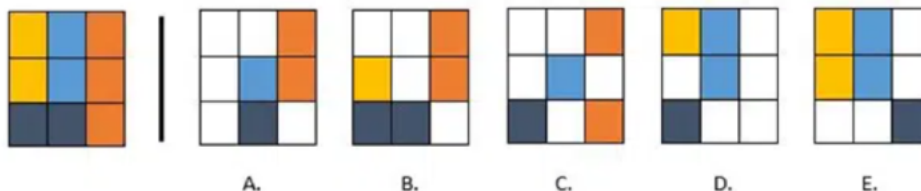
☐ c. Uncertain



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**10. Question**

Which THREE choices are needed to create the figure on the left? Only pieces of the same colour may overlap.



☐ a. A

☐ b. B

☐ c. C

☐ d. D

☐ e. E

**11. Question**

Which THREE of the following words have the same meaning?

☐ a. outstanding

☐ b. atypical

☐ c. intractable

☐ d. distinguished

☐ e. mediocre

**12. Question**

What is the missing number in the series:

3, 9, 81, 15, 21, 71, \_\_, 33, 61

☐ a. 56

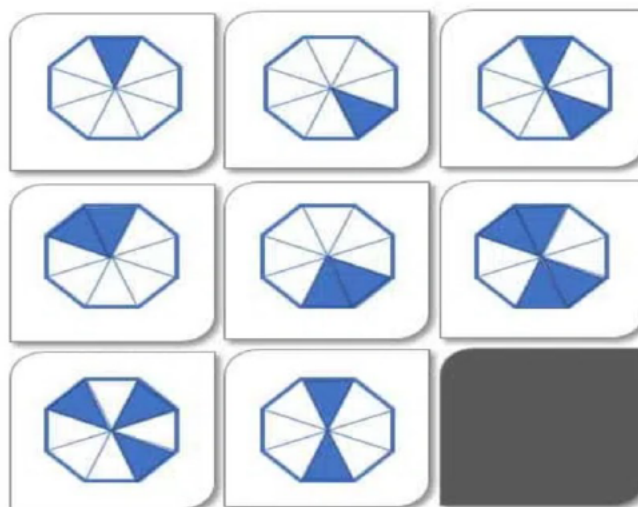
☐ b. 22

☐ c. 27

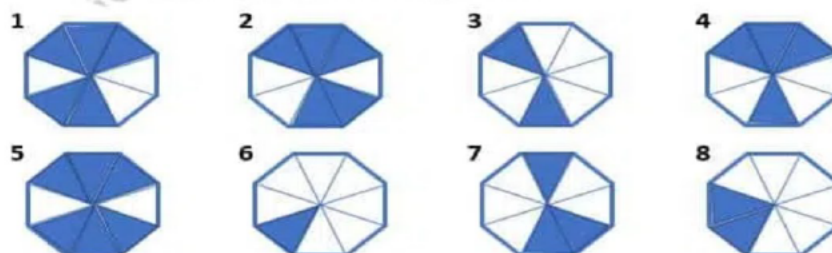
☐ d. 25

**13. Question**

Which figure belongs in the empty spot?



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**14. Question**

The words allude and elude have \_\_\_\_\_ meanings.

☐ a. same

☐ b. opposite

☐ c. unrelated

**15. Question**

A movie premiered this weekend.

250 people attended the first showing. Of the 250, 75 were adults above the age of 40, 50 were between the ages of 20 and 40, and 25 were teenagers ages 13-19. What percentage of the attendees were children 12 and under?

☐ a. 35%

☐ b. 25%

☐ c. 60%

☐ d. 40%

**16. Question**

If the first two statements are true, is the third statement true?

1. Mr. Reed teaches all of the advanced math classes at his school.
2. Billy attends Mr. Reed's school and is in an advanced math class.
3. Mr. Reed is Billy's math teacher.

