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Comparative Analysis Of Mental Workload In Adaptive Human-Robot Collaboration During Assembly Tasks

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Abstract

One of the most rapidly evolving aspects of this digital transformation is the increasingly advanced collaboration between humans and machines. Collaborative robots, or cobots, are especially advantageous and most used in assembly tasks, where the high payload and repeatability characterizing traditional robotic systems need to be combined with the skills and flexibility of human operators. The work showed that during the collaboration between cobots and operators, the so-called Human-Robot Collaboration (or HRC), allows for improved productivity and a reduced mental workload in industrial manufacturing assembly tasks. The paper analyses the mental workload and productivity of an assembly task where participants performed the task in three different scenarios: a) assembly task without the robot (standard scenario); b) assembly task with the robot (collaborative scenario); c) assembly task with the robot and guided throughout the task (guided collaborative scenario). The analysis of mental workload and productivity is shown in three different time periods for three consecutive halves of analysis during the task, each lasting 30 minutes. The analysis was conducted for three participants. The results show how mental workload decreased from the first to the third scenario while the productivity index increased. The analysis of mental workload was performed through the innovative electroencephalogram (EEG) sensor cap, while the analysis of productivity was performed through observational methods (checklist).

Keywords: human-robot collaboration, EEG, mental workload, neuroergonomics, lean production, IR5.0, human-centric design.

1. Introduction

The "human-centric" design manufacturing approach, which integrates and synergizes human and machine capabilities to create more harmonious and cooperative working environments where humans and robots collaborate more effectively, is at the center of the Fifth Industrial Revolution, or Industrial Revolution 5.0 (IR5.0) (Nahavandi., 2019). According to Reiman et al. (2021) the employment of human labour in manufacturing processes is changing to include supervision and teamwork with this new technology. The most quickly developing part of this digital revolution is the increasingly sophisticated human-machine cooperation. (Tiwari et al., 2022).

Specifically, the term "collaborative robot" or "cobot" was first used two decades ago to refer to a machine that allowed people to directly interact physically with computer-controlled manipulators (Peshkin et al., 2001). Modern cobots have developed into lightweight robotic arms, whereas the initial cobots were passive and controlled by humans.

Cobots are especially advantageous and most used in assembly tasks, where the high payload and repeatability characterizing traditional robotic systems need to be combined with the skills and flexibility of human operators (Matheson et al.,2019). One of the classifications proposed to describe the different ways in which cobots can work with humans distinguishes four levels of increasing collaboration: coexistence, when operator and cobot only share the same physical space without interaction;

synchronization, when operator and cobot share the same workspace, but work at different times; cooperation, when they work in the same workspace at the same time, but on separate tasks; collaboration, when they execute a task together, with one's actions having immediate consequences on the other (Vicentini, 2020). Although protective fence removal was a common early use of cobots, full collaboration applications will soon become more common, allowing cobots and operators to expand cognitive engagement through human behaviors (Hentout et al., 2019). According to Schmidt et al. (2015), the human operator and the cobot can be thought of as a dyad in this situation, able to interact both physically and mentally.

Examining contemporary workplaces as sociotechnical systems, also known as collaborative workplaces, where operators collaborate with these inventive systems while taking a human-centric approach to their design, can help address the relationship between work, technology, health, and well-being (Carayon et al., 2015).

According to Rosen and Wischniewski (2017), cobots should be built to work alongside operators, adjusting their behaviours based on the tasks at hand and the worker's emotional condition. This could lead to increased productivity and social recognition. According to a recent study, coworkers' stress levels are also influenced by the quality of their collaboration (Caiazzo et al.,2023). This evidence demonstrates the importance of creating truly collaborative activities in which human workers and robots collaborate in ways that encourage and challenge humans to view task completion as an opportunity to improve their health and well-being rather than as a source of frustration.

In this regard, human factors and ergonomics (HFEs) studies are aimed at investigating human interactions with elements of these complex systems (Stanton et al., 2012). HFE is critical in contemporary industrial environments because human beings are crucial players who allow smooth and physically safe workflows in workplaces filled with increasingly interconnected technologies. While cobots were primarily designed to promote optimal productivity performance by reducing uncertainty and instability in their cooperation with humans (Oliff et al., 2018), research in collaborative robotics has primarily focused on the development of technical solutions to implement human-robot physical interaction to preserve workers' physical safety (Khalid et al., 2016). Until recently, however, HFE has been largely overlooked in studies concerning industry 4.0 implementation (Bragança et al., cobots). Given the development of human-robot collaboration (HRC) in Industry 5.0, it is critical to comprehend the difficulties employees encounter when utilising cobots, particularly about their mental health and general wellbeing.

