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Assessing the Relationship between Cognitive Workload, Workstation Design, User Acceptance and Trust in Collaborative Robots

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Abstract: Collaborative robots are revolutionising the manufacturing industry and the way workers perform their tasks. When designing shared workspaces between robots and humans, human factors and ergonomics are often overlooked. This study assessed the relationship between cognitive workload, workstation design, user acceptance and trust in collaborative robots. We combined subjective and objective data to evaluate the cognitive workload during an assembly task in three different scenarios in which we manipulated various features of the workstation and interaction modalities. Our results showed that participants experienced a reduction in cognitive workload in each of the three trials, indicating an improvement in cognitive performance. Additionally, we found that user acceptance predicted perceived stress across the trials but did not significantly impact the cognitive workload. Trust was not found to moderate the relationship between cognitive workload and perceived stress. This study has the potential to make a significant contribution to the field of collaborative assembly systems by providing valuable insights and helping to bridge the gap between researchers and practitioners. This study can potentially impact companies looking to improve safety, productivity and efficiency.

Keywords: human–robot collaboration; cognitive workload; technology acceptance; trust; workstation

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1. Introduction

The Fourth Industrial Revolution is characterised by constant interaction between industrial systems and workers [1]. Many digital technologies are transforming the manufacturing industry by increasing the efficiency and effectiveness of daily collaboration while blurring the boundaries between the physical world and virtual space [2]. Among the many technologies, collaborative robots aim to maximise the capabilities of humans and robots by simultaneously working together towards a shared goal, combining the accuracy and performance of collaborative robots (e.g., prolonged repetitive tasks) with the flexibility and dexterity of humans (e.g., problem-solving, creativity) [3,4].

Unlike "traditional" industrial robots or parallel kinematics robots [5], collaborative robots (cobots) offer the operator the opportunity to interact safely with the robot, either voluntarily or not, in a shared and cage-free workspace [6]. Cobots are typically introduced to reduce physical and cognitive workloads, as well as improve safety and quality, and could impact various organisational aspects, such as productivity, flexibility and accuracy [7–9]. From a phenomenological perspective, cobots are defined as "quasi-others" or "more-than-things" that are considered interactive colleagues rather than machines [10,11]. Robots' appearance and behaviour were found to significantly influence workers' acceptance of the collaborative robot [12]. Since this is a young innovation that is rarely implemented practically in companies, researchers should investigate the role of acceptance in human–robot collaboration; together with usability and trust towards the robot, acceptance is highlighted as fundamental for optimal and reliable interaction [13–15].

Many organisations addressed the importance of human factors and ergonomics (HFE) in HRC. The role of HFE involves studying the ergonomics of human–robot interfaces, developing guidelines and standards for HRC, and conducting evaluations and assessments of human–robot systems. By considering the human factors and ergonomic aspects in the design process, the collaboration between humans and robots could be more effective, efficient and safe [16–18]. In recent years, there was an increasing number of studies in HRC that examined how to ensure an adequate level of safety in the shared workplace by reducing context-related risks, such as distrust towards automation, stress and cognitive overload [19–21], that could lead to cognitive failures. In addition, these cognitive ergonomics variables can also influence each other and exponentially increase safety risks for workers. For instance, low levels of trust are associated with a higher cognitive workload [22], which increases stress levels [23].

Based on the findings presented in the literature, the authors developed a set of integrative and human-centred design principles for the appropriate integration of cognitive ergonomics in collaborative assembly systems (CAS) [24]. This study followed on from the work of [24], which specifically investigated how the main variables of cognitive ergonomics (i.e., cognitive workload, acceptance, trust and perceived stress) are influenced by different features of industrial collaborative workstations and interaction patterns. The present work focused on cognitive workload and investigated its relationship with workstation design, user acceptance and trust in collaborative robots. In particular, the present study aimed to enrich the theoretical models by examining the role of acceptance in predicting cognitive workload and perceived stress and the role of trust in moderating the relationship between cognitive workload and stress.

2. Literature Review

In this section, we discuss the scientific literature on cognitive workload, perceived stress, user acceptance and trust in HRC to help readers to understand their impacts on users and why it is crucial to focus on these elements when designing and implementing CAS.

