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Development of a Neuroergonomic Assessment for the Evaluation of Mental Workload in an Industrial Human–Robot Interaction Assembly Task: A Comparative Case Study

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Abstract: The disruptive deployment of collaborative robots, named cobots, in Industry 5.0 has brought attention to the safety and ergonomic aspects of industrial human–robot interaction (HRI) tasks. In particular, the study of the operator's mental workload in HRI activities has been the research object of a new branch of ergonomics, called neuroergonomics, to improve the operator's wellbeing and the efficiency of the system. This study shows the development of a combinative assessment for the evaluation of mental workload in a comparative analysis of two assembly task scenarios, without and with robot interaction. The evaluation of mental workload is achieved through a combination of subjective (NASA TLX) and real-time objective measurements. This latter measurement is found using an innovative electroencephalogram (EEG) device and the characterization of the cognitive workload through the brainwave power ratio β/α, defined after the pre-processing phase of EEG data. Finally, observational analyses are considered regarding the task performance of the two scenarios. The statistical analyses show how significantly the mental workload diminution and a higher level of performance, as the number of components assembled correctly by the participants, are achieved in the scenario with the robot.

Keywords: collaborative robotics; neuroergonomics; IR5.0; human–robot interaction; mental workload; EEG; experimental design; ergonomic assessment; cobots; performance

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Citation: Caiazzo, C.; Savkovic, M.; Pusica, M.; Milojevic, D.; Leva, M.C.; Djapan, M. Development of a Neuroergonomic Assessment for the Evaluation of Mental Workload in an Industrial Human–Robot Interaction Assembly Task: A Comparative Case Study. *Machines* **2023**, *11*, 995. https://doi.org/10.3390/machines11110995

Academic Editors: Marcello Valori, Luca Gualtieri, José Saenz, Irene Fassi and Dan Zhang

Received: 12 August 2023
Revised: 9 October 2023
Accepted: 24 October 2023
Published: 26 October 2023

1. Introduction

The fifth industrial revolution, or Industry 5.0 (IR5.0), is on the verge of setting humans at the center of production systems by designing innovative industrial collaborative workplaces [1,2]. Contrary to the previous four industrial revolutions, in which the aim was to reduce the human role in manufacturing activities, this fifth industrial revolution emphasizes how technology should be used for the benefit of individuals, by focusing on the personalized demands and requirements of customers [3].

The current trend of IR5.0 envisions completely shared environments, where robots act on and interact with their surroundings and other agents, such as human workers and other robots [4]. Furthermore, IR5.0 sets wellbeing and satisfaction as crucial parts of social sustainability in industry. In other words, the new concept of IR5.0 smart factories addresses occupational health and safety (OHS) principles as pillars for the success of an organization [5–7].

Industrial collaborative robots, or cobots, allow improvement of the social sustainability and wellbeing of operators in industries, performing industrial tasks alongside operators in a fenceless shared environment [8]. The deployment of these machines opens the door to innovative interactive applications between the human and the operator, named human–robot interaction (HRI), combining the advantages of automation, such as accuracy and repeatability, with the flexibility and cognitive soft skills of humans [9,10]. In this regard, to combine the different perks of humans and robots, research studies have shown different degrees of HRI [11]. On the basis of these, safety principles are crucial in HRI applications [12–16].

Nevertheless, in manufacturing assembly tasks, ergonomic aspects are pivotal for the design of HRI activities, as assembly tasks account for almost half of the average workload in the actual manufacturing processes [17]. There are three different fields of ergonomics: physical, cognitive, and organizational ergonomics [18]. In HRI, physical and cognitive ergonomics play a major role in an effective and efficient HRI [13]. Physical ergonomics deals with human physical activity, regarding its limitations and capabilities [19]. Cognitive ergonomics deals with the mental processes of humans influenced by other systems involved in the environment [20].

Different authors set up HRI scenarios of assembly tasks to deal with ergonomic aspects [21–24]. Some research studies applied observational measurements and questionnaires to evaluate the improvement of the wellbeing of the operator in HRI [25,26]. Regarding the performance of the operator in HRI tasks, some authors pointed out that human–robot interactive tasks did not improve the level of performance, in terms of productivity, of the task [25]. In other research studies, authors suggested different physiological measurements in HRI applications as indicators of the wellbeing state of the operator using the deployment of physiological sensors [27–29]. Yet, these indicators did not concern the neuronal aspects of the operator's mental workload in HRI.

The introduction of cobots in workplace fenceless environments has highlighted crucial aspects regarding the mental state of operators in HRI [30,31]. This interest has brought attention to neuroergonomics, the discipline of neuroscience applied in ergonomics, in order to better analyze the mental workload representing the volume of mental work required of an employee to accomplish a task [32,33]. Proper workload level is the key to successfully enhancing the productivity and efficiency [34,35]. Lower levels of mental workload might be representative of an out-of-the-loop state of the operator when performing a task [36]. On the other hand, higher levels of mental workload might be a consequence of frustration and cognitive fatigue of the operator executing the task [37].

Different methodologies are adopted to analyze mental workload [38,39]. In HRI activities, questionnaires are of pivotal importance to analyze the mental state of the operator [40]. NASA TLX questionnaires are still the most deployed in the research field to assess the cognitive workload of the operator after having performed a task [35]. Other studies analyzed empirical methodologies to analyze the operator's performance through surveys and error analysis of participants to evaluate the impact of the cognitive state of the operator while working with the robot in HRI activities [41]. However, subjective interpretations are affected by bias in the analysis of mental workload.

Thus, in combination with these interpretations, physiological measurements are deployed to analyze the mental workload in HRI [42]. Different frameworks have been developed to evaluate the mental state of the operator. Villani et al. [28] defined the amount of cognitive workload through heart-rate variability in physical activity, using a stopwatch. However, the analysis did not show significant results in terms of mental fatigue. Other authors defined the level of mental fatigue using eye tracking [43]. The results showed an acceptable sensibility of the measurements in terms of task load, though the mental workload through the gaze behavior was not significantly different. In these studies, the presence of artifacts is crucial to discriminating the level of mental workload. However, cognitive analysis lacks direct measurements regarding the neuronal activity of the brain.