By combining the principles of conventional ergonomics with the latest developments in neuroscience, neuroergonomics arose as a separate topic of study in the field of ergonomics in the late 20th and early 21st centuries. It developed out of the necessity to comprehend the intricate relationships that exist between the working environment and brain functioning, especially when technology is incorporated into daily tasks more and more (Dehais et al., 2020). Raja Parasuraman and Matthew Rizzo's groundbreaking 2007 book "Neuroergonomics: The Brain at Work" popularised the term "neuroergonomics". By concentrating on the function of the brain in work-related activities and settings, they sought to close the knowledge gap between human factors/ergonomics and neuroscience (Parasaruman and Rizzo, 2006).

The examination of the operator's mental workload is a key component of neuroergonomics (Dehais et al., 2020b). It refers to the quantity and calibre of labour that is expected of a person. This can involve mental exercises, strenuous physical work, and emotional exhaustion. A person's workload is frequently evaluated based on how well their resources and abilities meet the demands placed on them. Understanding workload is critical to preventing overworked personnel in the context of ergonomics and workplace design, as this can result in stress, lower productivity, and health problems (Paliga, 2023). In order to ensure productivity and well-being, effective workload management seeks to strike a balance where workers are challenged but not overburdened. Although the field of neuroergonomics research has expanded dramatically in recent years, not many studies have been conducted to date (Berberian et al., 2017). Workload is examined using several measurement techniques. When analysing the mental workload of operators completing a task, subjective measurements—like questionnaires—are most frequently utilised in ergonomic studies (Fraboni et al., 2021). However, because of the bias, these measurements have limitations. Subjective assessments are used in conjunction with cutting-edge objective measurements to provide a comprehensive knowledge of mental workload. To analyze the operator's physiological status, various physiological metrics have been established (Novak et al., 2015). The electroencephalogram (EEG) is the most widely used of these, with applications ranging from medical to industrial settings. This is because of its adaptability, portability, real-time acquisition, and compatibility with participant wear, all of which preserve the operator's scalp brainwave signals during the recording process (Ismail and Karwowski, 2020). Different brainwaves are analysed using EEG equipment as markers of the operator's mental stress and relaxation as they are carrying out the task. EEG signal artefacts may originate from technical issues or from an individual's own actions, both physically and behaviorally. Expert eyes can examine these artefacts manually, however automatic artefact identification is recommended in automated system designs to prevent artefacts from tainting the outcomes (Katmah et al., 2021).

Several methods are used to get rid of artefacts. The authors used Independent Component Analysis (ICA) during the pre-processing stage to get rid of these artefacts. Ultimately, the mean value of the EEG signals was used to re-reference them (Ochoa, 2002). The next stage following pre-processing EEG signals is feature extraction. This paper intends to illustrate the mental workload index. Among these, markers of the mental effort are examined for beta (stress/engagement indicator) and alpha (relaxation indicator) (Fernandez et al., 1995; Ryu and Myung, 2005).

Finally, in lean manufacturing and quality management, Poka-yoke, also known as P-Y, is a concept that helps designers create procedures or systems that guard against human mistake (Nikolic et al., 2022). By preventing, fixing, or bringing attention to human errors as they happen, poka-yoke seeks to eradicate product flaws (Leva et al., 2018). Therefore, the decrease in mental workload is a result of the decrease in flaws, which leads to a gain in productivity (Ashar et al., 2021). In lean manufacturing, task distribution, efficiency, and mistake reduction all depend on an awareness of the ability to manage cognitive load.

