Human-robot collaboration in a repetitive assembly process: a preliminary investigation on operator's experience and product quality outputs.

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STRUCTURED ABSTRACT

Purpose – Human-Robot Collaboration (HRC) aims to combine the skills of humans with those of robots, representing a solution to increase the quality and reconfigurability of manufacturing processes. However, to fully exploit the benefits of HRC, human factors, including the operator's psychological well-being, must be considered. To this end, this paper proposes an experimental setting aimed at exploring human-related aspects during HRC.

Design/methodology/approach – In order to explore the effects of prolonged HRC in a repetitive assembly process, a novel experimental setup concerning the production process of a tile cutter is proposed. Each participant is asked to perform three assembly shifts: two in collaborative mode with cobot support and one in manual mode. The response variables collected in the study include the quality of the interaction performed, workload, affective state of the operator and physiological indicators of stress (heart rate variability and electrodermal activity). Process defectiveness is also tracked.

Findings – Preliminary results show that HRC sessions tend to generate more stress than manual assembly sessions. However, increasing familiarity with the collaborative task tends to reduce this effect. These results are confirmed by both subjective and physiological responses.

Research limitations/implications – The evidence for the results found is limited by the number of participants involved. An experimental campaign with a larger number of participants is needed to confirm the preliminary findings.

Originality/value – This paper proposes a novel experimental study aimed at recreating a work shift in a collaborative assembly workstation of a production process. This experimental setting draws attention to the need to investigate the implications of prolonged HRC. In addition, a non-invasive biosensor is implemented to investigate the state of humans during HRC.

Keywords: Human-robot collaboration, Industry 5.0, User experience, Assembly, Manufacturing.

Paper type: Research paper

INTRODUTION

Human-Robot Collaboration (HRC) represents a solution to increase the quality, flexibility and reconfigurability of manufacturing processes (Vicentini, 2020). HRC aims to combine the skills of humans with those of robots, while also enabling physical interaction in the industrial environment (Gervasi, Mastrogiacomo, *et al.*, 2020; ISO/TS 15066:2016, 2016).

In order to effectively implement HRC is important to address the problem with an holistic view, considering both technical and human-related aspects (Gervasi, Digiaro, *et al.*, 2020; Gervasi, Mastrogiacomo, *et al.*, 2020). Over the years, the focus on human factors is becoming increasingly important (Gervasi *et al.*, 2021; Gualtieri *et al.*, 2021; Vicentini, 2020). With the recent introduction of the Industry 5.0 concept, the need to make industry human-centered has been outlined ("Industry 5.0", 2021). Human factors must be taken into account to enhance the process quality. In HRC, humans are continuously exposed to close interaction with a robotic system, resulting in possible stressful and uncomfortable situations (McColl *et al.*, 2016; Xu *et al.*, 2015; Young *et al.*, 2015). These kinds of situations can undermine the quality of production process leading to the potential generation of defects.

In order to best support the operator's well-being and improve the interaction, it is necessary to first understand the operator's psychophysical state during HRC. To investigate these aspects, feedback from classic self-assessment tools (e.g., questionnaires) is often analysed. However, such tools do not provide real-time information on the state of the operator. The introduction of physiological measures makes it possible to compensate for this limitation, while also obtaining more objective measures that can even reveal a person's unconscious states or reactions (Argyle *et al.*, 2021; Charles and Nixon, 2019).

Some previous works have focused on evaluating the operator's state in various HRC settings (Arai *et al.*, 2010; Kühnlenz *et al.*, 2018; Kulić and Croft, 2007), however studies on exploring the human's state in a prolonged interaction with a cobot in a manufacturing context are lacking. The objective of this paper is to propose an experimental setting aimed at simulating a prolonged interaction with a cobot during a repetitive assembly process. The main novel elements proposed in this study are the following:

(i) the exploration of the operator state during entire work shifts though the analysis of both subjective and physiological responses, with particular attention towards stress and workload;

(ii) the observation of process defects that can occur during prolonged HRC;

(iii) comparison of operator state between manual and HRC assembly work shifts.

The paper is organized as follows. In the next section, a review of the literature on the user experience in HRC is provided, with particular focus on the implementation of physiological measures. Next, the research methodology is provided, describing in detail the experimental setting, the equipment and materials used, and the experimental procedure. Afterwards, preliminary results of the experimental setting implementation are presented and discussed. Finally, the concluding section explores limitations and future research directions.

LITERATURE REVIEW

HRC is a paradigm characterized by several aspects, both related to the robotic system and humans (Gervasi, Mastrogiacomo, *et al.*, 2020). The introduction of collaborative robots has allowed physical interaction with people, removing barriers between the human and robot workspace. However, the removal of these barriers also introduced new potential hazards to humans, requiring an evolution of safety standards. The introduction of ISO 10218-1 and ISO 10218-2 provided guidelines on workspace design and implementation of industrial robots, identifying a list of safety hazards. The subsequent ISO/TS 15066 expanded the possibilities of HRC, allowing for the implementation of higher levels of robot autonomy in close proximity to humans.

In order to fully exploit the potential of HRC, a careful planning of the interaction is also necessary. Wang *et al.* (2019) highlighted the need for intelligent and accessible collaborative system, introducing the concept of symbiotic HRC. HRC should allow the communication through natural modes, offer an easy and intuitive programming environment to instruct the cobot, and be more immersive through the use of wearable devices (e.g., AR glasses). Inkulu *et al.* (2021) provided a review on HRC, highlighting some main challenges and opportunities. Natural modes of communication (e.g., gestures and voice) allow intuitive interaction with robots and potentially reduce idle time, but these recognition methods need to be made more robust. Power force limiting techniques are useful to efficiently collaborate with low-payload robot, however they may be not suitable for high-payload and high-speed robots which requires the implementation of additional flexible safety methods to allow collaboration with humans. More research is also needed on advanced adaptive robot systems to enhance a greater reconfigurability of production processes and reduce potential production downtime.

Recently, increased attention has been focused on human factors involved in HRC. Khalid *et al.* (2016) presented an approach for the development of safe and cyber-secure HRC in the domain of heavy payload industrial robots. Potential hazards to be taken into account were identified, including physical and mental strain due to robot behavior or collaborative task. Galin and Meshcheryakov (2020) focused on how to efficiently implement HRC, leading to the identification of the influencing factors for both cobots and humans. The perception of the robot by the human and emotional and cognitive aspects were found influential for the effectiveness of HRC.