In this regard, the electroencephalogram (EEG) provides an online, objective, real-time, and quantitative direct measure of neuronal activity. Through EEG pre-processing phase, it is possible to remove those artifacts that could affect the acquisition of the signals [44]. Furthermore, EEG has found a vast application in different fields [45,46]. Zakeri et al.

highlighted the application of EEG in smart factories to evaluate mental stress [30]. From the analysis and pre-processing of EEG signals, research studies analyzed the real-time human brainwaves responses [47–49]. In the literature review, different power ratios of the brainwaves were considered to assess the mental state of the human in a relaxation (Alpha waves) or stress/engagement (Beta waves) phase [50,51]. In this research paper, the ratio β/α is considered for the analysis of the mental workload.

As EEG deployment in HRI manufacturing activities is still in its infancy, authors have suggested that objective measurements should be deployed alongside conventional subjective and observational ones for a better comprehension of the cognitive state of the operator [30,41,52]. Although these studies defined different metrics for the evaluation of the HRI task performance, the analyses did not highlight the application of EEG in HRI to investigate the neuronal activity of the operator during the tasks.

Regarding the HRI scenarios, many studies suggested that cobots reduce the operator's mental workload [53,54]. On the other hand, other studies are showing that cobots increase workload [55–57]. However, these studies are only based on subjective measurements through surveys or questionnaires. These arguments indicate that there is still a need to investigate mental workload in HRI tasks through objective studies [58,59].

This paper presents a comparative analysis of two laboratory experimental scenarios (standard and collaborative scenario) in which the participants performed manual assembly tasks with and without the interaction of the robot in a modular assembly workstation. The goal of this analysis is to show how significantly the participants' mental workload is reduced while either working or not alongside the robot through the combination of objective (EEG), subjective (NASA TLX), and observational measurements. The objective analysis is performed through the EEG cap, mounted on the participant, collecting the neuronal activity from the scalp. The measurement allowed a real-time, direct, safe, and non-obtrusive acquisition of data while the participant accomplished the task in both scenarios. Regarding the subjective analysis, at the end of the test, for each scenario, the participant answered questions through the NASA TLX to have a subjective response of the state of the participant while performing the task. Furthermore, observational measurement was performed to analyze the productivity index in terms of components assembled correctly in the different scenarios. The paper aims to cover the research gap through a combination of metrics (EEG—β/α, NASA TLX, and performance) to evaluate the mental workload and performance of the operator while working with the robot in HRI tasks.

Section 2 presents the material and methods adopted for this research paper. Section 3 presents the results coming from the objective and subjective measurements. Section 4 presents a discussion of these results and the limits of the study. Finally, Section 5 presents the conclusion with further steps of the ongoing research.

2. Materials and Methods

2.1. Participants Selection

A total of 9 male university students (N_participants = 9, mean age: 23.3 $\pm$ 3.3 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 $\pm$ 16.4 kg, and the mean height was 184.2 $\pm$ 5.8 cm. None of the subjects had previous experience in the assembly workplace or with the robot. Subjects were not under the influence of any medication that could interfere with EEG.

Participants were instructed not to drink any alcohol on the day before and the day of their participation in the study, as well as not to drink coffee at least three hours before they participated in the study. They assured us that they had slept well the night before the test. All participants had normal or corrected-to-normal vision. Participants were all male, and right-handed. They did not have any experience working with the robot.

Table 1. Characteristics of the candidates.

Candidate Number	Age	Body Weight (kg)	Height (cm)
1	26	94	188
2	24	105	190
3	26	80	188
4	23	78	177
5	23	95	185
6	20	100	180
7	22	84	190
8	22	83	178
9	24	78	182

2.2. Experimental Design

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) [21]. 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.

Additionally, the workstation was electrically height-adjustable according to the anthropometric characteristics of the participants and designed to allow the implementation of other modules such as the collaborative robot cell to perform collaborative tasks.

To perform the tests, the participants assembled a prototype model of an industrial product, which is an abstraction of the connection plate consisting of a metal base made of sheet steel with built-in threaded elements and a transparent acrylic cover connected by an aluminum hinge (combination of three materials). For educational purposes, the prototype is lightweight, has no sharp edges, and is composed of plastic material, see Figure 1. The designed task recalled the wire-harnessing activities carried out in manufacturing workplaces. The selection of this task, recalling the wire-harness assembly tasks, came from a lack of research studies regarding the neuroergonomic analysis of these activities with the involvement of supportive technologies, such as robots [60].

(**a**) (**b**)

Figure 1. (**a**) Assembly components used for the laboratory experiments: the components are of plastic, no sharp edges, and lightweight, ideal for educational purposes and (**b**) components in real case scenarios: these components also consist of metal parts.

For the comparative analysis, the participants conducted two different types of experiments in the same laboratory environment (N_tests = 18): standard scenario (SS) in which the participant performed the task without any intervention (the robot) in the workplace and collaborative scenario (CS) in which the participant performed the task interacting with the robot in the workplace. The two scenarios are presented in Figure 2. The duration of the activity for each test was 90 min. The number of components to assemble performing the overall test in both scenarios was 75 (N_components = 75). The distribution of the components was randomized.

(**a**) (**b**)

Figure 2. (**a**) Standard scenario (SS): the assembly task is performed by the participant without any external intervention in the workplace and (**b**) collaborative scenario (CS): the assembly task is performed by the participant interacting with the robot in the workplace.

The two test 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 [61].

Upon their arrival, participants familiarized themselves with the materials and the environment. Each candidate was given clear instructions on how to perform the tests and explained the goal of the activity. Before the tests, they signed the formal consent for ethical approvement to conduct experiment, approved by the administration of the University of Kragujevac. Then, they were equipped with the EEG cap and let them seat on the adjustable ergonomic work chair. These steps were identical for both scenarios. At the beginning, each candidate was trained for 15 min before the beginning of the activity in both scenarios, following the protocol set for the experiments. To avoid memory bias, in the collaborative scenario training, the participant did not have any interaction with the robot. After the training phase, in both scenarios, the participant started the tests after being in a rest condition for a period of 5 min as baseline for the tests.

During the experiments, the temperature was maintained at 23 ± 1.5 °C. The tests were conducted in the morning, starting at 9 a.m.

During the tests, other electrical and electromechanical equipment were turned off. The computer connected to the EEG system via Bluetooth was set at the maximum possible distance to limit possible electrical interference. Smartphones and other electronic devices were placed out of the workstation. Moreover, nobody was allowed to enter the laboratory during the experiments. These conditions were identical for both scenarios in order not to affect the results.

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

1. Take the plate located on the right side of the participant and set it on the work desk of the workstation [21]. 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 collaborative scenario, 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 [62];

2. 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;
3. 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.

2.3. Collaborative Scenario

To perform the task in the collaborative scenario, the industrial collaborative robot used for the tests was the MELFA ASSISTANT from Mitsubishi Electric, shown in Figure 3a [63].

