Analyzing psychophysical state and cognitive performance in human-robot collaboration for repetitive assembly processes

Production Engineering (2024) 18:19–33
https://doi.org/10.1007/s11740-023-01230-6

ASSEMBLY AND AUTOMATION

Analyzing psychophysical state and cognitive performance in human-robot collaboration for repetitive assembly processes

Riccardo Gervasi[1] · Matteo Capponi[1] · Luca Mastrogiacomo[1] · Fiorenzo Franceschini[1]

Received: 18 July 2023 / Accepted: 26 September 2023 / Published online: 6 October 2023

Abstract

One of the main paradigms of Industry 5.0 is represented by human-robot collaboration (HRC), which aims to support humans in production processes. However, working entire shifts in close contact with a robotic system may introduce new hazards from a cognitive ergonomics perspective. This paper presents a methodological approach to monitor the evolution of the operator's psychophysical state noninvasively in shifts of a repetitive assembly process, focusing on stress, mental workload, and fatigue. Through the use of non-invasive biosensors, it is possible to obtain objective information, even in real time, on the operator's cognitive load and stress in a naturalistic manner (i.e., without interrupting or hindering the process). In the HRC setting, recognition of the operator's psychophysical state is the first step in supporting his or her well-being and can provide clues to improve collaboration. The proposed method was applied to a case study aimed at comparing shifts performed both manually and with a cobot of a repetitive assembly process. The results showed significant differences in terms of process performance evolution and psychophysical state of the operator. In particular, the presence of the cobot resulted in fewer process failures, stress and cognitive load especially in the first phase of the work shift. The case study analyzed also showed the adequacy of noninvasively collected physiological data in providing important information on the evolution of the operator's stress, cognitive load, and fatigue.

Keywords Human-robot collaboration · Industry 5.0 · Physiological data · Repetitive assembly · Cognitive ergonomics · Process failures

Abbreviations

ECG	Electrocardiogram
EDA	Electrodermal activity
EEG	Electroencephalography
HRC	Human-robot collaboration
HRV	Heart rate variability
PPG	Photopletismogram
PSNS	Parasympathetic nervous system
SCL	Skin conductance level
SCR	Skin conductance response
SNS	Sympathetic nervous system

✉ Fiorenzo Franceschini
fiorenzo.franceschini@polito.it

Riccardo Gervasi
riccardo.gervasi@polito.it

Matteo Capponi
matteo.capponi@polito.it

Luca Mastrogiacomo
luca.mastrogiacomo@polito.it

[1] DIGEP (Department of Management and Production Engineering), Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy

1 Introduction

Human-robot collaboration (HRC) has spread as a new approach whereby humans and collaborative robots (also called cobots) work together in a shared environment. By sharing space, time and goals, HRC may leverage the strengths of both parties to achieve better results productivity and quality performances [1–3]. In manufacturing, collaborative robotics mainly finds application in assembly processes. In a collaborative assembly process, tasks are allocated between humans and cobots, working symbiotically to assemble a product [4, 5]. The main issues present in an assembly process involve not only physical ergonomics and operator safety, but also cognitive aspects. Optimization of cognitive ergonomics may enable reduction of errors, improvement of performance and facilitation of operators' decision-making process [6]. Collaborative robotics has the potential to provide not only physical but also cognitive support to the operator.

Extensive research has shown that HRC encompasses a wide variety of dimensions, including human factor [7]. Fatigue and stress are gaining increasing attention as they may result in poor performances of operators in manufacturing processes, as well as impacting their well-being. For this reason, it is important to be able to monitor the psychophysical state of operators by obtaining information noninvasively and without hindering their work [8]. In addition, the implementation of cobots may improve both quality of the production system and humans' well-being, but to date the study of the effects of HRC in repetitive assembly processes has received limited attention [9, 10].

This paper aims to explore the evolution of the psychophysical state (focusing on stress, cognitive load, and fatigue) and performance of operators during continuous interaction with a collaborative robot in a repetitive assembly process. In addition, a naturalistic and noninvasive approach to gather information about the operator's psychophysical state is also emphasized.

An experimental setting involving 4 h assembly work-shifts of a case-study product (i.e., a tile cutter) was designed and implement. The assembly work-shifts were performed both manually and with the support of a cobot, in order to highlight potential effects of HRC. Three main aspects were analyzed:

i. Number and type of process failures, to address the evolution of process quality and humans' performance over time.
ii. Physiological responses (i.e., electrodermal activity and heart rate variability) collected noninvasively, to measure stress, cognitive load, and fatigue experienced in prolonged repetitive assembly processes.
iii. Relationship between process failures and physiological responses, to explore the influence of process failures on operator psychophysical state.

This paper is organized as follows. Section 2 presents a literature review on HRC in industrial contexts, providing also details on the use of physiological data. In Sect. 3 the experimental methodology proposed and adopted is described in detail. Section 4 shows the main results, analyzing process failures and physiological responses. The main findings are summarized and discussed in Sect. 5. Finally, Sect. 6 contains conclusions and future works.

2 Literature review

HRC has received considerable attention in recent years. HRC involves humans and robots sharing the same workspace and time in order to pursue a common goal and work simultaneously [11]. The great potential of this technology lies in the possibility to combine the dexterity of the human operator with the repeatability and precision of the robot [1, 2]. However, the coexistence of humans and cobots in the same workspace has raised several safety concerns thus leading to a wide variety of methodologies to improve it [12–14]. In this regard, ISO standards (i.e., ISO 10218-2:2011 [15] and ISO/TS 15066:2016 [16]) were also established to ensure safe operations in human-robot collaboration tasks. The main safety hazards involved in HRC include physical contact and collision, pinch points and trapping, robot speed and force. The most commonly used strategies to mitigate these hazards involve limiting robot speed and force, implementing proximity sensors or vision systems to avoid collisions, or integrating corrective actions systems that lead to collision avoidance without stopping the robot operation [17, 18].

Safety represents only one of the variables that can impact the efficiency of a collaborative assembly process. Gervasi et al. [7] introduced a framework summarizing several critical dimensions to be considered in evaluating HRC (i.e., autonomy, information exchange, team organization, adaptivity and training, task, human factors, ethics and cybersecurity). A multidimensional approach is also followed by Hoffman [19] who proposed a methodology for assessing HRC fluency by making use of a set of objective metrics (human idle time, robot idle time, concurrent activity) and other subjective metrics related to human perception of the cobot. Kokotinis et al. [20] recently proposed a tool for evaluating HRC quality, based on metrics related to human (e.g., safety, ergonomics, and trust), robot (e.g., autonomy, manipulation ability, and costs), and interaction (e.g., interaction ability, workspace and time sharing).

In the field of HRC evaluation, there is a growing interest in the analysis of cognitive aspects and affective states involved, with special attention to stress and mental workload [9, 21, 22]. To enhance quality, Ahmed et al. [23] highlighted the importance of controlling both human and process parameters and their influence on assembly quality. A similar approach was followed by Quenehen et al. [24] who assessed quality of different human-robot collaboration modes through an energy expenditure model taking into account economic and ergonomic indicators. Some classic metrics used in case studies are based on participants' performance, such as the number of errors, occurrence of conflicts, task completion rate, and response time [25]. Another method is to obtain subjective feedback through questionnaires and surveys, mainly focused on reporting perceived workload, anxiety, pleasantness, situation awareness, and so on. Some of the most widely used tools in this area include the System Usability Scale (SUS) [26], Self-Assessment Manikin (SAM), NASA-TLX [27], Subjective Workload Assessment Technique (SWAT) [28], and Instantaneous Self-Assessment of workload (ISA) [29]. Compared to performance-based metrics, the use of questionnaires or surveys is particularly suitable in evaluating the interaction with a robot in the case of tasks with a qualitative nature and rather limited duration [30]. However, a limitation is their use in contexts where there is interest in analyzing the evolution of the user experience in more complex and longer duration tasks [31]. In fact, in these cases, obtaining subjective feedback would imply task interruption, which can potentially undermine the naturalistic setting of an experiment. One way to circumnavigate this obstacle is to collect and analyze physiological data from users.

2.1 Physiological data analysis in HRC

In recent years, the exploitation of physiological data to obtain objective information concerning cognitive activity and affective state of users involved in HRC has received increasing attention. [8, 32]. Khamaisi et al. [33] developed a comprehensive approach to identify potential stressful situation for workers, combining questionnaires, operators' feedback and the analysis of psycho-physiological responses. Similarly, Gervasi et al. [34] explored how different robot configurations may impact user experience collecting also physiological response.