Cognitive workload is a cognitive state described as a proportion between the operator's available cognitive resources and the cognitive demands of the task [25]. With limited cognitive resources, excess demands could be a risk factor that affects workers' safety [26] and performance [27]. Previous research on cognitive overload, which is defined as a state of high cognitive workload [28], showed mixed results, with some studies considering it desirable [29] and others considering it harmful [30]. According to [30], high levels of cognitive workload due to mental fatigue or inattention interfere with the assembly task, resulting in a longer processing time and higher muscle activity. High levels of cognitive workload can also impact gaze behaviour, as some authors found an association with longer fixation durations and a lower frequency of fixations [31]. On the other hand, a low workload occurs when few resources are required to complete the task and many resources are available. Although less prevalent, it can still affect performance, reducing alertness and attention [25]. In this scenario, an appropriate level of cognitive workload needs to be targeted to manage the impact on the operator, especially in terms of performance and safety. In the present study, we aimed to investigate the effect of workstation and interaction design features on cognitive workload using subjective and objective metrics and their relationship with factors such as technology acceptance and perceived stress.

Perceived stress is predicted by cognitive workload [23], with both constructs fundamentally influencing both safety and performance, as they lead to human errors. The transactional model of stress and coping views stress as a mismatch between external demands and individual resources [32]. This definition emphasises the crucial importance of the person's interpretation of an event (i.e., whether it is threatening or not) and whether the external and internal pressures exceed available resources and the ability to cope with them. In the HRC context, the robot's human likeness and proximity are the main stressors leading to a biological response. Ref. [33] highlighted that minimum-jerk trajectories (MJTs), which is a robot-motion-planning system that minimises acceleration changes and human effort, help to decrease the operator's levels of perceived stress, as they are considered familiar and predictable. Arai et al. [34] found that when designing a system, it might be important to limit the human–robot relative distance and the robot's speed, which should report its movements in advance. The efficacy of the robot's notifications before conducting a behaviour is useful, as humans are negatively affected by non-predictable robot movements, scoring lower well-being and performance scores [35–37]. It could be argued that individuals that are more accepting of technology may be more likely to use it, resulting in less cognitive workload and stress when engaging with technology. In addition, individuals are less likely to feel stressed when they believe that technology is helpful and easy to use. In contrast, individuals who have a negative attitude towards technology are more likely to reject it and, therefore, find using it stressful. This is because they perceive the technology as difficult to use or unhelpful.

Acceptance is "the demonstrable willingness within a user group to employ the technology for the tasks it is designed to support" [38]. The main model addressing this topic is the technology acceptance model (TAM), theorised by [39], who proposed the key role of two factors: perceived usefulness and perceived ease of use. The former is defined as the extent to which the person believes that using a particular system would improve job performance, while the latter is represented as the extent to which the person believes that using the system would be free of effort [39]. Both elements have a direct influence on the user's attitude, which is an important determinant of the individual acceptance or rejection of the system. Previous studies in HRC highlighted the importance of robot motion planning in increasing user acceptance, as the human co-agent is able to predict the robot's movements quickly and accurately [40,41]. These properties are reflected in point-to-point MJTs, which produce psychologically acceptable motions without causing disturbing or uncomfortable feelings in the operators [42,43]. In addition, previous authors highlighted the importance of automated notifications that can change the users' awareness of the situation [44]. For example, ref. [45] found that installing a visual status indicator on the robot's wrist could improve HRI efficiency and effectiveness, which are two key elements of usability, which is a construct that strongly correlates with acceptability.

Trust was considered an external predictor in many extended versions of TAM over the last decade, especially as a key factor influencing the perception of usefulness: the more the worker trusts the innovative tool, the more valuable it is perceived to be and the more likely it is to be used. An acceptable level of trust must be obtained to avoid failure: a dysfunctional calibration could turn trust into a risk factor that leads to safety-related problems for both the organisation and the operator [46]. Over-trust occurs when the operator trusts the system too much and delegates tasks that exceed the robot's capabilities, while under-trust arises when the operator does not count on the robot's capabilities. Previous authors emphasised the importance of specific design elements of the robot, such as size and appearance, and the robot's performance in influencing the operator's trust [47–49]. As highlighted in another study [22], human trust in a robot is determined by the degree of autonomy of the robot, which affects task efficiency and workload. We can thus assume that trust might moderate the relationship between cognitive workload and perceived stress. Trust can, in fact, influence how individuals perceive and respond to situations. In the case of a disproportion between the operator's available cognitive resources and the cognitive demands of the task, individuals who trust a robotic system may be more likely to believe that the system is competent and able to handle complex tasks, which could reduce their perceived stress. On the other hand, individuals who do not trust a robotic system may be more likely to doubt their abilities and may, therefore, experience higher levels of perceived stress, which could lead to human errors.

