Physical and Mental Workload Assessment in Human-Robot Collaboration Workplaces - A Review

Guilherme Deola Borges[1], Andre Cardoso[1], Hatice Gonçalves[1], Ana Colim[1], Paula Carneiro[1], Pedro Arezes[1]

[1] *ALGORITMI Research Centre, School of Engineering, University of Minho, Guimarães, 4800-058, Portugal*

ABSTRACT

Human-Robot Collaboration (HRC) systems are often chosen to improve ergonomics in manual tasks. There are many metrics available to quantify the ergonomic benefits when implementing an HRC. It is important to understand which metrics (ergonomic methods, tests, questionnaires) are being used by researchers in terms of physical and mental workloads assessment. Therefore, this work aimed to review the literature on the subject and to provide key information for further investigations. A literature review was carried out in four databases and the findings were categorized into theoretical surveys and empirical studies from the last five years. Results show the emerging research fields that were identified and analyzed. The metrics used to assess physical and mental workloads were discussed and a new meaning for these results is proposed in the sense of using a global ergonomic risk assessment as input in simulation models.

Keywords: Ergonomics, Human Factors, Risk Assessment, Industry 4.0

INTRODUCTION

Human-Robot Collaboration (HRC) increases in importance due to new developments in industry 4.0. Effective collaboration between humans and robots means a combination of their skills: precision, speed, and fatigue-free operation of the robot; cognitive and sensorimotor of the human. The relevant human factors to the context of the HRC system were compiled by (Rücker *et al.* 2019).

Manufacturing industries sometimes do not successfully implement HRC systems due to a lack of understanding of human and social-related issues (Charalambous *et al.* 2016). In general, greater collaboration induces less physical workload on workers, as some tasks are allocated to the robot. On the other hand, greater collaboration could increase mental strain, although it depends on the level of human trust, robustness, and reliance on the HRC system (Vazquez and Jabi 2019). Physical fatigue is a transient inability of muscles to maintain a load, a decrease in the maximal force that the involved muscles can produce, and develops due to sustained physical activity (Enoka and Duchateau 2008). Mental fatigue is a transient decrease in maximal cognitive performance resulting from prolonged periods of cognitive activity (Marcora *et al.* 2009). In Gualtieri (2021) the literature was reviewed regarding safety and ergonomics in HRC. The present work focuses on revising only ergonomic assessment studies in HRC systems.

METHOD

The current state of the art regarding risk assessment in HRC was organized by synthesizing the empirical studies where physical and mental workloads were considered. We applied the Systematic Search Flow (SSF) method (Ferenhof and Fernandes 2016) because it is based on a systematic and replicable approach. The SSF method includes a research protocol followed by an analysis of all the relevant studies and their synthesis. Therefore, it is characterized by a scientific process that aims to avoid researcher bias.

We used four of the main scientific databases: Scopus, Web of Science, Science Direct, and PubMed. The search contained the following terms and variations: (ergonomics OR 'human factors') AND ('human-robot collaboration' OR HRC OR cobot) AND (assembly OR industry OR manufacture OR production). To be included in this review, the documents needed to be available in English with full-text access in Google Scholar® and Research Gate®.

The databases were accessed on April 10, 2021, and the query was limited to search in the titles, keywords, and abstracts from the last 5 years. In total 415 documents were downloaded and exported to the Mendeley bibliographic referencing software. After excluding the duplicates, the portfolio resulted in 320 full-text documents assessed for eligibility. The inclusion criteria is that the article reports a case study where ergonomic aspects were taken into account in an HRC system. The papers that were considered not relevant or out of scope were excluded by the authors and 67 were considered for a preliminary overview of ergonomic metrics in HRC systems. Finally, 23 papers were included in the portfolio for analysis.

RESULTS AND DISCUSSION

Ergonomic methods for physical assessment can be divided into three categories: self-reports, observational methods, and direct methods (David 2005). Advantages and limitations are described as follows (David 2005): self-reports can be used to collect data on exposure to physical factors using questionnaires, however, results are limited by worker's perceptions and answers; observational methods are widely used to evaluate postures and movements of the workers, however, it requires an ergonomic expert to assess workplace hazard through observation; and direct measurement provides data using sensors (e.g., cameras, wearables) during task execution, however, it is more complex to apply as it often requires to place devices on the worker's body. The selection of ergonomic methods is based on their characteristics, the characteristics of the task, and the nature of the problem (Berlin and Adams 2017). In this literature review, we pursuit papers that applied either technologies for physical ergonomic measurement (Table 1) or NASA Task Load Index (NASA-TLX) questionnaire for measuring mental workload (Table 2). Physical ergonomics is discussed in terms of communication between human and robot as human can wear sensors for motion tracking or the robot is equipped with sensor cameras to capture human intentions. Cognitive ergonomics is subjective, in which mental workload is compared for different groups of workers (age, gender) or different robot configurations (level of collaboration, robot speed).

