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A Human-centred Methodology to Assess Collaborative Automation Solutions

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Abstract

Integrating collaborative automation in manufacturing often fails because it neglects workers' expectations, which leads to insufficient acceptance and negative employee experiences. This paper presents a comprehensive human-centred methodology for evaluating collaborative automation systems by examining four key dimensions: task, automation, people and organisational characteristics. The approach combines qualitative assessments with quantitative indicators. Two industrial application cases applying collaborative robotics illustrate the application of the method and highlight its usefulness in identifying areas for improvement. The methodology has proven to be a practical assessment that helps practitioners quickly identify key areas of focus without initially requiring extensive quantitative analyses.

Keywords: collaborative robotics; human factors; industry 5.0;

1. Introduction

The traditional focus on automation capabilities, with limited attention to workers, has created a gap between the potential and the effectiveness of collaborative automation systems. Motivated by this issue, this paper provides a methodology to assess collaborative automation systems, considering human-centred and organisational aspects necessary to maximise collaborative automation systems' potential [5]. Collaborative automation aims to support workers by sharing workloads and promoting human-automation teamwork, optimising production, and enhancing worker well-being [18, 10]. However, poorly designed or managed systems can add to worker demands rather than serve as a resource [22, 5].

The Job Demands-Resources (JD-R) Model explains the link between job characteristics, well-being, and organisational outcomes [7]. Job demands, such as high pressure and ineffective leadership, can lead to job strain, reducing efficiency and motivation, thereby negatively affecting organizational performance [2]. Conversely, environments where job resources like social support and user-friendly interfaces foster well-being. Moreover, resources encourage job crafting, enabling employees to actively shape their roles by adjusting task execution or suggesting technological enhancements[8]. Considering the dual potential of collaborative automation as either a strain or support to workers, it is crucial to examine its integration through the lens of the JD-R Model: *"Is collaborative automation a demand or a resource?"*

The paper is organised as follows: Section 2 reviews relevant literature, Section 3 presents the methodology, Section 4 discusses its application in two industrial use cases, and Section 5 outlines future research.

2. Existing Methods and Frameworks

To guide designers and managers of automated technology, this article introduces a comprehensive methodology based on the JD-R Model, which identifies the criteria for assessing technology demands and resources. From this perspective, a literature review has been conducted on collaborative automation assessment and adoption methods involving job quality, automation and robotics acceptance, and workers' well-being in collaborative automation, particularly in collaborative robotics. Other works propose similar methodologies. However, the one proposed in this paper provides a practise-friendly approach

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that includes a structured checklist and rating scales to facilitate the evaluation and optimization of collaborative automation solutions. For example, valuable conceptual frameworks for evaluating human-robot collaboration provide a broader and more theoretical approach [12]. In contrast, our work provides a structured and rapid methodology for direct implementation in industrial settings. Moreover, by integrating task, automation, organisation and human factors, the proposed methodology ensures a comprehensive assessment that not only considers technical performance but also enhances worker well-being and organisational effectiveness [1].

Some authors focus on the personal factors of workers, like cognitive workload, collaboration fluency, trust, acceptance, satisfaction, stress, and usability [3, 15, 9]. Other contributions also consider technical, organisational, and societal factors [20, 16]. Similarly, a systematic literature review on human-centred approaches to Human-Robot Collaboration (HRC) suggests workers and task design factors [21]. All these contributions can be clustered into four dimensions: worker, task, automation and organisational characteristics.

Task characteristics: this dimension reflects the properties of tasks within collaborative settings, such as pace, repetitiveness, complexity, autonomy, and flexibility [2, 13, 23]. Operators benefit from autonomy in decision-making; hence, technology should not constrain them by enforcing rigid, preprogrammed actions, as this would undermine their decision-making capacity. Achieving a balanced workload between humans and automation is critical, as predictable and informative systems can reduce workload and prevent errors arising from overload or underload conditions.

Automation characteristics: this dimension addresses automation attributes, such as predictability, transparency, flexibility, and usability [23, 6, 3]. Worker satisfaction depends on comprehending the system's state and functionality. Frustration arises when system objectives are unclear. Predictable automation enables anticipation of its actions, reducing stress caused by unmet expectations. Tailoring automation to accommodate individual needs and working styles can enhance satisfaction. Flexibility for diverse tasks is key in HRC environments.