It is possible to derive information about a user's psychophysical state through the analysis of physiological parameters such as heart rate [35, 36], blood pressure [37], skin conductance [38, 39], respiratory rate [40], pupil dilation [41], electroencephalography (EEG) [42], and electromyography (EMG) [30].

The collection of physiological data is accomplished using biosensors that are usually applied to humans. Especially in manufacturing, the implementation of noninvasive wearable biosensors proves to be crucial in order to obtain information about the operator's state [31]. This would also allow to not hinder the operator during dynamic processes and to maintain as naturalistic as possible the data collection setting.

Heart activity and electrodermal activity (EDA) are among the physiological parameters most commonly used in HRC to monitor cognitive activity and stress and with high potential for real-world application in manufacturing settings [8]. This potential stems mainly from (i) the widespread of noninvasive wearable biosensors (e.g., wristbands) for monitoring heart activity and EDA, (ii) a not-particularly high difficulty in analyzing and interpreting their signals, and (iii) a relatively low implementation cost.

Heart monitoring is a common method used in fitness and working contexts for assessing user experience [43]. It is quite easy and cheap to implement and can be performed by electrocardiography (ECG) or photopletismography (PPG) (Fig. 1). Heart rate is regulated by sympathetic and parasympathetic inputs and can vary according to the body's physical needs [44]. It is also modulated by numerous factors, such as stress, psychological state, physical activity, medications, hormonal status, and illness. Heart rate variability (HRV) represents the variation in the time interval between heartbeats (called R-R intervals) and has been used in several studies to objectively assess psychological stress [45]. HRV is reported to be an index of the influence of both the parasympathetic nervous system (PSNS) and the sympathetic nervous systems (SNS). PSNS is referred to as the part of the nervous system responsible for "rest and digest" activities, i.e., responsible for the internal functions when resting and relaxing [46]. PSNS has opposite functions to those of the SNS, basically undoing the work of SNS after a stressful situation. SNS is the division of the autonomic nervous system that mediates the neuronal and hormonal response to stress and arousal, commonly known as the "fight or flight" response [47].

Regarding heart activity, SNS stimulation leads to an increase in blood pressure and heart rate, while PSNS stimulation leads to a decrease in them. In healthy individuals, high resting HRV indicates balanced activation of the SNS and the PSNS [44]. This variability, indeed, reflets the ability of the cardiovascular system to rapidly adjust and cope with uncertainty and sudden environmental changes [45]. During acute stress, activity of the SNS increases and the PSNS is suppressed, leading to an imbalance that leads to a lower

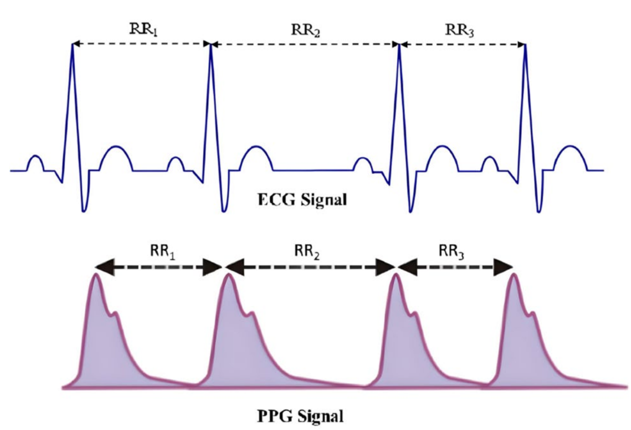

Fig. 1 Example of electrocardiography (ECG) or photopletismography (PPG) signals with R-R intervals [49]

HRV. Upon dissipation of the stress source, HRV returns to the initial state of balanced activation.

EDA, sometimes also known as galvanic skin response or skin conductance, refers to the measurement of the continuous changes in the electrical conductance (i.e., capacity to conduct a flow of electrical current) of the skin in response to sweat secretion by the eccrine sweat glands [48].

The eccrine sweat glands (Fig. 2a) have a secretory segment (located in the skin hypodermis) innervated by sudomotor fibers connected to the SNS. Upon activation of the SNS, the sweat gland duct fills with sweat, which in turn increases skin conductance due to ions contained in sweat. Therefore, EDA is considered a marker of SNS activity, which is related to stress and arousal [48].

Changes in EDA can be decomposed in short term (phasic) or relatively long lasting (tonic) (Fig. 2b) [50]. Phasic component reflects rapid changes in the EDA within a few seconds, called skin conductance responses (SCRs), resulting from an underlying sympathetic reaction. These reactions can be induced by external stimuli, e.g., stressors. Therefore, their analysis can provide information on the level of arousal and stress. Tonic component, also called skin conductance level (SCL), corresponds to slow changes in the EDA resulting from the tonic activity of sympathetic innervation of the eccrine sweat gland. Prolonged stress and increase of cognitive load are typically associated to a slow increase of EDA, i.e., an increase of SCL.

3 Methodology

In this section, a methodology is proposed to noninvasively study the user's experience and psychophysical state (i.e., stress, cognitive load, and fatigue) during shifts in an assembly process. In order to investigate also the potential support of a cobot in repetitive assembly processes, 4 h shifts of a tile cutter assembly process were designed and implemented at the "Politecnico di Torino" at Mind4Lab [52]. The study involved twelve participants (six males and six females) between the ages of 20 and 25 who had no prior experience with cobots.

A more detailed description of the methodology and assembly process will follow in the next sections.

3.1 Case study: tile cutter assembly process

Participants were asked to assemble repetitively a tile cutter. Each participant performed the assembly process in two 4 h sessions, one in a manual setting (*Manual*) and the other in conjunction with a cobot (*HRC*). The order of the two modalities was randomized for each participant. In *HRC* modality, the UR3e cobot [53] was used. Participants were briefed on the cobot's actions and automatic emergency stop on impact (i.e., power and force limiting safety system). Figure 3a and b show the final assembled product and the components, respectively. Figure 4 shows the assembly workstation with the UR3e cobot and supports for the assembly. Table 1 contains the list of the operations for both the *HRC* and *Manual* modalities and shows the agent performing them. The assembly of the tile cutter can be broken down into 4 macro-phases:

1. The assembly of the base holders.
2. The assembly of the cutting mechanism.
3. The insertion of rail rods into the cutting mechanism and the joining with the base.
4. Completion of the tile cutter screwing the handle.

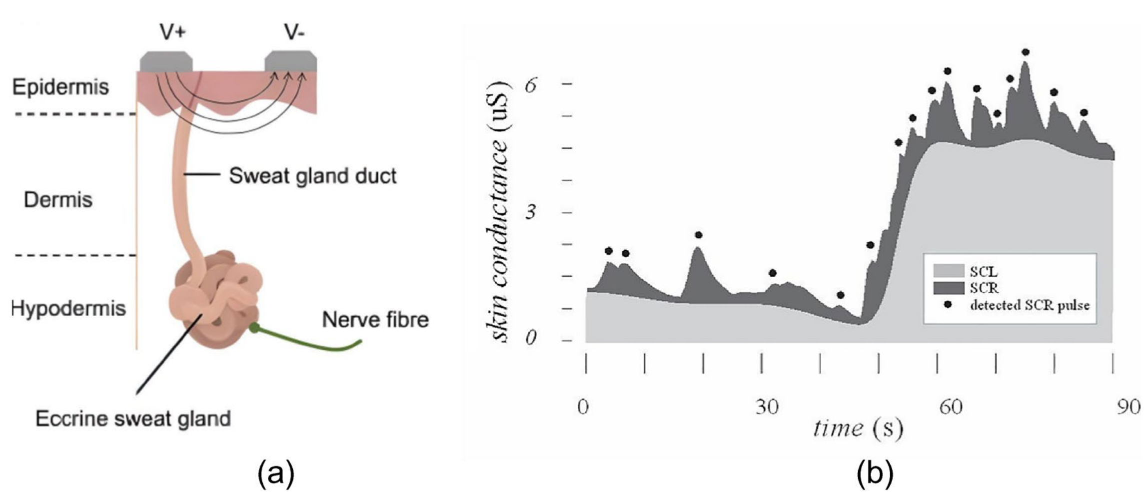

Fig. 2 **a** Representation of an eccrine sweat gland and electrodermal activity (EDA) measurement principle [50]. **b** Example of EDA signal with its decomposition in skin conductance level (SCL) and skin conductance response (SCR) [51]