Thus, the aim of this research paper is to show how the deployment of cobots with further Lean practices (P-Y mechanisms) allow to reduce operators' mental workload, through a neuroergonomic analysis with EEG devices, and enhance productivity in a manufacturing assembly task. Three different scenarios are set: a) assembly task without the robot (standard scenario); b) assembly task with the robot (collaborative scenario); c) assembly task with the robot and guided throughout the task (guided collaborative scenario / P-Y collaborative scenario). The analysis of mental workload and productivity is shown in three different time periods for three consecutive halves of analysis during the task, each one of 30 minutes. The analysis was conducted for three participants. The results show how mental workload decreased from the first to the third scenario, while the productivity index increased. The analysis of mental workload was performed through the innovative electroencephalogram (EEG) sensor cap and shown through the brainwave power ratio beta/alpha. On the other hand, the analysis of productivity is defined through observational methods (checklist).

2. Material and methods

A total of 3 male university students (N_participants = 3, mean age: 25 ± 3 years) were selected for the study (Table 1). All participants were briefed about the task process and objectives and signed a consent form, established by the administration of the Faculty of Engineering, University of Kragujevac (FINK), Serbia. The mean body weight was 88.5 ± 3.4 kg, and the mean height was 184.2 ± 3.8 cm. None of the subjects had previous experience in the assembly workplace and even with the robot. Subjects were not under the influence of any medication that could interfere with EEG.

Participants were told not to consume any alcohol the day before or the day of the study, and they were also told not to have coffee at least three hours before to the study. They claimed to have had a good night's sleep the night before the exam. Every participant's vision was either normal or corrected to normal. All the participants were right-handed men. They lacked any prior experience interacting with the robot.

The experimental tests were conducted in the modular industrial assembly workstation, designed at the laboratory of the Faculty of Engineering, University of Kragujevac, Serbia (FINK) (Savkovic et al., 2022). The laboratory set-up was equipped with:

- a touchscreen PC for task definition and stimulus application.
- lighting LED system to regulate the light and produce a soft shadow to put less strain on the eyes of the participant in the test.
- an audio 5.0 system to simulate the sounds of the industrial environment.
- an adjustable ergonomic work chair to let the participant sit during the tests.

Furthermore, the workstation was built to facilitate the integration of other modules, such as the collaborative robot cell, to carry out collaborative tasks. It was also electrically height-adjustable based on the anthropometric features of the participants.

A prototype model of an industrial product, an abstraction of the connection plate, comprising a transparent acrylic cover attached by an aluminium hinge (a combination of three materials) and a metal base made of sheet steel with integrated threaded elements was assembled by the participants in order to accomplish the tests. The prototype is made of plastic, is lightweight, and does not have any sharp edges for teaching reasons (Caiazzo et al., 2023). The task's design recalled the wire harnessing tasks performed in manufacturing environments. Lack of research on the neuroergonomic analysis of these tasks with the use of assistive technology, like robots, led to the selection of this challenge, which is reminiscent of the wire harness assembly tasks. (Navas-Reascos et al., 2022).

For the comparative analysis, the participants conducted three different types of experiments in the same laboratory environment (N_tests = N_participants x N_scenarios = 9): I) standard scenario (SS) in which the participant performed the task without any intervention (the robot) in the workplace; II) collaborative scenario (CS) in which the participant performed the task interacting with the robot in the workplace; III) guided collaborative scenario (GCS) in which the participant performed the task with the robot and guided throughout the task. The three scenarios are presented in Figures 1 and 2. The duration of the activity for each test was 90 minutes. The number of components to assemble performing the overall test in the scenarios was 75 (N_components = 75). The distribution of the components was randomized.

The scenarios took place in different periods of the year with a minimum timespan of four months. The reason was not to have a memory bias in the comparison of the cognitive workload in the two scenarios (Xiao-Ming and Jie-Fang, 2009).

Participants got familiar with the surroundings and the materials as soon as they arrived. Each candidate received comprehensive instructions outlining the purpose of the activity along with guidance on how to complete the assessments. Prior to the testing, they signed a formal consent form granting the University of Kragujevac's administration ethical approval to conduct the experiment. After that, they were given an EEG cap and allowed to sit in an ergonomic work chair that could be adjusted. The procedures were the same in both cases. At the beginning, each candidate was trained for 15 minutes before the beginning of the activity in both scenarios, following the protocol set for the experiments. To avoid memory bias, in the collaborative scenarios training, the participant did not have any interaction with the robot. After the training phase, in all the scenarios, the participant started the tests after being in a rest condition for a period of 5 minutes as baseline for the tests.