Worker characteristics: this dimension encompasses the skills, expertise, attitudes towards automation, and interpersonal relationships of individuals within collaborative environments [6, 19, 16]. Resistance to collaborative automation may stem from fears of job replacement or insufficient technical competence, contributing to job strain. Practical knowledge and hands-on experience foster confidence and positive attitudes towards automation.

Organisation characteristics: this dimension captures strategies for integrating automation and managing the workforce, including training, recognition, and support structures [19, 4]. Comprehensive training enhances workers' skills in interacting with automation, while regular feedback and recognition boost motivation and job satisfaction. Effective communication and support mitigate uncertainty about new technologies. Involving workers in automation planning and providing problem-solving support are essential for successful implementation.

3. The Human-centred Methodology

The methodology, outlined in Fig. 1, is implemented through a concise checklist to facilitate the assessment of collaborative automation. It also incorporates four key indicators, one per characteristic, to provide an overview of the current level of implementation of collaborative automation systems, determining whether it functions more as a resource or a demand. It is organised into four key domains: task, automation, worker, and organisation. Each domain includes relevant items to be evaluated qualitatively along a gradient from 1 to 3 [1]. Additionally, quantitative indicators enhance the assessment depth.

This methodology is specifically tailored for designers and managers, emphasising accessibility and ease of use, as demonstrated by the two use cases. Simplicity and rapid applicability are critical in professional environments where time and resource constraints often prevail. By serving as an initial, approachable layer of assessment, this methodology enables practitioners to quickly identify key areas of focus without becoming mired in extensive quantitative analyses at the outset. This approach facilitates early intervention and promotes iterative improvements. While acknowledging potential subjectivity and non-exhaustiveness, the methodology encourages thoughtful reflection rather than prescribing rigid actions, fostering a deeper engagement with the complexities inherent in each dimension of collaborative systems.

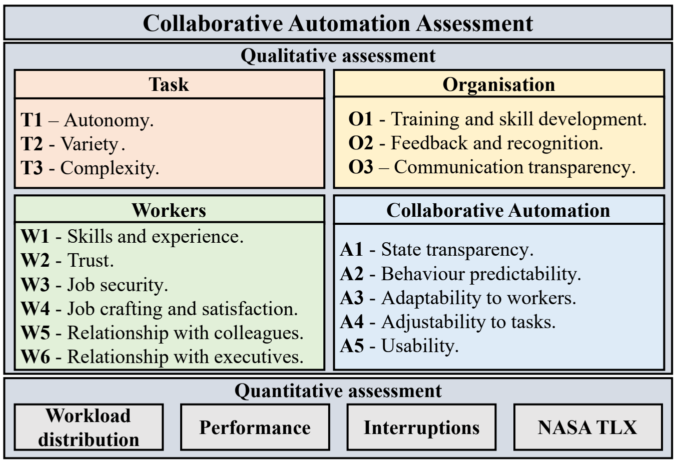


Fig. 1: The main elements of the methodology.

Sections 3.1, 3.2, 3.3, and 3.4 refer respectively to the characteristics of task, automation, workers, and organisation that have to drive the design and adoption of collaborative automation, that support the assessment. All these characteristics must

[1] For ease of use, a three-level scale was chosen to ensure that the methodology remains suitable for practitioners and accessible in the industry. It is consistent across different dimensions, whereas a more detailed (e.g., five-level) scale would lead to ambiguous assessment criteria, making it more difficult for non-experts to recognise minor differences between levels. In this way, a clear distinction is made between inadequate, acceptable and optimal conditions.

be evaluated with respect to a task[2] supported by a collaborative automation system together one or more workers.

3.1. Task Characteristics

T1 - Autonomy. The space for creativity, flexibility, and adaptability of humans during the task.
1. **Poor**: little control over timing, decisions and methods of completing the task.
2. **Moderate**: partial autonomy over timing, decisions and methods.
3. **Adequate**: significant control over timing, decisions and methods.

T2 - Variety. Variability in the operations undertaken by the worker within the task.
1. **Poor**: operations are mechanical and repetitive.
2. **Moderate**: same operations most of the time.
3. **Adequate**: task varying in pace, content, location, etc.

