Application of photoplethysmography signals for healthcare systems: An in-depth review

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 232 (2024) 2249–2258

Procedia Computer Science

www.elsevier.com/locate/procedia

5th International Conference on Industry 4.0 and Smart Manufacturing

A human-centered perspective in repetitive assembly processes: preliminary investigation of cognitive support of collaborative robots

Riccardo Gervasi[a,*], Matteo Capponi[a], Dario Antonelli[a], Luca Mastrogiacomo[a], Fiorenzo Franceschini[a]

[a]*Department of Management and Production Engineering, Politecnico di Torino, C.so Duca degli Abruzzi 24, Torino 10129, Italy*

Abstract

Human-robot collaboration (HRC) is one of the paradigms of the emerging Industry 5.0, aimed at supporting humans in production processes. However, the introduction of an industrial robotic system in close contact with a human opens new challenges not only for safety but also for ergonomics. This paper aims to study whether the introduction of a collaborative robot into an assembly process can support the human operator not only physically but also cognitively. To address this research question, shifts of a repetitive assembly process were implemented in both manual and HRC settings. The two settings were compared over time by analyzing the evolution of generated process failures and physiological response, revealing potential differences in process quality and operator stress.

Peer-review under responsibility of the scientific committee of the 5th International Conference on Industry 4.0 and Smart Manufacturing

Keywords: Human robot collaboration; Cognitive ergonomics; Physiological response.

1. Introduction

Human-robot collaboration (HRC) has emerged as a new paradigm for humans and collaborative robots (or cobots) to work together in a shared environment [1]. By joining the capabilities of cobots and humans, HRC can increase productivity, flexibility, and process quality in manufacturing [2]. One of the main industrial applications of cobots are in assembly processes [3].

* Corresponding author. Tel.: +39-011-090-7236
E-mail address: riccardo.gervasi@polito.it

Peer-review under responsibility of the scientific committee of the 5th International Conference on Industry 4.0 and Smart Manufacturing
10.1016/j.procs.2024.02.044

The in-depth study of HRC involves several dimensions, including human-related aspects such as human factors [4]. Fatigue and stress have become key factors in manufacturing since they may lead to negative performances of operators [5]. The adoption of cobots may affect not only system efficiency and flexibility, but also the well-being of human operators [6, 7]. However, little attention has been paid to the analysis of cognitive support of collaborative robotics in repetitive assembly processes.

The aim of this paper is to explore the evolution of operator performance and physiological response over time during emulated shifts of a repetitive assembly process, comparing a classical manual setting with an HRC one. The following research questions will be addressed: (i) *Are there differences in the evolution of operator process failures between a repetitive HRC and manual assembly process?* (ii) *How does the robot impact operator stress over time?*

To this end, four-hour shifts involving a repetitive assembly of a reference case study (i.e., a tile cutter) was implemented in two modalities: manual and HRC. The study analyzes (i) the number and type of process failures to track the evolution of human performance and learning rate, as well as (ii) physiological signals measuring physical exertion, stress, and cognitive workload over time.

The paper is organized as follows. Next section describes the experimental methodology. Afterwards, the main experimental results are reported. Finally, discussion of the main findings and conclusions are presented.

2. Methodology

To examine whether a cobot can provide aid in repetitive assembly processes, 4-hour shifts of assembling a tile cutter were conducted at Mind4Lab at "Politecnico di Torino" involving the UR3e cobot [8]. Twelve participants (six males and six females), aged 20 to 25 with no prior experience with cobots, were involved in the study.

2.1. Assembly process

A tile cutter assembly process was implemented in two modalities: *HRC* and *Manual*. Fig. 1 shows the four main phases that compose the assembly:

Phase 1: The supports for the rail rods are mounted on the base.
Phase 2: The cutting mechanism is assembled.
Phase 3: The cutting mechanism with base is joined through the rail rods.
Phase 4: The tile cutter is completed by mounting the handle.

Table 1 contains the detailed list of operations of the assembly process, also showing their allocations between human operator and cobot in the *HRC* modality. In *Manual* modality, cobot's operations are carried out by the operator. A single tile cutter assembly takes approximately 240s, leading to about 60 products in a 4-hour shift. In total, the experimental data refer to approximately 720 assemblies.

2.2. Process failures

To keep track of operator's performance over time, the number and type of process failures were collected. Four main macro-groups of process failures were identified:

- *Incorrect part selection* (D1): the operator picks up a component not needed to perform the following task.
- *Incorrect part positioning* (D2): the operator places a component in a way that is not suitable for proceeding with the next task.
- *Incorrect part assemblies* (D3): the operator misassembles a component.
- *Part droppings* (D4): the operator drops components/screws/nuts/washers or tools.