Physical assessment

Observational methods are well-established tools, however, sensor-based direct measurements are more precise and can be real-time updated. Some softwares embed ergonomic modules based on standard ergonomic assessment worksheets such as RULA, REBA, and EAWS. Table 1 presents the studies that approached technology to qualify and quantify ergonomic risks in HRC workplaces.

Table 1: Studies that used technologies for ergonomic measurement in HRC.

Ref.	Year	Measurement technique	Complement
(Kim *et al.* 2021)	2021	Xsens (REBA) / EMG	Safety
(Ferraguti *et al.* 2020)	2020	ASUS Xtion (RULA)	Questionnaire (usefulness)
(Paletta *et al.* 2020)	2020	EDA (stress)	
(El Makrini *et al.* 2019)	2019	Skeleton joint angles (REBA)	Assembly time
(Kim *et al.* 2019)	2019	Stereo-vision camera	Productivity
(Peternel *et al.* 2019)	2019	Camera with machine learning (fatigue)	
(Parsa *et al.* 2019)	2019	Camera with deep learning (REBA)	
(Lorenzini *et al.* 2019)	2019	Xsens	
(Kim *et al.* 2018)	2018	Xsens / EMG	
(Nguyen *et al.* 2016)	2016	Microsoft Kinetics (EAWS)	

(Thomas *et al.* 2016)	2016	Famos Robotic (DHM)	REBA
(Pini *et al.* 2016)	2016	Delmia V5 (DHM)	Fatigue (RULA / EE)

REBA (Rapid Entire Body Assessment); RULA (Rapid Upper Limb Assessment); EAWS (Ergonomic Assessment Work-Sheet); EE (Energy Expenditure); EMG (Electromyography); EDA (Electrodermal Activity); DHM (Digital Human Modeling). Wearable motion tracking based on inertial sensors: Xsens; Microsoft Kinect; ASUS Xtion.

An important component of the human systems integration plan should be a verification and validation process that provides a clear way to evaluate the success of human systems integration. The human systems integration team should develop a test plan that can easily be incorporated into the systems engineering test plan. The effectiveness and performance of the human in the system need to be validated as part of the overall system. It may seem more attractive to have stand-alone testing for human systems integration to show how the user interacts with controls or displays, how the user performs on a specific task. This methodology can address the performance of the human operator or maintainer concerning the overall system. The most important thing is to develop a close relationship between human systems integration and systems engineering.

- Wearable

Human motion can be captured by wearable sensors to communicate gestures to the robot. (Kim *et al.* 2021) proposed a method to minimize overloading joint torque while considering manipulability. The workers were equipped with Xsens and EMG sensors for motion track and muscle activity. A comparison between six standard and one optimized task configuration was made. Results showed that the optimized configuration presented significantly higher manipulability capacity of the arm, which could positively affect the task production, although the overall joint torque is lower in three of the predefined configurations. (Ferraguti *et al.* 2020) proposes an architecture for an optimal posture, in which the robot is programmed to always offer the human a comfortable position corresponding to a minimum RULA level. The tracking of the human body is performed with ASUS Xtion and the results showed that the strategy optimizes ergonomic posture when executing tasks. (Paletta *et al.* 2020) investigated how cognitive stress affects eye-hand coordination in multi-tasking processes. Measures were made by EDA biosensors (arousal) and eye-tracking glasses. Results demonstrated a high correlation between stress and error. (Lorenzini *et al.* 2019) proposed a fatigue model to estimate the risk in repetitive light-weight tasks. The model takes into account the variability of the load and the individual perception of the fatigue. The whole-body tracking motion sensors (Xsens) process data in real-time to avoid fatigue accumulation by optimizing HRC. (Kim *et al.* 2018) proposed a real-time technique for reducing joint torque in HRC, in which overload alerts the human about consequent injuries. Measurement of the whole-body human motion was made using Xsens. EMG was also used to confirm the reduction of muscular activity. The optimized scenario resulted in less than 40-50% joint torques in the shoulder and elbow.

