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Enhancing Inclusive Manufacturing through Human-Machine Reciprocal Learning: A Trust-based Framework

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Abstract: This paper introduces a trust-based human-machine reciprocal learning (HMRL) framework to foster inclusive manufacturing by providing integrated cognitive support for neurodiverse workforces in human-robot collaborative (HRC) environments. The framework's architecture comprises five key modules: cognitive assessment, real-time object detection, natural language processing, a multi-modal instruction interface, and collaborative robotics. A reciprocal learning mechanism facilitates continuous improvement in both the machine learning models and the personalized assistance provided to workers with cognitive differences. Evaluation across diverse manufacturing scenarios demonstrates significant gains in assembly performance, including improved quality and reduced cycle time. This HMRL framework lays the groundwork for symbiotic human-robot manufacturing. -

Keywords: Human-Machine Reciprocal Learning, Inclusive Manufacturing, Cognitive Assessment, Natural Language Processing, Collaborative Robotics.

1. INTRODUCTION

The integration of human-robot collaboration (HRC) in modern manufacturing has become necessary as industries strive to combine human cognitive capabilities with robotic precision [1]. This convergence promises enhanced productivity, flexibility, and quality in manufacturing, particularly in complex assembly tasks where neither complete automation nor purely manual operations are optimal [2], [3].

Despite these potential benefits, an effective implementation of HRC faces significant challenges in establishing mutual trust among the components of the mixed human, robotic work team and in the increased cognitive load generated by the interaction between human and machine [3]. While collaborative robots can perform repetitive tasks with high precision, human operators often experience increased cognitive fatigue when interpreting and responding to robot actions [4]. This cognitive burden is especially evident in diverse workforce environments, where operators may possess a variety of cognitive profiles and divergent information processing capabilities. [1].

Recent estimates suggest that up to 17% of the workforce may be neurodiverse, representing individuals with naturally varying neurological functioning. As manufacturing jobs become increasingly specialized, the inclusion of neurodiverse workers is gaining recognition as a crucial dimension of organizational diversity. However, existing manufacturing systems rarely consider the specific needs of neuroatypical operators, potentially limiting both individual performance and organizational success [5].

A critical limitation of current human-machine systems lies in their approach to trust development. Most existing solutions employ unidirectional instruction systems, where either the machine adapts to human behaviour or humans adjust to unresponsive machine guidance [6], [7], [8]. Such systems often fail to create a truly collaborative environment where mutual trust between human operators and machines can be effectively established and maintained. This trust deficit create distressing situations where operators may feel uncertain about robot intentions or capabilities, leading to reduced efficiency and increased stress levels [9].

The reason for this lack of trust lies in the lack of empathy: a mechanism that estimates HRC performances and human cognitive stress and adapts the task to maximize performance and minimize stress. On the contrary, this mechanism is innate in human teams, where the members are bounded by empathy, emulation, easy communication and the understanding of the mutual goal. The systems' effectiveness is further compromised by its limited if not inexistent capacity to evolve procedures, that is to utilize environment feedback for their continuous improvement.

To address these challenges, this paper proposes an innovative Human-Machine Reciprocal Learning (HMRL) framework. It consists in the integration of five modules designed to facilitate trust-based collaboration. At its core, the cognitive assessment module continuously monitors and develops the operator-machine relationship. A real-time object detection component provides comprehensive process monitoring. A natural language processing module ensures effective communication and instruction generation, complemented by a multi-modal instruction interface that allows multiple communication channels. The fifth module, named collaborative robotics, provides precision assistance to the operator.

Through a comprehensive reciprocal learning mechanism, the system enables continuous improvement where human-in-the loop allows the robot to face tasks that require flexibility, machine-in-the-loop reduce the cognitive load and assist the challenges of neuroatypical workers. It is a self-improving system that builds trust through transparent interaction and adaptation to individual cognitive profiles. The framework maintains high manufacturing standards through personalized support strategies and dynamic knowledge accumulation,

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while actively fostering mutual trust between operators and automated systems.

2. THEORETICAL FOUNDATIONS

This section presents three fundamental theories and their integration as the conceptual basis for our approach.