In order to better understand and support the operator during HRC, cognitive and psycho-physical aspects should also be taken into account. Concepts like mental workload, stress, demand, strain and fatigue have been widely discussed in literature, being particularly interesting for the manufacturing context (Gawron, 2008; Wickens, 2008; Young *et al.*, 2015). Assessment of these constructs is often performed through self-reporting tools, such as the NASA-TLX (Hart and Staveland, 1988) and the Subjective Workload Assessment Technique (SWAT) (Reid and Nygren, 1988). However, this kind of tools are poorly suited to continuous monitoring in naturalistic settings, such as production lines (Marinescu *et al.*, 2018). In order to overcome these limitations, in recent years there has been an increasing focus on the implementation physiological measures for the comprehension of the operator's state (Argyle *et al.*, 2021; Bradley and Lang, 1994). So far, different works on this topic have been presented, however only few of them are focused on industrial HRC. Kulić and Croft (2007) evaluated the impact of an industrial robot motion on subjective and physiological responses (i.e., Heart Rate Variability (HRV) and ElectroDermal Activity (EDA)) with various trajectory types presented to human participants. Results revealed an increased mental stress for fast and closely passing movements, but the scenario was static in terms of interaction with the robot. Arai *et al.* (2010) conducted a similar study with an industrial manipulator, evaluating the impact of robot movement at different speeds and distances from the operator on EDA. However, also in this scenario, participants were not actively involved in the interaction with the robot. Kühnlenz *et al.* (2018) studied the impact of different trajectory profiles of a standard industrial robot on users' mental stress, assessed through HRV and EDA. Although the participant was actively involved in the task compared to other studies, there was still limited interaction with the robot.

RESEARCH METODOLOGHY

In the present study, a collaborative assembly task has been designed and implemented within the "Mind 4 Lab" (Manufacturing Industry 4.0 Laboratory) at "Politecnico di Torino" to investigate user experience, operator affective state, workload and stress in prolonged industrial HRC. The collaborative task consists in assembling a tile cutter and has been designed to recreate a typical workstation of a production cycle in an industrial context using the cobot UR3e with a collaborative gripper (

Figure 1). In order to reproduce typical working conditions of an industrial context, a set of 4-hour shifts have been implemented. Each operator is asked to perform three assembly shifts: two in collaborative mode with cobot support and one in manual mode.

Figure 1 - Collaborative robot UR3e (Mind 4 Lab, Politecnico di Torino-DIGEP).

Experimental setup

The task considered in this study concerns the assembly of a tile cutter (Figure 2). Figure 3 shows the ten components of the tile cutter and the five bolts with their respective identifiers. Before beginning the assembly task, the components are arranged on a tray as shown in Figure 4 and then the tray is placed in the work area (Figure 5). The collaborative task lasts approximately 252s, leading to the production of approximately 50 tile cutters in a 4-hour shift.

Figure 2 - Final assembly of the tile cutter (44 x 14 x 9 cm).

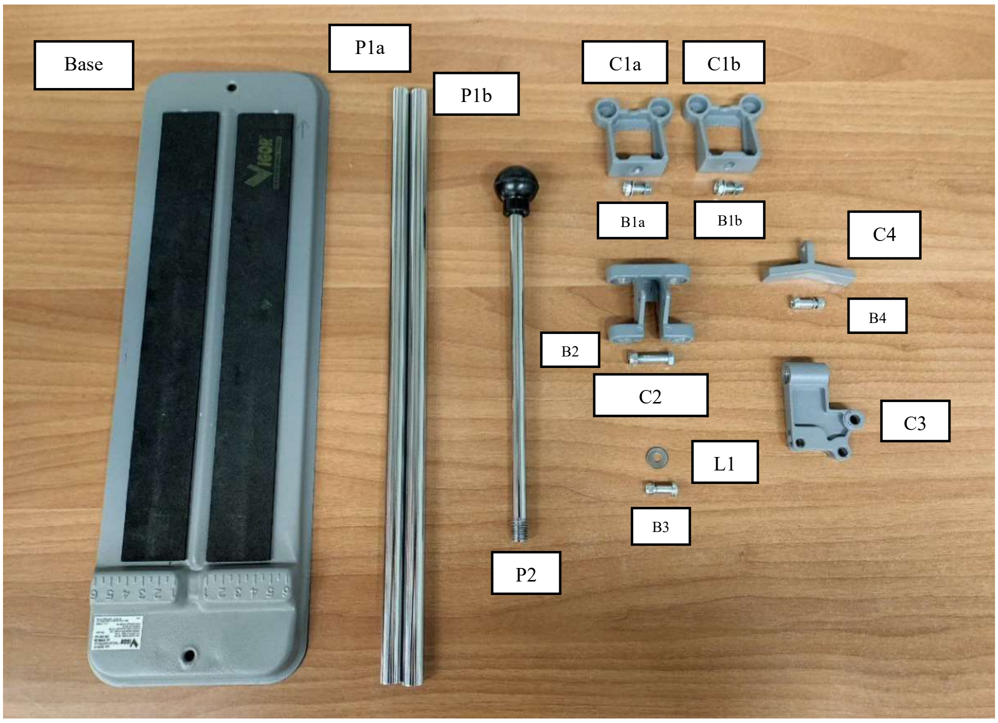


Figure 3 - Tile cutter components and bolts with their respective identifiers.

Table 1 - List of the tile cutter components with their respective identifiers.

Identifier	Component
Base	Base plate of the tile cutter.
C1a	Support for the rails of the tile cutter.
C1b	Support for the rails of the tile cutter.
B1a	Bolt for fixing the rail support to the base plate.
B1b	Bolt for fixing the rail support to the base plate.
C2	Joint component between the rails and the cutting mechanism.
B2	Bolt for joining C2 with C3.
C3	Component of the cutting mechanism.
L1	Washer blade to cut the tile.
B3	Bolt for joining the washer blade with C3.
C4	Component to break the tile.
B4	Bolt for joining C3 with C4.
P1a	Rail rod of the tile cutter.
P1b	Rail rod of the tile cutter.
P2	Handle of the tile cutter.

Figure 4 - Tray with workpieces of the tile cutter.