- Image-based

Sensor cameras are often used to inform the robot about human intentions. (El

Makrini *et al.* 2019) describes a framework for task allocation in HRC gearbox assembly considering human body posture. The human tracking system uses a depth camera-based that assesses the skeleton joint angles provided by the human tracking system. The data are used to calculate REBA manually. It has been concluded that setting the workload limit at the desired level leads to a decrease of 14% in the overall assembly time. (Kim *et al.* 2019) proposes a real-time adaptation in HRC. The task was optimized to human intentions and captured movements by a stereo-vision camera. The results showed a lower overloading effect in all joints compared to the initial configurations, contributing to better ergonomics. (Peternel *et al.* 2019) uses a camera with machine learning techniques and a musculoskeletal model to estimate online the human muscle fatigue. Thus, the robot can switch configuration of task production to facilitate safer and more ergonomic work. (Parsa *et al.* 2019) presents a deep learning system using camera videos to segment human actions. The real-time ergonomic risk is computed based on the skeletal model extracted from the videos and calculates the REBA scores assigned for each action. (Nguyen *et al.* 2016) uses the Microsoft Kinect sensor embedded with EAWS to assess workers' posture and optimize the pose of the workpiece to be processed. When the risk exceeds an acceptable score, the system alerts the worker and suggests a more natural posture. Results show that all postures were critical and after optimization the majority of the postures were acceptable.

- Digital Human Modeling

DHM is a human simulation solution to design and evaluate workstations, worker safety, and system performance. It can embed ergonomic modules based on the ergonomic method such as RULA, REBA, EAWS to identify critical postures and to plan the assistance of a robot. (Thomas *et al.* 2016) shows a concept to implement HRC based on the task-specific movements of the employee that is simulated using DHM in the virtual environment Famos Robotic. HRC system is simulated considering employee's physical constraints combined with REBA to assess postures. (Pini *et al.* 2016) is based on a DHM and simulation of the human body at the platform Delmia V5 to propose a modified model that integrates RULA and Energy Expenditure as ergonomic metrics to calculate fatigue. Results show that implementing HRC unburdens the human operator and increases the overall ergonomic level as the fatigue index drastically dropped.
In summary, different technologies are being applied to assess physical risk in HRC and it is often seen that traditional ergonomic methods are embedded in these softwares.

Cognitive assessment

NASA-TLX is a subjective, multidimensional assessment tool that rates perceived workload to assess a task (NASA 1986). NASA-TLX is divided into six items: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration. A weighting scheme is used to compute an overall workload score. NASA-RTLX is referred to when weighting the items was not considered. Table 2 presents the case studies where NASA-TLX and NASA-RTLX were used to assess cognitive ergonomics in HRC systems. The column labeled as "complement" presents other relevant factors taken into account.

Table 2: Studies that used NASA-TLX in HRC.

Ref.	Year	Cognitive	Complement
(Rossato *et al.* 2021)	2021	NASA-TLX	UX / SUS / TAM
(Hopko *et al.* 2021)	2021	NASA-TLX	SART
(Gervasi *et al.* 2020)	2020	NASA-TLX	EAWS / SUS (trust)
(Pantano *et al.* 2020)	2020	NASA-TLX	Safety
(Sadrfaridpour and Wang 2018)	2018	NASA-TLX	Cycle time Questionnaire (trust, satisfaction)
(Materna *et al.* 2018)	2018	NASA-TLX	SUS (mental demand)
(Rahman and Wang 2018)	2018	NASA-RTLX	Productivity, trust, quality
(Koppenborg *et al.* 2017)	2017	NASA-TLX	Cycle time / Error rates Questionnaires (risk, anxiety)
(Ustunel and Gunduz 2017)	2017	NASA-RTLX	
(Sadrfaridpour, Saeidi, and Wang 2016)	2016	NASA-TLX	Questionnaire (trust)
(Sadrfaridpour, Saeidi, Burke, *et al.* 2016)	2016	NASA-TLX	Performance (trust scale)

UX (User Experience); SUS (System Usability Scale); TAM (Technology Acceptance); SART (Situation Awareness Rating Technique).

The following discussion is divided into studies that used the NASA-TLX to make mental workload comparisons: between groups (i.e., by gender; by age); and between different HRC configurations (i.e., with varying levels of automation).