2.1 Human-Robot Collaboration

Human-robot collaboration (HRC) has evolved significantly over the past decade, transitioning from simple coexistence to sophisticated symbiosis [10]. The fundamental principle of HRC emphasizes the synergistic integration of human cognitive capabilities with robotic precision and repeatability [11]. Recent advances in HRC have highlighted the importance of mutual adaptation and shared control in collaborative tasks [12]. Additionally, trust has emerged as a critical factor in HRC effectiveness, with research demonstrating its impact on team performance and user acceptance [13], [14].

2.2 Cognitive Load Theory in Manufacturing

Cognitive Load Theory (CLT), originally developed by Sweller (1988), has found significant applications in manufacturing contexts [15]. In the case of HRC, cognitive load manifests in three forms: intrinsic load (task complexity), extraneous load (interface design), and germane load (learning process) [16], as shown in Fig.1.

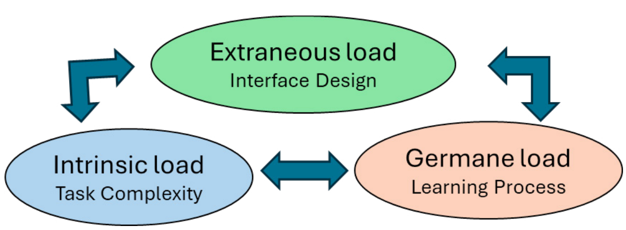

Figure 1. Cognitive Load Components in Manufacturing.

Understanding these cognitive load components is crucial for designing effective collaborative systems, particularly when considering operators with diverse cognitive capabilities [17]. Recent studies have demonstrated that optimizing cognitive load through appropriate information presentation and task structuring can significantly improve operator performance and reduce errors in manufacturing settings [17].

2.3 Inclusive Manufacturing

The concept of inclusive manufacturing has gained prominence as industries recognize the importance of accommodating workforce diversity [18]. This theoretical framework emphasizes the need to design manufacturing systems that can adapt to different cognitive profiles and learning styles. Given that neurodiversity can influence cognitive and learning abilities, fostering an inclusive work environment necessitates adapting task instructions to individual worker preferences and implementing feedback mechanisms designed to minimize cognitive load. An inclusive work environment must be organized as described in Fig. 2.

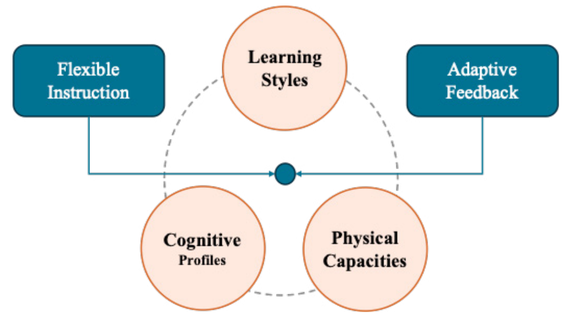

Figure 2. Inclusive Manufacturing Framework

2.4 Integration of Theoretical Frameworks

The principles of CLT guide the implementation of HRC and the pursuit of inclusive manufacturing practices. Trust emerges as the unifying element that connects these frameworks: it serves as the foundation for effective collaboration in HRC [19], influences cognitive load management through increased operator confidence [20], and enables truly inclusive manufacturing by fostering psychological safety for diverse operators [21].

In HRC trust enables effective role allocation and task sharing through transparent interactions [22], leading to improved decision-making and reduced cognitive strain [23]. This trust-based efficiency directly impacts cognitive load theory, as operator confidence influences information processing capabilities [24].

The inclusive manufacturing perspective emphasizes adapting trust-building mechanisms to diverse cognitive profiles. Studies show that personalized trust approaches improve outcomes for neurodiverse operators [25], leading to systems that dynamically adjust strategies based on individual characteristics. These integrated principles, HRC theory [26], cognitive load management [27], and inclusive manufacturing [28] directly informed our HMRL framework's cognitive assessment and trust-building mechanisms.

3. IMPLEMENTATION PHASES

Building upon the integrated theoretical framework, this HMRL implementation progressed through developmental stages focused on trust-building and cognitive support in manufacturing environments.