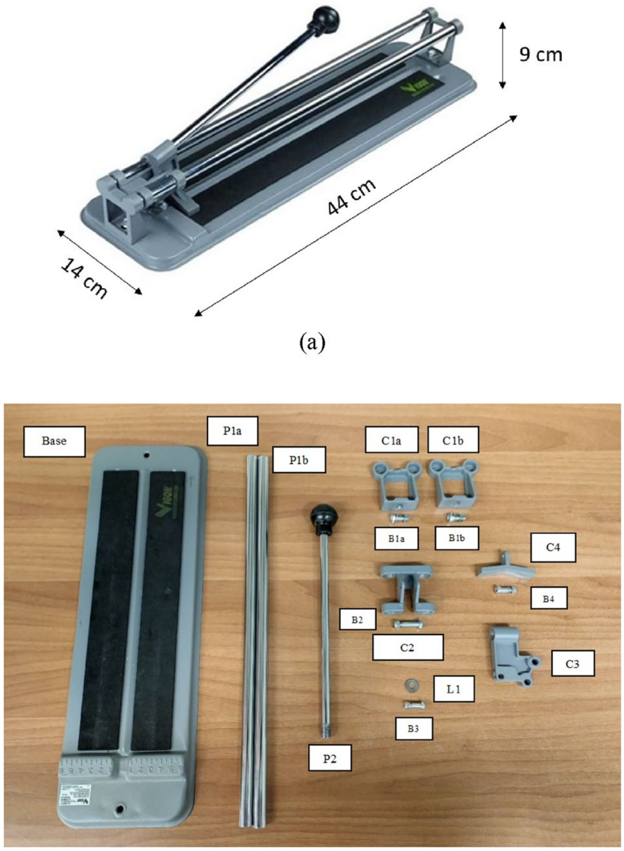

Fig. 3 **a** Tile cutter and **b** components of the tile cutter with their tags [52]

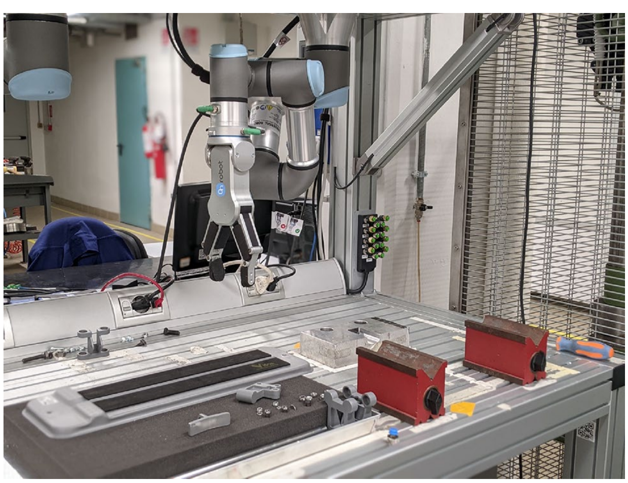

Fig. 4 Assembly workstation setting with the cobot UR3e

The assembly of a tile cutter lasted about 240s, leading to the production of about 60 products in a 4 h shift. Overall, considering all the participants who joined the experimental campaign, a total of 720 tile cutter were assembled.

3.2 Process failures

In order to investigate the evolution of human operator's performance over time and the contextual learning rate, the occurrence and type of process failures caused by humans were collected. In this regard, Table 2 contains a taxonomy of possible human process failures for the assembly process under analysis. Four main macro-groups of human process failures were identified:

- *Incorrect part selection (HF1)*: the operator selects a component, screw, nut, or washer that is not required to perform the subsequent task.
- *Incorrect part positioning (HF2)*: the operator positions a component, screw, nut, or washer in an unsuitable way, making it difficult or even impossible to perform the following task.
- *Incorrect part assemblies (HF3)*: the operator incorrectly assembles different components.
- *Part droppings (HF4)*: the operator accidentally drops a component, screw, nut, washer, or tool.

To investigate potential differences between manual and collaborative assemblies in terms of learning rate, the learning curve of human process failures will be analyzed. Learning curves have been widely addressed in manufacturing-related literature. Different learning models were proposed over the years, and one of the most common is the power law learning curve [54, 55]. In this study, a power law learning model will be implemented to investigate the evolution of process failures caused by humans in both modalities. The aforementioned learning model can be expressed as follows:

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

where a and b are the model coefficients and represent the starting performance and learning rate, respectively, while c represents the asymptotic steady-state [56, 57]. In this paper, it was assumed $c = 0$, since: (i) there are no external conditions preventing the operator from reaching the 0-failure scenario, (ii) the number of trials is limited, leading to the well-known Wright's model [58]. In our case, 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. The R package "stats" [59, 60] was used for fitting learning models thought nonlinear least squares [61] and calculating confidence intervals for the coefficient estimates.

In the HRC setting, the occurrence of robot failures was tracked. Possible types of failures of the cobot include missed or incorrect grasping of a component, dropping a component during movement, colliding with objects or operator, and system errors/blocks. This kind of information

Table 1 Operation list of the tile cutter assembly for both HRC and Manual modality [52]

Phase	Operation	Allocation	
		HRC	Manual
Phase 1: Assembling the base holders	(1) Picking the Base from the tray to assembly area	Cobot	Human
	(2) Assembling components C1a and C1b to either side of the Base. Screwing with soft tightening of bolts B1a and B2b (assembly A1)	Human	Human
	(3) Placing sub-assembly A1 out of the assembly area	Cobot	Human
Phase 2: Assembling the cutting mechanism	(4) Picking component C2 to the assembly area and holding it	Cobot	Human
	(5) Assembling component C3 with component C2 via bolt B2 (assembly A2)	Human	Human
	(6) Assembling blade L1 with component C3 via bolt B3 (assembly A3)	Human	Human
	(7) Assembling component C4 with component C3 via bolt B4 (assembly A4)	Human	Human
	(8) Placing assembly A4 out of the assembly area	Cobot	Human
Phase 3: Assembling the cutting mechanism with the base	(9) Picking assembly A2 to the assembly area	Cobot	Human
	(10) Picking assembly A4 to the assembly area	Human	Human
	(11) Inserting rods P1a and P2b into holders of assembly A4 (assembly A5)	Human	Human
	(12) Inserting the assembly A5 into the holders of components C1a and C1b of assembly A1	Human	Human
	(13) Tightening the bolts B1a and B1b (assembly A6)	Human	Human
Phase 4: Completing the tile cutter	(14) Screwing rod P2 into the holder of component C3 of assembly A6 (assembly A7)	Human	Human
	(15) Picking assembled product and placing it in the tray	Cobot	Human

Table 2 Taxonomy of human process failures for the assembly process

Group of process failures	Process failures	Description
HF1 - Incorrect part selection	Incorrect component selection	The operator picks up a component not needed for the next task
	Incorrect screws/nuts/washers selection	The operator picks up a screw/nut/washer not needed for the next task
HF2 - Incorrect part positioning	Incorrect component positioning	The operator places a component in a position not suitable to perform the next task
	Incorrect screws/nuts/washers positioning	The operator places a screw/nut/washer in a position not suitable to perform the next task
HF3 - Incorrect part assembly	Incorrect assembly of components	The operator assembles a component incorrectly
	Incorrect assembly of screws/nuts/washers	The operator uses the wrong screws/nuts/washers to join components
HF4 - Parts dropping	Dropping of components	The operator drops a component
	Dropping of screws/nuts/washers	The operator drops screws/nuts/washers
	Dropping of tools	The operator drops a tool

may provide clues to the operator's user experience in the HRC, and their relationship to physiological responses will be explored.

3.3 Physiological signal collection

The noninvasive biosensor Empatica E4 [62] was used to collect data on various physiological responses of participants. Physiological data were then analysed to investigate the evolution of stress, fatigue and cognitive exertion of human operators performing repetitive assembly processes. The device records two types of physiological information: EDA data at 4 Hz and heart rate data through PPG at 64 Hz. From PPG, R-R intervals were obtained, and the Root Mean Square of Successive Differences of R-R intervals (RMSSD) was used as HRV index due to its common use as stress and fatigue indicator [63].

"Ledalab", a MATLAB-based software, was used to process EDA data. Through Continuous Decomposition Analysis (CDA) [64], the EDA signal was decomposed into phasic and tonic activity signals. Through the analysis of tonic activity (i.e., SCL), information on cognitive load evolution can be obtained. In contrast, through the analysis of the phasic activity signal, skin conductance responses

(SCRs) (i.e., amplitude changes from the SCL to a peak of the response) can be identified providing information on arousal and stress.

In this study, for each trial, average SCR, SCL and RMSSD were computed to investigate the evolution of stress, cognitive load, and fatigue [65, 66].