(**a**) (**b**)

Figure 3. (**a**) Mitsubishi MELFA ASSISTA cobot and (**b**) VGC10 Electrical Vacuum Gripper.

A crucial aspect in the design of the collaborative scenario was the placement of the robotic workstation. It was essential to design the collaborative scenario, considering the presence of the participant in the workstation, without changing the location of other systems in the workplace [64]. The selection of the robot's speed was of paramount importance to set a human–robot interactive activity as the participant worked simultaneously and in proximity to the cobot. In this regard, the robot station was placed 1000 mm from the operator. The cobot speed selected to perform an HRI task was 250 (mm/s), according to the literature review and the technical characteristics of the cobot for an interactive activity [63,64]. In addition, the robot and the operator worked on the same side of the assembly workstation. The motivation for this disposition was to respect the original layout of the task in the standard scenario.

The robot gripper used to carry the pieces was the VGC10 Electrical Vacuum Gripper, shown in Figure 3b, suitable for HRI activities [65]. The gripper provided a pneumatical inner force detecting if it was either gripping the piece or not. The selection of this gripper was necessary to pick and place light objects with a thin layer. The gripper was also customizable and facilitated the joint action between the robot and the human during the phase of grasping from the latter. In this case study, considering the design of the prototypal plate that candidates had to assemble, the limit force set to let the robot move and return to the initial position was defined at 20 kPa. Furthermore, the logic defined in this phase allowed to interact the human with the robot: only when the operator grasped the piece, the robot "understood" to move back and pick the other piece. The type of interaction, according to the literature review, is a sequential collaboration [11]. A representation of the cobot and gripper action is presented in the flowchart below, Figure 4.

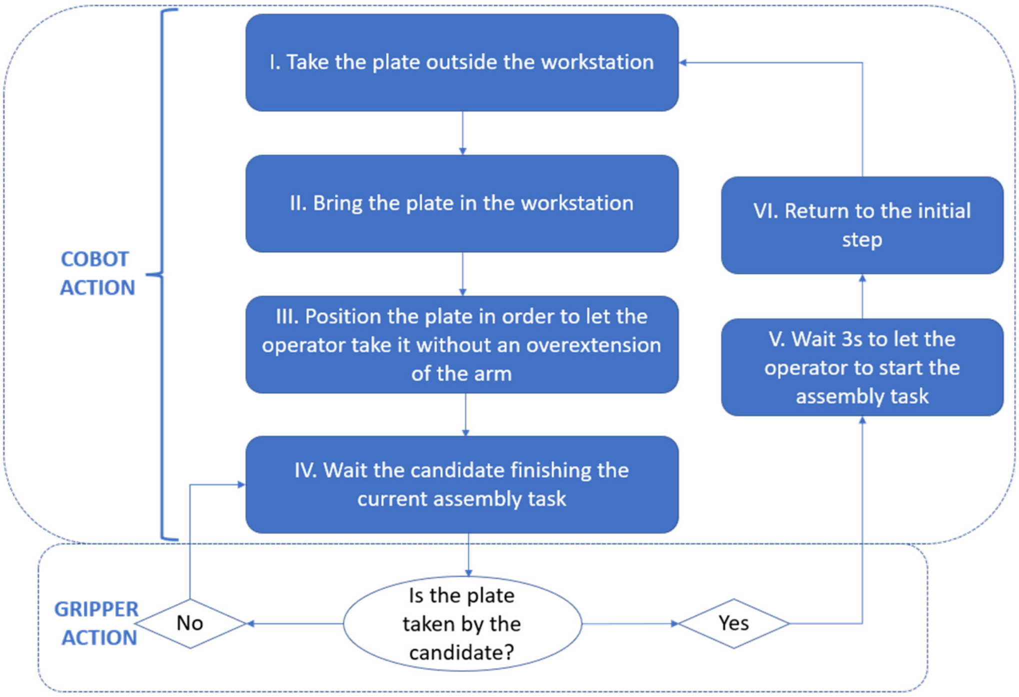

Figure 4. Sequential collaboration: cobot and gripper action logic.

2.4. Neuroergonomic and Performance Assessment

To evaluate the mental workload, objective and subjective measurements were deployed. About the latter, wearable devices are chosen depending on the tasks to be executed and the workplace characteristics and requirements. In general, the physiological sensors should be selected to ensure a reliable monitoring of the workers' state. Indeed, not all of them might be selectively optimal since they are sensitive to physical activity. In our laboratory experiments, we collected neuronal physiological data through the electroencephalography (EEG) cap.

The data were collected through the electrodes mounted on the cap to the scalp of the participants. Each electrode measured the voltage produced by the neuronal activity from the region of the brain in which it is placed. EEG data were recorded with the SMARTING wireless EEG system [66]. The small and lightweight EEG amplifier (85 × 51 × 12 mm, 60 g) was tightly connected to a 24-channel electrode cap. The communication between the SMARTING and the recording computer was established through a Bluetooth connection. The electrode cap contained sintered Ag/AgCl electrodes that were placed based on the International 10–20 System [67].

The experimental procedure imposed that the electrode impedances had to be set below 5 kΩ, which was confirmed by the device acquisition software. A referential procedure was set up for the montage of the wireless, portable, and non-intrusive electrode system cap. The EEG cap device is shown in Figure 5. EEG was recorded from 24 scalp locations. From Figure 6, the considered electrodes included frontal (Fp1, Fp2, AFz, F3, F7, Fz, F4, F8), central (Cz, CPz, C3, and C4), temporal (T7, T8), parietal (CPz, Pz, P3, P4, P7, P8), occipital (O1 and O2), and midbrain (M1 and M2) locations.

Data were collected through the software SMARTING STREAMER 3.4.3, which allowed a computer to interact with the devices. The EEG metric evaluation was defined by analyzing the neuronal brainwave pawer ratio β/α as indicators of stress/engagement or relaxation during the tests.