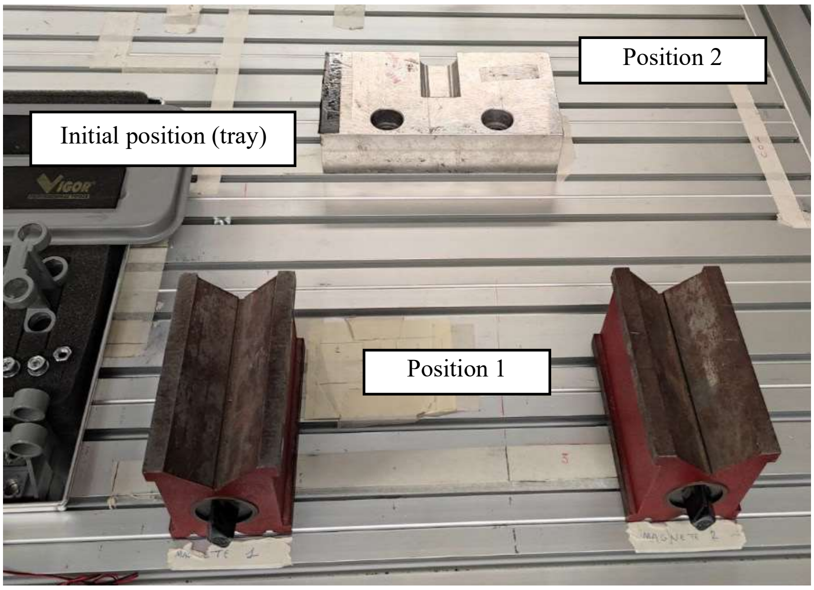


Figure 5 - Work area with reference positions used during the collaborative assembly task.

Table 2 contains the list of operations of the collaborative assembly task, which can be decomposed in four main phases:

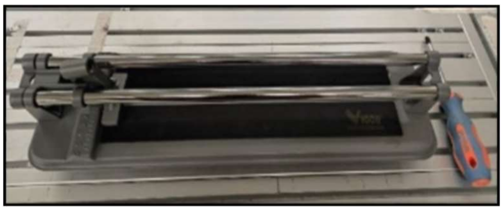
Phase 1. In the first phase, the cobot brings the base of the tile cutter closer to the operator, placing it in the assembly area, and then the operator assembles the two side supports. When the operation is finished, the cobot moves the base with the supports out of the assembly area.

Phase 2. In the second phase, the operator assembles the cutting mechanism with the support of the cobot, which holds the main component in an ergonomic position.

Phase 3. In the third phase, the cobot brings the base with supports back to the assembly area and then the operator assembles the cutting mechanism using the rods.

Phase 4. In the last phase, the operator screws the handle to the cutting mechanism, completing the assembly, and finally the cobot moves the tile cutter onto the tray.

Table 2 - Operation list of the tile cutter assembly task.

Phase	Operation	Allocation	Estimated time (s)
Phase 1: Assembling the base holders (Assembly A1). 	Op1: Moving the Base from the tray to assembly area (Position 1).	Cobot	9s
	Op2: Assembling components C1a and C1b to either side of the Base. Screwing with soft tightening of bolts B1a and B2b (Assembly A1).	Human	44s
	Op3: Moving assembly A1 out of the assembly area (Position 2).	Cobot	4s
Phase 2: Assembling the cutting mechanism (Assembly A4). 	Op4: Moving component C2 to assembly area (Position 1).	Cobot	7s
	Op5: Assembling component C3 with component C2 via bolt B2 (Assembly A2).	Human	50s
	Op6: 180° rotation of assembly A2.	Cobot	3s
	Op7: Assembling blade L1 with component C3 via bolt B3 (Assembly A3).	Human	24s
	Op8: Assembling component C4 with component C3 via bolt B4 (Assembly A4).	Human	35s
	Op9: Moving assembly A4 to the tray (Initial position).	Cobot	7s
Phase 3: Joining the cutting mechanism with the base (Assembly A6). 	Op10: Moving assembly A2 to assembly area (Position 1).	Cobot	9s
	Op11: Moving assembly A4 to assembly area (Position 1).	Human	2s
	Op12: Inserting rods P1a and P2b into holders of assembly A4 (Assembly A5).	Human	7s

	Op13: Inserting the assembly A5 into the holders of components C1a and C1b of assembly A1.	Human	14s
	Op14: Tightening the bolts B1a and B1b (Assembly A6).	Human	13s
Phase 4: Completing the tile cutter (Assembly A7). 	Op15: Screwing rod P2 into the holder of component C3 of assembly A6 (Assembly A7).	Human	13s
	Op16: Moving assembly A7 to the tray.	Cobot	11s

Equipment and materials

In order to collect the operator's feedback on his experience during the various experimental sessions, a set of self-reporting tools have been implemented. In addition to an initial questionnaire aimed at collecting demographics, the self-reporting tools considered include questionnaires on the perceived quality of interaction with the cobot, perceived workload, and affective state.

The questionnaire on interaction quality (Table 3) is based on Baraglia *et al.* (2016) and Hoffman (2019). The questionnaire is composed of 7 items, which collect participant's perception of robot helpfulness, interaction safety and naturalness, team efficiency and fluency, comfort, and robot trustworthiness:

Q1. Robot helpfulness represents how helpful the robot is in accomplishing a certain task.
Q2. Interaction safety refers to how safe the HRC is perceived.
Q3. Interaction naturalness concerns the easiness of the interaction with the robot.
Q4. Team efficiency represents how efficient the collaboration is.
Q5. Team fluency refers to the level of coordination during the collaborative task.
Q6. Comfort represents how at ease a person feels during HRC.
Q7. Robot trustworthiness represents how reliable the robot is perceived to be during HRC.

Each item is evaluated on a 7-point Likert-scale (from "strongly disagree" to "strongly agree") (Franceschini *et al.*, 2007).