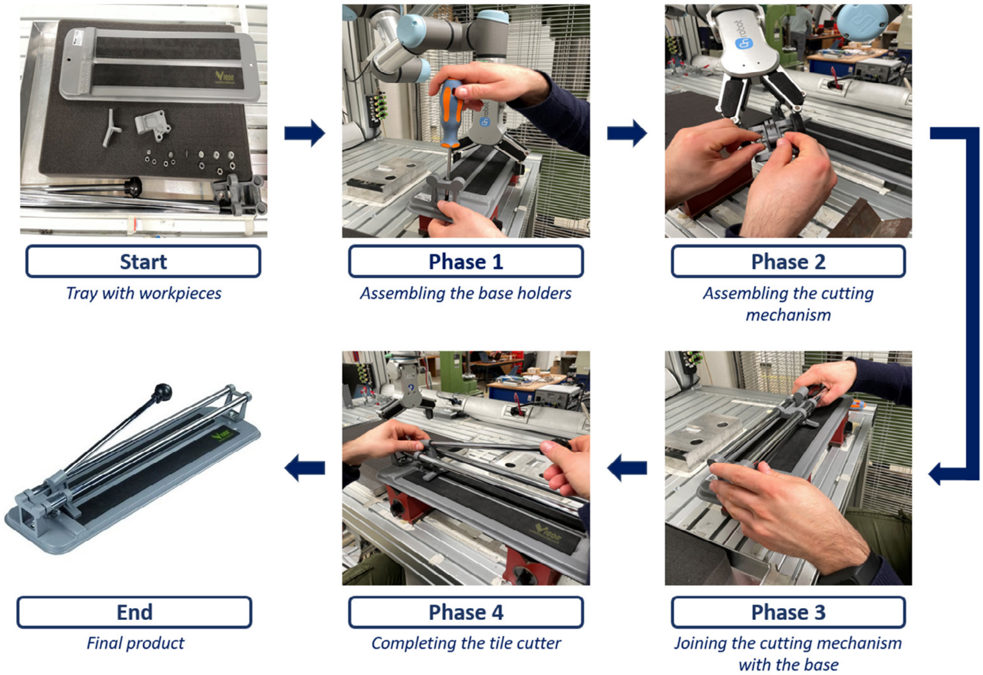

Fig. 1. Main phases of the tile cutter assembly.

Table 1 – Sequence of the operations in the tile cutter assembly process for *HRC* modality.

Phase	Operation allocation	
	Human	**Cobot**
Phase 1		**1.** Picking the Base and placing it in the workarea.
	2. Soft screwing of lateral supports to the base.	
		3. Placing sub-assembly (base and lateral supports) out of the workarea.
Phase 2		**4.** Picking the sliding support.
	5. Screwing the cutting support component to the sliding support. **6.** Screwing blade to the cutting support component. **7.** Screwing the tile blocker to the cutting support component.	
		8. Placing the cutting component out of the workarea.
Phase 3		**9.** Picking the subassembly (base and lateral supports) and place it back in the work area.
	10. Picking cutting component. **11.** Insertion of the two rods in the cutting component. **12.** Insertion of rods against the lateral supports. **13.** Final tightening of lateral supports to the base.	
Phase 4	**14.** Screwing the handle to the cutting component.	
		15. Picking the final product.

To better highlight potential differences between HRC and manual assembly from a cognitive point of view, the learning curve phenomenon for process failures will be explored. Among the different learning curve models, the power-law is one of the most used [9, 10]. In the present study, the evolution of process failures for each modality will be modeled with a power-law learning curve of the following form [11]:

$$Y = a \cdot Trial^{b} + c \tag{1}$$

where a represents the starting performance at the first trial, b is the learning rate (i.e., the learning velocity), and c represents the asymptotic steady-state performance [12, 13]. In our case, c was set equal to 0 since there are no technical limitations in operator learning that cannot lead to a steady state of zero failures and the number of trials considered is limited, leading to the classical Wright's learning model widely used in manufacturing [12, 14]. In addition, the lower b is, the faster the learning and consequently the achievement of zero failures. Y is the response variable, i.e., the process failures. $Trial$ represents the number of trials performed by the operator.

2.3. Physiological signal collection

Various physiological responses were collected with the noninvasive biosensor Empatica E4 [15] to obtain information on the evolution of operator stress, cognitive effort, and fatigue during the assembly process. The device allowed to collect electrodermal activity (EDA) data at 4Hz and photopletismogram (PPG) data at 64Hz. Heat rate (HR) data were derived by processing and analyzing PPG data though an internal Empatica algorithm. By analyzing the heart rate, information on stress and fatigue can be obtained.