3.4 Experimental procedure

At the beginning, each group of participants was briefed about the objectives and the detailed procedure of the experimental study. Secondly, participants were conducted to their work-area where they were given detailed information of the assembly process to perform. Meanwhile, the participant in charge of assembly was equipped with the Empatica E4 on the left wrist and a 15 min wait period was observed to ensure an appropriate adherence of the electrodes, so as to acquire reliable EDA data. Next, the participant was asked to relax and stand still to record 2 min of "baseline", i.e., the physiological signals at rest. Next, the repetitive assembly process was randomly selected in one of the two modalities (i.e., *Manual* or *HRC*) and began for a 4 h work-shift. A 10 min break was also scheduled after 2 h of work, in order to simulate real-life working conditions. The other two participants monitored the whole process by recording process failures and product defects. At the end of the 4 h work-shift, general unstructured feedbacks on the experiment were collected. In the second shift, the same procedure was followed for the remaining modality (i.e., *HRC* or *Manual*). Therefore, each group of participants performed the 4 h work shift in both modalities with random order.

4 Results

In this section, the obtained experimental results are presented.

4.1 Process failures

Figure 5 shows the evolution of the average number across participants of human process failures for both *Manual* and *HRC* settings. Slightly more failures were present in the *Manual* setting, although there was some overlap between the curves. Figure 6 shows the comparison of the fitted learning curves with the power law model for each modality. 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 provides clues on the cognitive support of the cobot 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.

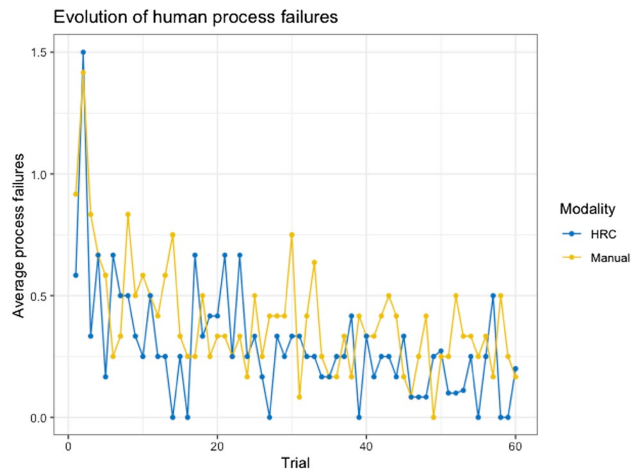

Fig. 5 Evolution over trials of average human process failures for both HRC and Manual modalities

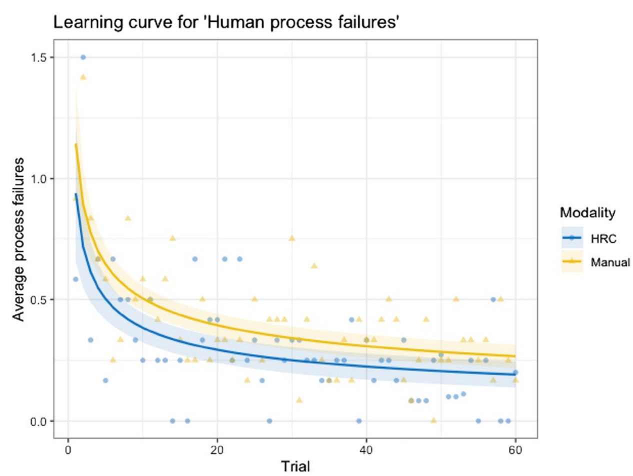

Fig. 6 Comparison of the fitted power-law learning curves between HRC and Manual modalities for human process failures

Table 3 contains the parameter estimates of the power-law learning curves. It can be seen that the two learning curves have a rather similar learning rate (*HRC*: $b = -0.3889$; *Manual*: $b = -0.3558$), while the initial value of average process failures is higher in the manual setting (*HRC*: $a = 0.9398$; *Manual*: $a = 1.1444$). However, it was not possible to conclude that the difference was statistically significant since the 95% confidence intervals overlap.

Figure 7 shows the evolution of average across participants human process failures categorized into incorrect part selections (*HF1*), incorrect part positionings (*HF2*), incorrect part assemblies (*HF3*), and part droppings (*HF4*). No significant differences emerged between

Table 3 Fitted power-law learning curve models for human process failures

Response variable	Modality	Coefficient	Value	Confidence interval (95%)
Human process failures	HRC	a	0.9398	[0.6605, 1.2191]
		b	− 0.3889	[− 0.5066, − 0.2712]
	Manual	a	1.1444	[0.9072, 1.3815]
		b	− 0.3558	[− 0.4352, − 0.2764]

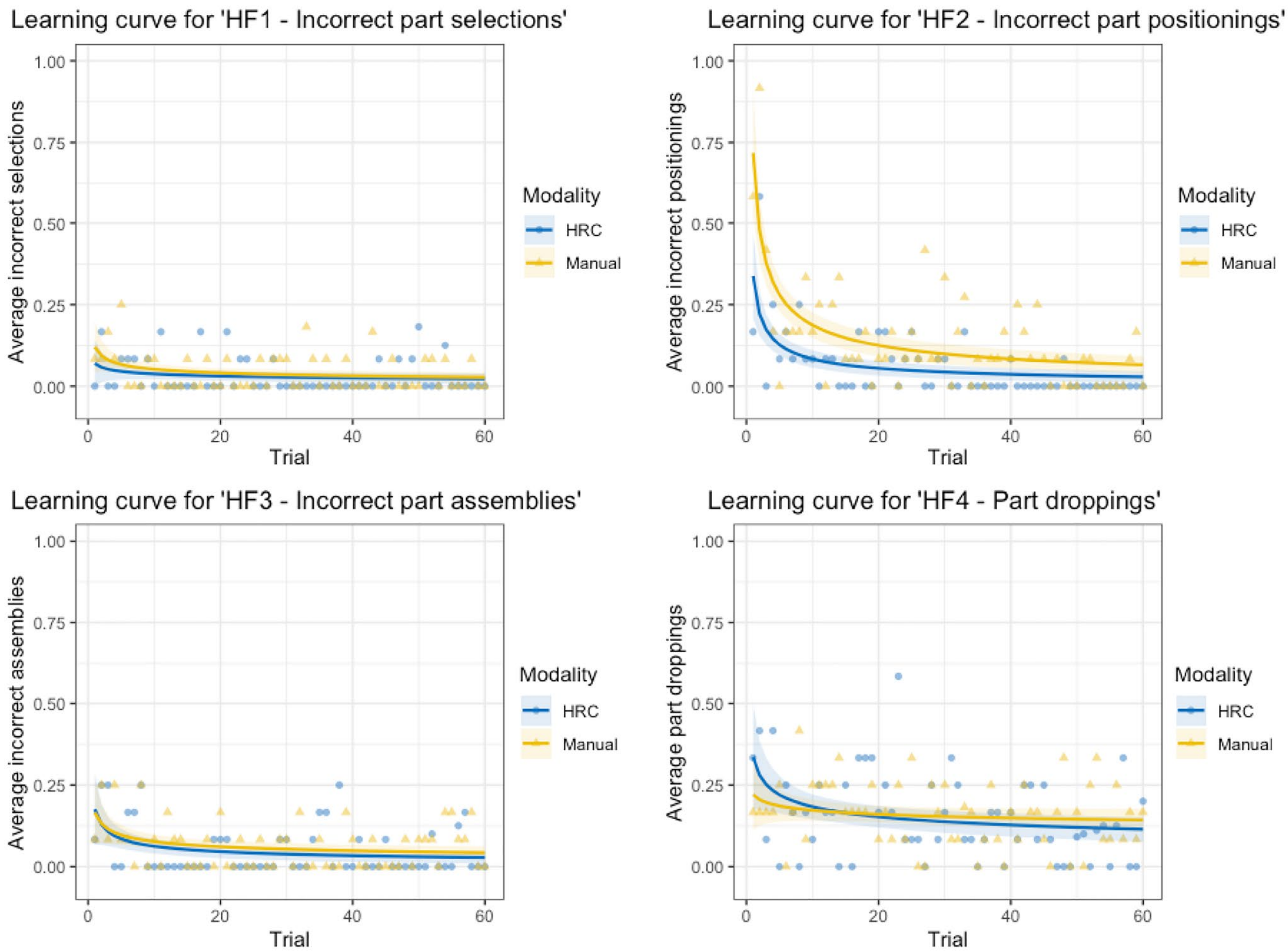

Fig. 7 Comparison between HRC and Manual modalities for the categories incorrect part selections, positionings and assemblies and part droppings

Manual and *HRC* modalities, except in incorrect part positionings. Observing the curves, more incorrect part positionings can be noted in the *Manual* setting. Several failures of this kind were observed during the assembly of the cutting mechanism. 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 the C2 component in the same way, it was easier for the operator to remember how to correctly position the other components. This effect is also reflected by the coefficients of the learning curves (Table 4), where the starting performance was better in the *HRC* modality (*HRC*: $a = 0.3375$; *Manual*: $a = 0.7172$). In addition, this difference was statistically significant as there was no overlap between the confidence intervals. The learning rate in the *Manual* setting had a slightly higher magnitude (*HRC*: $b = -0.6073$; *Manual*: $b = -0.5834$) to compensate for the higher initial gap, however, the difference with the *HRC* setting was not significant when observing the confidence intervals.