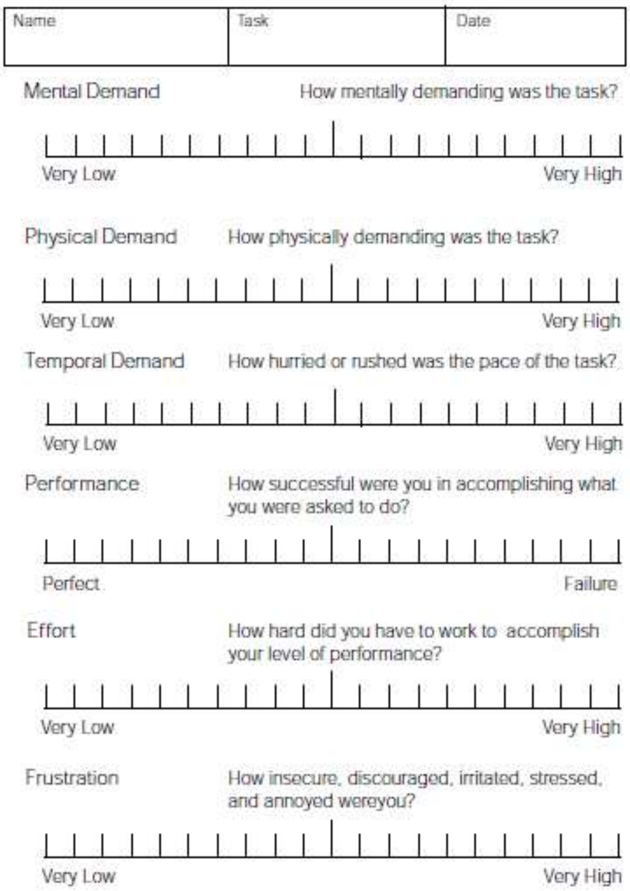
Table 3 - Questionnaire for interaction quality.

Item No.	Questionnaire item	Dimension
Q1	The robot was helpful in accomplishing the task.	Robot helpfulness
Q2	I felt the interaction was not safe.	Interaction unsafety
Q3	The collaboration felt natural.	Interaction naturalness
Q4	The robot and I worked efficiently together.	Team efficiency
Q5	The robot and I worked fluently together.	Team fluency
Q6	I felt uncomfortable with the robot.	Discomfort
Q7	The robot was trustworthy.	Robot trustworthiness

The commonly-used NASA-TLX (Hart and Staveland, 1988) has been implemented to assess operator workload (Figure 6). It decomposes the workload in six dimensions:

- Mental demand, which represents the amount of mental and perceptual activity required by the task.
- Physical demand, referring to the amount of physical activity required by the task.
- Temporal demand, which concerns how much time pressure is perceived due to the task pace.
- Performance, referring to the degree of success and satisfaction with the results obtained in performing the task.
- Effort, which refers to how hard one had to work (mentally and physically) to achieve a certain level of performance.
- Frustration, representing the amount of irritation, stress, and annoyance felt during the task.

Each dimension is rated on a 0-100 scale with 5-point steps (see Figure 6), and the final workload score is obtained by averaging the dimension ratings.



Name	Task	Date

Mental Demand — How mentally demanding was the task?
Very Low — Very High

Physical Demand — How physically demanding was the task?
Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?
Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?
Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?
Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?
Very Low — Very High

Figure 6 - NASA-TLX questionnaire (Hart and Staveland, 1988).

The SAM (Bradley and Lang, 1994; Lang, 1980) is a widely used image-based assessment tool to measure the affective reaction to a certain situation or event. It is based on the Pleasure-Arousal-Dominance (PAD) model, which represents affective states on three dimensions:

- Valence (or pleasure), which describes the positivity or negativity of an elicited emotion (e.g., fear, anger, or boredom tend to be negative emotions, whereas relaxation or joy tend to be positive emotions).
- Arousal, which refers to how excited a person is, regardless of whether the excitement derives from a positive or negative emotion (e.g., boredom and relaxation are characterized by low arousal, whereas euphoria, fear, or anger tend to have a high arousal).
- Dominance, which describes how much one feels in control of a situation, i.e., a feeling of control and influence over one's surroundings and others (e.g., fear or anxiety are usually characterized by low dominance, while relaxation or anger by a high dominance).

Figure 7 shows the original 9-point scale SAM, which has been used in the study to collect affective state of the participants during the experimental sessions.

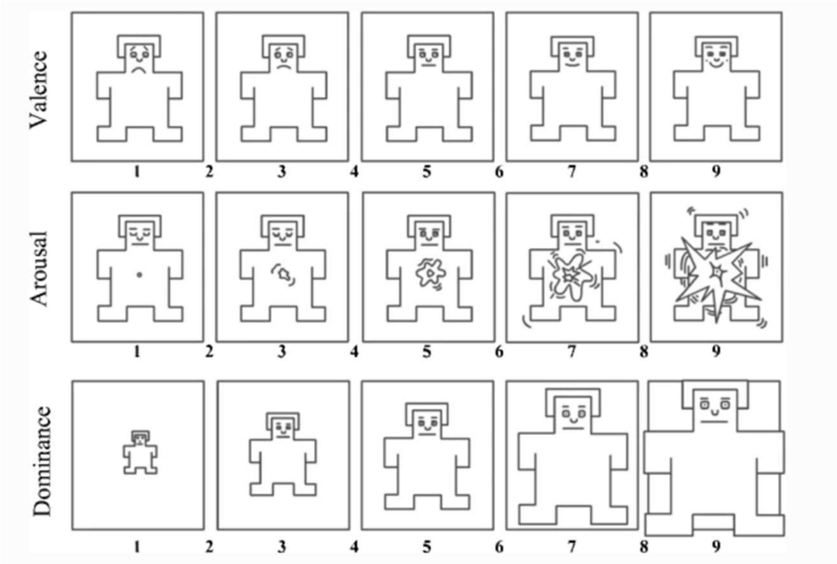


Figure 7 - Self-Assessment Manikin (SAM) with its three dimensions for affective state: valence, arousal, and dominance (Bradley and Lang, 1994).

In addition to classical self-reporting tools, the Empatica E4 wristband (Figure 8) has also been used to obtain a measure of physiological stress. This non-invasive biosensor allows to collect EDA data at 4Hz, heart data through Photopletismogram (PPG) at 64Hz, and 3-axis accelerometer data at 32Hz. The device also provides the heart rate NN-intervals. PPG and EDA data are used as arousal and stress indicators, evaluating HRV and average Skin Conductance Response (SCR) in each experimental session.

Figure 8 - The Empatica E4 biosensor (“Empatica”).

EDA data are processed using the MATLAB-based software “Ledalab”. Continuous Decomposition Analysis (CDA) (Benedek and Kaernbach, 2010) is performed to decompose the EDA signal into continuous signals of phasic and tonic activity. Tonic activity refers to long-term fluctuations in EDA that are not specifically elicited by external stimuli and is best characterized by changes in Skin

Conductance Level (SCL). In contrast, 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 Responses (SCRs) (i.e., amplitude changes from the SCL to a peak of the response) can be identified. In this study, the average SCR is used as an arousal and stress indicator in each experimental session. From heart data, HRV measures can be derived and used as an arousal and stress indicator. In this study, the Root Mean Square of Successive Differences between adjacent NN-intervals (RMSSD) was considered as measure of HRV due to its common use (Kim *et al.*, 2018; Young *et al.*, 2015).