T3 - Complexity. Complexity of the operations in terms of experience and skills required.
1. **Poor**: routine, well-defined tasks requiring limited experience and skills.
2. **Moderate**: involving several steps, requiring moderate problem-solving skills
3. **Adequate**: operations requiring advanced problem-solving, critical thinking, and adaptability.

3.2. Collaborative Automation Characteristics

A1 - State transparency. Accessibility and comprehensibility for the worker of the processes underlying automation.
1. **Poor**: the system does not inform the worker about its state and logics.
2. **Moderate**: the system provides some information to the worker about its state and logics.
3. **Adequate**: the system provides clear and consistent information to the worker about its state and logics.

A2 - Behaviour predictability. Predictability and coherence of the system behaviour with respect to the workers' expectations.
1. **Poor**: the automation shows unpredictable behaviour.
2. **Moderate**: the automation has some unpredictable behaviour.
3. **Adequate**: the automation's behaviour is predictable with workers' expectations.

A3 - Adaptability to workers. Capacity of the automation system to adapt dynamically its behaviour to the workers' behaviour.
1. **Poor**: the automation is not adaptable.
2. **Moderate**: the automation is partly adaptable.
3. **Adequate**: the automation is largely and dynamically adaptable.

A4 - Physical support. Capacity of the automation system to be flexible enough to fit the workers' physical demands (e.g., body height, hand dominance) and individual way of working to ensure physical and mental relief.
1. **Poor**: the automation is not or is poorly adjustable to physical preferences.
2. **Moderate**: a few automation characteristics and functions can be adjustable.
3. **Adequate**: automation functions and settings are highly adjustable to workers' needs and preferences.

A5 - Ergonomics. The ability of the automation system's interface to be user-friendly and ergonomically structured, featuring clear symbols, consistent feedback, practical input mechanisms, and seamless interaction.
1. **Poor**: the interface is poorly designed; the interaction is frustrating.
2. **Moderate**: the interface usability is limited in some of its features (e.g., difficulty in manipulating the controls, poor feedback, etc.)
3. **Adequate**: automation interface and interaction are ergonomically designed.

3.3. Workers Characteristics

W1 - Skills and experience. Suitability and familiarity of the workers' skills, knowledge, and experience with the automation system.
1. **Poor**: skills, knowledge, and experience must be significantly developed.
2. **Moderate**: skills, knowledge, and experience require further integration.
3. **Adequate**: workers possess the necessary skills, knowledge, and experience, not requiring additional training.

W2 - Trust. Trust in the robot is tied to the sense of control over the situation, safety in carrying out activities, and the reliability of automation.
1. **Poor**: the worker completely trusts or does not trust the automation system.
2. **Moderate**: the worker considers the automation reliable in certain aspects.
3. **Adequate**: trust is well-balanced, and the autonomy distribution between the parties is functional.

W3 - Job security. Workers consideration on the threat of automation as a replacement concern.
1. **Poor**: workers feel easily replaceable by automation.
2. **Moderate**: workers are concerned that automation may eventually replace them.
3. **Adequate**: workers feel valued and not easily replaceable by automation.

W4 - Job crafting and satisfaction. Workers' perceptions of automation in relation to their job's control space and adaptability to individual needs.
1. **Poor**: workers see no benefit in introducing automation.
2. **Moderate**: workers have concerns about their ability to adapt and control their job characteristics.
3. **Adequate**: workers are satisfied with their jobs and view automation as a supportive tool.

[2] The task refers to a specific set of activities or operations carried out as part of the production process to convert raw materials into finished products.

W5 - Relationship with colleagues. The influence of the automation solution on maintaining relationships among colleagues in the work environment.

1. Poor: there is no possibility for interaction with colleagues during the task.

2. Moderate: interaction with colleagues is possible only at certain times.

3. Adequate: interaction with colleagues is always possible.

W6 - Relationship with executives. Workers' perceptions of the management's regard for their well-being and interests during the implementation of new technologies.

1. Poor: executive decisions are perceived as not considering workers' well-being.

2. Moderate: executives' decisions are perceived as partially considering workers' well-being.

3. Adequate: executives are perceived as trustworthy and have the well-being of workers in mind.

3.4. Organisation Characteristics

O1 - Training and skill development. Capacity of the organisation to provide comprehensive training programs to enhance technical skills in working with collaborative automation and adaptability to changing work demands.