The aims of this study were threefold. First, we investigated the impact of workstation and interaction design guidelines [24] on users' cognitive workload by combining subjective measures with eye-tracker data. As the guidelines are implemented in different scenarios, we expected to see a decrease in participants' cognitive workload, indicating that they could handle the demands of the tasks more efficiently.

Second, we aimed to understand the relationship between cognitive workload and perceived stress in collaborative tasks, as well as the association between cognitive workload and the acceptance of cobots. We expected that participants with a higher acceptance of cobots will have improved cognitive workload and lower levels of perceived stress.

Third, we tested a moderation model to investigate the potential moderating effect of trust on the relationship between cognitive workload and perceived stress. We hypothesised that higher levels of trust will result in a weaker association between the two variables.

3. Materials and Methods

3.1. Participants

In this study, 14 participants (11 males and 3 females, with an average age of 31.6 years and a standard deviation of 4) were recruited from the Smart Mini Factory Lab of the University of Bozen-Bolzano. The Smart Mini Factory Lab is a research facility that focuses on developing and implementing Industry 4.0 technologies and concepts in a mini factory setting. The lab aims to provide an environment for researchers, students and industry partners to explore and test new technologies and methodologies related to the Internet of things (IoT), big data analytics, artificial intelligence and other advanced technologies in the context of smart manufacturing.

Recruiting participants during the COVID-19 pandemic presented significant difficulties, as restrictions were imposed on allowing non-academic individuals access to the laboratory. Only participants with minimal background in DIY activities were eligible to participate. All participants reported having no prior or limited experience interacting with robots or other forms of automation. Most participants (13 out of 14, or 92.9%) were Italian, with one being proficient in Italian but not Italian by origin. Participants were recruited on a voluntary basis.

3.2. Experimental Setup

A makeshift workstation was developed for the experiment. Figure 1 shows the workstation structure and components. The workstation consisted of a table with assembly jigs, commands (button array and virtual button) for HRI, an emergency stop, some boxes for storing and removing assembly components, an LCD screen for displaying instructions and other information about the status of the robot systems (graphical user interface), a vision system for human–robot interaction and safety purposes, and a screwdriver. Participants were asked to work with a collaborative robot, namely, the Universal Robot UR3 model, to build a simplified version of a pneumatic cylinder. The robot was equipped with a collaborative gripper from Robotiq. The application was programmed through the Polyscope interface using Polyscript, which is a proprietary language of Universal Robot.

The participants' point of view of the workstation is shown in Figure 2. Further details about the system components and integration are described in [50].

To begin, a training session (without the robotic system) was conducted at a separate, designated workstation to minimise the impact of limited knowledge of the process and the learning effect of different trials. Second, a repeated measure design was implemented across three distinct and sequential scenarios (scenario 1, scenario 2 and scenario 3). Table 1 illustrates the features of the workstation and robot for each of the three scenarios. The guidelines were gradually implemented across the scenarios, with increasing levels of robot speed, autonomy, trajectories, user commands, notifications to the users and safety training measures.

Figure 1. Workstation structure and components.

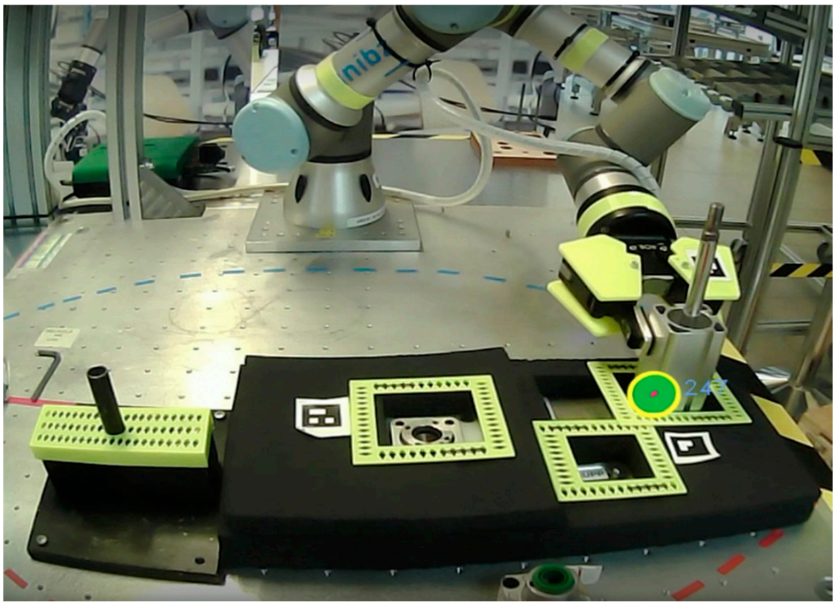

Figure 2. Participant's point of view of the workstation.