Experimental procedure

Figure 9 reports the flowchart of an experimental session. After explaining the objectives of the study and its procedure, the participant is seated in the experiment location and the various steps of the assembly task are presented. Afterwards, the Empatica E4 biosensor is firmly placed on the participant's left wrist and 15 minutes are waited for the electrodes to adhere well to the skin and to obtain reliable EDA data. The participant is asked to fill the initial questionnaire, which includes demographics. Next, the participant is invited to relax and remain still to record 2 minutes of physiological signals at rest (i.e., the baseline of the physiological signals). After this phase is completed, the participant begins the 4-hour shift of the assembly task. In order to simulate realistic working conditions, within the shift a 10-minute break is provided every two hours of work. During the work shift, another operator supervises each session by taking note of occurring process defects. At the end of the work shift, the participant reports his affective state during the task through the SAM, fills the NASA-TLX and the questionnaire on the quality of interaction with the cobot. At the conclusion of the session, the participant is asked for general unstructured feedback about the overall experience. Each participant performs three assembly shifts: two in collaborative mode with cobot support and one in manual mode. In manual assembly, the interaction quality questionnaire is not administered.

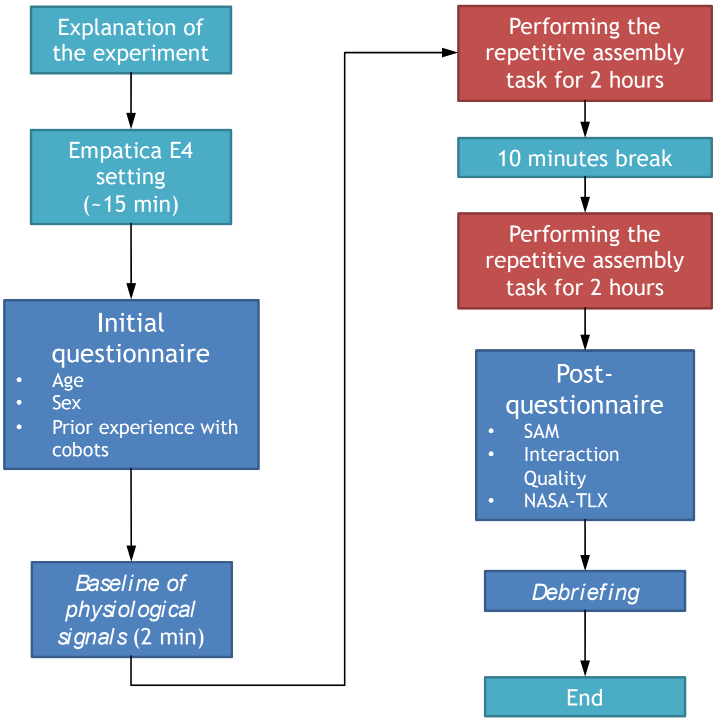


Figure 9 - Flow-chart of the experimental session (4-hour shift).

PRELIMINARY RESULTS

In order to test the proposed experimental setting, a participant with no previous experience interacting with a cobot was involved. The participant performed two collaborative assembly sessions and one manual assembly session. This allowed us to compare potential differences in response variables between two HRC assembly sessions and between a manual assembly session with an HRC one. Preliminary results obtained are reported in the following subsections.

Prolonged HRC interaction

In order to explore the effects on prolonged HRC assembly sessions, two 4-hour shifts has been carried out. Figure 10 shows the scores obtained on the various dimensions of the interaction quality questionnaire. Interestingly, in the first session the interaction with the cobot was not perceived as particularly fluid and natural (3-"somewhat disagree"), however the perception of these aspects improved significantly at the end of the second session leading to a positive evaluation. This result denotes a learning effect intrinsic to repetitive interactions with the cobot.

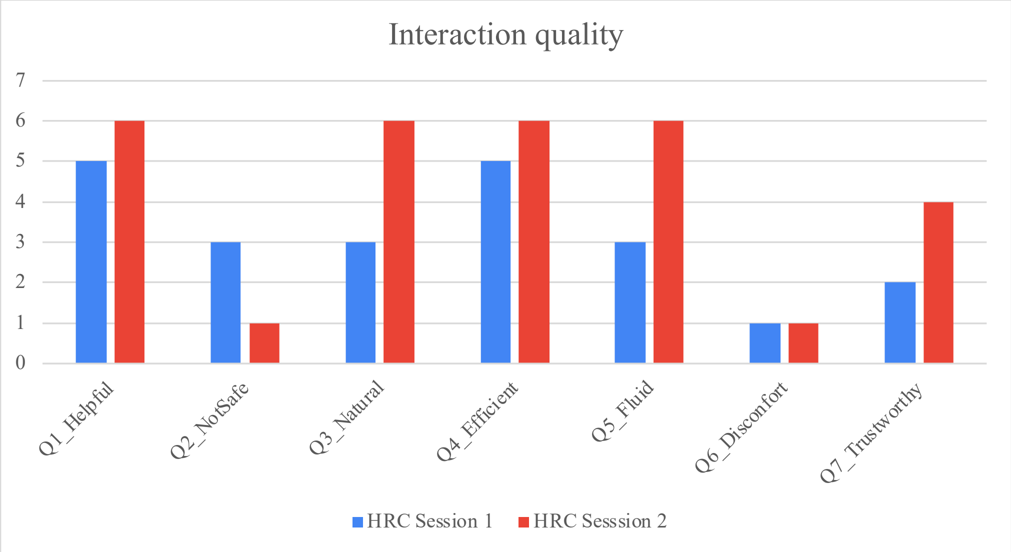


Figure 10 - Comparison of interaction quality ratings between the first HRC assembly session and the second one.

Regarding the perceived workload, from Figure 11 it can be noticed a decrease from the first HRC session to the second one. This is mainly due to a significant decrease in the *Effort* and *Frustration* dimensions, highlighting a greater familiarity with the collaborative task. A further decrease in perceived workload is present in the manual assembly session. In this case, the absence of the robot increased the perception of physical effort, however mental effort and frustration decreased significantly. This initial finding highlights a possible psychological influence of the cobot on operator stress.