1. Poor: training is absent or superficial, covering only some technical procedures.

2. Moderate: training programs focus primarily on technical procedures.

3. Adequate: training programs enhance workers' skills, adaptability, and proactivity.

O2 - Feedback and recognition. Capacity of the organisation to provide feedback and recognition for workers' contributions in task execution and working with collaborative automation.

1. Poor: no feedback is provided.

2. Moderate: feedback is given only on rare occasions.

3. Adequate: feedback is frequent and comprehensive.

O3 - Communication transparency. Efforts of the organisation in offering details about the timing, methods, and impacts of collaborative automation implementation before, during, and after installation.

1. Poor: no information is provided.

2. Moderate: information is superficial.

3. Adequate: information is clear and comprehensive.

3.5. Quantitative Indicators

Q1 - Workload Distribution. This describes allocating task-related work between the human operator and collaborative automation. It must be measured as the percentage of total task cycle time the worker spends on the task. For optimal distribution, the worker's workload should constitute 40-60% of the total task cycle time.

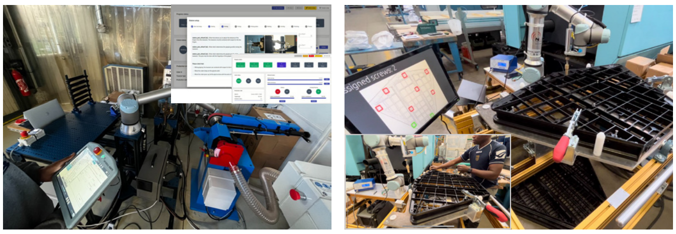
Q2 - Interruptions. This evaluates the frequency and impact of disruptions that impede task completion, such as unexpected system alerts, system stoppages, or manual intervention. Using system monitoring tools or event logs, measurement methods include tracking and logging interruption events, including their frequency, duration, and impact on task completion time. It must be measured as the number of interruptions that exceed the task cycle time. Acceptable limits would be fewer than two interruptions per shift, with minimal task delay.

Q3 - Quality. This quantifies the efficiency and effectiveness of completing tasks or achieving goals within the collaborative automation setup. It must be measured comparing the in-quality units over the total produced ones.

Q4 - NASA Task Load Index (NASA-TLX). This measures perceived workload across multiple dimensions such as mental demand, physical demand, temporal demand, effort, performance, and frustration. The measurement must be performed using the NASA-TLX [14] questionnaire to gather subjective ratings from workers. The assessment must follow the NASA-TLX's procedure, and the worker must have experienced the Work Cell (WC) and its process for at least one shift. Scores should ideally remain within a moderate workload range, avoiding excessive mental or physical demands to ensure optimal performance and well-being.

4. Industrial Application Cases

The methodology was applied to evaluate the tasks within two WCs (Fig. 2) that demonstrate different approaches towards collaborative automation adoption. These WCs adopt collaborative robots. Results are reported in Table 1.



(a) Work cell 1 (b) Work cell 2

Fig. 2: Analysed work cells.

WC 1 (video industrial setting) operates within a Small and Medium Enterprise (SME) specialised in hand tools, involving high-dexterity tasks performed by skilled artisans with limited technological proficiency. Tasks, primarily manual or semi-automated (e.g., polishing), incorporate a collaborative robot (UR10) for welding and polishing hand-tweezers in a shared workspace, as detailed in [17]. Quick parameterisation procedures simplify use for non-experts, though worker involvement remains limited. The cell includes a mobile UR10 station, welding/polishing machines, a workbench, a feeding system, an automatic jig, and a laser scanner.

WC 2 (video lab setting, video industrial setting) was deployed in an injection moulding SME with 25 production lines staffed by skilled operators and assemblers proficient in machine tending but not in programming. The WC, using a Universal Robots UR5e mounted on a manual station, performs screwdriving via an end-effector and provides workers with task-specific data through a Human Machine Interface. Empatica E4 wristband data, combined with the dominant hand and