Table 1. Workstation and robot features in each scenario.

Feature	Scenario 1	Scenario 2	Scenario 3
Robot's speed	Lower than nominal values	Higher than nominal values	Set by participants (nominal, slower, higher)
Robot's autonomy	Low	High	Intermediate
Robot's trajectories	Point-to-point trapezoidal velocity profile trajectories	Point-to-point trapezoidal velocity profile trajectories	Minimum-jerk trajectories
Type of commands	Touch button	Gesture recognition system	Set by participants (touch or gesture recognition)
Notifications	Only instructions	Instructions and robot's status	Instructions and robot's status and speed
Training on safety	No info to participants	Basic training	Full training (including commands and GUI)

The assignment of the scenarios was non-randomised, as the idea was to gradually improve the interaction conditions by changing different elements of the context. In each trial, some features of the collaborative workstation and the robot were manipulated according to the guidelines presented in [24].

A questionnaire was administered to participants to assess the effect of feature manipulation on the selected cognitive variables. Participants were asked to complete the survey before the experiment began and between each scenario. In addition, gaze behaviour was measured throughout the whole duration of the experiment using a Pupil Labs eye tracker [51] to assess the participants' cognitive workload.

3.3. Measures

Table 2 illustrates the variables and the measures. Appendix A shows the items that were used.

Table 2. List of variables and measures.

Variable	Method		
		Reference	**Number of Items**
User acceptance	Semantic differential	Reduced version of the "System Acceptance Scale" [52]	6 items
	Likert scale	Adapted version of the "System Usability Scale" [53]	5 items
Cognitive workload	Likert-type scale	Reduced version of "NASA-TLX" [54]	1 item
Perceived stress	Semantic differential	"Short Stress Questionnaire" [55]	5 items
Trust	Likert scale	Adapted version of the "Trust in Industrial Human-Robot Interaction Questionnaire" [56]	9 items
		Measures	**Unit of Measurement**
Gaze behaviour	Eye tracker	Number of fixations and fixation duration	ms (for fixation duration)

3.3.1. Cognitive Workload

Users' cognitive workload was measured using subjective (i.e., NASA-TLX) and objective measurement tools (i.e., eye tracker). The former required participants to answer a single item (i.e., "How mentally demanding was the task?") on a 5-point Likert-type scale (1 = "Very Low"; 5 = "Very High") derived from the NASA-TLX [54]. An eye-tracking system was also used to record the gaze behaviour, specifically the number of fixations and fixation duration in milliseconds. Eye-tracking systems are commonly used to measure cognitive workload, as a high cognitive workload is associated with longer fixation durations and fewer fixations [30].

3.3.2. User Acceptance

User acceptance of the robot was assessed by combining two scales. The first was the Acceptance Scale [52]. Participants were asked to rate what level of these adjective continuums (e.g., "Effective/Superfluous", "Pleasant/Unpleasant") they ascribed to the robotic system on a five-point semantic differential scale (from 1 to 5). A different response scale identifies the original version of the scale (−2; +2), which was modified to correspond to the System Usability Scales ratings. In the present sample, item number three ("Bad"—"Good"), number seven ("Assisting"—"Worthless") and number eight ("Undesirable"—"Desirable") were eliminated as they misled participants in their evaluation of the interaction.

The second scale was the System Usability Scale [53], which was slightly modified to address the robotic system. Participants were asked to express their level of agreement rated (from "1 = Strongly Disagree" to "5 = Strongly Agree") with the following statements: (1) "I think I would like to use the robot frequently", (2) "I found the robot's behaviour to be mostly predictable", (3) "I found the various functions in the robot were well-integrated", (4) "I found the robot to work appropriately." and (5) "I found that the robot could be operated and managed intuitively". Cronbach's alpha reliability coefficient was assessed for each scenario, scoring $\alpha = 0.909$ in scenario 1, $\alpha = 0.852$ in scenario 2 and $\alpha = 0.873$ in the last scenario.