3.1 Initial Trust-Building Implementation

The initial implementation featured an OMRON TM5-900 collaborative robot integrated with a YOLO-based vision system for real-time object detection and sequence verification, as shown in Fig. 3. The system synchronized robot movements with operator actions through real-time visual feedback, achieving 99.5% accuracy in component recognition [29] (accuracy = (Number of Correct Predictions) / (Total Number of Predictions)). The two case studies are the assembly of different mechanical parts: a two shafts gearbox and a horizontal bare-shaft centrifugal pump. The common characteristics of both parts is the long assembly sequence that pose cognitive challenges to the neurodiverse operator. The assembly can be executed without welding and the weight of every part is largely below the load limits.

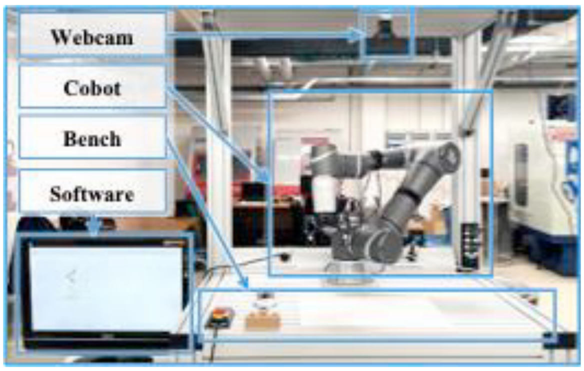

Figure 3. HRC system hardware setup, showing the OMRON TM5-900 robot, vision system, and workstation layout

3.2 Cognitive Assessment and Trust Calibration

Building upon insights gained from the initial implementation, the framework was enhanced through the development of a cognitive load assessment system that continuously calibrated trust levels. This advancement introduced fuzzy logic-based evaluation methods that monitored multiple trust dimensions simultaneously, including competence, predictability, and process.

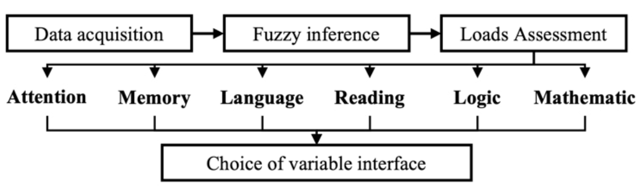

Figure 4. The scheme of cognitive load assessment.

The cognitive load assessment (CL), illustrated in Fig. 4, evaluates six key cognitive domains: attention, memory, language, reading, logic, and mathematics. This comprehensive assessment provides real-time insights into operator cognitive states, enabling dynamic trust calibration and personalized support strategies.

The CL assessment methodology analyses factors influencing a process, starting with initial conditions (e.g., task difficulty, tool complexity) that are then affected by other factors within the process (e.g., number of sub-operations, workstation layout) before ultimately impacting the outcome (e.g., assembly performance). These factors can be categorized as relating to the task itself, the workstation, the overall work environment and every factor that could influence the individual's physiological state [18]. As most of the factors are determined on a qualitative basis and use categorial metrics, a fuzzy inference approach was introduced to generate the assessment.

As illustrated in Fig. 5, the system employs a HMRL paradigm, establishing iterative learning loops that enable continuous refinement of both the system's understanding of operator needs and its adaptive support strategies.

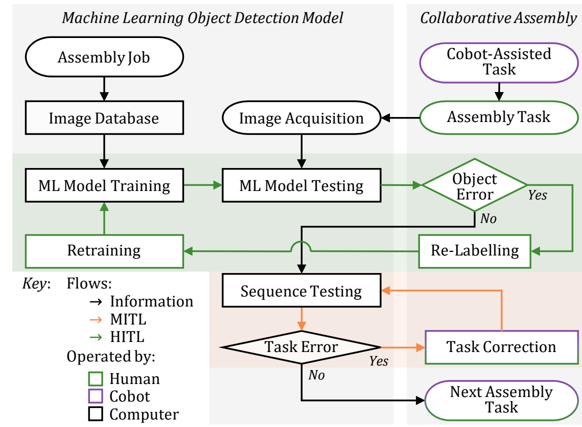

Figure 5. RHML paradigm

The improvements in HRC are the system's cognitive assessment and dynamic adaptation capabilities proving especially effective for stable collaboration with operators of diverse cognitive profiles. The reciprocal learning mechanism reduced cognitive load while maintaining high manufacturing standards, as evidenced by reduced error rates and improved task completion times across various assembly operations [18].