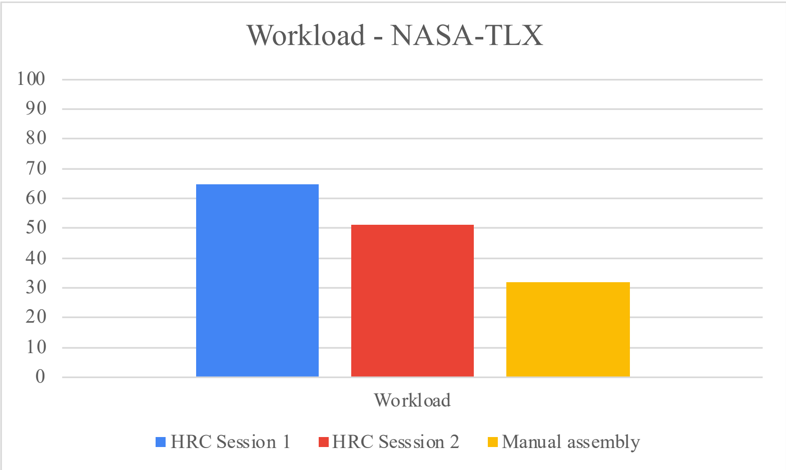


Figure 11 - Comparison of workload scores of NASA-TLX between the three experimental sessions.

Figure 12 shows the affective state during the three sessions. An interesting decrease in arousal can be seen between the first HRC session and the second session which suggests a potential decrease in stress. A further decrease in arousal can be observed in the manual assembly session. In addition, the absence of the cobot also led to a greater sense of dominance of the situation by the operator.

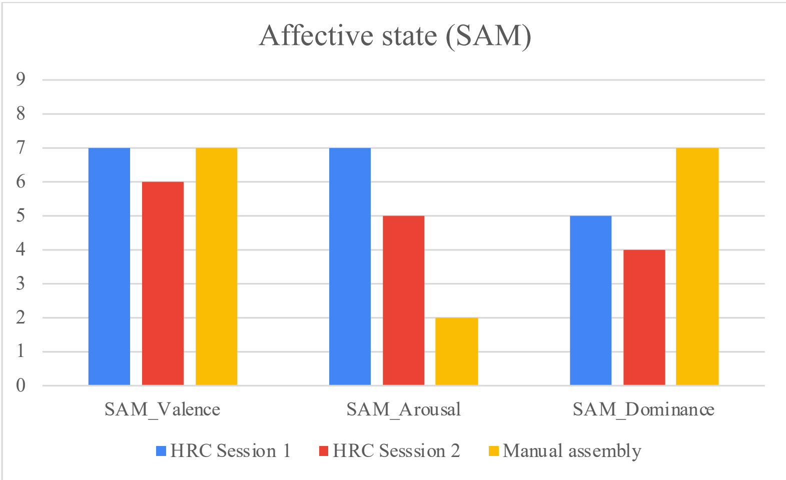


Figure 12 - Comparison of SAM dimensions ratings between the three experimental sessions.

A confirmation of these effects can be found in the physiological responses (HRV and EDA). From the Figure 13 a similar trend to that of arousal can be seen for HRV and average of SCRs. Lower heart rate variability (i.e., lower RMSSD) is associated with higher operator stress, while a higher average of SCRs is associated with higher operator stress. A consistent decrease in stress can be seen between the first and second HRC sessions, highlighting the importance of familiarity with the collaborative task. However, a further decrease in stress can be observed in the manual assembly session, due to the absence of the cobot in the task.

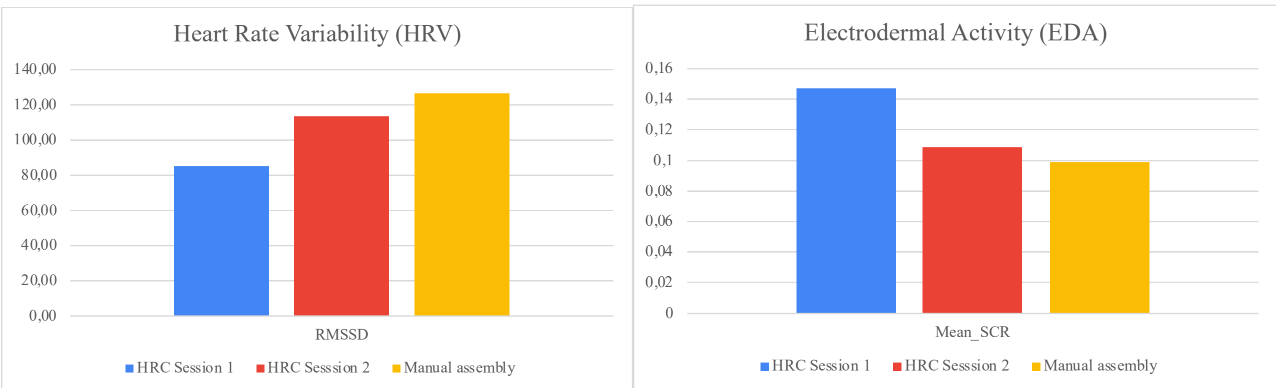


Figure 13 - Comparison of physiological stress indicators (RMSSD for HRV and average of SCRs for EDA) in the three experimental sessions.

Figure 14 shows an example of a 2-hour EDA signal during the first HRC session. As can be seen, the actions of the robot have caused an instantaneous increase in EDA and this effect has sometimes persisted over time with a general increase in the trend of the signal. This increase in trend is also indicative of an increase in cognitive effort on the part of the operator. Such situations were found especially in HRC sessions.

Figure 15 illustrates the process defectiveness detected during the various experimental sessions. Examples of process defects include falling tools, components, screws or nuts, and incorrect picking or assembly of components with self-correction of the defect. During the first HRC session, the highest number of defects were observed, mainly due to falling parts or incorrect assembly of components. The lowest number of defects was observed in the manual assembly session. It is possible to note that most of the defects were observed in the presence of greater operator's stress (Figure 13).