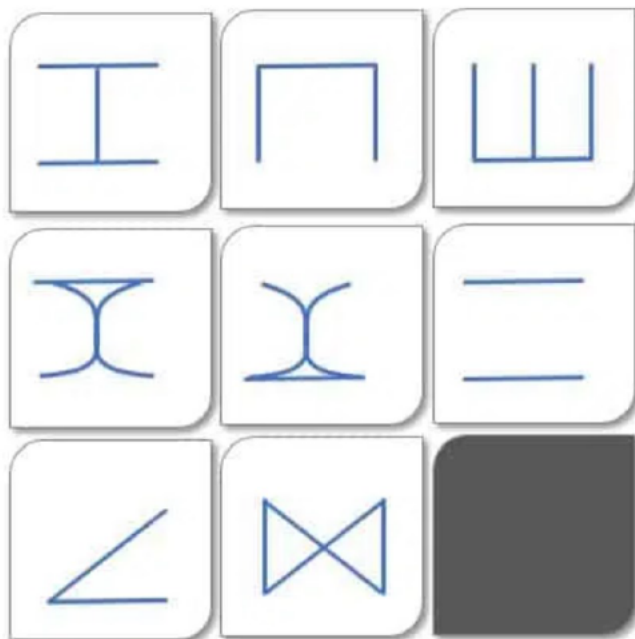
☐ a. Yes

☐ b. No

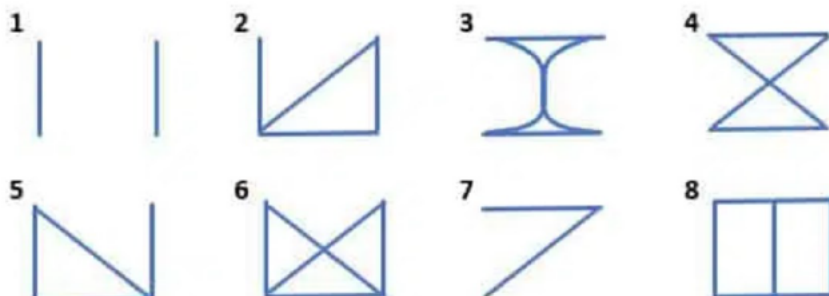
☐ c. Uncertain

**17. Question**

Which figure belongs in the empty spot?



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**18. Question**

Angie's profits for March totaled \$5400. If she profited nine times more in March than in April, what were April's profits?

☐ a. \$700

☐ b. \$48,600

☐ c. \$600

☐ d. \$900

**19. Question**

If a store sold 25 pairs of socks, making a 25% profit (i.e., percent of sales) of \$150, how much did they charge for each pair?

☐ a. \$30

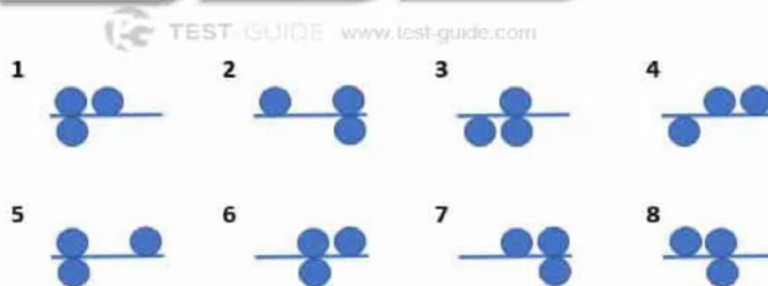
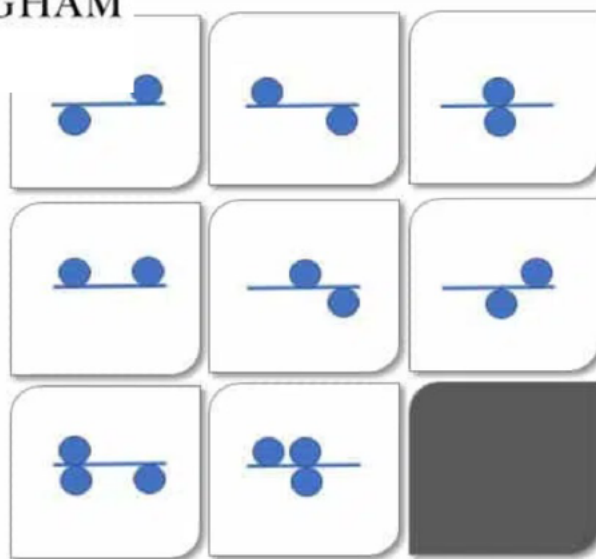
☐ b. \$15