3.3 Natural Language Processing Enhancement

The next phase focused on strengthening human-machine trust through improved communication capabilities. Advanced natural language processing enabled context-aware instruction generation aligned with operator preferences and real-time explanation of system decisions. This enhanced transparency proved crucial for trust development, particularly in complex assembly scenarios.

The enhanced framework utilized a multi-layered approach to instruction delivery, as shown in Fig. 6. This system comprised several integrated components: a diagnosis module for error detection, an instruction development module for personalized guidance generation, and a prognosis module for implementation monitoring.

> Hey [operator's name], It looks like there was a small mistake in the assembly process. In step S6, you picked up the wrong component.
> Here's what to do to fix it:
> 1. Stop the current task.
> 2. Remove the 'Drive shaft companion flange' from the assembly area.
> 3. Find and pick up the correct component: 'Hex cap screw (big), C26'.
> 4. Thread the 'Hex cap screw (big), C26' by hand into the threaded hole above the support (C1).
> After you're done, double-check your work to make sure that the 'Hex cap screw (big), C26' is properly installed.
> If you need any more help, just let us know.

Figure 6. Digital instructions transcription for error

The implementation achieved performance improvements, particularly in error handling efficiency. Preliminary experimental tests resulted in a 61.8% reduction in component-related error handling time and a 41.4% reduction in tool-related error handling time. The context-aware instruction generation and real-time system feedback created clearer communication pathways between operators and the robotic system, facilitating more effective collaboration in complex assembly scenarios.

3.4 Logic-Assisted Assembly Implementation

The subsequent development phase enhanced the system's logical reasoning capabilities through the implementation of a Logic-Assisted Assembly Support (LoAS) system focused on transparent decision-making processes. The system provided real-time visualization of assembly sequences and intelligent error classification while dynamically generating instruction flowcharts based on operator interactions. Fig. 7 presents the architecture of this advanced implementation.

This implementation introduced sophisticated error detection mechanisms through real-time monitoring of assembly sequences and intelligent error classification. The system's dynamic flowchart generation capability represented a significant advancement in visual assembly guidance, automatically creating and updating instructions based on real-time operator actions.

While this system was conceived to assist dyslexic workers, it proved effective also with neurotypical workers thanks to enhanced error detection and dynamic instruction generation. The system's ability to adapt its support level based on real-time monitoring of assembly sequences enabled operators to complete complex tasks with greater efficiency while reducing supervisor intervention requirements.

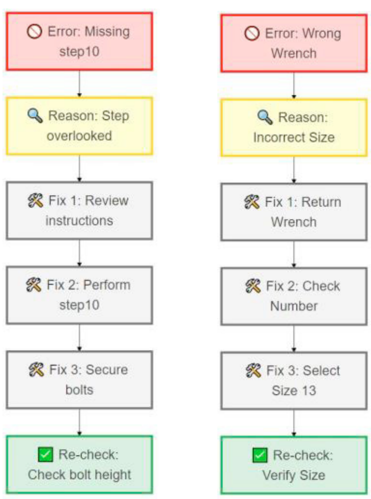

Figure 7. Logic-assisted flowchart

3.5 Multi-modal Interface Integration

The final implementation phase provides a graphical user interface (GUI) that uses a display, as shown in Figure 8, to provide information. Based on cognitive load assessment, the system can prioritize different communication channels by modifying this base interface - either enhancing or reducing certain elements while maintaining the core GUI structure. While critical instructions remain visible in the primary GUI, supplemental formats (flowcharts, audio cues, or simplified text) are added or removed as needed. This layered approach helps maintain consistency while allowing for cognitive load-based adjustments. This approach reduces specific cognitive loads and is activated on request by the worker either neurodiverse or simply in difficulty with the task.

Rather than switching between completely different interfaces, the system modifies the presentation of information through targeted enhancements - such as introducing step-by-step flowcharts while reducing text density or adding audio cues while simplifying visual elements. It is still under test the introduction of an Augmented Reality system that uses a projector to avoid distracting the gaze from the work area.