Table 4 Fitted power-law learning curve models for each category of human process failure

Response variable	Modality	Coefficient	Value	Confidence interval (95%)
HF1 - Incorrect part selections	HRC	*a*	0.0699	[0.0003, 0.1394]
		b	– 0.2756	[– 0.6310, 0.0798]
	Manual	*a*	0.1196	[0.0435, 0.1958]
		b	– 0.3641	[– 0.6098, – 0.1183]
HF2 - Incorrect part positionings	HRC	*a*	0.3375	[0.2085, 0.4666]
		b	– 0.6073	[– 0.8079, – 0.4068]
	Manual	*a*	0.7172	[0.5277, 0.9066]
		b	– 0.5834	[– 0.7172, – 0.4497]
HF3 - Incorrect part assemblies	HRC	*a*	0.1760	[0.0690, 0.2829]
		b	– 0.4516	[– 0.7097, – 0.1934]
	Manual	*a*	0.1656	[0.0726, 0.2587]
		b	– 0.3341	[– 0.5449, – 0.1232]
HF4 - Part droppings	HRC	*a*	0.3362	[0.1782, 0.4942]
		b	– 0.2633	[– 0.4295, – 0.0970]
	Manual	*a*	0.2205	[0.1150, 0.3261]
		b	– 0.1062	[– 0.2596, 0.0471]

4.2 Physiological response

In order to compare physiological response, data were standardized for each participant as physiological signals may be influenced by personal characteristics. The following formula was used to obtain the z-scores:

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

where z_{ij} and x_{ij} are respectively the i-th z-score and observation of participant j, $\bar{x}_j$ the sample mean for participant j, and s_j the sample standard deviation for participant j. To check for significant differences between the *Manual* and *HRC* setting the paired t-test was implemented, as the normality assumption was not rejected by the Shaipiro-Wilks [67] test for each response variable.

Figure 8a shows the evolution of the average SCR across participants over the work shift, comparing the *Manual* and *HRC* settings. It can be noted that in general the *Manual* setting higher values were observed, implying higher stress for participants. This difference was also found to be highly significant by the paired t-test ($p < 0.001$). Observing the trend of the average SCR, the *Manual* setting shows a decreasing trend while the *HRC* setting an increasing one. Initially in the *Manual* setting the stress was quite high, mainly due to a learning phase of the task, while in the *HRC* setting it tended to be lower. This was due to the cobot providing cognitive support to the participants, helping them to more easily remember the assembly steps and how to join certain parts through its operations. The observed difference in terms of stress resulted highly significant in the first half of the shift ($p < 0.001$). However, after about half of the shift,

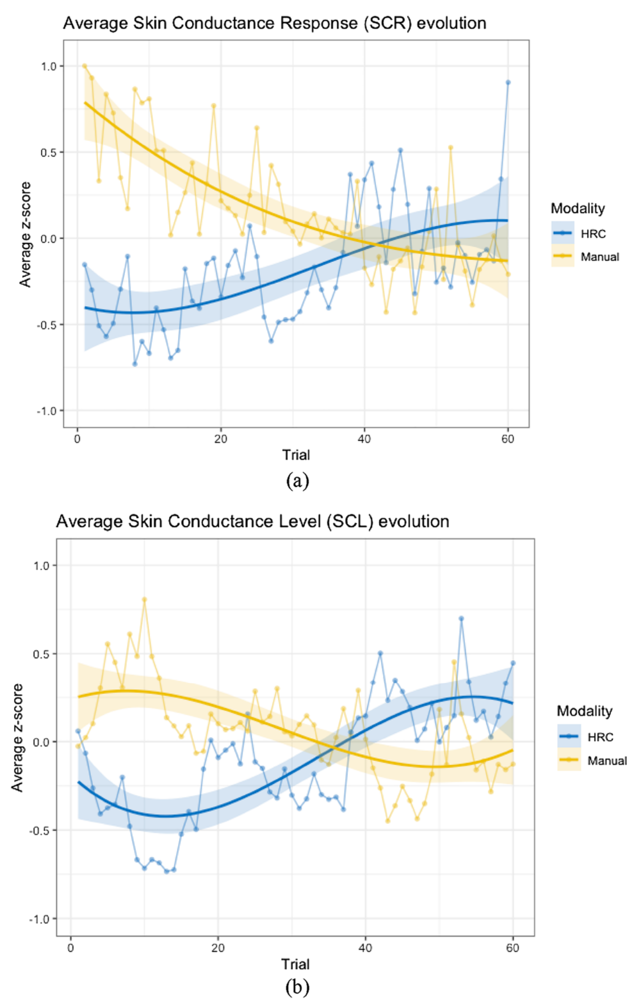

Fig. 8 Comparison between HRC and Manual modalities for the evolution of the standardized average **a** SCR and **b** SCL. Underlying trends with confidence bands are highlighted

the difference between the two settings narrowed until it was no longer significant ($p=0.428$). The increase in stress in the *HRC* setting may have been caused by the fact that the cobot began to be perceived also as a limitation for the operator in the second part of the shift. Several participants wished that cobot could be faster as they had to wait for the cobot concluding its operations to continue with the process, consequently reducing the control of the task time.

Figure 8b contains the evolution of the average SCL across participants over the trials for both the *Manual* and *HRC* settings. Overall, in the *Manual* setting slightly higher values were observed, revealing a significant difference by the paired t-test ($p=0.0155$). It is interesting to note a different behavior of the average SCL between the first and second part of the shift. In the first part, significantly higher SCL values were observed in the *Manual* setting ($p<0.001$), highlighting a greater prolonged use of cognitive resources due mainly to having to learn the assembly process. Interestingly, significantly lower values were observed in the *HRC* setting in this phase, providing additional evidence of the cognitive support of the cobot. However, as the trials progressed, the average SCL tended to increase in the HRC setting, slightly exceeding the values in the *Manual* setting in the second part of the shift ($p=0.0223$). This phenomenon points to a gradual increase in prolonged cognitive stress mainly due to having to adjust to the pace of the cobot when faster or simultaneous actions would have been welcome once the operator became familiar with the assembly process.

Figure 9 shows the evolution of the average RMSSD across the trials, comparing the *HRC* and *Manual* settings. Both curves show an increasing trend, indicating a gradual reduction in initial stress mainly resulting from the learning phase of the task. In addition, the two curves tend to overlap considerably across trials, implying no significant difference between the two modalities in terms of HRV by the paired t-test ($p=0.071$). Even focusing only on the first and second part of the shift, no significant difference emerged ($p=0.092$ and $p=0.370$ respectively), although a slight decrease in the average RMSSD can be noted toward the end of the shift for the HRC setting.

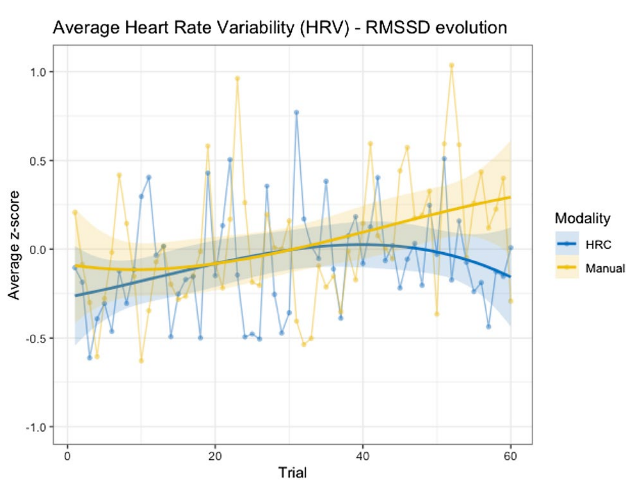

Fig. 9 Comparison between HRC and Manual modalities for the evolution of the standardized average RMSSD. Underlying trends with confidence bands are highlighted

4.3 Relationship between process failures and physiological response

In this section, the relationships between process failures and physiological response are explored. Figure 10 shows the Pearson's coefficients (ρ) obtained for both *Manual* and *HRC* settings, as well as the significance level of each coefficient obtained through a t-test. A high magnitude of Pearson's coefficient indicates a strong correlation between the two variables, while if the value is close to zero the correlation is very low.

