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Exploring Cognitive Load Dynamics in Human-Machine Interaction for Teleoperation: A User-Centric Perspective on Remote Operation System Design

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Abstract— **Teleoperated robots, especially in hazardous environments, integrate human cognition with machine efficiency, but can increase cognitive load, causing stress and reducing task performance and safety. This study examines the impact of the information available to the operator on cognitive load, physiological responses (e.g., GSR, blinking, facial temperature), and performance during teleoperation in three conditions: C1 - in presence, C2 - remote with Visual feedback, and C3 - remote with telepresence robot. The findings from our user study involving 20 participants show that information availability significantly impacts perceived cognitive load, as evidenced by the differences observed between conditions in our analysis. Furthermore, the results indicated that blinking rates varied significantly among the conditions. The results also underline that individuals with higher error scores on the spatial orientation test (SOT), reflecting lower spatial ability, are more likely to experience failure in conditions 2 and 3. The results show that information availability significantly affects cognitive load and teleoperation performance, especially depth perception of the robot's actions. Additionally, the thermal and GSR data findings indicate an increase in stress and anxiety levels when operators perform conditions 2 and 3, thus corroborating an increase in the user's cognitive load.**

I. Introduction

In Human-Robot Interaction (HRI), understanding the cognitive dynamics among humans, robots, and their interactions within the environment has become essential for assisting humans in their various activities and tasks. As robots increasingly integrate into diverse environments, ranging from the manufacturing industry to household settings, understanding the cognitive demands placed on human users during robotic interaction, teleoperation, and collaboration is paramount. The application of robotic teleoperation persists in situations considered hazardous, complex, or costly for human workers across sectors such as nuclear [1], military, and healthcare, among others. Manual robotic teleoperation involves a human operator commanding a manipulator or driving a vehicle to accomplish a task while simultaneously monitoring the scene using camera images, thereby increasing cognitive load. Cognitive load, denoting the mental effort expended in working memory, holds a crucial role in determining the effectiveness, safety, and satisfaction of teleoperation tasks. Many factors influence cognitive load, such as the complexity of tasks, the user's familiarity with the system, their profile (e.g., personality, perspective taking ability), the necessity to avoid kinematic singularities during manipulation, and the interface design that supports effective communication between humans and robots [2], [3]. All these factors unavoidably impact cognitive load, inherently affecting task performance.

This paper introduces a methodology for assessing cognitive load during robotic teleoperation. It integrates physiological measurements (GSR and facial temperature), subjective evaluations (NASA-TLX) [4], and behavioral cues (blink rate) to offer a holistic understanding of the cognitive load experienced by users. Furthermore, this study attempts to investigate correlations between task performance and user's personality, while exploring the impact of information availability on cognitive load. Information availability refers to the amount of data the user has access to during operation, which can significantly influence cognitive load; increased information availability can potentially reduce cognitive load, while limited information can increase it [5] [6].

This study aims to analyze the cognitive load on users during robot teleoperation, laying the groundwork for future advancements in robotics to minimize this load and simplify human-robot interactions. By identifying key factors contributing to cognitive strain, our goal is to inform the development of more intuitive teleoperation systems, enhancing usability and facilitating seamless human-robot collaboration.

The paper is structured as follows: Section II describes relevant related work. Our experimental design and findings are detailed in Sections III and V, respectively. Finally, conclusions and insights into future research directions are provided in Section VI.

II. Related Work

Teleoperation, between humanoid robots and manipulators, introduces cognitive challenges due to the complexity of the systems and environmental uncertainties. In [7], the integration of human intelligence with robotic functions underscored the challenges encountered during teleoperation in unstructured environments. The authors in [8], link the mental workload of teleoperation to spatial cognitive abilities, utilizing EEG data to emphasize the significance of

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this association in performance evaluations. More recently, research presented in [9] demonstrates the impact of robot autonomy on cognitive load and operator confidence, indicating that while affected by autonomy, these factors do not interact as expected. Collectively, these researches aim to enhance both operator experience and system efficiency, advocating for the development of assistive technologies tailored to the cognitive state of the operator.

Exploring cognitive load in robotic teleoperation is crucial for enhancing teleoperation interfaces due to its intricate measurement. This endeavor aims to empower operators to navigate complex tasks without cognitive overload, thereby enhancing performance and safety. Recent studies emphasize the importance of utilizing physiological and behavioral metrics to assess cognitive load effectively. For instance, the authors in [8] [7] underscored the attributes of mental workload in teleoperator manipulators, with a specific focus on spatial cognitive abilities. This endeavor aligns with the observations made by Klein et al. [10], who examined perceived mental workload and stress among novice operators utilizing minimally invasive laparoscopic and robotic surgical interfaces, suggesting substantial cognitive demands posed by such interfaces. In [11], a correlation between blinking rate (BR) and the complexity of a task was found. This correlation highlights how the information processing mechanism of a task impacts the dynamics of the blinking rate. Additionally, exposure to various visual or auditory stimuli, as demonstrated in [12] and [13], can also influence BR. However, very few works focused on blinking as a predictor of the cognitive load of teleoperators [14].