- Comparison between groups

(Hopko *et al.* 2021) studied the interplay of operators' gender, their cognitive fatigue states, and varying levels of automation on HRC. In the analyzed situation, women perceived higher mental demand when fatigued than males. With increased assistance of the robot, women felt performed better while men did not. (Ustunel and Gunduz 2017) performed an experiment about the effects of workplace design considering both extended cognition and gender differences in cognitive load. For the gender differences, NASA-RTLX was used. Results showed no significant differences between male and female groups for each NASA-TLX item. (Rossato *et al.* 2021) investigated the subjective experience of younger and senior workers interacting with an HRC. They compared to group (senior vs. adult operators) and modality (manual vs. tablet) effects on acceptance, UX, usability, and task load related to HRC. For the task load assessment, the NASA-TLX was employed. They find out that higher physical demand, higher temporal pressure, and higher frustration were reported by senior workers in the manual modality, while adult workers reported a higher perceived performance. (Gervasi *et al.* 2020) proposed a framework to evaluate and compare HRC configurations according to eight latent dimensions: autonomy, information exchange, adaptivity and training, team organization, task, human factors, ethics, and cyber security. Within the human factors dimension, the NASA-TLX was used to assess workload. They simulated an assembly task in laboratory, and although the study does not present results for each of the six items, the global workload resulted in 32.5/100.

- Comparison between HRC configurations

Interaction in HRC configurations was compared in (Pantano *et al.* 2020): normal interaction, provided by the robot through a smart pad, interface with gaze and touch inputs. The overall workload calculated through NASA-TLX was 16.15 (Normal), 13.03 (Gaze), and 9.21 (Touch). (Materna *et al.* 2018) proposed an interaction system to reduce the mental demands and attention switching by centering all interaction elements in the shared workspace. To evaluate the proposed approach and to discover the main usability issues of the early prototype, they carried out user experience testing using NASA-TLX, which resulted in a global workload of 33.3. Human trust in robots and robots' trust in humans are considered in (Rahman and Wang 2018). Real-time trust measurement of computational models was developed to test three schemes (no trust, one-way trust, and two-way trust) regarding productivity, quality, team fluency, situation awareness, and the six dimensions of the NASA-TLX. Results were better when human and robot trust each other.

Robot speed conditions were carried out for different HRC. As robots execute movements at high levels of automation, they adapt their speed and movement path to situational demands. (Koppenborg *et al.* 2017) experimentally investigated the effects of movement speed and path predictability of an HRC on the human operator. They used NASA-TLX to compare low-speed conditions (40.7) to high-speed conditions (44.7). (Sadrfaridpour, Saeidi, and Wang 2016, Sadrfaridpour, Saeidi, Burke, *et al.* 2016, Sadrfaridpour and Wang 2018) studied HRC considering robot performance tying robot speed to human mental workload considering three conditions. In the manual condition, the participant can adjust the robot path velocity during the entire experiment. In the pHRI-based approach, the robot motion is synchronized with that of the human. In the integrated scenario, trust and human performance are included for better joint human-robot system performance. The workload was assessed by NASA-TLX, and the overall workload for each scheme was 30.9 (manual), 25.7 (pHRI), and 19.1 (integrated).

In summary, unlike physical assessment, the cognitive workload has a subjective characteristic, and it is more often assessed through NASA-TLX in HRC. NASA-RTLX that was proposed in (Ustunel and Gunduz 2017, Rahman and Wang 2018) indicates that a specific questionnaire for cognitive workload could be developed to be a new standard in HRC. There are also studies proposing a computational model for real-time trust measurement (Rahman and Wang 2018) and an electrodermal sensor for stress measurement (Paletta *et al.* 2020).

3.3 Research gaps and opportunities

Categorizing a risk is often used by management for decision-making (Borges, G. D., Carneiro, P., & Arezes 2021). According to the aim of this work, the literature review provided key information for further investigations on the topic of physical and cognitive risk assessment in HRC systems. It would be interesting: to use the results as input in simulation models to understand the behavior of an HRC system over time;

and to develop a global risk assessment including physical and mental workloads specifically for HRC systems.

CONCLUSIONS

Physical risk assessment was discussed in terms of communication between human and robot (wearables, image-based, and digital human modeling). The mental workload was analyzed through empirical studies that applied the NASA-TLX questionnaire comparing different groups of workers (age, gender), or different robot configurations (level of collaboration, robot speed). Finally, there are opportunities to develop techniques and questionnaires for ergonomic risk assessment specifically in HRC systems. These results could also be input for simulation models to predict the system's behavior.