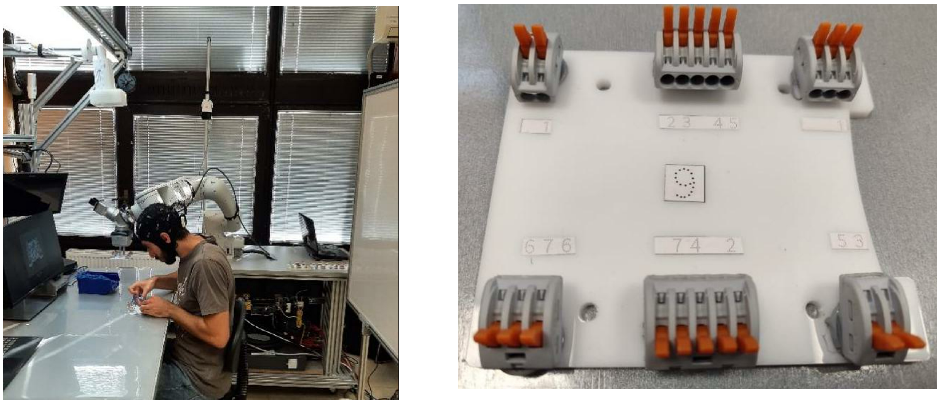
A constant temperature of 23 ± 1.5 °C was maintained throughout the trials. At nine in the morning, the tests took place. Other electrical and electromechanical devices were shut off for the duration of the tests. To reduce any potential electrical interference, the computer that was Bluetooth-connected to the EEG system was situated as far away from the device as possible. Electronic items, including smartphones, were kept outside of the workplace. Furthermore, during the studies, no one was permitted inside the facility. To ensure that the outcomes were unaffected, these requirements were the same for both situations.

The assembly tasks performed by the participants consisted of different steps performed in both scenarios:

- Take the plate located on the right side of the participant and set it on the work desk of the workstation (Savkovic et al., 2022). In the standard scenario, the plates are set in lots, and placed on the right side of the operator in the manual assembly desk area. On the other end, in the other scenarios, the cobot carried the plate to the operator on the right side, entering the manual assembly area and waiting for the participant to finish the task. The cobot positioned the plate to be taken by the participant. In this phase, ergonomic principles were considered to let the participant grasp the component without overextending the arm (Stanton et al., 2012).
- Take seven wires from the container, one by one, set in the assembly area, and connect them to the plates. The connections were supported by the illustration from the installed PC touchscreen. The participant did not know which order scheme would appear on the monitor. The combination of the schemes' connection was randomized in order not to affect the results. In the standard scenario, the participant performed the task without any external presence in the assembly area. On the other side, in the collaborative scenario, while the operator assembled the scheme, the robot moved back to pick and carry the other scheme to the position to be picked up by the participant. Furthermore, in the collaborative guided scenario, the participant was guided to accomplish the task following the labels attached to the schemes to avoid errors, as shown in Figure 2.b.
- Set the plate on the slide located to the left side after having performed the task and touch the PC touchscreen to progress to the next scheme.

(a) (b)

Fig. 1. (a) Standard Scenario (SS): the assembly task is performed by the participant without any external intervention in the workplace; (b) Collaborative Scenario (CS): the assembly task is performed by the participant interacting with the robot in the workplace.



(a) (b)

Fig. 2. (a) Guided Collaborative Scenario (GCS): the assembly task is performed by the participant alongside the robot and guided through P-Y to reduce errors during the task; (b) The particularity of the third scenario is the presence of P-Y principles through number labels helping the operator accomplish the task.

To perform the task in the collaborative scenario, the industrial collaborative robot used for the tests was the MELFA ASSISTANT from Mitsubishi Electric (Mitsubishi Electric).

The participant worked alongside and close to the cobot, therefore choosing the robot's speed was crucial to setting up an interacting human-robot engagement. The robot station was positioned 1000 mm apart from the operator in this regard. Based on the technical specifications of the cobot for an interactive activity and the literature analysis, the cobot speed chosen to complete an HRI task was 250 (mm/s) (Arai et al., 2010). Furthermore, the operator and the robot shared a workspace on the same side of the assembly line. Respecting the task's original layout in the typical scenario served as the driving force behind this disposition.