Research on cognitive load and stress has highlighted the critical role that information availability plays in human performance and cognitive workload. Sweller established in [5] that the amount and organization of information presented to individuals significantly affects cognitive load during problem-solving tasks, and that greater information availability could reduce cognitive strain. Similarly, Hancock and Warm [6] proposed a dynamic model that illustrates how variations in information availability and task demands affect sustained attention and cognitive workload over time. Understanding these dynamics is crucial for designing effective human-machine interfaces and systems that optimize information presentation to minimize cognitive load and improve task performance in complex environments.

Furthermore, the authors in [15] used both GSR and blinking to measure cognitive load in arithmetic and reading tasks, and several different levels of cognitive load were identified. A non-intrusive method to assess mental workload during driving using facial temperature variation was developed in [16]. A significant correlation between temperature changes in the nose region and subjective workload scores, where increased workload ratings corresponded to decreased nose temperature, was found. Another study [17] investigated whether cognitive load could be inferred from facial temperature variation, focusing on two regions of interest (ROIs), namely the nose and forehead. A literature review by Ioannou et al. [18] identified key ROIs—including the nose, forehead, chin, cheeks, periorbital regions, and maxillary area that provide valuable insights into an individual's internal state based on temperature fluctuations. Other recent papers have also focused on stress measurement using face temperature variation [19] and on human-centred interface evaluation by using user's physiological state and task execution time [20]. These investigations highlight the potential utility of physiological measures like galvanic skin response (GSR), facial temperature, and blink frequency as objective indices of cognitive load during teleoperation tasks.

Augmented reality (AR) has emerged as a promising technology to reduce cognitive load in robotic teleoperation. A study on the impact of AR on robot programmers during the teaching process found that AR could significantly affect several dimensions of workload, including mental demand and task completion time [21] [22] [9]. This suggests that AR could be a valuable tool for improving user interfaces in teleoperation, making complex tasks more manageable and less cognitively demanding [23].

In addition to empirical investigations, theoretical frameworks and assessment methodologies have been developed to enhance the comprehension and measurement of cognitive load. Among these tools are the NASA Task Load Index (NASA-TLX) [4] and the Big Five personality questionnaire [24], which are utilized to evaluate cognitive load and examine how individual differences might impact teleoperation performance [8], [22]. By offering a holistic perspective on the operator's cognitive state and personality traits, these instruments shed light on effective strategies for managing cognitive load in Human-Robot Interaction (HRI) scenarios [25].

Measuring cognitive load in robotic teleoperation is a multifaceted area of research that integrates physiological measures, shared autonomy, augmented reality, and theoretical frameworks. The integration of these methodologies and technologies is essential to developing teleoperation systems that are both efficient and easy to use, ensuring that operators can perform complex tasks without undue cognitive stress [25].

We propose a novel approach by incorporating psychological assessments, performance metrics, and physiological measurements to evaluate cognitive load in teleoperated robotics, tailored to individual user profiles. Using the NASA Task Load Index (NASA-TLX), we assess user perceptions and subjective evaluations of cognitive load in conjunction with direct performance assessments. We measure blinking rates, facial temperature, and Galvanic Skin Response (GSR) to obtain objective indicators of cognitive load. This multifaceted approach, combining subjective assessments with objective performance and physiological data, establishes new connections between user psychological characteristics, task performance, and physiological states, offering a comprehensive framework for understanding and mitigating cognitive load in real-world teleoperation settings.

III. Experimental Design

A. Robotic Platforms and Sensors

The experimental framework is centered around two advanced robotic platforms:

- The UR5 manipulator robot [26] mounted on a Husky mobile robotic platform [27] as shown in Figure 1 (a). The UR5, a 6-axis lightweight arm, offers a payload of 5 kg, a reach of 850 mm, a precision of ±0.1 mm, and is equipped with an intuitive programming interface and advanced safety features, making it ideal for precise manipulation tasks [26]. Teleoperation is facilitated through a 6-degree-of-freedom joystick, providing intuitive and precise control over the UR5's movements, critical for investigating the operator's cognitive load.
- Double3 [1] robot (see Figure 1 (b)) is a telepresence robot that consists of a mobile base with wheels and a tablet or screen that displays the user's face, allowing them to see the environment and communicate with others as if they were physically present.

(a) (b)

Fig. 1. Robot Platforms: (a) URSky Robot Platform; (b) Double3 robot

During the experiment, we used both RGB and thermal cameras to record participants' facial features. The RGB camera is a Logitech HD webcam C930e (1080p, 30FPS), and the thermal camera is an Optris PI 640i USB-powered Infrared Camera (640×480, 32FPS, temperature range -20° C˜100°C). These two cameras were fixed on a tripod.

To quantitatively measure the cognitive load of each participant in our teleoperation experiments, we used noninvasive physiological sensors, specifically galvanic skin response (GSR) sensors. For this purpose, we used Shimmer3 GSR+ units [2], known for their accuracy and sensitivity in detecting electrical skin conductance, which correlates with physiological stimulation associated with cognitive load [28]. These sensors provide a portable, non-intrusive solution that minimizes participant discomfort while still allowing for continuous real-time data collection. With an adjustable sampling rate of up to 128 Hz, these devices capture subtle variations in GSR, providing valuable insights into the cognitive demands imposed during teleoperation tasks. Studies have shown that GSR is effective for measuring physiological stimulation and cognitive load in a variety of experimental settings, providing reliable data without the discomfort or potential interference associated with more invasive measures such as cardio-respiratory monitoring [29] [30]. This approach ensures a robust and reliable measurement of cognitive load while prioritizing participant comfort and data integrity.