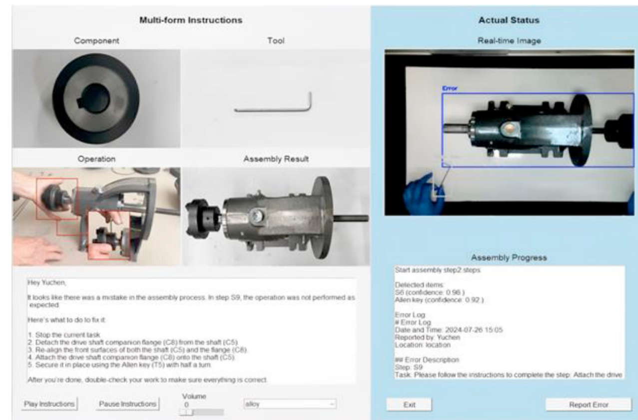

Figure 8. The multi-modal instruction system

4. HMRL SYSTEM FRAMEWORK

Building upon the implementations discussed above, this section presents a trust-centered HMRL framework where continuous trust assessment drives the integration of specialized components. The overall architecture illustrated in Fig. 9 facilitates bidirectional trust building through reciprocal learning loops while supporting diverse cognitive needs in manufacturing environments.

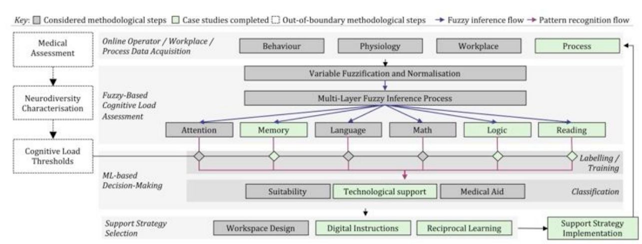

Figure 9. Comprehensive HMRL framework

The proposed architecture implements two primary feedback loops for seamless human-robot interaction: the human-in-the-loop corrects the object detection model and provides cognitive stress feedback, while the machine-in-the-loop delivers adaptive instructions and correct the worker cognitive mistakes, like wrong assembly sequence. The cognitive assessment module ensures system adaptations to the specific operator weakness in some cognitive area: attention, memory, language, logic, math or reading. Through processing multiple input streams including behavioural metrics and physiological data, the system maintains a dynamic understanding of operator state that informs trust-building strategies.

Central to the framework's operation is the real-time object detection module, which leverages advanced computer vision algorithms for high-speed component recognition. This module monitors assembly operations while performing error detection and classification, providing crucial spatial tracking data for robot guidance. The natural language processing module enhances system-operator communication through context-aware instruction generation, processing error narratives and operator feedback to formulate adaptive messages aligned with individual cognitive needs.

To accommodate diverse cognitive profiles, the framework incorporates a multi-modal instruction interface combining visual guidance through augmented reality, audio instructions with noise cancellation, and haptic feedback for critical operations. This interface can be customized to match individual operator preferences, ensuring optimal information delivery. The collaborative robot system provides precision assembly assistance while ensuring safe interaction through real-time path planning and adjustment capabilities.

The framework's learning mechanisms enable continuous improvement through both machine learning and human skill development. The human-to-machine pathway analyzes operator performance data and successful operation patterns, while the machine-to-human flow delivers personalized instructions based on accumulated knowledge. A dynamic knowledge repository maintains successful patterns and operator profiles, creating a self-improving system where operator actions inform adaptations and system responses guide operator development.

5. Discussion and Future Directions

5.1 Implementation Guidelines

The successful implementation of the HMRL framework requires robust technical infrastructure, particularly for real-time vision processing and cognitive assessment. Organizations should adopt a modular implementation approach, beginning with basic components like the multi-modal instruction system before incorporating more advanced features. Critical success factors include careful lighting control for vision systems and establishment of appropriate trust calibration benchmarks through initial human-robot interaction monitoring.

5.2 Current Limitations

While demonstrating promising results, the HMRL framework faces certain limitations in its current implementation. The cognitive assessment module requires further refinement to accurately capture the full spectrum of cognitive diversity in manufacturing environments. The reciprocal learning mechanism, though effective in controlled environments, needs additional validation across diverse manufacturing scenarios. While the multi-modal interface successfully accommodates different learning styles, the system's ability to dynamically switch between communication modes based on real-time cognitive state assessment could be enhanced.