The EDA data were processed using "Ledalab", a MATLAB-based software. Through continuous decomposition analysis (CDA) [16], the phasic activity was extracted from the EDA signal. Phasic activity refers to short-term fluctuations in EDA which have been elicited by a usually identified and externally presented stimulus. Through the analysis of the phasic activity signal, skin conductance response (SCR) peaks can be detected and their frequency provides information on arousal and stress. A threshold of 0.05 µS was used for selecting significant SCR peaks.

Skin conductance level (SCL) was also derived through CDA, representing the long-term variations of EDA (i.e., tonic activity). The slow fluctuations can occur in response to prolonged or continuous stimuli, providing information on prolonged stress and cognitive effort.

In this study, the average HR, number of SCR peaks, and average SCL were computed for each trial to investigate the evolution of fatigue, stress, and cognitive effort [17, 18]. Z-scores for HR and SCL were used, as this type of standardization allows the removal of each person's bias related to heart activity and SCL, thus providing a better framework for comparison between participants. The following formula was used to calculate the z-scores:

$$z_{ij} = \frac{x_{ij} - \overline{x}_j}{s_j} \tag{2}$$

where z_{ij} is the i-th z-score for participant j, obtained by the ratio of the difference between the observation x_{ij} and the sample mean for participant j ($\overline{x}_j$) with the sample standard deviation for participant j (s_j).

2.4. Experimental procedure

At the beginning, each participant was informed about the objectives and procedure of the study. Next, the participant was guided to the work area and was presented with the details of the assembly task. The Empatica E4 was placed on the left wrist of the participant and a wait time of 15 minutes was observed to ensure the electrodes properly adhered in order to obtain reliable EDA data. Next, he/she was instructed to relax and remain still to record 2 minutes of physiological signals at rest. Following this, the 4-hour assembly task work shift began, during which a 10-minute break was provided every two hours to simulate real-life working conditions. Another person oversaw the process by keeping track of process failures. At the end of the shift, each participant was asked for general feedback on the overall experience. Each participant carried out the 4-hour shift in both manual modality (*Manual*) and HRC modality (*HRC*) with random order.

3. Results

In this section, the obtained results are presented. For each response variable, no relevant effect was observed due to the order of the modalities.

3.1. Process failures

Fig. 2 shows the evolution of the average number of process failures over the 12 participants for both manual and HRC settings and the fitted learning curves with the power law model. Slightly more process failures were present in the manual setting, although there was some overlap between the curves. The learning curve for the manual modality was found to be above that of the HRC modality, highlighting the tendency to observe more process failures in the manual setting. This phenomenon may be due to the fact that the cobot was also a cognitive support for the operator during assembly. In fact, participant feedback revealed that the cobot, indirectly with its operations, helped the operator in remembering the various assembly steps, thus making fewer mistakes.

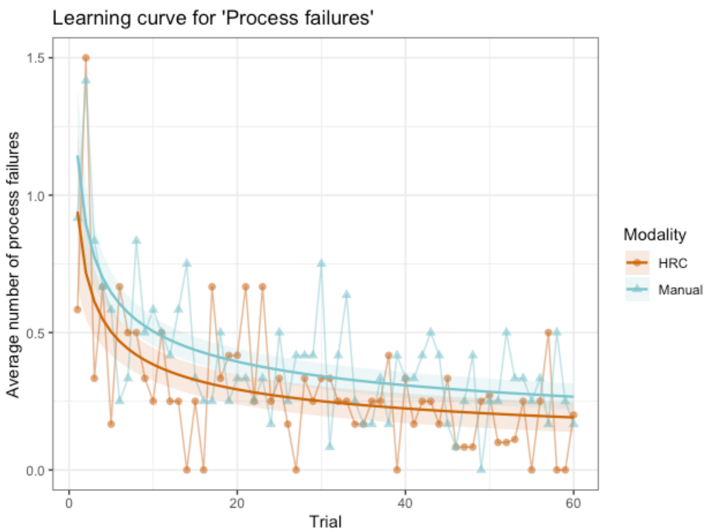

Fig. 2. Comparison between *HRC* and *Manual* modalities of average process failures evolution and fitted power-law learning curves.

Table 1 contains the parameter estimates of the power-law learning curves, which resulted all significant as 0 was not contained in each of the 95% confidence intervals. It can be seen that the two learning curves have a rather similar learning rate (*HRC*: b = -0.389; *Manual*: b = -0.356), while the initial value of average process failures is higher in the manual setting (*HRC*: a = 0.940; *Manual*: a = 1.144). However, it was not possible to conclude that the difference was statistically significant since the 95% confidence intervals overlap.

Table 2 - Fitted power-law learning curve models for process failures.