[1]https://www.doublerobotics.com

[2]https://shimmersensing.com/product/shimmer3-gsr-unit/

B. Questionnaires

Participants had to fill out several questionnaires during the experiment. Before starting the experiment, all participants were asked to fill out a demographics form (gender, age, background). They also had to fill out the Big Five Personality Inventory (Short Form) and the Spatial Orientation Test (SOT). After each condition, the participants had to fill out the NASA Task Load Index (TLX). The questionnaires are detailed below.

1) Big Five Personality Inventory (Short Form): Before starting the experimental tasks, participants were instructed to complete the short Big Five Personality Inventory form [31]. This questionnaire assesses an individual's five personality traits: Extroversion, Neuroticism, Agreeableness, Conscientiousness, and Openness. Each trait is evaluated using 10 items rated on a 5-point Likert scale, ranging from "Strongly disagree" (1) to "Strongly agree" (5). The purpose of this initial assessment was to identify potential individual personality variations that could influence cognitive load and performance during subsequent robotic teleoperation tasks.

2) Spatial Orientation Test (SOT): In [32], it was demonstrated that perspective-taking ability can influence task performance. The Spatial and Orientation Test (SOT) [32], [33] serves as a reliable and predominantly strategy-free assessment of perspective-taking ability. SOT assesses the ability of an individual to imagine different perspectives or orientations in space. The test contains 12 items and the participants have 5 minutes to complete these items. Participants are instructed to visualize themselves positioned at one object while facing another object. They are then prompted to indicate (via drawing) the direction to the target object. Participants are restricted from physically rotating their body or the booklet and must identify the target object before marking it on the circle. The initial score on the spatial orientation test is an error score, where a higher value indicates lower spatial ability.

3) NASA Task Load Index (TLX): Following each robotic teleoperation condition, participants filled out the NASA Task Load Index (NASA-TLX) [34] to evaluate the cognitive load induced by the task. The NASA-TLX is a subjective workload assessment tool that gauges six dimensions of workload: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration, with each dimension rated on a 20-point scale. This tool is especially useful for assessing the cognitive demands of tasks involving human-machine interaction, such as robotic teleoperation, offering valuable insights into participants' perceived workload and task complexity.

C. Scenario

The task assigned to participants involved teleoperating the UR5 robotic arm to move six bottles of different shapes, weights, and heights. These bottles were arranged in a row on a table with a 10 cm gap between each, and the goal was to transfer them into an empty box located at the end of the row. Participants were required to complete the task within five minutes, utilizing a 6 degrees of freedom joystick to control the manipulator. This task was designed in a real-world object manipulation scenario, to evaluate participants' precision, spatial awareness, and cognitive load management across different conditions.

Participants were required to complete the task under three distinct conditions to evaluate the influence of visual perspective and mobility on cognitive load and teleoperation performance. The three conditions are detailed below:

- C1: In-Presence - The participant controls the robot while physically present in the same environment. This condition entails direct observation of the robotic arm and its surroundings, enabling participants to rely on natural depth perception and visual feedback to accurately measure distances and manipulate the robot (see Figure 2).

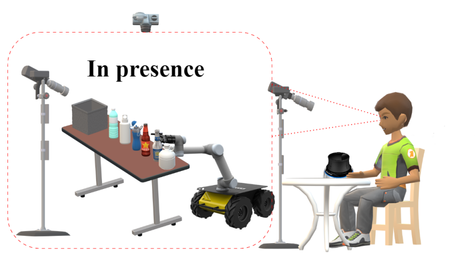

Fig. 2. In presence - C1

- C2: Remote Operation with Visual Feedback - The participant controls the robot manipulator to execute the task while viewing the scene through a top-down view provided by an overhead camera, which eliminates depth cues and challenges participants to adapt their control strategies without direct perception of the depth (see Figure 3)

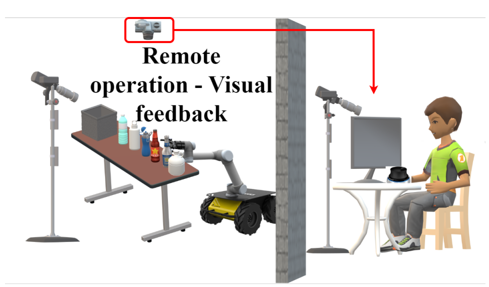

Fig. 3. Remote operation with visual feedback - C2

- C3: Remote Operation - The participant remotely controls the robot manipulator using visual feedback transmitted by a mobile telepresence robot (Double3 robot). Participants possess complete control over the movements of this robot, granting them the freedom to navigate the scene as desired within the task's time constraints. This setup aims to investigate the impact of enhanced mobility and dynamic viewing angle adjustments on the operator's cognitive load and the accuracy of teleoperated manipulations (refer to Figure 4).