In the *Manual* setting, it can be seen that significant correlations emerged only with EDA. The occurrence of failures by humans generally resulted in a consistent increase in SCR ($\rho=0.56$) (Fig. 11). This means that process failures caused rather rapid sympathetic reactions, leading to increased stress on the part of the operator. Observing the correlations with the different types of human failures, incorrect positioning (*HF2*) and assembly (*HF3*) contributed significantly to the increase in SCR ($\rho=0.46$ and $\rho=0.28$, respectively). Incorrect selection also resulted in an increase in SCR, although it was not found significant. This effect is related to the realization of having commit a process failure, which can cause a rapid reaction (i.e., sympathetic activation) in the operator, thereby increasing his/her stress. The occurrence of failures by humans resulted also in a slight significant increase in SCL ($\rho=0.31$), i.e., an increase in the cognitive load. Looking at the correlations between the different types of human failures, the incorrect assembly (*HF3*) was the one that most affected SCL ($\rho=0.22$).

In fact, once realized the incorrect assembly of a component, figuring out how to remedy requires a certain amount of mental resources that is reflected in the increase of SCL.

In the *HRC* setting, no significant correlations emerged between process failures and physiological responses (Figs. 10 and 11). Neither process failures resulting from the cobot seemed affect the users' physiological response. This fact suggests that in the *HRC* setting the observed increases in stress, cognitive load, and fatigue may not be attributable to process failures, but may arise, for example, from the process itself. Thus, the presence of the cobot could mitigate the negative effects on the operator due to process failures. From previous sections, it should be noted that significantly lower mean SCR and mean SCL were observed in the *HRC* setting than in the *Manual* one, especially in the learning phase in

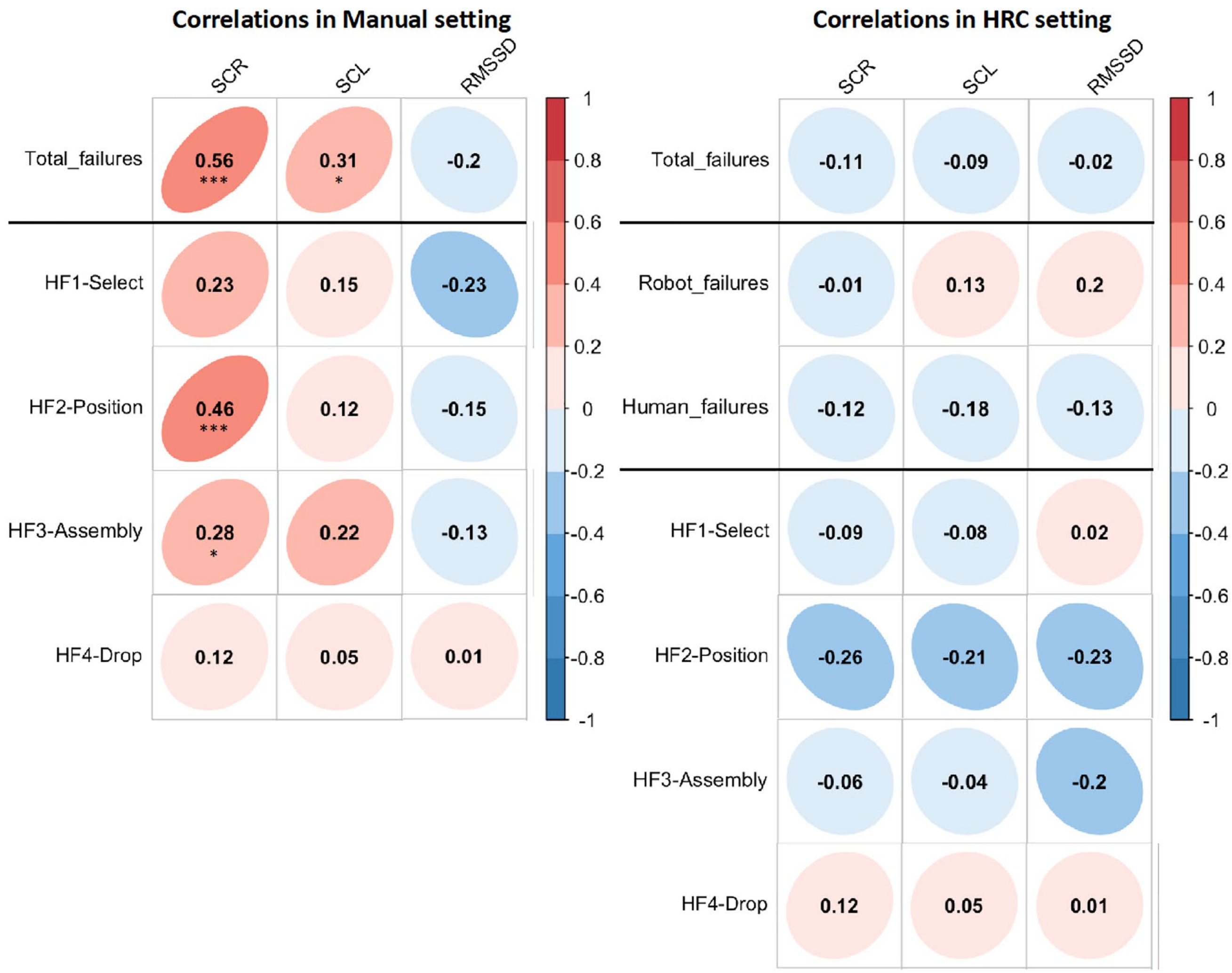

Fig. 10 Pearson's correlation coefficients between process failures and physiological response for both HRC and Manual modalities. Significance of the correlation is reported as follows: (*) $0.05 > p \geq 0.01$, (**) $0.01 > p \geq 0.001$, (***) $p < 0.001$

which the greatest number of failures were found. These results put even more emphasis on the cognitive support of the cobot in processes and suggests that the physiological response trends observed for the *HRC* setting can be attributed to a natural process of operator fatigue during the shift.

5 Discussion

In the case study analyzed, concerning a repetitive assembly process, interesting differences emerged in terms of process failures and physiological responses of the operator between the *Manual* and *HRC* setting.

Analysis of the evolution of human process failures revealed highly significant differences between the two settings. In particular, there were generally significantly fewer failures in the *HRC* setting, especially in the learning phase. From the detailed analysis of the types of human failures, it was found that the cobot provided significant support from the cognitive point of view especially in avoiding incorrect part positionings. In fact, the participants' feedback showed that the cobot's actions helped to remember the various assembly steps especially at the beginning. In addition, the fact that the cobot always handed the components in the same way created less uncertainty about the correct positioning and assembly of the components. From a production rate perspective, *Manual* and *HRC* settings were comparable.

Regarding the psychophysical state of operators, the information obtained from EDA proved most useful in bringing out significant differences between the *Manual* and *HRC* settings. The presence of the cobot resulted in significantly lower values of SCR and SCL, especially in the first part of the work shift. Initially, indeed, in the *Manual* setting the average SCR was quite high, which

Fig. 11 Scatter plot between total process failures and average SCR comparing Manual and HRC modalities. Dotted lines, with and confidence bands, represent the relationship between the two variables

highlights a distinctly high stress resulting mainly from learning the task. In contrast, significantly lower values were observed in the *HRC* setting, highlighting greater relaxation on the behalf of the operator in the learning phase. These results further corroborate the cognitive support role of the cobot in manufacturing assembly processes. As the trials progressed, there was a gradual increase in SCR in the *HRC* setting, although reaching values in the average range and similar to those found in the *Manual* setting. In contrast, a fairly significant increase was shown in the SCL, leading to values higher than the *Manual* setting toward the end of the shift. This phenomenon also emerged in the RMSSD analysis, although it was not significant. The increased demand for cognitive resources at this stage is due to a process of fatigue and slight frustration of the participants. In fact, toward the end of the shift several participants would have liked to be even more efficient desiring the cobot to be faster in performing its operations. This feedback shows the need to allow operators to customize and adapt HRC according to their needs in order to ensure an optimal and fully profitable experience with such technology.

Finally, relating process failures and physiological responses revealed further interesting differences between the *HRC* and *Manual* setting. In the *Manual* setting, the occurrence of human failures resulted in a negative effect on the psychophysical state of the operator, translating into a consistent increase in SCR (i.e., stress) and a slight increase in SCL (i.e., cognitive load). Surprisingly, these effects were not significant in the HRC setting. This result suggests that the presence of the cobot may also help to contain potential negative effects on the operator from process failures. In addition, the observed stress and cognitive load may therefore result from other factors, such as the configuration of the interaction with the cobot [34].