Response variable	Modality	Coefficient	Value	Confidence interval (95%)
Process failures	*HRC*	a	0.940	[0.661, 1.219]
		b	-0.389	[-0.507, -0.271]
	Manual	a	1.144	[0.907, 1.382]
		b	-0.356	[-0.435, -0.276]

Fig. 3 shows the evolution of process failures categorized into incorrect part selections (D1), incorrect part placements (D2), incorrect part assemblies (D3), and part droppings (D4). No significant differences emerged between manual and HRC modalities, except for D2. Observing the curves, more incorrect part placements can be noted in the manual setting. One of the main difficulties encountered by the participants was to correctly position the components of the cutting mechanism. Since the cobot always presented and held one of the components in the same way, it was easier for the operator to remember how to correctly position the others. This effect is also reflected by the coefficients of the learning curves, where the starting performance was better in the HRC modality (*HRC*: $a = 0.338$; *Manual*: $a = 0.717$). In addition, this difference was statistically significant as there was no overlap between the 95% confidence intervals (*HRC*: $CI_a = [0.209, 0.467]$; *Manual*: $CI_a = [0.528, 0.907]$). The learning rate in the HRC setting had a slightly higher magnitude (*HRC*: $b = -0.607$; *Manual*: $b = -0.583$), however, the difference with the manual setting was not significant when observing the 95% confidence intervals (*HRC*: $CI_b = [-0.808, -0.407]$; *Manual*: $CI_b = [-0.717, -0.450]$).

3.2. Physiological response

A descriptive analysis of the physiological responses will be provided in this section, comparing the different modalities within each participant.

Fig. 4 contains the evolution of the z-scores for average HR along the trials comparing *HRC* and *Manual* modalities for each participant. In general, the curves tended to overlap, consequently there were no glaring differences between the values of the two assembly modalities. However, for 2 out 12 participants (i.e., 1 and 3) higher average HR can be observed in *HRC* modality in the first half of the shift, potentially suggesting greater initial stress than in the *Manual* setting. No particular trend generally emerged in both settings. However, slightly decreasing trends can be observed in the *HRC* setting for participants 1, 3, and 7, but an increasing one for participant 6. Therefore, comparison of the average HR showed no clear difference between the *HRC* and *Manual* setting.

The evolution of the number of SCR peaks comparing the two assembly modalities is reported for each participant in Fig. 5. Observing the *Manual* setting, there was a tendency for a stationary or decreasing trend (participants 1, 7, 8, 9, and 11). In addition, at the beginning of the shift, values tended to be higher than in the HRC setting, revealing a significant difference (Wilcoxon signed-rank test: p-value<0.001). This result highlights greater stress in the early phase of the manual setting, mainly due to having to learn and become familiar with the task. This aspect highlights the support of the cobot from a cognitive point of view, especially in a learning phase. It is interesting to note that for a group of participants (i.e., participants 1, 3, 9, 11, and 12) there was an increasing trend in the number of SCR peaks in the *HRC* setting. This growth in stress is likely due to the fact that some participants began to perceive the cobot as an obstacle to their efficiency once they learned the task. In particular, they would have liked the cobot to be faster in performing its operations. However, despite the increasing trend, the maximum values observed were less than or similar to those of the *Manual* setting (except for participant 3).

Fig. 6 shows the evolution of the z-scores for average SCL along the trials comparing *HRC* and *Manual* modalities for each participant. The trends observed in the *Manual* setting were decreasing or stationary (except for participant 7), indicative of a progressive reduction in cognitive effort. For the *HRC* setting, increasing trends were observed in several participants (i.e., participants 1, 3, 6, 9, 11, and 12), mainly attributable to a sense of frustration with the cobot. In fact, once the collaborative assembly process was learned, most participants would have liked the cobot to be faster in its operations. Thus, not being able to change the speed of the cobot led to a sense of powerlessness and frustration. However, it is worth noting that at the beginning of the trial, mean SCL values tended to be higher in the *Manual* setting (participants 2, 4, 5, 7, 8, 10, and 11), revealing a significant difference (Wilcoxon signed-rank test: p-value<0.001). This fact suggests a lower use of cognitive resources in the learning phase due to the presence of the cobot during the operations.

These preliminary results highlighted how differently operators can experience a certain work setup and how important it is to take into account any user preferences when implementing new technologies to obtain the full benefits.