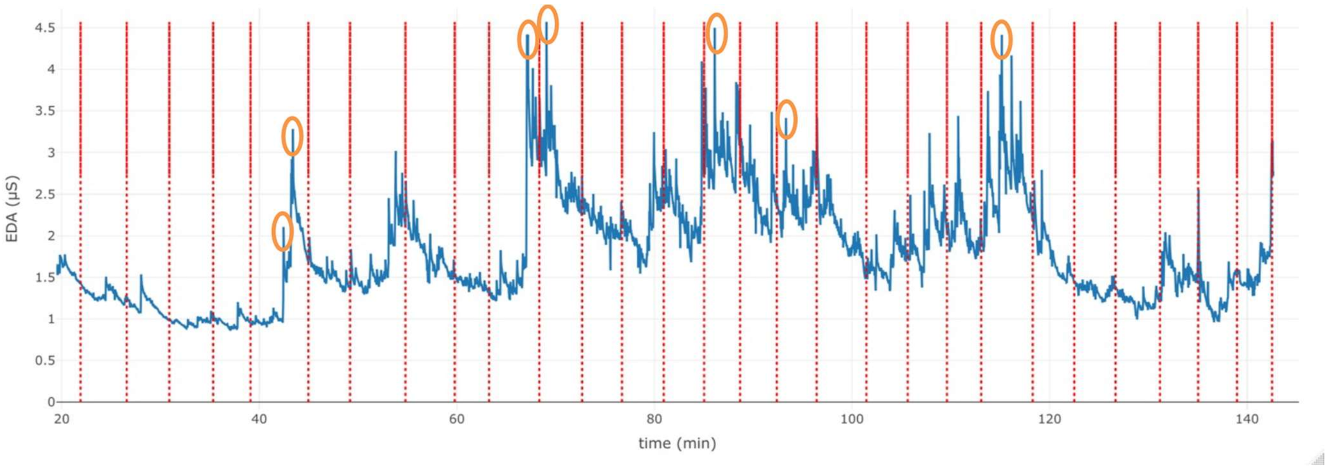


Figure 14 - Example of a 2-hour EDA signal during an HRC session. The peaks highlighted (SCRs) can be attributed to actions of the cobot that generated stress in the operator. Dashed vertical lines separate the various assembly tasks of the tile cutter.

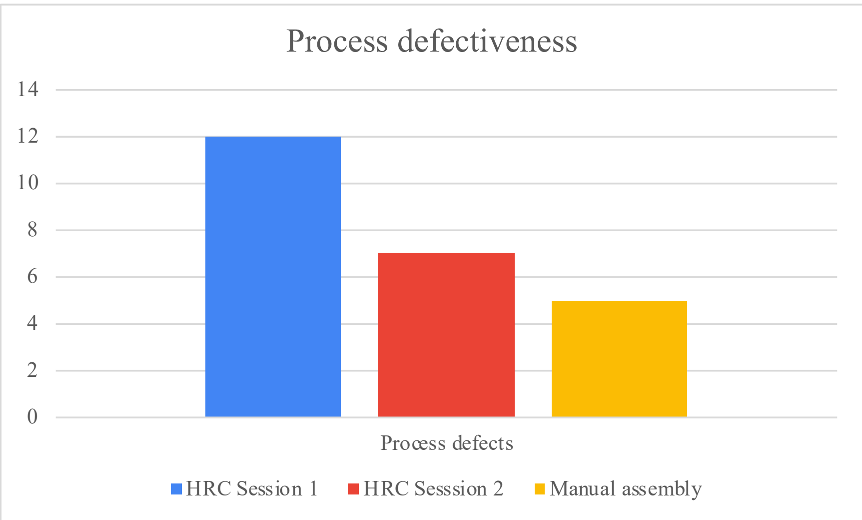


Figure 15 - Comparison of process defectiveness between the three experimental sessions.

DISCUSSION AND CONCLUSIONS

In this paper, a novel experimental setting is proposed in order to reproduce a set of 4-hour work shifts of a repetitive collaborative assembly task. Through the implementation of this setting, it is possible to conduct studies on the effects of a prolonged interaction with a cobot on human state and process defect in a manufacturing context. Moreover, thanks to the integration of non-invasive biosensors, it is possible to obtain objective information on the psychophysical state of the operator without interfering with the task. The objective is to investigate operator experience and stress in relation to HRC in repetitive tasks, as well as defect generation. As highlighted in the concept of Industry 5.0, the human being is an integral part of production processes and the improvement of his well-being and enhancement has significant implications on the quality of processes and products. The preliminary results obtained show the importance of familiarity with the collaborative task in order to preserve human well-being and improve the quality of interaction. However, it has also emerged that interaction with the cobot can introduce more cognitive stress than a classical manual setting, although it lightens the physical workload of the operator. This first result highlights the importance of also taking into account psycho-cognitive aspects when introducing a collaborative robotic system in a workstation in order to obtain the maximum benefit from HRC. It could also be noted that increased operator stress resulted in more process defects, however this phenomenon requires further investigation.

A limitation of the proposed experimental setting is represented by the time resources required for its implementation; however, they prove necessary in longitudinal studies, especially when investigating long-term effects of HRC. A limitation of this study is the preliminary nature of the reported results. Future studies will focus on expanding our findings by increasing the sample of participants and further exploring the phenomena involved.

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REFERENCES

Arai, T., Kato, R. and Fujita, M. (2010), "Assessment of operator stress induced by robot collaboration in assembly", *CIRP Annals*, Vol. 59 No. 1, pp. 5–8.

Argyle, E.M., Marinescu, A., Wilson, M.L., Lawson, G. and Sharples, S. (2021), "Physiological indicators of task demand, fatigue, and cognition in future digital manufacturing environments", *International Journal of Human-Computer Studies*, Vol. 145, p. 102522.

Baraglia, J., Cakmak, M., Nagai, Y., Rao, R. and Asada, M. (2016), "Initiative in robot assistance during collaborative task execution", *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pp. 67–74.

Benedek, M. and Kaernbach, C. (2010), "A continuous measure of phasic electrodermal activity", *Journal of Neuroscience Methods*, Vol. 190 No. 1, pp. 80–91.

Bradley, M.M. and Lang, P.J. (1994), "Measuring emotion: The self-assessment manikin and the semantic differential", *Journal of Behavior Therapy and Experimental Psychiatry*, Vol. 25 No. 1, pp. 49–59.

Charles, R.L. and Nixon, J. (2019), "Measuring mental workload using physiological measures: A systematic review", *Applied Ergonomics*, Vol. 74, pp. 221–232.

"Empatica". *Empatica*, available at: https://www.empatica.com/research/e4 (accessed 13 April 2022).

Franceschini, F., Galetto, M. and Maisano, D. (2007), *Management by Measurement*, Springer, Berlin, Heidelberg, available at:https://doi.org/10.1007/978-3-540-73212-9.