The VGC10 Electrical Vacuum Gripper, an HRI-suitable robot gripper, was utilised to relocate the parts. The gripper had an internal pneumatic force that allowed it to sense whether the item was being gripped or not. This gripper had to be chosen in order to pick and position light things with a thin coating. Additionally customisable, the gripper made it easier for the human and robot to work together when the latter was grabbing. The limit force in this case study was chosen at 20 kPa in order to allow the robot to move and return to its starting position, taking into account the design of the prototype plate that applicants had to construct.

In our laboratory trials, we acquired neuronal physiological data using the electroencephalography (EEG) cap, developed by mBrainTrain, Serbia, to objectively analyse the mental workload. The program SMARTING STREAMER 3.4.3, which enabled communication between a computer and the devices, was used to gather data. The neural brainwave pawer ratio β/α was analysed to determine the EEG metric evaluation by looking for signs of stress, engagement, or relaxation during the testing.

To assess the mental workload subjectively, each scenario's participants completed the NASA TLX at the conclusion of the test (Fiorineschi et al., 2020). The NASA TLX is a multifaceted, subjective evaluation tool used to gauge participants' levels of frustration, effort, performance, and mental, physical, and temporal demands during the task in both scenarios.

Finally, regarding the performance assessment, a specific checklist was prepared to discriminate between correct and incorrect components accomplished by the participants to evaluate the efficiency of the overall session.

3. Results

The MWL indexes are shown for the three scenarios for each participant in Figure 3.

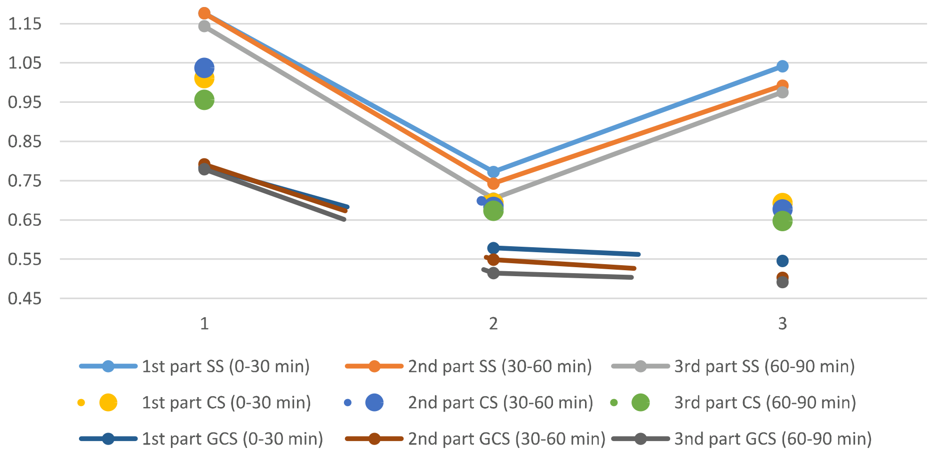


Fig. 3. Mental Workload (Y-axis) represented over the participants (X-axis), in three consecutive parts of the task session (30 minutes each) analyzed in the standard (SS – highlighted in dashes) and collaborative scenario (CS – highlighted in lines).

The MWL index is lower in the collaborative scenarios (CS and CGS) than in the standard scenario (SS). In particular, the MWL in the CGS is the lowest than in the other two scenarios, in line with other research studies (Tropshuh et al., 2021; Gualtieri et al., 2022). This is consistent with other research studies regarding the correlation of the operator’s workload with the deployment of Poka-Yoke principles (Romero et al., 2022). Generally, the task with the robot allowed to reduce the mental workload of the participant compared to the assembly task and is drastically reduced in the guided collaborative scenario.

Regarding the questionnaire through the NASA-TLX, the results are shown in Figure 4 below:

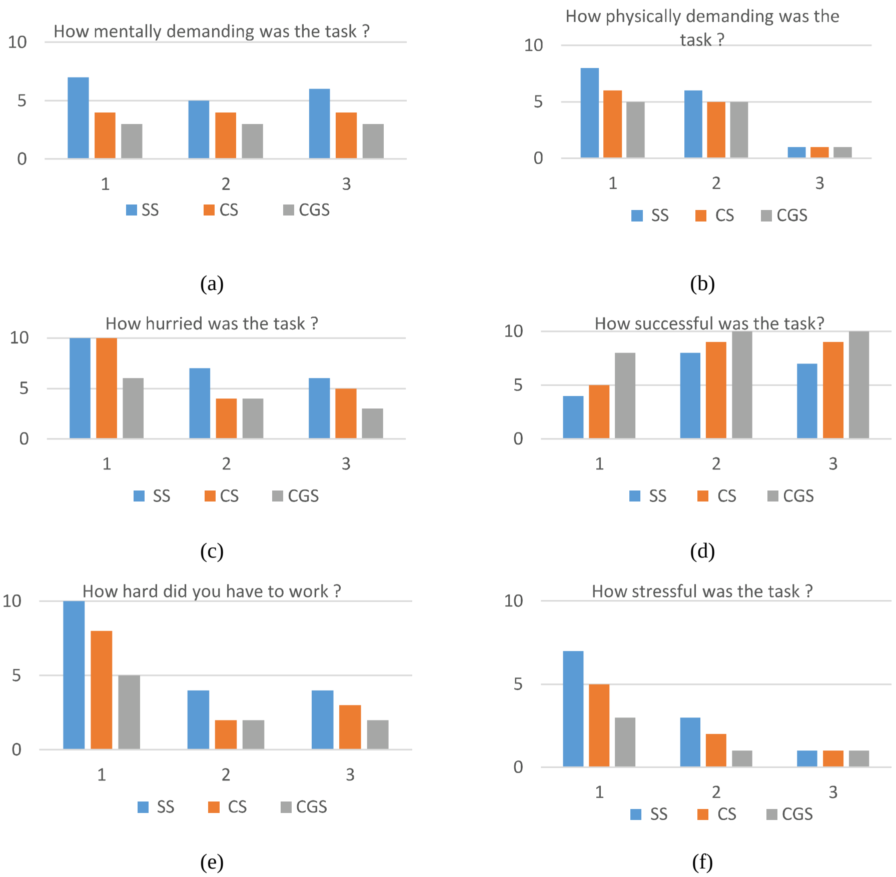


Fig. 4. NASA TLX results: (a) Mental workload; (b) Physical workload; (c) Temporal Demand; (d) Performance; (e) Effort; (f) Frustration. In terms of marks, 0 is the lowest and 10 is the highest value.

In line with the NASA-TLX, the level of stress is lower in the collaborative and collaborative-guided scenario than in the standard scenario. Also, the participants felt that the task was more successful in the collaborative guided scenario.

Finally, the level of performance, in terms of productivity (i.e. the number of pieces assembled correctly) is shown in Figure 5 below:

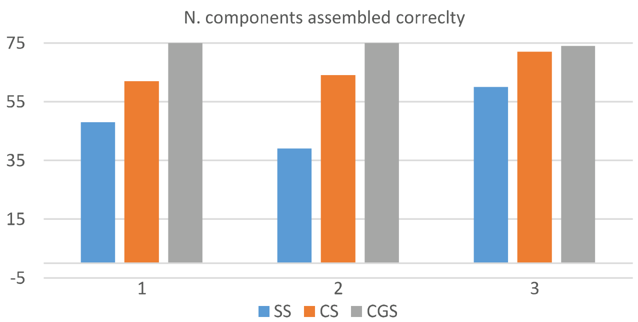


Fig. 5. Number of assembly components accomplished correctly in the standard scenario and collaborative scenario – Y axis, over the participants – X axis.

The number of components assembled correctly is the highest in the CGS. This is in line with the the results shown with the NASA-TLX and with the lean principles regarding a higher level of productivity (Romero et al., 2022).

4. Conclusion

The goal of this paper is to show through a comparative analysis the impact of the cobot in an assembly task in terms of mental workload through the EEG methodology. The power of the EEG method consists of a direct objective method that allows to acquire real-time data from the brain activity of humans. Furthermore, the method avoids any form of bias.

The design of the experiments was set up to conduct neuroergonomic tests in a laboratory assembly task. The initial results showed a lower level of MWL index in the collaborative scenarios (CS and CGS). These results are promising for further studies regarding the impactful aspects of MWL in industrial assembly activities. The comparative analysis is crucial to determine the rate of MWL when the robot co-participate in the tests. However, the study needs further tests and correlations with other data to provide a thorough explanation of the behavioral state of the operator during these activities. Also, the study must analyze the validity of data through a comprehensive statistical analysis. Further analyses would be conducted for more participants and more data would be provided from the tests.

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