5.3 Future Research Directions

Based on the present findings, several promising avenues for future research are apparent. Firstly, the development of advanced cognitive state assessment algorithms, capable of capturing temporal fluctuations in operator performance, warrants priority. Secondly, research should investigate the implementation of automated interface mode switching, driven by real-time cognitive load evaluations. Thirdly, refining the trust-building mechanism through a more granular analysis of individual operator preferences and behavioral patterns is crucial. Finally, enhancing the system's capacity to facilitate knowledge transfer across diverse manufacturing contexts, while preserving personalized adaptations, represents a significant research objective.

6. CONCLUSIONS

The development of the HMRL framework represents a significant advancement in trust-based manufacturing, demonstrating how integrated cognitive support and reciprocal learning can transform human-robot collaboration. Through its novel trust assessment mechanisms and adaptive learning loops, the framework addresses a critical gap in existing manufacturing systems - the need for sustained mutual trust between human operators and robotic systems. Implementation results demonstrate that this trust-centered approach significantly improves both operator experience and task performance compared to traditional collaborative systems, as evidenced by reduced error handling times and improved assembly completion rates.

The broader implications of this trust-based approach extend beyond immediate manufacturing efficiency gains. First, the framework establishes a new paradigm for human-robot collaboration where mutual trust serves as the foundation for continuous improvement. Second, the demonstrated success in building and maintaining operator trust across diverse cognitive profiles provides a practical model for inclusive manufacturing. While the framework was devised to support neurodiverse operators, experiment shows a beneficial improvement in the quality of work also for neurotypical ones. Third, the framework's ability to adapt trust-building strategies based on individual operator characteristics offers insights for future Industry 5.0 implementations, where human-centricity will be paramount.

REFERENCES

[1] S. Li *et al.*, “Proactive human–robot collaboration: Mutual-cognitive, predictable, and self-organising perspectives,” *Robot. Comput.-Integr. Manuf.*, vol. 81, p. 102510, Jun. 2023, doi: 10.1016/j.rcim.2022.102510.

[2] “Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook | J. Manuf. Sci. Eng. | ASME Digital Collection.” Accessed: Nov. 04, 2024. [Online]. Available: https://asmedigitalcollection.asme.org/manufacturingscience/article/142/11/110804/1085487/Artificial-Intelligence-in-Advanced-Manufacturing

[3] U. Eswaran, V. Eswaran, V. Eswaran, and K. Murali, “Human–Robot Collaboration Analyzing the Challenges and Opportunities of Integrating Soft Computing Algorithms in Manufacturing Environments,” in *Evolution and Advances in Computing Technologies for Industry 6.0*, CRC Press, 2024.

[4] R. Gervasi, M. Capponi, D. Antonelli, L. Mastrogiacomo, and F. Franceschini, “A human-centered perspective in repetitive assembly processes: preliminary investigation of cognitive support of collaborative robots,” *Procedia Comput. Sci.*, vol. 232, pp. 2249–2258, Jan. 2024, doi: 10.1016/j.procs.2024.02.044.

[5] R. LeFevre-Levy, A. Melson-Silimon, R. Harmata, A. L. Hulett, and N. T. Carter, "Neurodiversity in the workplace: Considering neuroatypicality as a form of diversity," *Ind. Organ. Psychol.*, vol. 16, no. 1, pp. 1–19, Mar. 2023, doi: 10.1017/iop.2022.86.

[6] H. Liu and L. Wang, "Human motion prediction for human-robot collaboration," *J. Manuf. Syst.*, vol. 44, pp. 287–294, Jul. 2017, doi: 10.1016/j.jmsy.2017.04.009.

[7] V. Villani, F. Pini, F. Leali, and C. Secchi, "Survey on human–robot collaboration in industrial settings: Safety, intuitive interfaces and applications," *Mechatronics*, vol. 55, pp. 248–266, Nov. 2018, doi: 10.1016/j.mechatronics.2018.02.009.

[8] S. El Zaatari, M. Marei, W. Li, and Z. Usman, "Cobot programming for collaborative industrial tasks: An overview," *Robot. Auton. Syst.*, vol. 116, pp. 162–180, Jun. 2019, doi: 10.1016/j.robot.2019.03.003.