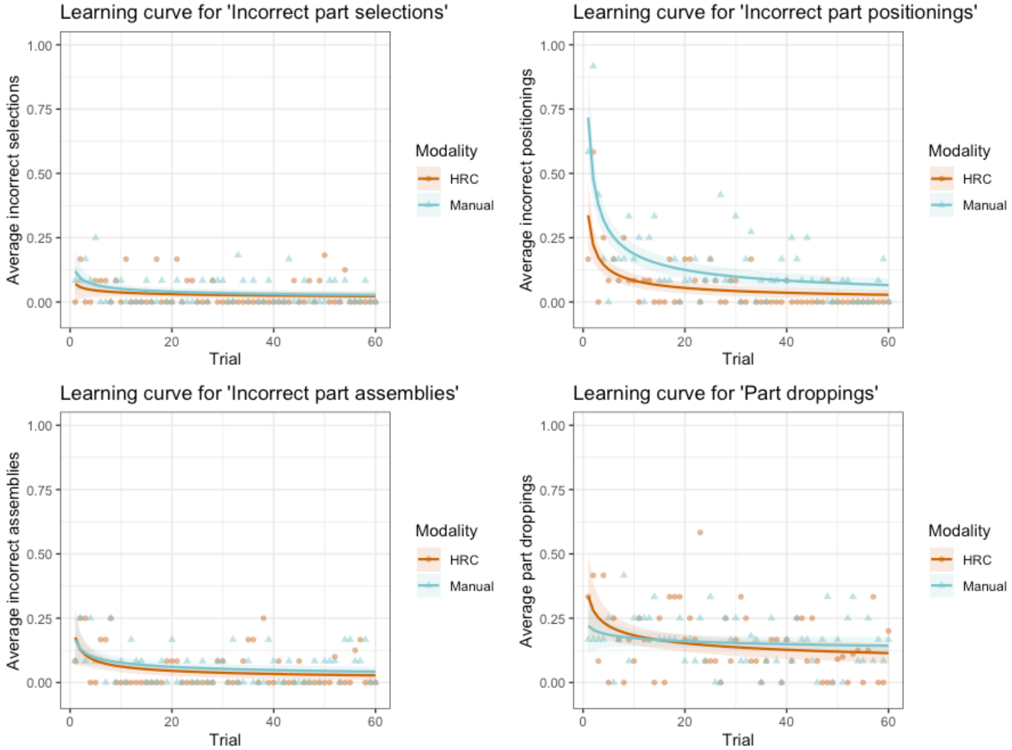

Fig. 3. Comparison between *HRC* and *Manual* modalities for the categories incorrect part selections, positionings and assemblies and part droppings.

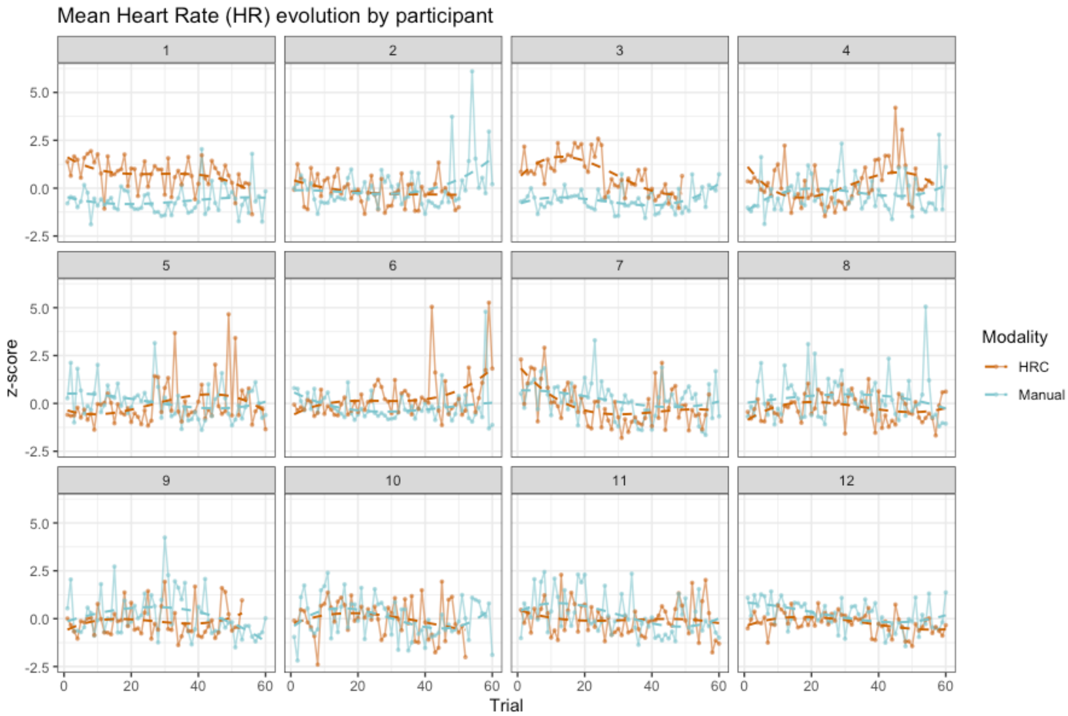

Fig. 4. Comparison of the evolution of average heart rate (*Mean_HR*) between *Manual* and *HRC* modality for each participant. Dotted lines represent the trend.