☐ c. \$20

☐ d. \$24

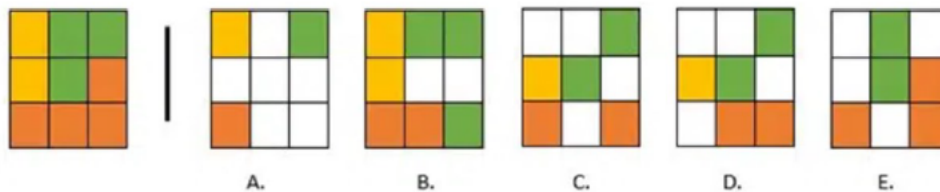


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## 21. Question

Which THREE choices are needed to create the figure on the left? Only pieces of the same color may overlap.



**22. Question**

Apathetic is to sympathetic as \_\_\_\_\_ is to concerned.

☐ a. callous

☐ b. compassionate

☐ c. merciful

☐ d. kind

**23. Question**

What is the missing number in the series:

7, 12, 19, \_\_, 39, 52

☐ a. 28

☐ b. 26

☐ c. 33

☐ d. 29

**24. Question**

A family is planning a vacation, traveling 300 miles from their house.

If they plan to stop at parks to allow the children to play every two hours, how many parks will they visit before they reach their destination assuming they travel 60 mph?

☐ a. 3

☐ b. 1

☐ c. 2

☐ d. 4



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**25. Question**

In the following set of words, which THREE words have similar meanings?

☐ a. endure

☐ b. persevere

☐ c. quit

☐ d. persist

☐ e. alienate

**26. Question**

The words gallant and valiant have \_\_\_\_\_ meanings.

☐ a. Same

☐ b. Opposite

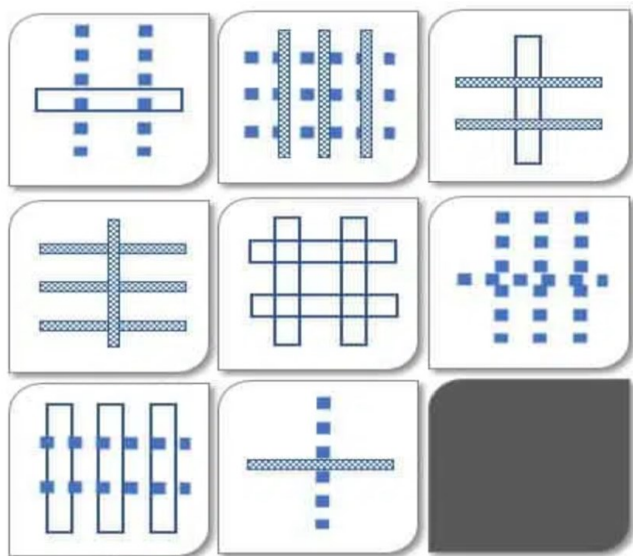
☐ d. Unrelated



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27. Question

Which figure belongs in the empty spot?



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- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8



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**29. Question**

What is the next number in the series:

4, 5, 11, 34, 137, —

☐ a. 237

☐ b. 549

☐ c. 459

☐ d. 686

**30. Question**

Accept and except have \_\_\_\_\_ meanings.