	Work cell 1	**Work cell 2**
T1	(1). The process procedures are always the same for the worker.	(2). The workers engage in both sequential and parallel processing with the cobot. They can also choose the desired operations sequence.
T2	(2). The worker is assigned to the WC supervision and buffer refill. In the remaining time, he/she can be assigned to other jobs.	(2). While the worker has some degrees of freedom, he/she mostly performs the same routine every three minutes.
T3	(1). The worker has to refill the buffer and supervise the WC. The technician handles the WC setup.	(2). The worker has simple tasks to be executed. However, process supervision and cobot interaction require some problem-solving.
A1	(3). Workers have access to a GUI. They can parametrise the part program and manage production orders and equipment.	(2). The workers can access a GUI that provides information on the assigned tasks. However, no explanations are provided about the decisions.
A2	(2). If the parametrisation is not properly performed, quality issues may occur in the polishing process.	(3). After a few cycles needed to learn the cobot's modus operandi, the worker can easily understand how it operates.
A3	(1). The WC does not consider this aspect.	(2). The cobot adapts its speed in the lab setting based on the distance between the tool and the worker's hands.
A4	(1). The WC does not consider this aspect.	(3). The dynamic task assignment considers the worker's perceived fatigue and hand dominance.
A5	(2). The GUI assists workers in parameterising the part program by providing all necessary instructions, but it lacks a user-centred design approach.	(2). The interaction mostly relies on the functions of the cobot's teach pendant and a few other interfaces (e.g., the workbench's button).
W1	(2). Parameterisation heavily depends on the workers' experience with the process.	(3). The worker has been instructed to re-activate the cobot's operations in case of issues. No additional skills are required.
W2	(2). With the proper setup, the workers trust the automation solution. Some non-conformities still need to be solved	(3). All the workers testing the solution provided positive feedback about the interaction with the cobot.
W3	(2). After an initial sentiment of "a cobot cannot perform these tasks as we do", the workers recognise the technology potential.	(3). The WC has been designed for human-robot collaboration. It cannot operate without a worker.
W4	(2). Younger workers demonstrate learning readiness. Conversely, more experienced workers exhibit less enthusiasm.	(3). All the workers testing the solution provided positive feedback about the possibility of working with cobots in more processes
W5	(3). The workers can easily interact with their colleagues.	(3). The workers can easily interact with their colleagues.
W6	(2). The WC is the company's initial venture into this technology. It required substantial effort. Workers are currently sceptical.	(3). The company now operates two cobotic WCs, relying on worker participation, supported by a trust-based relationship with executives.
O1	(2). The company has a plan to train a few of its workers.	(1). No specific training is in place; workers learn by working in.
O2	(1). No recognition or feedback procedures are in place.	(1). No recognition or feedback procedures are in place.
O3	(2). A comparative analysis between the manual and the cobotic WC has been performed.	(2). A comparative analysis between the manual and the cobotic WC has been performed.
Q1	More than 95% of the workload is assigned to the cobot	The workload is equally distributed. Depending on the task assignment, the worker's workload changes between 60% and 70%
Q2	Interruptions are rare. During the validation phases, only two occurred in a one-day shift.	Interruptions occurred more than two times a day with new workers with no experience with the process. With skilled workers, the process can be quickly restored in less time than the total cycle duration.
Q3	100% success rate thanks to the sensorised screwdriver and worker supervision.	The test performed on four types of tweezers and various batches showed a 97% success rate.
Q4	The WC does not consider this aspect.	The assessment of 5 workers reported an average of 6.03 (improvement of 35% from the manual WC).

Table 1: Work cells evaluation. The assessment is provided in brackets (< *assessment* >) and was carried out in a workshop session by the authors in collaboration with the managers and workers of the companies.

Work-in-Progress (WIP) features, enables dynamic task allocation between the cobot and worker [11].

The proposed methodology allowed the managers to evaluate if all relevant aspects have been considered to achieve effective collaborative automation that guarantees workers' efficiency and well-being while guaranteeing proper execution of the required tasks and being harmonised within the organisation. The overall assessment can be represented using radar diagrams that identify the characteristics and the single evaluation criteria that have been adequately addressed and the ones that would need further improvement or optimisation for each analysed collaborative manufacturing cell (Fig. 3).