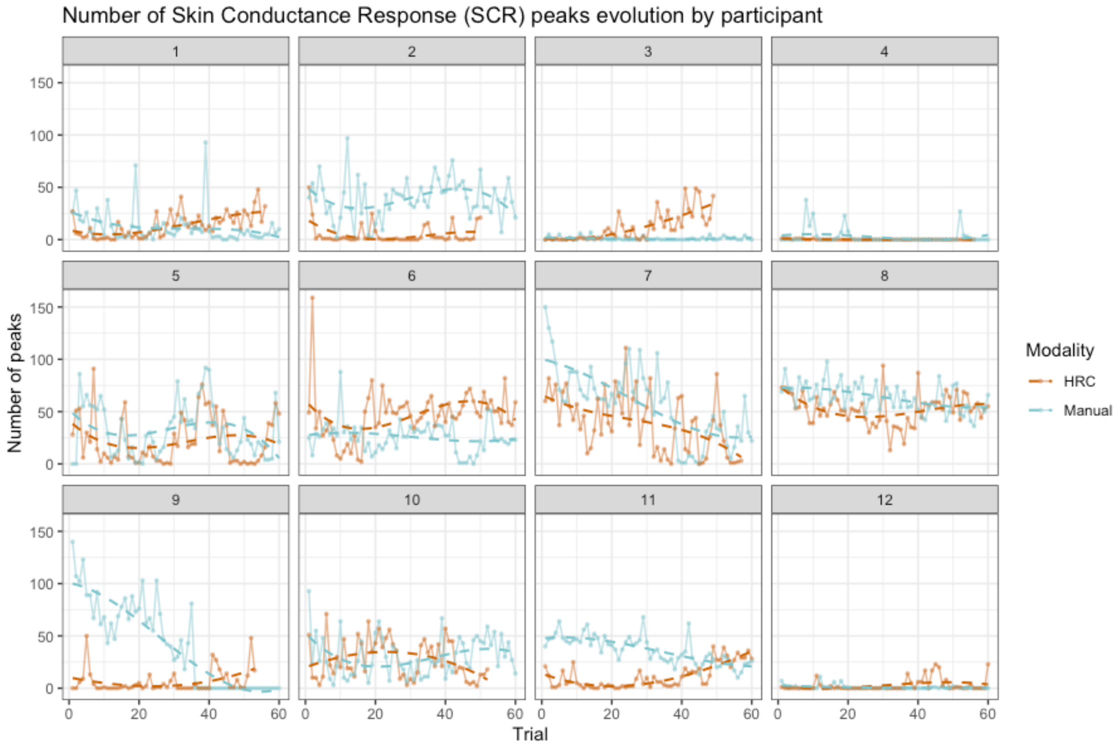

Fig. 5. Comparison of the evolution of number of SCR peaks between *Manual* and *HRC* modality for each participant. Dotted lines represent the trend.