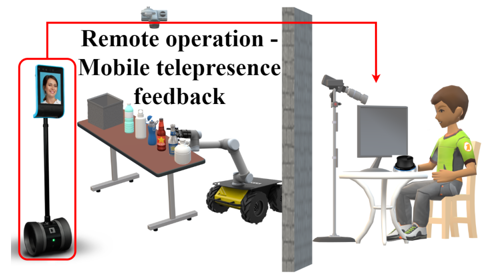

Fig. 4. Remote operation with mobile telepresence feedback - C3

The experiment followed a single-session within-subjects design, where each participant experienced all three conditions in a randomized order.

The experimental setup is shown in Figure 5.

D. Task Performance and User's Modelling

ROS was used to process both thermal and RGB images, as depicted in Figure 5. The extracted temperatures and AU (Action Units) data were saved into a .csv file. The data processing was done offline. Thermal images were extracted using the Optris Drivers ROS node, which publishes the facial thermal data [35]. Subsequently, temperatures of the facial regions of interest (ROIs), including the nose, cheeks, and forehead, were obtained throughout the experiment at a frame rate of 125 FPS. The Dlib facial expressions Python library was utilized to extract this information for each participant at the same rate it was captured, as illustrated in Figure 6. This process was conducted offline following each experiment.

Within this study, we gathered diverse parameters for each participant to measure their task performance, encompassing their performance success rates and completion times. Additionally, we recorded data on AU45 (blinking) and GSR as indicators of participants' cognitive load and stress during the manipulation task in the three conditions. We consider two GSR features (i.e., accumulative GSR - AccGSR and the number of peaks) and two blink features (i.e., the total number of blinks and the blink rate). For the blinking, we used the OpenFace ROS node to extract an approximation of the total number of blinking of each participant, and the rate of blinkings per minute per condition [36]. For GSR measurement, we utilized a two-finger and ear configuration for each participant. Subsequently, various processing filters were applied using the Consensus Pro software provided by Shimmer to eliminate unwanted noise [37].

IV. Hypotheses

Several hypotheses focused on cognitive load in robotic teleoperation were formulated:

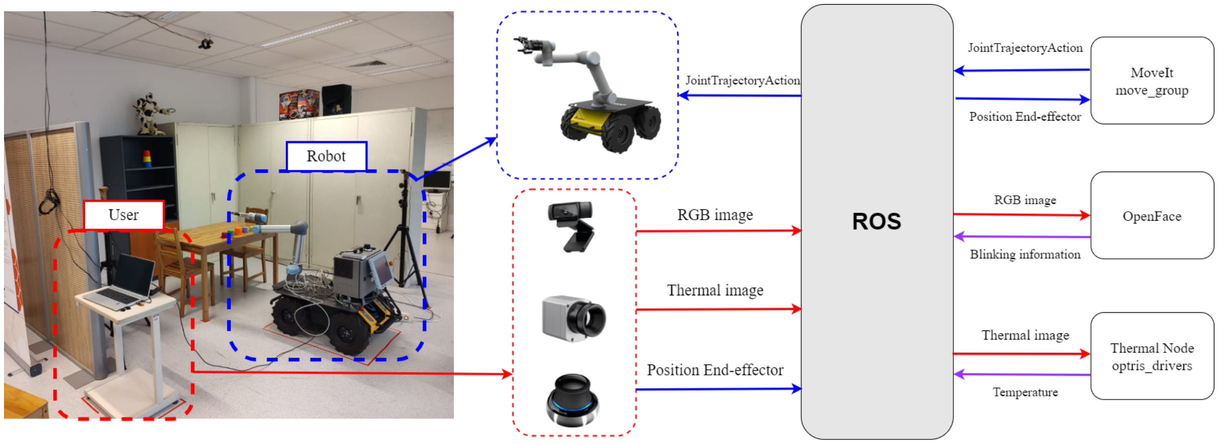

Fig. 5. Experimental setup: The participant operates the UR5 mounted on the Husky robot using a 3D mouse and the MoveIt package for inverse kinematics. Additionally, two cameras record the temperature and blinking rate of the user throughout the experiment.

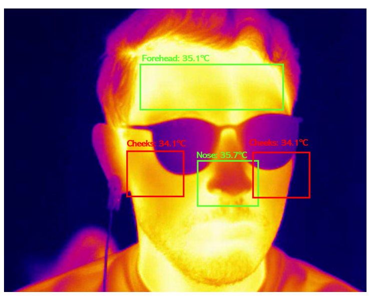

Fig. 6. Example of the thermal data extraction - ROIs

- **H1:** Poor task performance, characterized by lower success rates and longer completion times, will correspond to an increase in the participant's cognitive load as measured by the NASA Task Load Index (NASA TLX).
- **H2:** In Condition 1, where the participants are physically present in the same environment as the robot, it is expected that they will experience lower cognitive load compared to Conditions 2 and 3, as indicated by physiological features such as blinking rates, facial temperature, and GSR. Conversely, in Condition 3, where participants remotely control the robot using visual feedback from a mobile telepresence robot, it is hypothesized that cognitive load will be lower than in Condition 2, where visual feedback is provided via a top-down view from an overhead camera.
- **H3:** Participants operating under Condition 2 (Remote Operation with Visual Feedback), which presents challenges in depth perception will experience higher cognitive load compared to those in Condition 1 (In-Presence) and Condition 3 (Remote Operation with Mobile Telepresence Feedback) concerning NASA-TLX.