Other assistive technologies, such as augmented reality (AR) or artificial intelligence (AI) based vision systems, can also provide cognitive support to the human operator, contributing to the reduction of failures in the context of assembly processes. These tools are particularly suitable for guiding the operator in real time, however they can burden mental load of operators. Collaborative robots provide both physical and implicit cognitive support to the operator, and the integration of other assistive technologies can enable the provision of more information. However, having to manage and process additional information can increase the operator's mental load especially on prolonged processes. Further investigation of this topic in terms of user experience is needed.

Finally, implementation of HRC systems can provide a favorable return of investment (ROI) over time, particularly when they lead to substantial reductions in quality errors and defects, increased production efficiency, and improved product consistency [68]. However, it is important to note the ROI is highly dependent on the application [69]. Form a human-centered perspective, the implementation of HRC can relieve operators from repetitive or highly physically demanding tasks. This would allow operators to focus on more complex, value-added tasks that require problem-solving and decision-making skills, potentially leading to productivity gains and greater satisfaction.

6 Conclusions

This paper aimed to propose a methodology to obtain information on the performance and psychophysical state of operators in a continuous and noninvasively during entire shifts in an HRC production process. An implementation of this methodology was shown in a case study of a repetitive assembly process of a tile cutter, aimed at comparing shifts performed in *Manual* and *HRC* modality in terms of physiological response and process failure evolution.

In terms of performance, the use of the cobot implied a significant reduction in human failures, such as incorrect part positionings or assemblies, highlighting the cognitive support of the cobot. This role was further investigated and confirmed through the analysis of physiological responses, which showed a significant reduction in stress and cognitive load especially in the first half of the work shift. By also relating process failures to physiological responses, it was observed that in the *Manual* setting the occurrence of failures resulted in a significant increase in stress and operator cognitive load. However, these relationships did not emerge significant in the *HRC* setting, suggesting that the observed physiological responses may result from other factors, such as the configuration of the interaction with the cobot. This result contributes to the need to develop collaborative robotic systems that can meet operator preferences in order to fully exploit the supportive role of this technology.

Future work will focus on exploring and implementing other noninvasive biosensors to assess their added value on understanding the operator's state. In addition, future work will also focus on developing systems that can process real-time information about the operator's state to support the operator in personalizing HRC.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by RG and MC. The first draft of the manuscript was written by RG and MC under the supervision of LM and FF. All authors read and approved the final manuscript.

Funding Open access funding provided by Politecnico di Torino within the CRUI-CARE Agreement. 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.

Data availability The datasets generated and analysed during this study are not currently publicly available.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval The authors respect the Ethical Guidelines of the Journal.

Consent to participate Informed consent was obtained from all individual participants included in the study.

References

1. Bauer A, Wollherr D, Buss M (2008) Human–robot collaboration: a survey. Int J Humanoid Robot 05:47–66. https://doi.org/10.1142/S0219843608001303
2. Villani V, Pini F, Leali F, Secchi C (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. Colgate JE, Wannasuphoprasit W, Peshkin MA (1996) : Cobots: robots for collaboration with human operators. In: Proceedings of the 1996 ASME international mechanical engineering congress and exposition. pp. 433–439
4. Wang L, Gao R, Váncza J, Krüger J, Wang XV, Makris S, Chryssolouris G (2019) Symbiotic human-robot collaborative assembly. CIRP Ann 68:701–726. https://doi.org/10.1016/j.cirp.2019.05.002
5. Lippi M, Marino A (2021) Human multi-robot physical interaction: a distributed framework. J Intell Robot Syst 101:35. https://doi.org/10.1007/s10846-020-01277-y
6. Brolin A, Thorvald P, Case K (2017) Experimental study of cognitive aspects affecting human performance in manual assembly. Prod Manuf Res 5:141–163. https://doi.org/10.1080/21693277.2017.1374893
7. Gervasi R, Mastrogiacomo L, Franceschini F (2020) A conceptual framework to evaluate human-robot collaboration. Int J Adv Manuf Technol 108:841–865. https://doi.org/10.1007/s00170-020-05363-1
8. Gervasi R, Barravecchia F, Mastrogiacomo L, Franceschini F (2023) Applications of affective computing in human-robot interaction: state-of-art and challenges for manufacturing. Proc Inst Mech Eng Part B J Eng Manuf 237:815–832. https://doi.org/10.1177/09544054221121888
9. Gualtieri L, Fraboni F, De Marchi M, Rauch E (2022) Development and evaluation of design guidelines for cognitive ergonomics in human-robot collaborative assembly systems. Appl Ergon 104:103807. https://doi.org/10.1016/j.apergo.2022.103807
10. Gervasi R, Capponi M, Mastrogiacomo L, Franceschini F (2023) Manual assembly and human–robot collaboration in repetitive assembly processes: a structured comparison based on human-centered performances. Int J Adv Manuf Technol. https://doi.org/10.1007/s00170-023-11197-4
11. Krüger J, Lien TK, Verl A (2009) Cooperation of human and machines in assembly lines. CIRP Ann 58:628–646. https://doi.org/10.1016/j.cirp.2009.09.009
12. Zanchettin AM, Ceriani NM, Rocco P, Ding H, Matthias B (2016) Safety in human-robot collaborative manufacturing environments: metrics and control. IEEE Trans Autom Sci Eng 13:882–893. https://doi.org/10.1109/TASE.2015.2412256
13. Robla-Gómez S, Becerra VM, Llata JR, González-Sarabia E, Torre-Ferrero C, Pérez-Oria J (2017) Working together: a review on safe human-robot collaboration in industrial environments. IEEE Access 5:26754–26773. https://doi.org/10.1109/ACCESS.2017.2773127
14. Liu H, Qu D, Xu F, Du Z, Jia K, Song J, Liu M (2022) Real-time and efficient collision avoidance planning approach for safe human-robot interaction. J Intell Robot Syst 105:93. https://doi.org/10.1007/s10846-022-01687-0
15. ISO 10218-2:2011 (2011) Robots and robotic devices — safety requirements for industrial robots — part 2: robot systems and integration. Presented at the, Geneva, CH
16. ISO/TS 15066 (2016) :: Robots and robotic devices — collaborative robots. In: ISO., Geneva, CH (2016)
17. Michalos G, Makris S, Tsarouchi P, Guasch T, Kontovrakis D, Chryssolouris G (2015) Design considerations for safe human-robot collaborative workplaces. Procedia CIRP 37:248–253. https://doi.org/10.1016/j.procir.2015.08.014
18. Tsarouchi P, Makris S, Chryssolouris G (2016) Human–robot interaction review and challenges on task planning and programming. Int J Comput Integr Manuf 29:916–931. https://doi.org/10.1080/0951192X.2015.1130251