3.3.3. Perceived Stress

Participants were asked to reflect on how they felt while performing the task and answer the Short Stress Questionnaire (SSSQ) [55], rating items on a 5-point semantic differential scale. Participants were asked to rate how they felt according to the following statements: (1) "Irritated/Calm", (2) "Concerned/Quiet", (3) "Motivated to finish the task/Demotivated to finish the task", (4) "Skilled/Unqualified" and (5) "At ease/ Discomfort". Cronbach's alpha reliability was measured in scenario 1 ($\alpha = 0.671$), scenario 2 ($\alpha = 0.278$) and scenario 3 ($\alpha = 0.448$), highlighting poor reliability in the present sample.

3.3.4. Trust

Participants' trust was assessed using a slightly adapted version of the Trust in Industrial Human–Robot Interaction questionnaire [56]. The scale consisted of a total of 9 items (e.g., "The speed with which the gripper picked up and released the components made me uneasy") rated on a 5-point Likert scale (from "1 = Strongly Disagree" to "5 = Strongly Agree"). It is a self-reported measure that is used to understand how and when trust develops in a human–robot collaboration. In scenarios one, two and three, Cronbach's alpha reliability was measured, giving coefficients of $\alpha = 0.73$, $\alpha = 0.56$ and $\alpha = 0.48$, respectively.

3.4. Data Analysis

Considering that one of the aims was to compare the cognitive workload mean scores across three different trials, Friedman's test was conducted for each scenario due to the relatively low research sample and the non-normal data distribution. As previously mentioned, three surveys were administered, one after each trial, to evaluate the operator's cognitive experience. Moreover, a post hoc analysis was conducted on the eye-tracker data to verify the effects of feature manipulation on the objective workload assessment. The two parameters examined were the number of fixations and fixation duration during each scenario. The post hoc analysis was conducted with Wilcoxon signed-rank tests, and a Bonferroni correction was applied to examine where the differences occurred.

To test for the positive association between NASA-TLX's results and eye-tracker data, Spearman correlation analysis was conducted to quantify the intensity and meaning of the relationship between the cognitive workload objective and subjective measures.

A simple linear regression analysis was performed to test for the role of acceptance in decreasing risk factors, such as cognitive workload and perceived stress. First, a simple linear regression was used to test whether acceptance significantly predicted cognitive workload, whereas a simple linear regression was used to test whether acceptance significantly predicted perceived stress.

To test for the role of trust in decreasing risk factors, such as cognitive workload and perceived stress, a moderated regression analysis was computed using PROCESS, which is a computational tool provided by [57]. In particular, model 1 for simple moderation was selected.

In all of the statistical computations, the results were evaluated in terms of statistical significance ($p < 0.05$), as well as effect size with Cohen's d values of 0.2, 0.5 and 0.8, as well as Pearson's r values of 0.10, 0.30 and 0.50, corresponding to small, moderate and large effects, respectively [58]. Statistical analyses were performed with IBM SPSS Statistics Subscription (Version 26).

4. Results

Our results show that implementing guidelines had a significant effect on participants' cognitive workload, as indicated by the NASA-TLX scores in different scenarios (χ^2 (2) = 8.24, $p < 0.05$). The median perceived effort levels were 1 (0 to 1.3), 1 (0 to 2) and 0

(0 to 1) for trials 1, 2 and 3, respectively. Post hoc analysis with Wilcoxon signed-rank tests and Bonferroni correction showed a significant reduction in cognitive workload between scenarios 2 and 3 ($Z = -2.646$, $p = 0.008$), but no significant differences between scenarios 1 and 2 ($Z = -0.816$, $p = 0.414$) or between scenarios 1 and 3 ($Z = -1.890$, $p = 0.059$). However, there was a statistically significant reduction between scenario 2 and scenario 3 ($Z = -2.646$, $p = 0.008$).