First, we hypothesize that increased cognitive load correlates with poor performance in collaborative tasks with robots, mirroring Oviatt's [38] findings suggesting that increased task difficulty or performance under optimal conditions can increase cognitive load, thereby affecting task efficiency and satisfaction. We posit that increased access to information for operators will result in improved task performance and consequently decrease cognitive load during interactions with robots. This assertion is supported by Chen et al. [39], who highlighted a notable human factors challenge in remote operations stemming from the lack of depth cues, which complicates operators' perception of spatial relationships and depth. Thus, this rationale supports the selection of Conditions 2 and 3. Furthermore, Mayer and Moreno's [40] cognitive theory of multimedia learning posits that judicious provision of information can alleviate cognitive load while boosting learning and performance. These findings support our hypotheses.

V. Experimental Results

A. Participants

Twenty individuals participated in this experiment, comprising 7 females and 13 males, who are students at Institut Polytechnique de Paris (IP Paris). Their ages range from 21 to 26 years (8 participants, 40%), from 26 to 34 years (11 participants, 55%), and above 34 years (1 participant, 5%), respectively. As with any study involving a relatively small sample size, the findings may not generalize to larger or more diverse populations, thus necessitating caution when extrapolating the results beyond similar contexts.

The participant's personality tests results are shown in the table I.

B. General Performance Results

Figure 7 illustrates the average success rates and completion times across the three conditions of the robotic teleoperation tasks, showing significant differences.

Condition 1, with a success rate of 100% (average time: 3 minutes and 54 seconds), emerged as the scenario where participants demonstrated the highest proficiency. Conversely, the high decrease in performance in Condition 2, characterized by a success rate of 35% (average time: 4 minutes and 46 seconds), implies a significant increase in cognitive load, possibly attributable to greater task complexity or less

TABLE I
PARTICIPANTS PERSONALITY TRAITS

	Extroversion	Neuroticism	Agreeableness	Conscientiousness	Openness
Low	7	4	4	12	4
High	13	16	16	8	16

intuitive human-robot interfaces. Condition 3, with a success rate of 55% (average time: 4 minutes and 29 seconds), represents a nuanced middle ground, indicating a moderate task difficulty level.

The small improvement observed in Condition 3 may be partly attributed to the usage of Double3 telepresence robot. This additional dimension of interaction could have enhanced spatial awareness and provided a more immersive control experience, potentially easing cognitive load despite the inherent task challenges. The mobile robot's capability to offer a dynamic viewpoint might have mitigated task execution difficulties, thus accounting for the performance improvement compared to Condition 2.

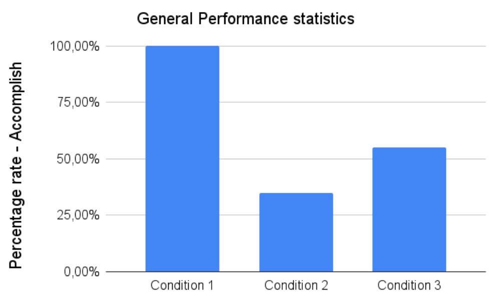

Fig. 7. General performance results

C. Cognitive Load Results

Analyzing the NASA Task Load Index (NASA-TLX) results provides insight into the perceived cognitive load across the three experimental conditions in robotic teleoperation tasks, as represented in Figure 8. Notably, no participants rated any of the conditions as having a low cognitive load, highlighting the inherent complexity and demand of the tasks across all scenarios. In Condition 1, the distribution of cognitive load perceptions leans towards the middle, with 6 participants categorizing it as medium, 9 as somewhat high, 4 as high, and 1 as very high. This suggests that while the task was challenging, it was not excessively difficult for the majority of participants.

On the contrary, Conditions 2 and 3 show a notable increase in cognitive load ratings. For Condition 2, no participants found the cognitive load to be medium; instead, 3 rated it as somewhat high, 15 as high, and 2 as very high, indicating a pronounced increase in task difficulty and cognitive demand. Condition 3 similarly showed no medium ratings, with 6 participants feeling the cognitive load was somewhat high, 8 rated it as high, and 6 as very high. The progression in the perceived cognitive load from Condition 1 through Conditions 2 and 3 underscores the complexity and demands placed on participants, with Conditions 2 and 3 particularly highlighting the tasks' challenges and the substantial cognitive effort required to navigate them, as depicted in the percentage breakdown in Figure 8. This analysis not only sheds light on the varying levels of difficulty across conditions but also emphasizes the need to consider cognitive load management in the design of robotic teleoperation tasks to optimize human-robot interaction efficiency.

To validate H1, Pearson correlation analyses was conducted between TLX scores and performance, yielding a negative correlation of *r = -0.276, p = 0.33*. Additionally, Pearson correlation analyses was also performed between TLX scores and completion time, revealing a positive correlation of *r = 0.615, p <0.001*. Thus, Hypothesis 1 is validated.