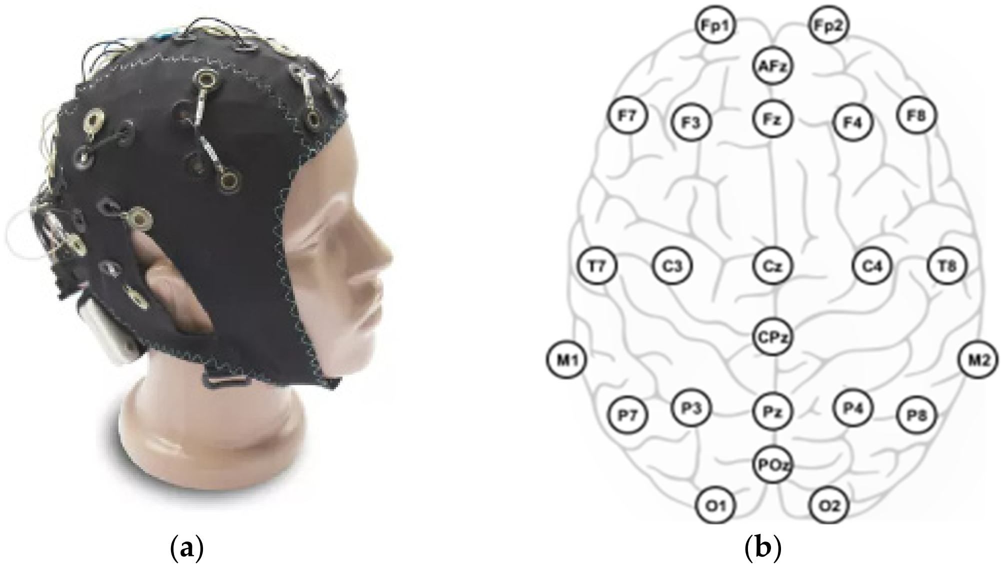

Figure 5. (**a**) Electroencephalogram (EEG) gel-based cap and (**b**) view of the localization of the electrodes on the scalp by the software SMARTING.

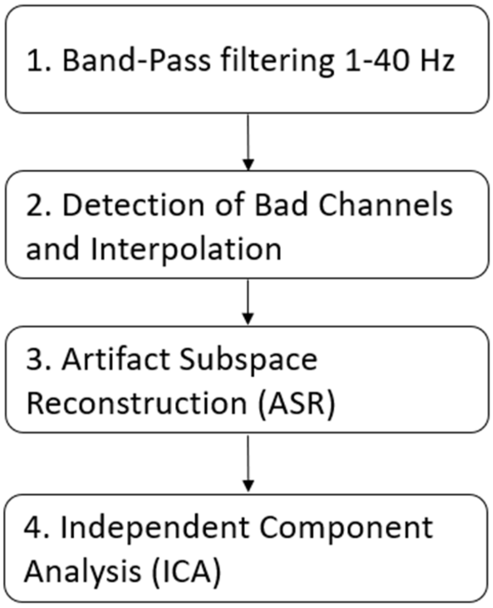

Figure 6. Flowchart of the EEG pre-processing phase.

Regarding the subjective measurement to analyze the mental workload, the NASA TLX was performed by the participants at the end of the test in each scenario [35]. NASA TLX is a multidimensional subjective assessment to evaluate the mental, physical, and temporal demands, the effort, the performance, and the level of frustration that participants had to undertake during the task in both scenarios.

Furthermore, open questions were asked to the participants at the end of the tests in the collaborative scenario to express their experience with the cobot, its fluency, and motion (if aggressive or not), how safe and comfortable the interaction with it, and if the workplace setting was better either in the standard or in the collaborative scenario.

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.

2.5. EEG Pre-Processing

The EEGLAB 2021.1 toolbox (MATLAB 2021.a) was used for preprocessing and data analysis. The data were grouped into different frequency bands [49]:

- Delta (0.5–4 Hz): generated in a state of sleeping;
- Theta (4–8 Hz); generated in REM phase;
- Alpha (8–12 Hz): produced in an awake state while being concentrated and relaxed;
- Beta (13–29 Hz): generated while being in a state of stress and engagement;
- Gamma (25–45 Hz): produced in a state of processing information and making voluntary movements.

A sampling rate of 250 Hz was used. Preprocessing EEG signals typically consists of filtering the signal to reduce the influence of artifacts such as eye movements, muscle tension, and noise [44]. In this study, the power ratio β/α was taken into consideration to evaluate the cognitive mental workload.

Regarding the noise, a band-pass filter of 1–40 Hz was applied for its reduction. The detection of bad channels allowed intervention in those channels that did not collect good-quality signals. In this regard, as the EEG cap had more channels in different parts of the scalp, it was possible to interpolate these channels with the ones near the area of interest of the scalp. The artifact subspace reconstruction (ASR) was an algorithm of Matlab that allowed the artifacts such as eye movements and muscle tension. Finally, the independent component analysis (ICA) was computed to separate the signals into additive components and define the independent components [68].

A representation of the steps of the EEG pre-processing phase is shown in the flowchart, in Figure 6.

3. Results

The MWL average index of the candidates, taking into consideration the standard (SS) and collaborative (CS) scenario through the objective measurement (EEG data), was observed in three consecutive halves of the tests (30 min each), and is presented in the Figure 7 below, from the Tables A1 and A2 (Appendix A), defined as the power ratio of brainwaves β/α (Beta—stress/engagement indicator, Alpha—relaxation indicator):

From Figure 8, in the standard scenario (SS), the mental workload slightly decreased along the task. Only with subjects 4 and 6 did the power ratio β/α increased in the second and third part of the task. From the analysis of variance with repeated measures—ANOVA RM—(α = 0.05), p-Value = 0.194, F = 2.459, F_crit = 3.633. The mental workload between the three parts of the test in the standard scenario is not significantly different (p-Value > α) and it is not possible to reject the null hypothesis ($H = H_0$).

On the other hand, in the collaborative scenario (CS), the mental workload decreased along with the activity for all the participants. From the ANOVA RM analysis (α = 0.05), p-Value = 0.00005, F = 19.32, F_crit = 3.633. In the collaborative scenario, the mental workload significantly decreased (p-Value < α) along the three parts of the tests observed and the null hypothesis is rejected ($H \neq H_0$).

Considering the variation between the overall parts of the two sessions, the MWL difference (Diff) is defined in Figure 8, from Tables A3 and A4 (Appendix A).

From the analysis of variance, ANOVA RM (α = 0.05), p-Value = 0.0001, F = 6.367, F_crit = 2.449. The variation in MWL among the parts is significant (p-Value < α) and the null hypothesis is rejected ($H \neq H_0$). To sum up, from the statistical analysis of the different periods during the activity, the overall tests in collaborative scenarios reported a more significant decrease in the mental workload of the participants than in the standard scenarios.