The number of fixations was significantly different between the scenarios (χ^2 (2) = 20.33, $p < 0.05$). The Bonferroni correction applied for the Wilcoxon signed-rank post hoc analysis was 0.036. The results showed that the number of fixations significantly decreased between scenario 1 and scenario 2 ($Z = 55.8$, $p < 0.05$). However, no statistical difference was reported between scenarios 2 and 3 ($Z = -30.1$, $p > 0.05$) nor between scenarios 1 and 3 ($Z = 25.7$, $p > 0.05$). The fixations duration did not statistically change across the three different scenarios (χ^2 (2) = 20.33, $p > 0.05$). Figure 3 shows the cognitive workload levels across the three different trials.

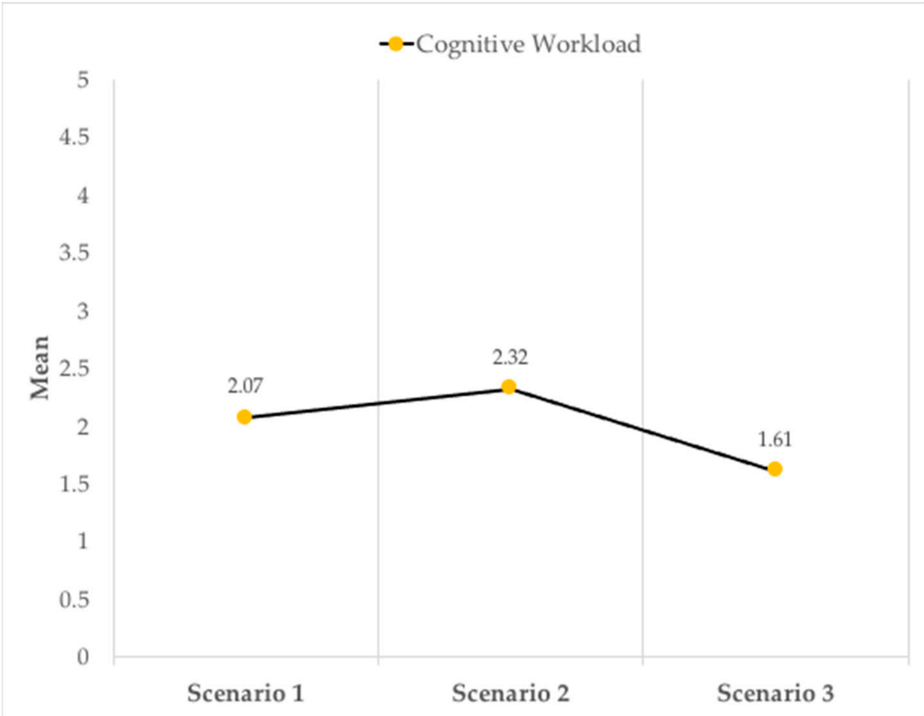

Figure 3. Friedman's test mean ranks of cognitive workload across the three trials.

Figure 4 shows the gaze behaviour in relation to the mean number of fixations and the mean duration of fixations for each scenario. Spearman correlation analysis was performed to assess the relationship between NASA-TLX and the eye-tracker data, and both measures were used to assess the cognitive workload in each scenario. In terms of the number of fixations, a strong and negative correlation was found between the objective and subjective measures in the first trial, which was statistically significant ($r = -0.797$, $n = 11$, $p = 0.003$). However, no correlation was found between the objective and subjective measures in trials 2 and 3. Similarly, no correlation was found between the objective and subjective measures for the fixation durations in the three trials.

A linear regression was performed to determine whether acceptance significantly predicted cognitive workload. However, no statistically significant evidence was found for trials 1, 2 and 3.

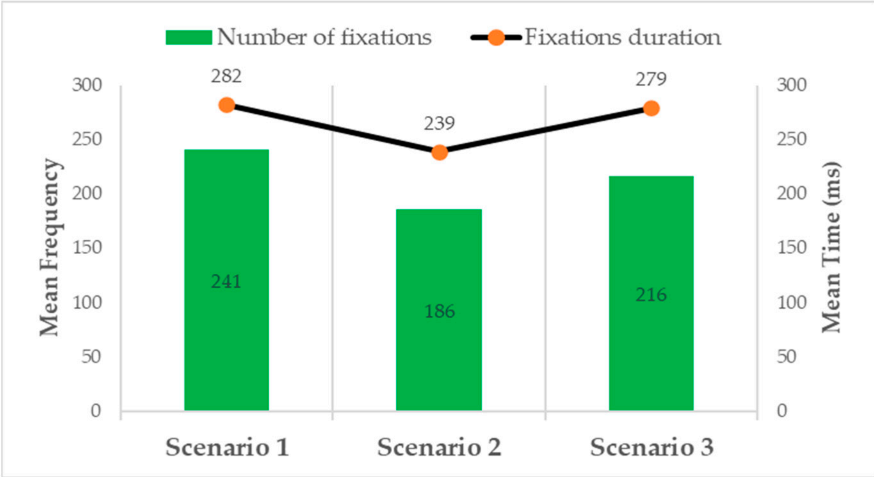

Figure 4. The number of fixations and fixation duration mean scores in the three trials.