Furthermore, we analyzed the NASA-TLX questionnaire results using a One-way ANOVA and Games-Howell Post-Hoc test. The Shapiro-Wilk test confirmed that our data followed a normal distribution, while Levene's test indicated a lack of homogeneity of variance. The ANOVA yielded a significant result (*F(2,57) = 9.916, p <0.001*). Post-Hoc tests revealed that the perceived cognitive load in Condition 1 was significantly lower than in Condition 2 (*p <0.001*) and Condition 3 (*p = 0.004*). This aligns with the intuitive understanding that Condition 1, being less difficult, would result in lower cognitive load. However, there were no significant differences between Conditions 2 and 3. Consequently, Hypothesis 3 is partially validated.

Furthermore, we conducted Pearson correlation analyses between SOT scores and performance in Conditions 2 and 3, considering that all participants succeeded in Condition 1. The results revealed significant negative correlations for both Condition 2 (*r = -0.793, p = 0.001*) and Condition 3 (*r = -0.759, p = 0.002*). This suggests that individuals with higher error scores on the spatial orientation test (SOT), reflecting lower spatial ability, are more likely to experience failure in Conditions 2 and 3.

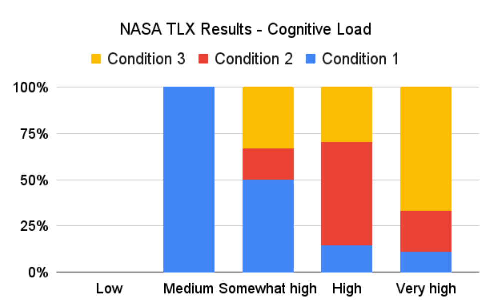

Fig. 8. NASA TLX Cognitive Load results

Throughout the experiment, we monitored both the total number of blinks and the frequency of blinks per minute across each condition. For the total number of blinks, we conducted a One-way ANOVA and Games-Howell Post-Hoc test, yielding a significant result (*F(2,57) = 57.022, p <0.001*). Specifically, the total number of blinks was significantly lower in Condition 1 compared to Condition 2 (*p <0.001*), and also lower in Condition 3 compared to Condition 2 (*p = 0.002*). Regarding the frequency of blinks per minute, our data met the assumption of homogeneity of variance. Using LSD as a Post-Hoc test, we found a significant difference (*F(2,57) = 8.371, p = 0.001*), indicating that the frequency of blinks per minute was significantly lower in Condition 1 compared to Condition 2 (*p <0.001*), and in Condition 3 compared to Condition 2 (*p = 0.021*). The observed increase in blink rate from Conditions 1 to 2 suggests an increase in stress or cognitive effort. Consequently, Hypothesis 2 was confirmed regarding blinking behavior.

We also conducted a *t-test* for blinking data between participants with high extroversion and participants with low extroversion. The findings indicate that in Condition 3, individuals with high levels of extroversion exhibited a higher blinking rate (*t(18) = 2.620,p = 0.017*). This observation aligns with previous literature suggesting that increased extroversion is associated with more frequent eye blinking, attributed to heightened dopaminergic activity and arousal [41]. In this context, the high blinking rate observed in Condition 3 may be attributed to factors associated with increased cognitive load and arousal.

Moreover, it's widely agreed that extroversion does not correlate with visuospatial ability [42].

No other significant correlations were found between personality traits and cognitive load across the three conditions.

We also computed the accumulative GSR and the number of peaks per minute from the GSR data. Subsequently, we conducted an One-way ANOVA among the three conditions for these measures. Regarding the accumulative GSR per minute, the analysis revealed *F(2,57) = 5.871, p = 0.005*. Post-hoc testing using the Games-Howell method indicated that this measure in Condition 2 was significantly higher than that in Condition 1 (*p = 0.005*). This outcome can be easily explained, considering that Condition 2 presents a higher level of challenge compared to Condition 1, likely inducing greater anxiety among participants. No other statistical results were found for GSR measures across the other conditions. Hypothesis 2 was partially confirmed regarding GSR data.

For instance, Figure 9 illustrates how a participant's skin conductance varies over time across the three experimental conditions. Notably, there is a significant difference in skin conductance levels among the conditions, indicating that the participant experienced the highest stress and cognitive load during the second condition. This observation supports Hypothesis 2 for this specific participant. Additionally, it is crucial to highlight the prominent peaks in the graph, indicating moments of high stress for the participant throughout the experiment. These peaks may coincide with events such as a bottle falling off the table or the robotic arm encountering a singularity, impeding successful task completion.