Galin, R.R. and Meshcheryakov, R.V. (2020), "Human-Robot Interaction Efficiency and Human-Robot Collaboration", in Kravets, A.G. (Ed.), *Robotics: Industry 4.0 Issues & New Intelligent Control Paradigms*, Springer International Publishing, Cham, pp. 55–63.

Gawron, V.J. (2008), *Human Performance, Workload, and Situational Awareness Measures Handbook*, 2nd ed., CRC Press, Boca Raton, available at:https://doi.org/10.1201/9781420064506.

Gervasi, R., Digiaro, F., Mastrogiacomo, L., Maisano, D. and Franceschini, F. (2020), "Comparing quality profiles in Human-Robot Collaboration: empirical evidence in the automotive sector", *Proceedings Book of the 4th International Conference on Quality Engineering and Management*, University of Minho, Portugal, pp. 89–114.

Gervasi, R., Mastrogiacomo, L. and Franceschini, F. (2020), "A conceptual framework to evaluate human-robot collaboration", *The International Journal of Advanced Manufacturing Technology*, Vol. 108 No. 3, pp. 841–865.

Gervasi, R., Mastrogiacomo, L., Maisano, D.A., Antonelli, D. and Franceschini, F. (2021), "A structured methodology to support human–robot collaboration configuration choice", *Production Engineering*, available at:https://doi.org/10.1007/s11740-021-01088-6.

Gualtieri, L., Rauch, E. and Vidoni, R. (2021), "Emerging research fields in safety and ergonomics in industrial collaborative robotics: A systematic literature review", *Robotics and Computer-Integrated Manufacturing*, Vol. 67, p. 101998.

Hart, S.G. and Staveland, L.E. (1988), "Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research", in Hancock, P.A. and Meshkati, N. (Eds.), *Advances in Psychology*, Vol. 52, North-Holland, pp. 139–183.

Hoffman, G. (2019), "Evaluating Fluency in Human–Robot Collaboration", *IEEE Transactions on Human-Machine Systems*, presented at the IEEE Transactions on Human-Machine Systems, Vol. 49 No. 3, pp. 209–218.

"Industry 5.0". *European Commission - European Commission*, Text, , available at: https://ec.europa.eu/info/research-and-innovation/research-area/industrial-research-and-innovation/industry-50_en (accessed 20 August 2021).

Inkulu, A.K., Bahubalendruni, M.V.A.R., Dara, A. and K., S. (2021), "Challenges and opportunities in human robot collaboration context of Industry 4.0 - a state of the art review", *Industrial Robot: The International Journal of Robotics Research and Application*, Vol. ahead-of-print No. ahead-of-print, available at:https://doi.org/10.1108/IR-04-2021-0077.

ISO 10218-2:2011. (2011), *Robots and Robotic Devices – Safety Requirements for Industrial Robots – Part 2: Robot Systems and Integration*, Standard No. ISO 10218-2:2011, International Organization for Standardization, Geneva, CH, available at: https://www.iso.org/standard/41571.html.

ISO/TS 15066:2016. (2016), *Robots and Robotic Devices – Collaborative Robots*, Standard No. ISO/TS 15066:2016, International Organization for Standardization, Geneva, CH, available

at: https://www.iso.org/standard/62996.html.
Khalid, A., Kirisci, P., Ghrairi, Z., Thoben, K.-D. and Pannek, J. (2016), "A methodology to develop collaborative robotic cyber physical systems for production environments", *Logistics Research*, Vol. 9 No. 1, p. 23.
Kim, H.-G., Cheon, E.-J., Bai, D.-S., Lee, Y.H. and Koo, B.-H. (2018), "Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature", *Psychiatry Investigation*, Vol. 15 No. 3, pp. 235–245.
Kühnlenz, B., Erhart, M., Kainert, M., Wang, Z.-Q., Wilm, J. and Kühnlenz, K. (2018), "Impact of trajectory profiles on user stress in close human-robot interaction", *at - Automatisierungstechnik*, De Gruyter, Vol. 66 No. 6, pp. 483–491.
Kulić, D. and Croft, E. (2007), "Physiological and subjective responses to articulated robot motion", *Robotica*, Cambridge University Press, Vol. 25 No. 1, pp. 13–27.
Lang, P.J. (1980), "Behavioral treatment and bio-behavioral assessment: Computer applications", in Sidowski, J.B., Johnson, J.H. and Williams, T.A. (Eds.), *Technology in Mental Health Care Delivery Systems*, Norwood, NJ: Ablex, pp. 119–137.
"Ledalab". available at: http://www.ledalab.de/ (accessed 23 June 2021).
Marinescu, A.C., Sharples, S., Ritchie, A.C., Sánchez López, T., McDowell, M. and Morvan, H.P. (2018), "Physiological Parameter Response to Variation of Mental Workload", *Human Factors*, SAGE Publications Inc, Vol. 60 No. 1, pp. 31–56.
McColl, D., Hong, A., Hatakeyama, N., Nejat, G. and Benhabib, B. (2016), "A Survey of Autonomous Human Affect Detection Methods for Social Robots Engaged in Natural HRI", *Journal of Intelligent & Robotic Systems*, Vol. 82 No. 1, pp. 101–133.
Reid, G.B. and Nygren, T.E. (1988), "The Subjective Workload Assessment Technique: A Scaling Procedure for Measuring Mental Workload", in Hancock, P.A. and Meshkati, N. (Eds.), *Advances in Psychology*, Vol. 52, North-Holland, pp. 185–218.
Vicentini, F. (2020), "Collaborative Robotics: A Survey", *Journal of Mechanical Design*, Vol. 143 No. 040802, available at:https://doi.org/10.1115/1.4046238.
Wang, L., Gao, R., Váncza, J., Krüger, J., Wang, X.V., Makris, S. and Chryssolouris, G. (2019), "Symbiotic human-robot collaborative assembly", *CIRP Annals*, Vol. 68 No. 2, pp. 701–726.
Wickens, C.D. (2008), "Multiple Resources and Mental Workload", *Human Factors*, SAGE Publications Inc, Vol. 50 No. 3, pp. 449–455.
Xu, D., Wu, X., Chen, Y.-L. and Xu, Y. (2015), "Online Dynamic Gesture Recognition for Human Robot Interaction", *Journal of Intelligent & Robotic Systems*, Vol. 77 No. 3, pp. 583–596.
Young, M.S., Brookhuis, K.A., Wickens, C.D. and Hancock, P.A. (2015), "State of science: mental workload in ergonomics", *Ergonomics*, Taylor & Francis, Vol. 58 No. 1, pp. 1–17.