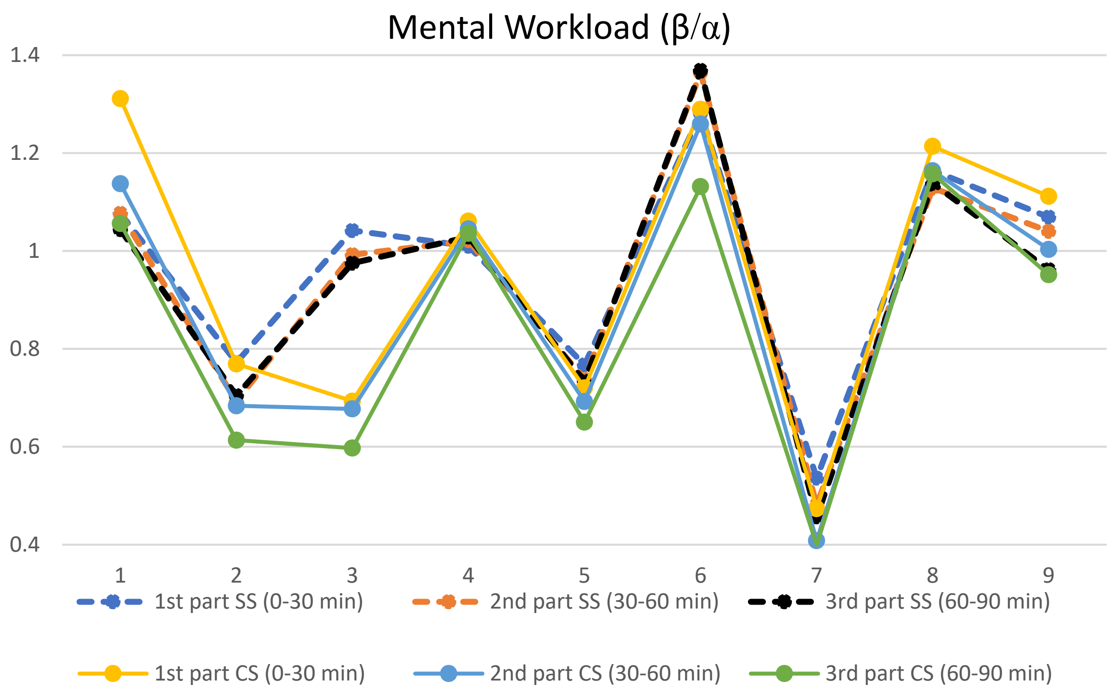

Figure 7. Mental workload (Y-axis) represented over the participants (X-axis), in three consecutive parts of the task session (30 min each) analyzed in the standard (SS—highlighted in dashes) and collaborative scenario (CS—highlighted in lines).

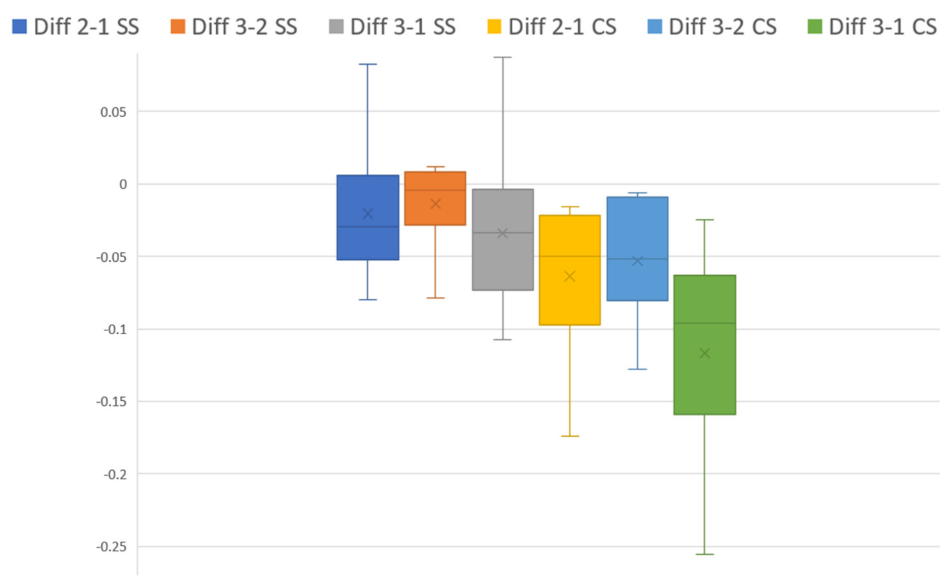

Figure 8. MWL variation (Y axis) between the three consecutive parts of the task session (30 min each) analyzed in the standard (SS) and collaborative scenario (CS).

Regarding the NASA TLX analysis (range between 0 and 10) [35], given at the end of the tests to the participants, the results are shown in Figure 9.

From the T-test analysis of the NASA TLX between the two scenarios ($\alpha = 0.05$): (a) mental demand, *p*-Value = 0.0004; (b) physical demand, *p*-Value = 0.08; (c) temporal demand, *p*-Value = 0.088; (d) performance, *p*-Value = 0.046; (e) effort, *p*-Value = 0.0085; and (f) frustration, *p*-Value = 0.01.