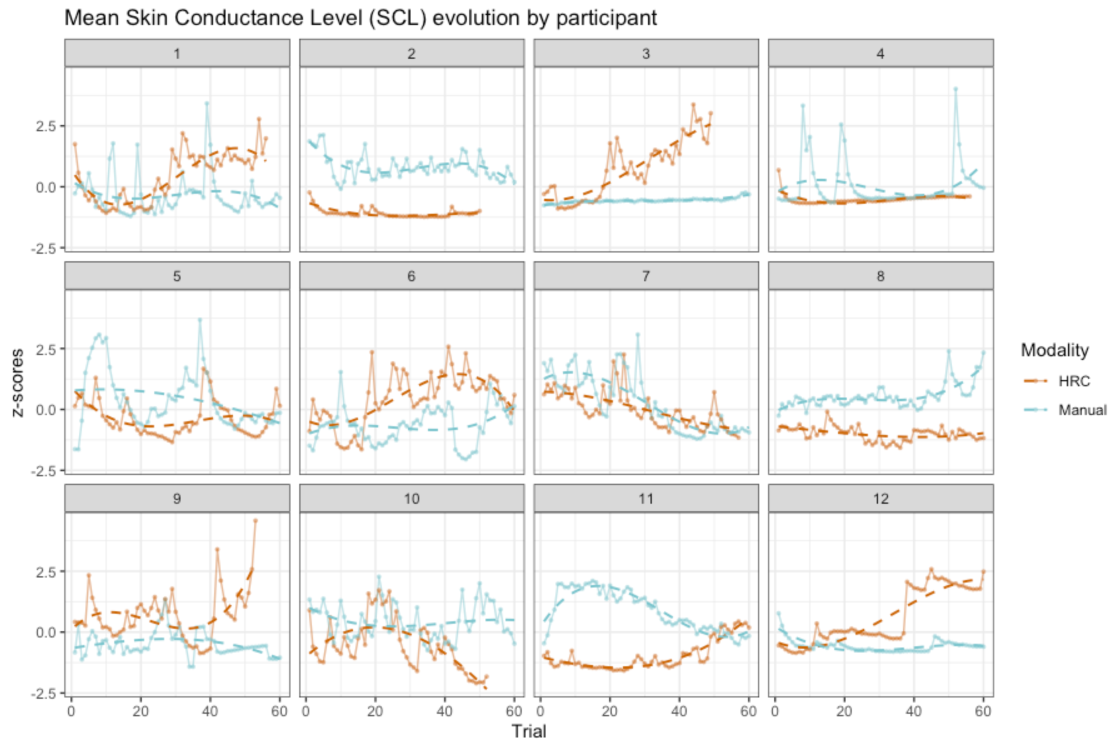

Fig. 6. Comparison of the evolution of average SCL between *Manual* and *HRC* modality for each participant. Dotted lines represent the trend.

4. Discussion and conclusions

The objective of the paper was to explore how the introduction of a cobot can impact the human operator cognitively over time in an assembly process by analyzing the evolution of process failures generation and physiological responses. 4-hour work shifts for a tile cutter assembly process were emulated in both manual and HRC modalities.

Some interesting results emerged from the comparison of the two modalities. Slightly more process failures were observed in the manual modality. In particular, more incorrect part placements were observed. Many participants, especially in the beginning, could not remember some operations or how to assemble some components together. The cobot's actions allowed to indirectly guide the operator in the assembly, helping to remember which operations to perform. In addition, the cobot helped the operator remember how to correctly position and assemble certain components by always handing them to the operator in the same way. These aspects highlight the contribution of the cobot in reducing the cognitive load involved in human operations, especially in the initial learning phase where better starting performance emerged.

The participants' physiological responses (i.e., heart activity and EDA) were collected during the assembly process and descriptively analyzed to provide some insights on the evolution of operator stress. Comparing the evolution of the average HR in the two modalities, no clear differences emerged. However, looking at the number of SCR peaks and average SCL higher values were often observed in the manual modality, especially in the initial learning phase. This result highlighted the cognitive support of the cobot in the learning phase also from a physiological viewpoint, reducing the initial operator stress. In general, operators' stress level tended to decrease or remain quite stationary over the shift. Interestingly, an increasing trend of stress in the HRC modality was observed in some participants. This increase can be traced to a sense of annoyance toward the cobot that gradually emerged once participants had fully learned how to carry out the assembly process. In order to feel more efficient in the process, some participants would have liked the cobot to be faster in its operations to reduce potential downtime as much as possible. This fact may provide a clue towards the need for human-centered collaborative process planning that can consider potential operator’s preferences in order to take full advantage of HRC.

The order of the modalities in which the assembly process was carried out did not reveal any particular differences in terms of the response variables. However, it could be observed that in switching from HRC to manual modality, the participants were initially slightly bewildered in the assembly operations, as they were also used to the support of the cobot in remembering the correct positioning of the parts. Similarly, in switching from manual to HRC modality, participants had to get used to the presence and pace of the cobot during various operations. However, further investigation of this phenomenon is needed.

In conclusion, from the preliminary results of the conducted study, the cobot proved to be particularly useful during the learning phase of the assembly process, both from the point of view of process quality and operator stress. This result suggests that cobot implementation may be quite useful in operator training. In addition, to take full advantage of the HRC's potential, the operator should be able to be able to adjust interaction parameters, such as the cobot's speed of movement, according to his or her needs.

Future work will focus on deepening the analysis of physiological responses to investigate their link to the operator's user experience. In addition, a larger sample of participants will be needed to strengthen the results and further investigate the role of the cobot as a cognitive support in repetitive tasks, by also involving people with different prior experience with cobots and broader age range.

Acknowledgements

This study was carried out within the MICS (Made in Italy – Circular and Sustainable) Extended Partnership and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.3 – D.D. 1551.11-10-2022, PE00000004). This manuscript reflects only the authors’ views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

References

[1] Gervasi, Riccardo, Luca Mastrogiacomo, and Fiorenzo Franceschini. (2020) "A conceptual framework to evaluate human-robot collaboration" *The International Journal of Advanced Manufacturing Technology* **108** (**3**): 841–865. https://doi.org/10.1007/s00170-020-05363-1.

[2] Villani, Valeria, Fabio Pini, Francesco Leali, and Cristian Secchi. (2018) "Survey on human–robot collaboration in industrial settings: Safety, intuitive interfaces and applications" *Mechatronics* **55**: 248–266. https://doi.org/10.1016/j.mechatronics.2018.02.009.