Likewise, a linear regression was performed to determine whether acceptance significantly predicted perceived stress in the three trials. In the first scenario, acceptance accounted for 72.5% of the explained variability in the perceived stress ($F(1,12) = 31.651$, $p < 0.001$). The final predictive model was as follows: perceived stress = 4.578 + (−0.696 * acceptance). In the second scenario, acceptance explained 40.1% of the variability in the perceived stress ($F(1,12) = 8.032$, $p < 0.05$). The final predictive model was as follows: perceived stress = 2.886 + (−0.349 * acceptance). In the third scenario, acceptance accounted for 40.3% of the explained variability in perceived stress ($F(1,12) = 8.113$, $p > 0.05$). The final predictive model was as follows: perceived stress = 2.669 + (−0.219 * acceptance).

A moderated regression analysis was used to investigate whether trust negatively moderated the relationship between cognitive workload and perceived stress. However, no significant evidence was found in the three different trials, meaning that we found no support that trust towards robots could influence how cognitive workload and perceived stress were related to each other.

5. Discussion

The results showed that perceived cognitive workload increased slightly from the first trial to the second one. However, it decreased significantly from scenario 2 to the last one, which was consistent with previous research [40,41] and highlighted the importance of minimal jerk, interaction types and feedback given to the users in minimising mental effort. The increase in cognitive workload in the second trial could have been due to the high number of changes and manipulations compared with trial number 1. In the third and final scenario, the cognitive workload decreased significantly, as the subject was able to adjust many different functions of the workstation, such as the robot's speed and the type of commands. Perceived autonomy is one of the most important factors that affect intrinsic motivation and lead to a better cognitive experience and well-being [59,60].

These findings appeared to be consistent with the results of the eye-tacker data, which demonstrated a statistically significant difference in the number of fixations across the three different scenarios; the duration of fixations was not significant. The number of fixations decreased sharply from scenario 1 to scenario 2. It increased significantly from scenario 2 to scenario 3, which was consistent with previous results from [29]; a high cognitive load is associated with fewer fixations. One of the most important results showed a strong and negatively significant correlation between NASA-TLX scores and the number of fixations in scenario 1. This could be due to the particular HRC conditions of the workstation for trial 1. Nevertheless, the absence of correlation between the objective and subjective metrics in trials 2 and 3 was quite relevant, and it could have been due to the different content activity and the input–output modality affecting eye movements. The way each individual engages with an interactive system is different and is influenced by the system design, as the content influences the users' fixations [61]. Visual representations of content can influence the location, duration and speed of fixation without cognitive engagement present.

According to our results, acceptance did not significantly predict the cognitive workload. As the literature suggests, higher acceptance of the collaborative robot should reduce the use of the cognitive resources used to work with the cobot. However, these results could have been due to other factors present in the scenarios, such as the way the status of the robot was communicated to the user. During the three trials, notifications were displayed on an LCD screen. Visual animations are often used to help users notice changes or to shift their attention [62]. In the present study, the visual alarm may have negatively impacted the user's awareness of the situation. Future studies should integrate auditory notification to create a multi-modal interaction (i.e., conveying information across two or more modalities) [63]. Indeed, auditory cues alert the user to an item that requires immediate attention, regardless of where the user is currently directing their gaze. The possible combination of auditory and visual alerts would improve situational awareness of change, thus somehow reducing the demands of the collaborative task [64].