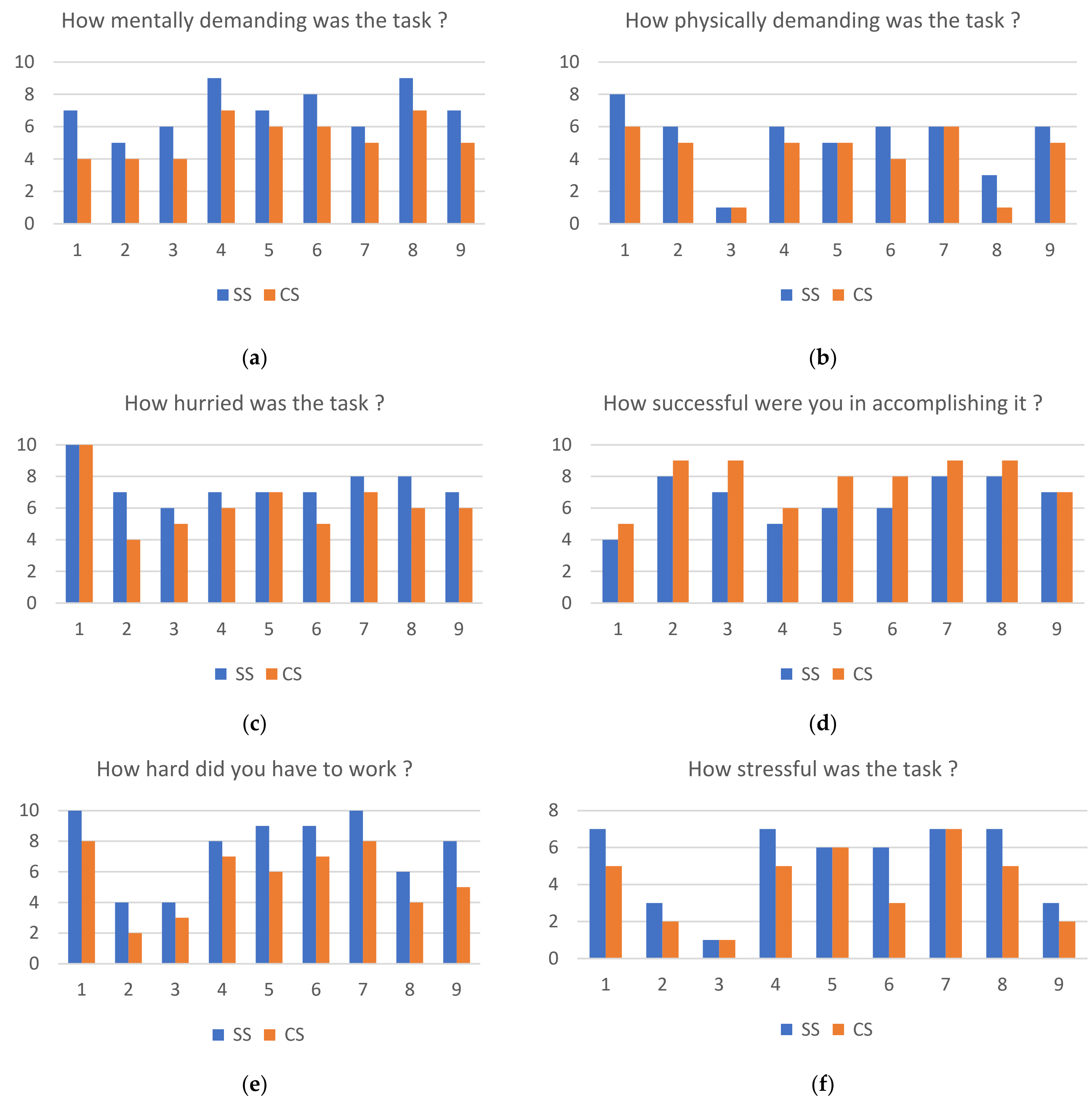

Figure 9. NASA TLX results: (**a**) mental workload; (**b**) physical workload; (**c**) temporal demand; (**d**) performance; (**e**) effort; and (**f**) frustration.

From the statistical analysis of NASA TLX results, the physical and temporal demand were not significantly different (p-value > α) between the standard and collaborative scenarios and the null hypothesis is not rejected (H = H_0). On the other hand, from the T-test analyses of the other subjective measurements mental demand, effort, performance, and frustration were significantly different (p-value < α) between the two scenarios, and the null hypothesis is rejected (H $\neq$ H_0). In line with the EEG analysis, the NASA TLX showed a lower level of mental workload of the participants in the collaborative scenario rather than in the standard scenario without the cobot.

In addition to the NASA TLX, further direct open questions were asked to the participant at the end of the experiments regarding the experience with and without the robot, its fluency motion and trajectory (if predictable or not), how safe and comfortable was the interaction with it and if the workplace setting was better either in the standard or in the collaborative scenario. From the answers of the participants, the assembly task with the robot was safer and more comfortable when it came to pick the plate from the gripper. Moreover, the experience was considered more educational and enjoyable. Regarding its motion, the participants did not feel scared when the robot was moving and its responsiveness when they grasped the pieces from the gripper was not aggressive. To conclude, the absence of the plates on the work desk, where the participant assembled the component, was perceived better in the collaborative scenario. The candidates had more space to assemble the component and were more confident to accomplish the task, feeling less distracted.

Finally, from the observational analysis carried out through the checklist regarding the performance of the participant in the two scenarios, the candidates accomplished the task more successfully in the CS rather than in the SS, Table A5. From the T-test analysis of performance between the two scenarios p-Value = 0.00018 ($< \alpha = 0.05$). The number of pieces accomplished, Figure 10, during the task in the CS was significantly higher. The time to conclude the task did not change between the two scenarios (Time Tests: 90 min). This is also in line with the temporal demand subjective measurement analyzed in the NASA TLX. Thus, in terms of efficiency, as the number of pieces correctly assembled over time, the activity in the collaborative scenario with the robot was more successful than in the standard scenario.

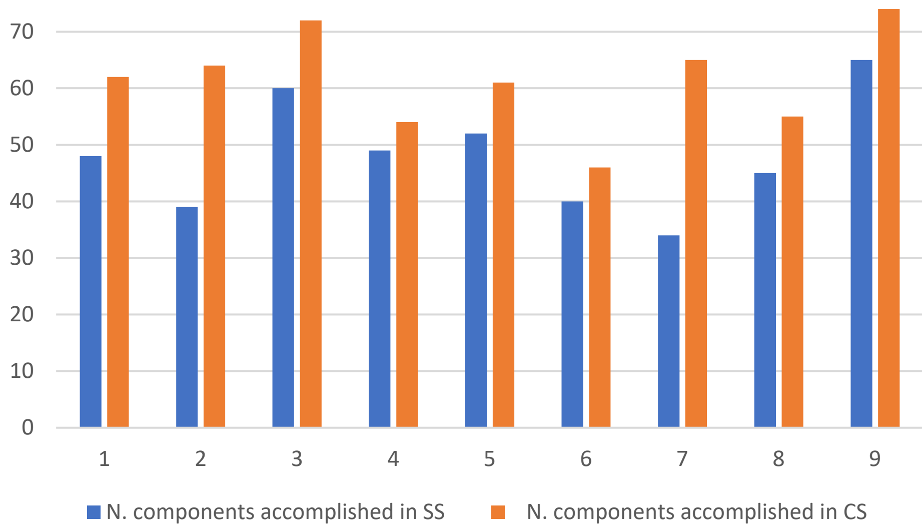

Figure 10. Number of assembly components accomplished correctly in the standard scenario and collaborative scenario—Y axis—over the participants—X axis.