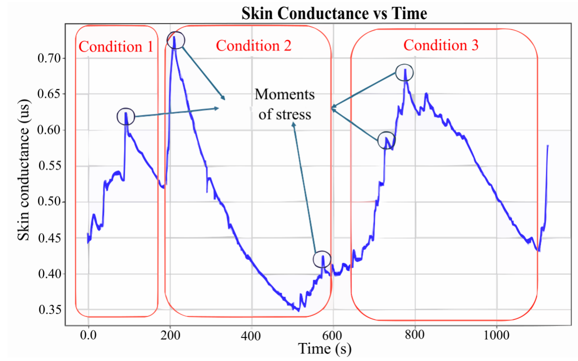

Fig. 9. Skin conductance example for one participant

Regarding the facial temperature, we computed the slope for nose temperature, forehead temperature, and cheeks temperature, followed by conducting an One-way ANOVA among the three conditions for these measures. For nose temperature, statistically significant differences were found *F(2,57) = 7.249, p = 0.002*, indicating that the nose temperature variation in Condition 1 is significantly slower than that in Condition 2 (*p = 0.001*) and Condition 3 (*p = 0.002*). However, there was no significant difference in nose temperature variation between Condition 2 and Condition 3. Furthermore, also for forehead temperature statistically significant differences were found *F(2,57) = 12.101, p <0.001*, showing that the forehead temperature variation in Condition 1 is significantly slower than that in Condition 2 (*p <0.001*) and Condition 3 (*p <0.001*). For cheeks temperature, the variation in Condition 1 is significantly slower than that in Condition 2 (*p <0.035*) and Condition 3 (*p <0.033*). Hypothesis 2 was partially confirmed regarding thermal data.

VI. Conclusions

This paper investigated the influence of operator-accessible information on cognitive load, physiological responses (e.g., GSR, blinking, facial temperature), and task performance across three teleoperation conditions: C1 - In-Presence, C2 - Remote with Visual Feedback, and C3 - Remote with Telepresence Robot. Our study validated the hypothesis that task performance, measured by success rates and completion times, is inversely related to cognitive load, as indicated by a significant Pearson correlation between performance metrics and NASA TLX scores. The impact of task complexity on operator stress levels was highlighted by the link between higher cognitive load and decreased success rates and prolonged completion times. Moreover, our investigations into the effect of operator's physical presence on cognitive load revealed that participants in the same environment as the robot (Condition 1) exhibited reduced cognitive load markers, such as decreased facial temperature and decreased blinking. The contrast was especially significant when comparing Conditions 2 and 3, where remote operation with mobile telepresence feedback (Condition 3) demonstrated lower cognitive load compared to overhead visual feedback (Condition 2). This observation was reinforced by significant results on blinking rates, temperature variation, and GSR data, highlighting the increase of cognitive load due to depth perception challenges in Condition 2. Together, these results emphasize the crucial importance of visual feedback quality and environmental context in effectively managing cognitive load during robotic teleoperation. Exploring the impacts of altering control interface properties on users' cognitive load and trust levels also represents promising avenues for further investigation.

VII. Acknowledgement

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References

[1] V. Pruks, K.-H. Lee, and J.-H. Ryu, "Shared teleoperation for nuclear plant robotics using interactive virtual guidance generation and shared autonomy approaches," in *2018 15th International Conference on Ubiquitous Robots (UR)*, 2018, pp. 91–95.

[2] T. H. a. V. G. P. W. M. Paas F., Tuovinen J. E., "Cognitive load measurement as a means to advance cognitive load theory," *Educational Psychologist*, vol. 38, no. 1, pp. 63–71, 2003.

[3] a. K. S. Sweller J., Ayres P., "Cognitive load theory." Springer, 2011.

[4] F. M. Calisto and J. C. Nascimento, "Nasa-tlx survey," 2018. [Online]. Available: http://rgdoi.net/10.13140/RG.2.2.26978.79044

[5] J. Sweller, "Cognitive load during problem solving: Effects on learning," *Cognitive Science*, vol. 12, no. 2, pp. 257–285, 1988.

[6] P. A. Hancock and J. S. Warm, "A dynamic model of stress and sustained attention," *Human Factors*, vol. 45, no. 1, pp. 113–126, 2003.

[7] R. J. C. R. Darvish K., Penco L. and P. J., "Teleoperation of humanoid robots: A survey," in *IEEE Transactions on Robotics*, 2023.

[8] Z. Q. Shao S. and L. Z., "Mental workload characteristics of manipulator teleoperators with different spatial cognitive abilities," *International journal of advanced robotic systems*, vol. 10, no. 1, 2019.

[9] J. Pan, J. Eden, D. Oetomo, and W. Johal, "Exploring the effects of shared autonomy on cognitive load and trust in human-robot interaction," 2024.

[10] R. M. M. G. D. C. D. J. F. Klein M., Warm J. and G. K., "Mental workload and stress perceived by novice operators in the laparoscopic and robotic minimally invasive surgical interfaces," *Journal of endourology*, 2012.

[11] Y. Tanaka and Y. Kiyoshi, "Blink activity and task difficulty," *Perceptual and Motor Skills*, vol. 77, no. 1, pp. 55–66, 1993.

[12] W. L. Stern, J. A and R. Goldstein, "The endogenous eyeblink," *Psychophysiology*, vol. 21, no. 1, pp. 22–33, 1984.

[13] K. Fukuda, "Eye blinks: new indices for the detection of deception," *International Journal of Psychophysiology*, vol. 40, no. 3, pp. 239–245, 2001.

[14] C. Bevan and D. S. Fraser, "Evaluating a mobile spontaneous eye blink tracker for use in tele-presence hri as a low bandwidth social communicative cue," in *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, 2016, pp. 618–623.