☐ a. Similar

☐ b. Different

☐ c. Unrelated



## **Appendix K Description and Administration of Alternative IQ Test within the Appendix**



### **Change in IQ Test Selection and Reasons for the Switch**

In the course of conducting our experiment, we originally intended to utilize an IQ test from the Mentel Up website as a primary assessment tool. However, we encountered a significant issue with this plan, which necessitated a change in our test selection. The following sections elaborate on the change and the reasons behind it:

#### **1. Unavailability of Desired Test on Mentel Up Website:**

The initial choice of using the Mentel Up website was based on its reputation and reliability in providing IQ tests. We had selected a specific IQ test from this website due to its alignment with our research objectives. Unfortunately, upon attempting to access the desired IQ test, we discovered that it was not available on the Mentel Up website. Despite our efforts to contact the website administrators and verify the availability of the test, we were unable to obtain access to it.

However, it should be mentioned during the actual study experiment all subject IQ test was based on the test from Mentel Up website and data analysis was based on

outcome test from this website and the analysis were not effected by this website unavailability.



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**2. Need for a Comparable Alternative:** Faced with the unavailability of the intended IQ test, we recognized the importance of maintaining the integrity of our experiment by ensuring that the alternative test we selected was comparable in terms of content, structure, and reliability. This led us to search for an alternative IQ test that could effectively replace the original one and provide reliable structure to be used within the research appendix for information purpose only.

**3. Selection of the Alternative IQ Test:** After extensive research and evaluation of various IQ tests available online, we identified an IQ test from the website <https://www.test-guide.com/free-iq-tests.html>. This test was chosen based on its alignment with the cognitive abilities we intended to measure in our experiment and its free accessibility. It was imperative for us to select an IQ test that would not introduce bias or confounding variables into our research and as it has been mentioned it has been only used for illustration purpose in the research appendix.

**4. Administration and Inclusion in Research Appendix:** We administered the alternative IQ test to our participants following the same protocols and procedures as we had

initially planned. To maintain transparency and provide readers with the necessary information, we have included details about the alternative IQ test in the research appendix. This includes a description of the test, instructions given to

participants, and any relevant data regarding its validity and reliability.

By making this change in our IQ test selection, the aim was to ensure the integrity of the research findings and uphold the highest standards of transparency and credibility. We believe that the alternative IQ test, while different from our original choice, still serves our research objectives effectively and allows for meaningful interpretation for readers.

## Appendix L The ethical approval process and confirmation of approval



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Dear Yongjing Wang and Adib Housaini,

**RE:** Enhancing Human-Robot Interaction in Telerobotics: Investigating the Impact of Cognitive and Information Processing on Human Operator's Situational Awareness, Attention and Cognitive Workload.

**Application for Ethical Review:** ERN\_3037-Aug2024

Your project has been considered in line with the University of Birmingham's research ethics processes and on the basis of the information you have provided, it is understood that while your project does involve human participants, the project raises no substantial research ethics issues and therefore no further ethics review is required.

Any adverse events occurring during the study should be promptly brought to the Committee's attention by the Principal Investigator and may necessitate further ethical review.

Please ensure that the relevant requirements within the University's Code of Practice for Research and the information and guidance provided on the University's ethics webpages (available at <https://intranet.birmingham.ac.uk/finance/accounting/Research-Support-Group/Research-Ethics/Links-and-Resources.aspx>) are adhered to.

Please be aware that whilst Health and Safety (H&S) issues may be considered during the ethical review process, you are still required to follow the University's guidance on H&S and to ensure that H&S risk assessments have been carried out as appropriate. For further information about this, please contact your School H&S representative or the University's H&S Unit at [healthandsafety@contacts.bham.ac.uk](mailto:healthandsafety@contacts.bham.ac.uk).

Kind regards,

The Co-Chairs of the Science, Technology, Engineering and Mathematics Committee

E-mail: [ethics-queries@contacts.bham.ac.uk](mailto:ethics-queries@contacts.bham.ac.uk)