19. Hoffman G (2019) Evaluating fluency in human–robot collaboration. IEEE Trans Hum Mach Syst 49:209–218. https://doi.org/10.1109/THMS.2019.2904558
20. Kokotinis G, Michalos G, Arkouli Z, Makris S (2023) On the quantification of human-robot collaboration quality. Int J Comput Integr Manuf. https://doi.org/10.1080/0951192X.2023.2189304
21. Gervasi R, Mastrogiacomo L, Franceschini F (2023) An experimental focus on learning effect and interaction quality in human–robot collaboration. Prod Eng 17:355–380. https://doi.org/10.1007/s11740-023-01188-5
22. Faber M, Mertens A, Schlick CM (2017) Cognition-enhanced assembly sequence planning for ergonomic and productive human–robot collaboration in self-optimizing assembly cells. Prod Eng 11:145–154. https://doi.org/10.1007/s11740-017-0732-9
23. Ahmed A, Guozhu J, Salam A, Nawaz MK (2019) : Reliability and quality control approach for collaborative assembly process. In: Proceedings of 2019 16th international bhurban conference on applied sciences and technology, IBCAST 2019. pp. 210–217
24. Quenehen A, Thiery S, Klement N, Roucoules L, Gibaru O (2020) Assembly process design: performance evaluation under Ergonomics consideration using several robot collaboration modes. IFIP Adv Inf Commun Technol 592 IFIP:477–484. https://doi.org/10.1007/978-3-030-57997-5_55
25. Steinfeld A, Fong T, Kaber D, Lewis M, Scholtz J, Schultz A, Goodrich M (2006) : Common metrics for human-robot interaction. In: Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction. pp. 33–40. Association for Computing Machinery, New York, NY, USA
26. Brooke J (1996) SUS—a quick and dirty usability scale. In: Jordan P, Thomas B, Weerdmeester B, McClelland I (eds) Usability evaluation in industry. CRC Press, London, pp 189–194
27. Hart SG, Staveland LE (1988) Development of NASA-TLX (task load index): results of empirical and theoretical research. In: Hancock PA, Meshkati N (eds) Advances in psychology. North-Holland, pp 139–183
28. Reid GB, Nygren TE (1988) The subjective workload assessment technique: a scaling procedure for measuring mental workload. In: Hancock PA, Meshkati N (eds) Advances in psychology. North-Holland, pp 185–218
29. Jordan CS, Brenner SD (1992) Instantaneous self-assessment of workload technique (ISA). Defence Research Agency, Portsmouth
30. Dehais F, Sisbot EA, Alami R, Causse M (2011) Physiological and subjective evaluation of a human–robot object hand-over task. Appl Ergon 42:785–791. https://doi.org/10.1016/j.apergo.2010.12.005
31. Peruzzini M, Grandi F, Pellicciari M (2017) Benchmarking of tools for user experience analysis in industry 4.0. Procedia Manuf 11:806–813. https://doi.org/10.1016/j.promfg.2017.07.182
32. Prati E, Peruzzini M, Pellicciari M, Raffaeli R (2021) How to include user eXperience in the design of human-robot interaction. Robot Comput Integr Manuf 68:102072. https://doi.org/10.1016/j.rcim.2020.102072
33. Khamaisi RK, Brunzini A, Grandi F, Peruzzini M, Pellicciari M (2022) UX assessment strategy to identify potential stressful conditions for workers. Robot Comput Integr Manuf 78:102403. https://doi.org/10.1016/j.rcim.2022.102403
34. Gervasi R, Aliev K, Mastrogiacomo L, Franceschini F (2022) User experience and physiological response in human-robot collaboration: a preliminary investigation. J Intell Robot Syst 106:36. https://doi.org/10.1007/s10846-022-01744-8
35. Dehais F, Causse M, Vachon F, Tremblay S (2012) Cognitive conflict in human–automation interactions: a psychophysiological study. Appl Ergon 43:588–595. https://doi.org/10.1016/j.apergo.2011.09.004
36. Kühnlenz B, Kühnlenz K (2016) Reduction of heart rate by robot trajectory profiles in cooperative HRI. In: Proceedings of ISR 2016: 47st international symposium on robotics. pp 1–6
37. Attarchi M, Dehghan F, Safakhah F, Nojomi M, Mohammadi S (2012) Effect of exposure to occupational noise and shift working on blood pressure in rubber manufacturing company workers. Ind Health 50:205–213. https://doi.org/10.2486/indhealth.MS1321
38. Kulić D, Croft E (2007) Physiological and subjective responses to articulated robot motion. Robotica 25:13–27. https://doi.org/10.1017/S0263574706002955
39. Arai T, Kato R, Fujita M (2010) Assessment of operator stress induced by robot collaboration in assembly. CIRP Ann 59:5–8. https://doi.org/10.1016/j.cirp.2010.03.043
40. Argyle EM, Marinescu A, Wilson ML, Lawson G, Sharples S (2021) Physiological indicators of task demand, fatigue, and cognition in future digital manufacturing environments. Int J Hum Comput Stud 145:102522. https://doi.org/10.1016/j.ijhcs.2020.102522
41. Marinescu AC, Sharples S, Ritchie AC, Sánchez López T, McDowell M, Morvan HP (2018) Physiological parameter response to variation of Mental workload. Hum Factors 60:31–56. https://doi.org/10.1177/0018720817733101
42. Jiang Y, Hong J, Wang W, Qu J (2016) Least squares method-based quantitative modeling on visual comfort for VDT display interface. Int J Adv Manuf Technol 84:381–391. https://doi.org/10.1007/s00170-015-8222-8
43. Hendrick NAS, Hedge A, Brookhuis K (2004). In: Salas E, Hal W (eds) Handbook of human factors and ergonomics methods. CRC Press, Boca Raton
44. Ali N, Tschenett H, Nater UM (2023) Biomarkers of stress and disease. In: Friedman HS, Markey CH (eds) Encyclopedia of mental health, 3rd edn. Academic Press, Oxford, pp 221–231
45. Shaffer F, Ginsberg JP (2017) An overview of heart rate variability metrics and norms. Front Public Health 5:258
46. Rea P (2014) Introduction to the nervous system. In: Rea P (ed) Clinical anatomy of the cranial nerves. Academic Press, San Diego, pp xv–xxix
47. Murison R (2016) Chap. 2—the neurobiology of stress. In: Al'Absi M, Flaten MA (eds) Neuroscience of pain, stress, and emotion. Academic Press, San Diego, pp 29–49
48. Boucsein W (2012) Electrodermal activity. Springer US, Boston, MA
49. Akhter N, Tharewal S, Gite H, Kale KV (2015) Microcontroller based RR-interval measurement using PPG signals for heart rate variability based biometric application. In: 2015 international conference on advances in computing, communications and informatics (ICACCI). pp 588–593
50. Regalia G, Resnati D, Tognetti S (2023) Sensors on the wrist. In: Narayan R (ed) Encyclopedia of sensors and biosensors. Elsevier, Oxford, pp 1–20
51. Geršak G, Drnovšek J (2020) Electrodermal activity patient simulator. PLoS ONE 15:e0228949. https://doi.org/10.1371/journal.pone.0228949
52. Gervasi R, Mastrogiacomo L, Franceschini F (2022) Human-robot collaboration in a repetitive assembly process: a preliminary investigation on operator's experience and product quality outputs. Proceedings book of the 5th international conference on quality engineering and management. International conference on quality engineering and management. Braga, Portugal, pp 72–92
53. Universal robots : collaborative robotic automation | Cobots from universal robots, https://www.universal-robots.com/
54. Yelle LE (1979) The learning curve: historical review and comprehensive survey. Decis Sci 10:302–328. https://doi.org/10.1111/j.1540-5915.1979.tb00026.x

55. Franceschini F, Galetto M (2003) Composition laws for learning curves of industrial manufacturing processes. Int J Prod Res 41:1431–1447. https://doi.org/10.1080/1352816031000075035
56. Anzanello MJ, Fogliatto FS (2011) Learning curve models and applications: literature review and research directions. Int J Ind Ergon 41:573–583. https://doi.org/10.1016/j.ergon.2011.05.001
57. Franceschini F (2002) Learning curves and p-charts for a preliminary estimation of asymptotic performances of a manufacturing process. Total Qual Manag 13:5–12. https://doi.org/10.1080/09544120120098528
58. Wright TP (1936) Factors affecting the cost of airplanes. J Aeronaut Sci 3:122–128. https://doi.org/10.2514/8.155
59. R Core Team (2022) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna
60. R Core Team : R: the R stats package, https://stat.ethz.ch/R-manual/R-devel/library/stats/html/00Index.html
61. Bates DM, Watts DG (1988) Nonlinear regression analysis and its applications. John Wiley and Sons, New York, NY
62. Empatica (2023) E4 wristband, https://www.empatica.com/research/e4. Accessed on 20 June 2023.
63. Kim H-G, Cheon E-J, Bai D-S, Lee YH, Koo B-H (2018) Stress and heart rate variability: a meta-analysis and review of the literature. Psychiatry Investig 15:235–245. https://doi.org/10.30773/pi.2017.08.17
64. Benedek M, Kaernbach C (2010) Decomposition of skin conductance data by means of nonnegative deconvolution. Psychophysiology 47:647–658. https://doi.org/10.1111/j.1469-8986.2009.00972.x
65. Taelman J, Vandeput S, Spaepen A, Van Huffel S (2009) Influence of mental stress on heart rate and heart rate variability. In: Vander Sloten J, Verdonck P, Nyssen M, Haueisen J (eds) 4th European conference of the international federation for medical and biological engineering. Springer, Berlin, pp 1366–1369
66. Liu Y, Du S (2018) Psychological stress level detection based on electrodermal activity. Behav Brain Res 341:50–53. https://doi.org/10.1016/j.bbr.2017.12.021
67. Shapiro SS, Wilk MB (1965) An analysis of variance test for normality (complete samples). Biometrika 52:591–611. https://doi.org/10.1093/biomet/52.3-4.591
68. Papanastasiou S, Kousi N, Karagiannis P, Gkournelos C, Papavasileiou A, Dimoulas K, Baris K, Koukas S, Michalos G, Makris S (2019) Towards seamless human robot collaboration: integrating multimodal interaction. Int J Adv Manuf Technol 105:3881–3897. https://doi.org/10.1007/s00170-019-03790-3
69. Caiazzo C, Nestić S, Savković M (2023) A systematic classification of key performance indicators in human-robot collaboration. In: Mihić M, Jednak S, Savić G (eds) Sustainable business management and digital transformation: challenges and opportunities in the post-COVID era. Springer International Publishing, Cham, pp 479–489