[15] N. Nourbakhsh, F. Chen, Y. Wang, and R. A. Calvo, "Detecting users' cognitive load by galvanic skin response with affective interference," *ACM Trans. Interact. Intell. Syst.*, vol. 7, no. 3, sep 2017. [Online]. Available: https://doi.org/10.1145/2960413

[16] C. K. Or and V. G. Duffy, "Development of a facial skin temperature based methodology for non-intrusive mental workload measurement," *Occupational Ergonomics*, vol. 7, no. 2, pp. 83–94, 2007.

[17] Y. Abdelrahman, E. Velloso, T. Dingler, A. Schmidt, and F. Vetere, "Cognitive heat: Exploring the usage of thermal imaging to unobtrusively estimate cognitive load," vol. 1, no. 3, sep 2017. [Online]. Available: https://doi.org/10.1145/3130898

[18] S. Ioannou, P. Morris, H. Mercer, M. Baker, V. Gallese, and V. Reddy, "Proximity and gaze influences facial temperature: a thermal infrared imaging study," *Frontiers in Psychology*, vol. 5, 2014. [Online]. Available: https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2014.00845

[19] *Reliable stress measurement using face temperature variation with a thermal camera in human-robot interaction*, 2015.

[20] K. A. Szczurek, R. Cittadini, R. M. Prades, E. Matheson, and M. Di Castro, "Enhanced human–robot interface with operator physiological parameters monitoring and 3d mixed reality," *IEEE Access*, vol. 11, pp. 39 555–39 576, 2023.

[21] G. M. M. N. S. G. Stadler S., Kain K. and T. M., "To err is robot: How humans assess and act toward an erroneous social robot," *Robot and Human Interactive Communication (RO-MAN)*, 2016.

[22] J. W. Cha G. and M. B., "Implications of personality on cognitive workload, affect, and task performance in remote robot control," in *IEEE Transactions on Robotics*, 2023.

[23] M. M. S. S. G. M. Mirning N., Stollnberger G. and T. M., "To err is robot: How humans assess and act toward an erroneous social robot," *Frontiers*, vol. 4, no. 1, 2017.

[24] M. S. Chmielewski and T. A. Morgan, *Five-Factor Model of Personality*. New York, NY: Springer New York, 2013, pp. 803–804. [Online]. Available: https://doi.org/10.1007/978-1-4419-1005-9_1226

[25] F.-S. D. Bukhari S.T.S., Anima B.A. and Q. W.M., "Cognitive approach to hierarchical task selection for human- robot interaction in dynamic environments," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2023.

[26] U. Robots, "Universal robots ur5," Universal Robots, Tech. Rep., 2017.

[27] Available online: https://clearpathrobotics.com/husky-unmanned-ground-vehicle-robot/.

[28] W. Boucsein, *Electrodermal Activity*. Springer Science & Business Media, 2012.

[29] H. D. Critchley, "Electrodermal responses: What happens in the brain," *Neuroscientist*, vol. 8, no. 2, pp. 132–142, 2002.

[30] G. G. Berntson, K. S. Quigley, and D. Lozano, "Cardiovascular psychophysiology," in *Handbook of psychophysiology*, 3rd ed., J. T. Cacioppo, L. G. Tassinary, and G. G. Berntson, Eds. Cambridge University Press, 2007, pp. 182–210.

[31] B. Rammstedt and O. P. John, "Measuring personality in one minute or less: A 10-item short version of the big five inventory in english and german," *Journal of research in Personality*, vol. 41, no. 1, pp. 203–212, 2007.

[32] M. Kozhevnikov and M. Hegarty, "A dissociation between object manipulation spatial ability and spatial orientation ability," *Memory and Cognition*, vol. 29, no. 5, pp. 745–756, 2001.

[33] M. Hegarty and D. Waller, "A dissociation between mental rotation and perspective-taking spatial abilities," *Intelligence*, vol. 32, no. 2, pp. 175–191, 2004.

[34] S. Hart and L. Staveland, "Development of nasa-tlx (task load index): Results of empirical and theoretical research." *In P.A. Hancock N. Meshkati (Eds.), Human Mental Workload*, pp. 139–183, 1988.

[35] G. M. May S. and P. M., "Optris drivers," 2018.

[36] S. E. McDorman B., "Openface for ros," 2016.

[37] S. Co, "Consensus pro."

[38] S. Oviatt, "Human-centered design meets cognitive load theory: designing interfaces that help people think," *Proceedings of the 14th annual ACM International Conference on Multimedia*, pp. 871–880, 2006.

[39] B. M. Chen JYC, Haas EC, "Human performance issues and user interface design for teleoperated robots," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, 2097.

[40] . M. R. Mayer, R. E., "Nine ways to reduce cognitive load in multimedia learning," *Educational Psychologist*, vol. 38, no. 1, pp. 43–52, 2003.

[41] H. Berenbaum and M. Williams, "Extraversion, hemispatial bias, and eyeblink rates," *Personality and Individual Differences*, vol. 17, no. 6, pp. 849–852, 1994. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0191886994900523

[42] S. Y. L. M. e. a. Sutin, A.R., "Five-factor model personality traits and cognitive function in five domains in older adulthood." *BMC Geriatr*, vol. 19, 2019.