In particular, it can be noted that in the case of WC 1, the tasks assigned to the human operator are limited and that the criteria related to the automation and workers' characteristics could be further optimised. In contrast, in the case of WC 2, the organisational aspects should be further addressed and improved to achieve more effective integration. Finally, while WC 1 assigns over 95% of the workload to the cobot, WC 2 reflects a more collaborative and flexible task-sharing approach. Interruptions in WC 1 were minimal but more controlled and quickly addressed in WC 2, even for inexperienced workers, highlighting better robustness and recoverability. While WC 1 experienced some cycle time increases despite quality improvements of 30%, WC 2 demonstrated a 17% throughput increase with a more efficient process flow. Lastly, WC 1 did not consider worker-perceived workload assessments, whereas WC 1 recorded a 35% improvement in perceived workload from manual processes, indicating a superior focus on operator experience and well-being. The acknowledgement of these problematic aspects also using a visual tool for qualitative aspects, representing a powerful starting point for the redesign of tasks and interactions within the WCs or to guide future developments.

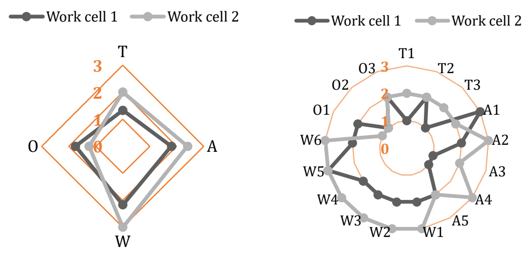


Fig. 3: Work cells evaluation: aggregated (left) and individual (right)

5. Conclusions

This work introduces a methodology to support the assessment of collaborative automation systems for both designers and managers, focusing on task, automation, worker, and organisational characteristics. Future improvements target adaptability and scalability by employing a modular framework that integrates additional dimensions based on specific industry needs. Prioritisation methods for characteristics will be developed, weighted by socio-technical requirements. We will also explore how the findings from these case studies can be generalised to guide the design of new collaborative work environments, transforming lessons learnt into practical implementation.

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References

[1] Arkouli, Z., Michalos, G., Kokotinis, G., Makris, S., 2024. Worker-centered evaluation and redesign of manufacturing tasks for ergonomics improvement using axiomatic design principles. CIRP Journal of Manufacturing Science and Technology 55, 188–209. doi:10.1016/j.cirpj.2024.10.001.

[2] Bakker, A.B., Demerouti, E., 2018. Multiple levels in job demands-resources theory: Implications for employee well-being and performance, in: Handbook of well-being. Noba Scholar.

[3] Baltrusch, S.J., Krause, F., De Vries, A.W., Van Dijk, W., De Looze, M.P., 2022. What about the human in human robot collaboration?: A literature review on HRC's effects on aspects of job quality. Ergonomics 65, 719–740. doi:10.1080/00140139.2021.1984585.

[4] Bettoni, A., Matteri, D., Montini, E., Gładysz, B., Carpanzano, E., 2021. An AI adoption model for SMEs: a conceptual framework. IFAC-PapersOnLine 54, 702–708. doi:10.1016/j.ifacol.2021.08.082.

[5] Bracco, F., Bruzzone, A.A., Carpanzano, E., 2023. Transfactory: Towards a New Technology-Human Manufacturing Co-evolution Framework, in: Valle, M., Lehmhus, D., Gianoglio, C., Ragusa, E., Seminara, L., Bosse, S., Ibrahim, A., Thoben, K.D. (Eds.), Advances in System-Integrated Intelligence. Springer International Publishing, Cham. volume 546, pp. 636–645. doi:10.1007/978-3-031-16281-7_60. series Title: Lecture Notes in Networks and Systems.

[6] C.W. Peeters, M., Plomp, J., 2022. For Better or for Worse: The Impact of Workplace Automation on Work Characteristics and Employee Well-Being, in: Petrillo, A., De Felice, F., Violeta Achim, M., Mirza, N. (Eds.), Digital Transformation - Towards New Frontiers and Business Opportunities. IntechOpen. doi:10.5772/intechopen.102980.

[7] Demerouti, E., Bakker, A.B., Nachreiner, F., Schaufeli, W.B., 2001. The job demands-resources model of burnout. Journal of Applied Psychology 86, 499–512. doi:10.1037/0021-9010.86.3.499.

[8] Demerouti, E., Hewett, R., Haun, V., De Gieter, S., Rodríguez-Sánchez, A., Skakon, J., 2020. From job crafting to home crafting: A daily diary study among six European countries. Human Relations 73, 1010–1035. doi:10.1177/0018726719848809.