The results showed that acceptance predicted perceived stress across the three trials. While the results of the third scenario were consistent with previous research [33]—namely, that the introduction of MJTs increased participants' feelings of predictability and familiarity—the results of the first and second scenarios were unexpected. These results suggested that the robot's non-human-like movements did not negatively affect user acceptance. One explanation could be related to the fact that humans were not focused on the robot's movements because they were busy with their work. Furthermore, the low payload (and reduced workspace) collaborative robot moving "relatively slowly" did not emphasise the movements too much, and thus, movement patterns were subtle and relatively difficult to detect. Other studies specifically focused on having the users look at different types of trajectories. In our case, however, the users were engaged with multiple aspects of the task. Another possible explanation for this result could be the Technology Readiness Index (TRI) of the present sample, which is defined as "the propensity of people to adopt and use new technologies to achieve goals in the home, life and work" [65]. It seems logical to assume that most of the participants in this study were motivated to adopt new technological tools because they were engineering students, researchers and members of the academic staff of the Department of Industrial Engineering. They could have also been optimistic about technology—which is a positive attitude towards technology and the belief that it gives people more control, flexibility and efficiency in their lives—and desired to be technological pioneers. In this scenario, previous authors [66] combined TR and TAM into a unique model (TRAM) that assesses how consumers' prior experiences and knowledge of technology in general influence the perceived usefulness and perceived ease of use of a technological tool, which ultimately affects intention to use.

Regarding the moderating effect of trust on the relationship between cognitive workload and perceived stress, no significant results were found. This could be related to the absence of significant differences in participants' trust towards the cobot in the three trials. In this study, the participants' trust in technology was already at an optimal level, given that they were aware of the tools and the possibility of facing faulty behaviours of the collaborative robot. People build their trust based on their previous experiences—both direct and vicarious—with a system and their expectations of its future performance; the more users trust a system, the more likely they are to develop positive beliefs about the positive outcomes of using that technology [67,68].

One of the main limitations of this study regards the relatively small sample size. A larger sample would have provided more reliable statistical results and increased the generalisability of the findings. However, recruiting participants was challenging due to the COVID-19 pandemic and restrictions imposed by national and local authorities, which prohibited non-academic individuals from accessing the laboratory. Additionally, the requirement for participants to have a background in DIY activities likely contributed to a sample with a larger proportion of males. Furthermore, self-selection bias may have played a role as participants were involved on a voluntary basis, potentially leading to a higher proportion of males being interested in the study due to the topic being more appealing to them.

6. Conclusions

The present study evaluated cognitive workload in a human–robot collaboration setting that assessed the relationship with workstation design, acceptance and trust. Our findings suggest that manipulating various features of the workstation and robot can lead to a reduction in cognitive workload and that user acceptance is associated with perceived stress in collaborative tasks. Additionally, our results provide evidence for the importance of considering human factors and cognitive ergonomics in the design of collaborative workstations. The study provides valuable insights into the effects of workstation design, user acceptance and trust on cognitive workload in a human–robot collaboration setting.

These findings have several implications for practitioners and researchers alike. For organisations, our results highlight the need to prioritise the ergonomic design of collaborative workstations to improve psychological well-being and performance. In addition, our findings suggest that promoting a positive attitude towards collaborative tasks may be beneficial for managing cognitive workload. For researchers, our study provides a starting point for further investigating the relationships between cognitive workload, acceptance and trust in HRC settings to improve the efficiency, productivity and safety of human–robot collaboration.

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Informed Consent Statement: Written informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data supporting the reported results can be obtained upon request to the corresponding author.

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

Appendix A

Items of the scales

System Acceptance Scale

1. Useful—Unuseful
2. Pleasant—Unpleasant
3. Nice—Annoying
4. Effective—Superfluous
5. Irritating—Likable
6. Raising alertness—Sleep-inducing

System Usability Scale

1. I think that I would like to use the robot frequently.
2. I found the robot unnecessarily complex.

3. I found that the robot was performing its tasks in a good way.
4. I found that the robot was not functioning according to the task to be performed.
5. I found that the robot was difficult to be used.

NASA-TLX

1. How mentally demanding was the task?

Short Stress Questionnaire

1. Irritated—Serene
2. Worried—Carefree
3. Motivated to complete the task—Unmotivated
4. Competent—Unskilled
5. Comfortable—Uncomfortable

Trust in Industrial Human–Robot Interaction Questionnaire

1. The way in which the robot moved made me feel uncomfortable.
2. The speed with which the robot picked and released the components made me feel uneasy.
3. I trusted that the robot was safe to cooperate with.
4. I was comfortable the robot would not hurt me.
5. I felt safe interacting with the robot.
6. I knew the gripper would not drop the components.
7. The robot gripper did not look reliable.
8. The gripper seemed like it could be trusted.
9. I felt I could rely on the robot to do what it was supposed to do.

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