[3] Bauer, Andrea, Dirk Wollherr, and Martin Buss. (2008) "Human–robot collaboration: a survey" *International Journal of Humanoid Robotics* **05** (**01**): 47–66. https://doi.org/10.1142/S0219843608001303.

[4] Gualtieri, Luca, Erwin Rauch, and Renato Vidoni. (2021) "Emerging research fields in safety and ergonomics in industrial collaborative robotics: A systematic literature review" *Robotics and Computer-Integrated Manufacturing* **67**: 101998. https://doi.org/10.1016/j.rcim.2020.101998.

[5] Gervasi, Riccardo, Khurshid Aliev, Luca Mastrogiacomo, and Fiorenzo Franceschini. (2022) "User Experience and Physiological Response in Human-Robot Collaboration: A Preliminary Investigation" *Journal of Intelligent & Robotic Systems* **106** (**2**): 36. https://doi.org/10.1007/s10846-022-01744-8.

[6] Gervasi, Riccardo, Federico Barravecchia, Luca Mastrogiacomo, and Fiorenzo Franceschini. (2023) "Applications of affective computing in human-robot interaction: State-of-art and challenges for manufacturing" *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* **237** (**6–7**): 815–832. https://doi.org/10.1177/09544054221121888.

[7] Gualtieri, Luca, Ilaria Palomba, Fabio Antonio Merati, Erwin Rauch, and Renato Vidoni. (2020) "Design of Human-Centered Collaborative Assembly Workstations for the Improvement of Operators' Physical Ergonomics and Production Efficiency: A Case Study" *Sustainability* **12** (**9**): 3606. https://doi.org/10.3390/su12093606.

[8] Gervasi, Riccardo, Matteo Capponi, Luca Mastrogiacomo, and Fiorenzo Franceschini. (2023) "Manual assembly and Human–Robot Collaboration in repetitive assembly processes: a structured comparison based on human-centered performances" *The International Journal of Advanced Manufacturing Technology* **126** (**3**): 1213–1231. https://doi.org/10.1007/s00170-023-11197-4.

[9] Yelle, Louis E. (1979) "The Learning Curve: Historical Review and Comprehensive Survey" *Decision Sciences* **10** (**2**): 302–328. https://doi.org/10.1111/j.1540-5915.1979.tb00026.x.

[10] Franceschini, Fiorenzo, and Maurizio Galetto. (2003) "Composition laws for learning curves of industrial manufacturing processes" *International Journal of Production Research* **41** (**7**): 1431–1447. https://doi.org/10.1080/1352816031000075035.

[11] Verna, Elisa, Gianfranco Genta, and Maurizio Galetto. (2023) "Effects of product complexity on human learning in assembly and disassembly operations" *Journal of Manufacturing Technology Management* **34** (**9**): 139–162. https://doi.org/10.1108/JMTM-04-2023-0135.

[12] Anzanello, Michel Jose, and Flavio Sanson Fogliatto. (2011) "Learning curve models and applications: Literature review and research directions" *International Journal of Industrial Ergonomics* **41** (**5**): 573–583. https://doi.org/10.1016/j.ergon.2011.05.001.

[13] Franceschini, Fiorenzo. (2002) "Learning curves and p-charts for a preliminary estimation of asymptotic performances of a manufacturing process" *Total Quality Management* **13** (**1**): 5–12. https://doi.org/10.1080/09544120120098528.

[14] Wright, T. P. (1936) "Factors Affecting the Cost of Airplanes" *Journal of the Aeronautical Sciences* **3** (**4**): 122–128. https://doi.org/10.2514/8.155.

[15] Empatica. (2022) "E4 wristband." https://www.empatica.com/research/e4. Accessed April 13.

[16] Benedek, Mathias, and Christian Kaernbach. (2010) "Decomposition of skin conductance data by means of nonnegative deconvolution" *Psychophysiology* **47** (**4**): 647–658. https://doi.org/10.1111/j.1469-8986.2009.00972.x.

[17] Taelman, Joachim, S. Vandeput, A. Spaepen, and S. Van Huffel. (2009) "Influence of Mental Stress on Heart Rate and Heart Rate Variability," in Jos Vander Sloten, Pascal Verdonck, Marc Nyssen, and Jens Haueisen (eds.) *4th European Conference of the International Federation for Medical and Biological Engineering*, 1366–1369. IFMBE Proceedings. Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-540-89208-3_324.

[18] Liu, Yun, and Siqing Du. (2018) "Psychological stress level detection based on electrodermal activity" *Behavioural Brain Research* **341**: 50–53. https://doi.org/10.1016/j.bbr.2017.12.021.