ACKNOWLEDGMENTS

The authors would like to acknowledge the European Structural and Investment Funds in the FEDER component for the support through the Operational Competitiveness and Internationalization Programme (COMPETE 2020) [Project n° 39479; Funding Reference: POCI-01-0247-FEDER-39479]; and FCT – Fundação para a Ciência e Tecnologia within the R&D Units Project Scope: UIDB/00319/2020.

REFERENCES

Berlin, C. and Adams, C., 2017. Ergonomics: Designing Work Systems to Support Optimal Human Performance. *In*: *Production Ergonomics*. London, 139–160.

Borges, G. D., Carneiro, P., & Arezes, P., 2021. Human Factors Effects on a Human-Robot Collaboration System: A Modelling Approach. *Congress of the International Ergonomics Association*, 829–838.

Charalambous, G., Fletcher, S., and Webb, P., 2016. Development of a human factors roadmap for the successful implementation of industrial human-robot collaboration. *International Conference on Human Aspects of Advanced Manufacturing*.

David, G.C., 2005. Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. *Occupational medicine*, 55 (3), 190-199.

Enoka, R.M. and Duchateau, J., 2008. Muscle fatigue: what , why and how it influences muscle function. *The Journal of Physiology*, 1, 11–23.

Ferenhof, H.A. and Fernandes, R.F., 2016. Demystifying the Literature Review as Basis for Scientific Writing: SSF Method. *Revista ABC*, 21 (3), 550–563.

Ferraguti, F., Villa, R., Talignani Landi, C., Maria Zanchettin, A., Rocco, P., and Secchi, C., 2020. A Unified Architecture for Physical and Ergonomic Human-

Robot Collaboration. *Robotica*, 38 (4), 669–683.
Gervasi, R., Mastrogiacomo, L., and Franceschini, F., 2020. A conceptual framework to evaluate human-robot collaboration. *International Journal of Advanced Manufacturing Technology*, 108 (3), 841–865.
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*, 67, 101998.
Hopko, S., Khurana, R., Mehta, R., and Pagilla, P.R., 2021. Effect of Cognitive Fatigue, Operator Sex, and Robot Assistance on Task Performance Metrics, Workload, and Situation Awareness in Human-Robot Collaboration. *IEEE Robotics and Automation Letters*.
Kim, W., Lee, J., Peternel, L., Tsagarakis, N., and Ajoudani, A., 2018. Anticipatory Robot Assistance for the Prevention of Human Static Joint Overloading in Human-Robot Collaboration. *IEEE Robotics and Automation Letters*, 3 (1), 68-75.
Kim, W., Lorenzini, M., Balatti, P., Nguyen, P.D.H., Pattacini, U., Tikhanoff, V., Peternel, L., Fantacci, C., Natale, L., Metta, G., and Ajoudani, A., 2019. Adaptable Workstations for Human-Robot Collaboration A Reconfigurable Framework for Improving Worker Ergonomics and Productivity. *IEEE Robotics & Automation Magazine*, 26 (3), 14–26.
Kim, W., Peternel, L., Lorenzini, M., Babic, J., Ajoudani, A., Babič, J., Ajoudani, A., Babic, J., and Ajoudani, A., 2021. A Human-Robot Collaboration Framework for Improving Ergonomics During Dexterous Operation of Power Tools. *Robotics and Computer-Integrated Manufacturing*, 68, 102084.
Koppenborg, M., Nickel, P., Naber, B., Lungfiel, A., and Huelke, M., 2017. Effects of movement speed and predictability in human–robot collaboration. *Human Factors and Ergonomics In Manufacturing*, 27 (4), 197–209.
Lorenzini, M., Kim, W., Momi, E.D., and Ajoudani, A., 2019. A new overloading fatigue model for ergonomic risk assessment with application to human-robot collaboration. *In*: *2019 International Conference on Robotics and Automation*. 1962–1968.
El Makrini, I., Merckaert, K., De Winter, J., Lefeber, D., Vanderborght, B., Makrini, I.E., Merckaert, K., De Winter, J., Lefeber, D., Vanderborght, B., El Makrini, I., Merckaert, K., De Winter, J., Lefeber, D., and Vanderborght, B., 2019. Task allocation for improved ergonomics in Human-Robot Collaborative Assembly. *Interaction Studies*, 20 (1), 102–133.
Marcora, S.M., Staiano, W., and Manning, V., 2009. Mental fatigue impairs physical performance in humans. *Journal of Applied Physiology*, 106, 857–864.
Materna, Z., Kapinus, M., Beran, V., Smrz, P., and Zemcik, P., 2018. Interactive Spatial Augmented Reality in Collaborative Robot Programming: User Experience Evaluation. *In*: *2018 27TH IEEE International Symposium on Robot and Human Interactive Communication (IEEE RO-MAN 2018)*. 80–87.
NASA, 1986. Nasa Task Load Index (TLX) v. 1.0 Manual.
Nguyen, T.D., Bloch, C., and Krüger, J., 2016. The Working Posture Controller: Automated Adaptation of the Work Piece Pose to Enable a Natural Working Posture. *Procedia CIRP*, 44, 14–19.
Paletta, L., Pszeida, M., Nauschnegg, B., Haspl, T., and Marton, R., 2020. Stress