4. Discussion

Regarding the objective analysis, the statistical analysis indicated that the mental workload, measured through EEG as the power ratio β/α (Beta—stress indicator, Alpha—relaxation indicator), observed in three consecutive parts of the tests, significantly decreased more in the collaborative scenario rather than in the standard scenario. Specifically, in the standard scenario, the mental workload was not significantly different in the three consecutive periods and some participants even showed an increase in the power ratio β/α, which is in line with [69]. On the other hand, in the collaborative scenario, the mental workload diminution is higher during the task. Specifically, in the second and third parts of the collaborative scenario, the diminution of the mental workload is higher, which is consistent with other studies [30,70].

These findings appeared to be consistent with the subjective analysis, through the NASA TLX, in which the measurements of mental demand, effort, and frustration showed a significant decrease in these parameters highlighted by the participant during the tasks with the robot, in line with other studies [49,50]. Nevertheless, physical and time demands were not significantly different in the two scenarios. An explanation would be that the participant performed the task seated on the chair for the whole test and the physical stress was not different in the two scenarios. Regarding the time demand, the interaction with the cobot did not decrease the time to complete the overall task. This is also in line with the average time completion of the components to assemble as it was the same for both scenarios. The time pressure was less demanding to accomplish the tasks and participants felt more relaxed while working with the robot, which is also in line with the significant diminution of the mental workload [69].

Finally, the checklist highlighted a higher level of performance, in terms of components correctly accomplished, in the collaborative scenario, in contrast with other findings [25]. To support this, in the NASA TLX participants felt more successful in the collaborative tasks, though the difference in results between the standard and collaborative scenario is not significant. Overall, the combination of these measurements highlighted a better performance of the participants in accomplishing the task in the collaborative scenario in terms of ergonomics and performance of the task.

These results are consistent with existing studies in which, from an ergonomic point of view, the accomplishment of a task was more successful in an HRI task than the conventional manual assembly task [70,71]. Moreover, these results are in line with further studies regarding the increase in performance of HRI applications in industrial manufacturing scenarios [23,72].

Regarding the comparative analysis, the authors rigorously designed the collaborative scenario to not modify and change the other systems involved already presented in the standard scenario. The reason was to analyze the MWL variation from one scenario to another, with the only cobot as a discriminant between the two scenarios. The implementation of the cobot in the workplace followed a rigorous design of the workstation to implement the cobot station respecting safety aspects [73].

Furthermore, for the comparative analysis, it was appropriate to consider the same participants for the tests in both scenarios to provide a proper comparison of the results between the two scenarios and to evaluate how the cobot intervention was influential in the collaborative task. To the best of our knowledge, this is the first study to evaluate the human performance and mental workload in a comparative analysis with the same number of participants and in which the only discriminant is the robot interacting with them in the workplace for an industrial HRI task.

Regarding the number of participants, the sample size was evaluated through ANOVA RM analysis within factors in the G*Power tool with an Effect size $\rho = 0.4$—moderate magnitude, error probability $\alpha = 0.05$, power $\beta = 0.8$, number of groups = 1, number of measurements = 6 (Number of periods observed during the task $\times$ Number of scenarios) [74,75]. Moreover, the number of candidates participating in a long laboratory session (90 min) and presented for this comparative analysis, performing the tests in two scenarios ($N\_tests = 18$), is in line with HRI tasks for ergonomic assessment research [70,71].

The methodology applied in this research paper shows the feasibility and validation of EEG measurement with subjective measurement (NASA TLX), and observational measures (checklist) in HRI tasks. The application of EEG has been rapidly increased due to its compatibility, efficiency, and practicability in various contexts [45,46]. Specifically, manual assembly tasks, such as wire-harnessing activities, are still the bottleneck of industrial processes. This has brought to the analysis and study of HRI solutions to let the operators work alongside robots. Thus, the study of the mental workload in HRI is pivotal [60]. However, the method to apply wireless, real-time, objective measurements such as EEG in industrial HRI tasks to define the mental workload in terms of brainwave activity is still at the beginning [52]. Some authors have presented a strategy to measure mental workload in smart factories. However, the efficacy of these studies did not show an effective difference between a scenario without the robot and with the robot [28,30,43]. Other studies presented the analysis of mental workload only through subjective measurements [70,71]. This study proposes an effective methodology where the results highlight a lower level of mental workload and stress (EEG and NASA TLX) and a higher level of performance in terms of components assembled correctly (checklist), in contrast with other studies. Furthermore, the motivation of our research study is to define an effective evaluation of mental workload through a neuroergonomic assessment through the analysis of mental workload with the application of different measurements. The study was conducted in two different scenarios, with the same number of participants to evaluate the mental workload of participants working with and without the robot. Other studies evaluated the cobot contribution in HRI tasks with different groups of participants or with the same group but with different types of tasks with the cobot [25,70]. In this study, to respect the comparison and maintain the cobot as the only discriminant between the two scenarios, it was reasonable to have the same participants.

This study presented some limitations and challenges. Firstly, the study was conducted on participants coming from the Faculty of Engineering, University of Kragujevac, Serbia. The candidates, having a technical and analytical background, could have a greater acceptance working with an innovative device such as the cobot and wearing the neuroergonomic EEG cap [76]. This could be the reason why the participants felt more confident while working with the cobot. Furthermore, the participants, having performed the tests in the collaborative scenario, could have had a better understanding of the task, already performed in the standard scenario. We do not exclude the possibility that this might affect the results in terms of performance and could be a limitation for the research study. However, participants performed the test after a period of four months from the tests performed in the standard scenario in order not to have a memory bias in line with other research studies in which the dynamic of brain memory is lost after a period of one month [61]. The recruitment phase was also a challenging process. In the first scenario (SS), the number of people recruited for the tests was double the number of candidates presented in this paper. Many students could not participate in the collaborative scenario for personal or academic activities, as the two test scenarios were conducted in different periods.

Secondly, the choice of the MWL parameter as the power ratio β/α was the most significant among other power ratios proposed in the literature review to discriminate the cognitive workload of the participants in the two scenarios. In other studies, other brainwaves were considered for the analysis of the mental workload, such as Theta waves [35,36]. However, still, nowadays, the choice of a stress indicator is debatable [49–52]. This is the reason why, in this study, the authors combined the quantitative analysis through the EEG with subjective measurements to define the variation in the cognitive aspects of the operator in the two scenarios.