[9] Di Pasquale, V., De Simone, V., Giubileo, V., Miranda, S., 2023. A taxonomy of factors influencing worker's performance in human–robot collaboration. IET Collaborative Intelligent Manufacturing 5, e12069. doi:10.1049/cim2.12069.

[10] D'Addona, D.M., Bracco, F., Bettoni, A., Nishino, N., Carpanzano, E., Bruzzone, A.A., 2018. Adaptive automation and human factors in manufacturing: An experimental assessment for a cognitive approach. CIRP Annals 67, 455–458. doi:10.1016/j.cirp.2018.04.123.

[11] Elias Montini, Vincenzo Cutrona, Samuele Dell'Oca, Andrea Bettoni, Giuseppe Landolfi, Paolo Rocco, Emanuele Carpanzano, 2024. An industrial human-robot collaboration case study for workers' well-being, in: Procedia CIRP.

[12] Gervasi, R., Mastrogiacomo, L., Franceschini, F., 2020. A conceptual framework to evaluate human-robot collaboration. The International Journal of Advanced Manufacturing Technology 108, 841–865. doi:10.1007/s00170-020-05363-1.

[13] Gombolay, M.C., Gutierrez, R.A., Clarke, S.G., Sturla, G.F., Shah, J.A., 2015. Decision-making authority, team efficiency and human worker satisfaction in mixed human–robot teams. Autonomous Robots 39, 293–312. doi:10.1007/s10514-015-9457-9.

[14] Hart, S.G., Staveland, L.E., 1988. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research, in: Advances in psychology. Elsevier. volume 52, pp. 139–183. doi:10.1016/S0166-4115(08)62386-9.

[15] Hopko, S., Wang, J., Mehta, R., 2022. Human Factors Considerations and Metrics in Shared Space Human-Robot Collaboration: A Systematic Review. Frontiers in Robotics and AI 9, 799522. doi:10.3389/frobt.2022.799522.

[16] Meissner, A., Trübswetter, A., Conti-Kufner, A.S., Schmidtler, J., 2021. Friend or Foe? Understanding Assembly Workers' Acceptance of Human-robot Collaboration. ACM Transactions on Human-Robot Interaction 10, 1–30. doi:10.1145/3399433.

[17] Montini, E., Agbomemewa, L., Daniele, F., Cutrona, V., Confalonieri, M., Ferrario, A., Rocco, P., Bettoni, A., 2023. A Smart Work Cell to Reduce Adoption Barriers of Collaborative Robotics, in: Advances in Production Management Systems. Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures, Springer Nature Switzerland, Cham. pp. 702–715. doi:10.1007/978-3-031-43662-8_50.

[18] Montini, E., Daniele, F., Agbomemewa, L., Confalonieri, M., Cutrona, V., Bettoni, A., Rocco, P., Ferrario, A., 2024. Collaborative Robotics: A Survey From Literature and Practitioners Perspectives. Journal of Intelligent & Robotic Systems 110, 117. doi:10.1007/s10846-024-02141-z.

[19] Paliga, M., 2022. Human–cobot interaction fluency and cobot operators' job performance. The mediating role of work engagement: A survey. Robotics and Autonomous Systems 155, 104191. doi:10.1016/j.robot.2022.104191.

[20] Paluch, S., Tuzovic, S., Holz, H.F., Kies, A., Jörling, M., 2022. "My colleague is a robot" – exploring frontline employees' willingness to work with collaborative service robots. Journal of Service Management 33, 363–388. doi:10.1108/JOSM-11-2020-0406.

[21] Simões, A.C., Pinto, A., Santos, J., Pinheiro, S., Romero, D., 2022. Designing human-robot collaboration (HRC) workspaces in industrial settings: A systematic literature review. Journal of Manufacturing Systems 62, 28–43. doi:10.1016/j.jmsy.2021.11.007.

[22] Sordan, J.E., Pimenta, M.L., Oprime, P.C., Rodrigues, Y.T., Marinho, C.A., 2021. Collaborative robotics: a literature overview from the perspective of production management. Revista Produção e Desenvolvimento 7. doi:10.32358/rpd.2021.v7.516.

[23] Tausch, A., Kluge, A., 2022. The best task allocation process is to decide on one's own: effects of the allocation agent in human–robot interaction on perceived work characteristics and satisfaction. Cognition, Technology & Work 24, 39–55. doi:10.1007/s10111-020-00656-7.