measurement in multi-tasking decision processes using executive functions analysis. *Advances in Intelligent Systems and Computing*, 953, 344–356.

Pantano, M., Regulin, D., Lutz, B., and Lee, D., 2020. A human-cyber-physical system approach to lean automation using an industrie 4.0 reference architecture. *Procedia Manufacturing*, 51, 1082–1090.

Parsa, B., Samani, E.U., Hendrix, R., Devine, C., Singh, S.M., Devasia, S., and Banerjeee, A.G., 2019. Toward Ergonomic Risk Prediction via Segmentation of Indoor Object Manipulation Actions Using Spatiotemporal Convolutional Networks. *IEEE Robotics and Automation Letters*, 4 (4), 3153–3160.

Peternel, L., Fang, C., Tsagarakis, N., and Ajoudani, A., 2019. A selective muscle fatigue management approach to ergonomic human-robot co-manipulation. *Robotics and Computer-Integrated Manufacturing*, 58, 69–79.

Pini, F., Ansaloni, M., and Leali, F., 2016. Evaluation of operator relief for an effective design of HRC workcells. *In*: *21st IEEE International Conference on Emerging Technologies and Factory Automation*. 1–6.

Rahman, S.M.M. and Wang, Y., 2018. Mutual trust-based subtask allocation for human–robot collaboration in flexible lightweight assembly in manufacturing. *Mechatronics*, 54 (July 2017), 94–109.

Rossato, C., Pluchino, P., Cellini, N., Jacucci, G., Spagnolli, A., and Gamberini, L., 2021. Facing with Collaborative Robots: The Subjective Experience in Senior and Younger Workers. *Cyberpsychology Behavior and Social Networking*, 1–8.

Rücker, D., Hornfeck, R., and Paetzold, K., 2019. Investigating ergonomics in the context of human-robot collaboration as a sociotechnical system. *International Conference on Human Factors in Robots and Unmanned Systems, 2018.*

Sadrfaridpour, B., Saeidi, H., Burke, J., Madathil, K., and Wang, Y., 2016. Modeling and control of trust in human-robot collaborative manufacturing. *In*: *Robust Intelligence and Trust in Autonomous Systems*. 115–142.

Sadrfaridpour, B., Saeidi, H., and Wang, Y., 2016. An Integrated Framework for Human-Robot Collaborative Assembly in Hybrid Manufacturing Cells. *2016 IEEE International Conference on Automation Science and Engineering (CASE)*, 462–467.

Sadrfaridpour, B. and Wang, Y., 2018. Collaborative Assembly in Hybrid Manufacturing Cells: An Integrated Framework for Human-Robot Interaction. *IEEE Transactions on Automation Science and Engineering*, 15 (3), 1178–1192.

Thomas, C., Stankiewicz, L., Grötsch, A., Wischniewski, S., Deuse, J., and Kuhlenkötter, B., 2016. Intuitive Work Assistance by Reciprocal Human-robot Interaction in the Subject Area of Direct Human-robot Collaboration. *In*: *Procedia CIRP*. 275–280.

Ustunel, Z. and Gunduz, T., 2017. Human-robot collaboration on an assembly work with extended cognition approach. *Journal of Advanced Mechanical Design Systems and Manufacturing*, 11 (5).

Vazquez, A.N. and Jabi, W., 2019. Robotic assisted design workflows: a study of key human factors influencing team fluency in human-robot collaborative design processes. *Architectural Science Review*, 62 (5), 409–423.