Thirdly, the setup and mounting of the EEG neuroergonomic cap were time consuming during the phase of preparation for the tests. Participants had to wait between 20 and 30 min to mount the EEG cap, due to the gel inserted on the electrodes. Indeed, the setup of EEG devices is still a long process. The main problem was the application of the gel in the electrodes to guarantee proper contact with the scalp. However, the latest EEG devices could overcome this problem with innovative electrodes without the presence of the gel, saving time during the set-up phase. Regarding the time for the task (1.5 h), the choice of this period for the classification of the mental workload was since time is one of the constraints in the analysis of mental workload. A shorter time could not have been sufficient for the quality of EEG data to analyze mental workload. On the other hand, a longer time could have affected the memory bias and hence the performance of the tasks [77,78]. Furthermore, longer time could have been a limitation for the number of participants conducting the tests as they could not participate for personal or academic reasons. This is also the reason why the number of participants decreased in the collaborative scenario.

Finally, although the results are significant, it should be noted that the experiments were conducted in a controlled environment such as the laboratory. Participants performed the tasks in the two scenarios in a sedentary position, in an isolated workplace. However, motion artifacts and noise are mostly dominant in industrial activities and EEG acquisition could be affected by the presence of these factors.

5. Conclusions

The applications of collaborative robots in production processes and work systems have been increasing in the last few years. The increase in these devices in fenceless industrial environments has brought attention to the study of the operator's cognitive workload while working with the robot. In this regard, wearable sensors are deployed to further investigate the human response in terms of cognitive workload.

The goal of this paper is to demonstrate the feasibility of assessing participants' workload employing a thorough analysis through subjective (NASA TLX), objective (EEG), and observational (checklist) measurements comparing the mental workload of participants in two different scenarios set in a laboratory environment. We designed two different scenarios: a standard scenario in which participants had to perform random manual assembly tasks without any external intervention; collaborative scenario, in which the participant had to perform the assembly task in collaboration with the robot. The design of the collaborative scenario is set considering ergonomic and safety aspects to implement the cobot in the modular workstation to let the participants interact without changing the location and involvement of other systems involved. The motivation of this study was to determine whether the mental workload index parameter could be significantly analyzed to discriminate the mental workload of the participant in the two scenarios. From the combination of different measurements, lower values of mental workload were assessed in the activities with the cobot. In addition, an increase in productivity in the collaborative scenario is highlighted through the observational analysis.

Further research will concern the analysis of the performance of the operator in a new scenario, a collaborative-guided scenario, to assess the impact of the adjunct of guided systems, such as the P-Y module. Authors would expect to have a drastic reduction in mental stress and a further increase in the performance of the system.

Author Contributions: Conceptualization, C.C., M.S. and M.D.; methodology, C.C., M.S. and M.P.; software, C.C., D.M. and M.P.; validation, C.C., M.S., M.P. and D.M.; formal analysis, C.C. and M.P.; investigation, C.C.; resources, M.D. and D.M.; data curation, C.C. and M.P.; writing—original draft preparation, C.C.; writing—review and editing, C.C., M.C.L. and M.D.; visualization, C.C., M.S. and M.P.; supervision, M.D. and M.C.L.; project administration, M.D.; and funding acquisition, M.D. All authors have read and agreed to the published version of the manuscript.

Funding: This study was fully funded by the European Commission, HORIZON 2020 Marie Sklodowska-Curie International Training Network Collaborative Intelligence for Safety Critical Systems, CISC (Grant Agreement ID: 955901).

Data Availability Statement: The data used in this study were not released publicly due to restrictions imposed by the University and company involved.

Acknowledgments: Authors acknowledge Ivan Macuzic, Full professor of the Faculty of Engineering, University of Kragujevac, Serbia, for the support and inspiration of this research study.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. MWL (β / α) in the standard scenario (SS), defined in three consecutive halves (30 min each).

Candidate Number	1st Half SSS	2nd Half SS	3rd Half SS
1	1.076603291	1.076561924	1.043664142
2	0.772474606	0.692860351	0.704460397
3	1.041756482	0.99235386	0.975106769
4	1.009762146	1.021124855	1.028503097
5	0.767191773	0.737818065	0.733678215
6	1.281920772	1.364712446	1.369240439

Table A1. *Cont.*

Candidate Number	1st Half SSS	2nd Half SS	3rd Half SS
7	0.535837045	0.480604662	0.456824445
8	1.164515278	1.128745483	1.13843409
9	1.069157344	1.040192943	0.96160846

Table A2. MWL (β/α) in the collaborative scenario (CS), defined in three consecutive halves (30 min each).

Candidate Number	1st Half CSS	2nd Half CS	3rd Half CS
1	1.311318282	1.137371269	1.055976196
2	0.769286117	0.683612302	0.613492
3	0.693132066	0.677324776	0.5973241
4	1.061111957	1.045100041	1.036104363
5	0.720308583	0.692526322	0.650369239
6	1.289545341	1.259335851	1.131426059
7	0.47350241	0.408151724	0.399456098
8	1.213856242	1.163920243	1.15775252
9	1.111803357	1.003185084	0.95138055

Table A3. MWL difference (β/α) in the collaborative scenario (SS), defined in three consecutive halves (30 min each).

Candidate Number	Diff. 2-1 SSS	Diff 3-2 SS	Diff 3-1 SS
1	-4.13672×10^{-05}	−0.0329	−0.03294
2	−0.079614255	0.0116	−0.06801
3	−0.049402622	−0.01725	−0.06665
4	0.011362709	0.007378	0.018741
5	−0.029373708	−0.00414	−0.03351
6	0.082791674	0.004528	0.08732
7	−0.055232382	−0.02378	−0.07901
8	−0.035769794	0.009689	−0.02608
9	−0.028964401	−0.07858	−0.10755

Table A4. MWL difference (β/α) in the collaborative scenario (CS), defined in three consecutive halves (30 min each).

Candidate Number	Diff. 2-1 CSS	Diff 3-2 CS	Diff 3-1 CS
1	−0.17395	−0.0814	−0.25534
2	−0.08567	−0.07012	−0.15579
3	−0.01581	−0.08	−0.09581
4	−0.01601	−0.009	−0.02501
5	−0.02778	−0.04216	−0.06994
6	−0.03021	−0.12791	−0.15812
7	−0.06535	−0.0087	−0.07405
8	−0.04994	−0.00617	−0.0561
9	−0.10862	−0.0518	−0.16042

Table A5. Number of assembly components accomplished correctly in the standard scenario (SS) and collaborative scenario (CS).

Candidate Number	N. Components Achieved in SSS	N. Components Achieved in CS	Variation
1	48	62	+14
2	39	64	+25

Table A5. *Cont.*

Candidate Number	N. Components Achieved in SSS	N. Components Achieved in CS	Variation
3	60	72	+12
4	49	54	+5
5	52	61	+9
6	40	46	+6
7	34	65	+29
8	45	55	+20
9	65	74	+9

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