[9] L. Wang *et al.*, "Symbiotic human-robot collaborative assembly," *CIRP Ann.*, vol. 68, no. 2, pp. 701–726, Jan. 2019, doi: 10.1016/j.cirp.2019.05.002.

[10] A. Ajoudani, A. M. Zanchettin, S. Ivaldi, A. Albu-Schäffer, K. Kosuge, and O. Khatib, "Progress and prospects of the human–robot collaboration," *Auton. Robots*, vol. 42, no. 5, pp. 957–975, Jun. 2018, doi: 10.1007/s10514-017-9677-2.

[11] E. Matheson, R. Minto, E. G. G. Zampieri, M. Faccio, and G. Rosati, "Human–Robot Collaboration in Manufacturing Applications: A Review," *Robotics*, vol. 8, no. 4, Art. no. 4, Dec. 2019, doi: 10.3390/robotics8040100.

[12] "Human–robot collaboration in industrial applications: Safety, interaction and trust - Iñaki Maurtua, Aitor Ibarguren, Johan Kildal, Loreto Susperregi, Basilio Sierra, 2017." Accessed: Nov. 04, 2024. [Online]. Available: https://journals.sagepub.com/doi/full/10.1177/1729881417716010

[13] "Trust in Automation: Designing for Appropriate Reliance - John D. Lee, Katrina A. See, 2004." Accessed: Nov. 15, 2024. [Online]. Available: https://journals.sagepub.com/doi/10.1518/hfes.46.1.50_30392

[14] P. A. Hancock, D. R. Billings, K. E. Schaefer, J. Y. C. Chen, E. J. de Visser, and R. Parasuraman, "A meta-analysis of factors affecting trust in human-robot interaction," *Hum. Factors*, vol. 53, no. 5, pp. 517–527, Oct. 2011, doi: 10.1177/0018720811417254.

[15] J. J. G. Van Merrienboer and J. Sweller, "Cognitive Load Theory and Complex Learning: Recent Developments and Future Directions," *Educ. Psychol. Rev.*, vol. 17, pp. 147–177, Jun. 2005, doi: 10.1007/s10648-005-3951-0.

[16] L. Longo and M. C. Leva, Eds., *Human Mental Workload: Models and Applications: First International Symposium, H-WORKLOAD 2017, Dublin, Ireland, June 28-30, 2017, Revised Selected Papers*, vol. 726. in Communications in Computer and Information Science, vol. 726. Cham: Springer International Publishing, 2017. doi: 10.1007/978-3-319-61061-0.

[17] A. Rajavenkatanarayanan, H. R. Nambiappan, M. Kyrarini, and F. Makedon, *Towards a Real-Time Cognitive Load Assessment System for Industrial Human-Robot Cooperation*. 2020. doi: 10.1109/RO-MAN47096.2020.9223531.

[18] A. Simeone, Y. Fan, D. Antonelli, A. R. Catalano, P. C. Priarone, and L. Settineri, "Inclusive manufacturing: A contribution to assembly processes with human-machine reciprocal learning," *CIRP Ann.*, May 2024, doi: 10.1016/j.cirp.2024.03.005.

[19] B. Sadrfaridpour and Y. Wang, "Collaborative Assembly in Hybrid Manufacturing Cells: An Integrated Framework for Human-Robot Interaction," *IEEE Trans. Autom. Sci. Eng.*, vol. PP, pp. 1–15, Sep. 2017, doi: 10.1109/TASE.2017.2748386.

[20] "Trust in Automation: Integrating Empirical Evidence on Factors That Influence Trust - Kevin Anthony Hoff, Masooda Bashir, 2015." Accessed: Nov. 15, 2024. [Online]. Available: https://journals.sagepub.com/doi/10.1177/0018720814547570

[21] "Individual Differences in Trust in Autonomous Robots: Implications for Transparency | Request PDF." Accessed: Nov. 15, 2024. [Online]. Available: https://www.researchgate.net/publication/337434343_Individual_Differences_in_Trust_in_Autonomous_Robots_Implications_for_Transparency

[22] G. Charalambous, S. Fletcher, and P. Webb, "The Development of a Scale to Evaluate Trust in Industrial Human-robot Collaboration," *Int. J. Soc. Robot.*, vol. 8, no. 2, pp. 193–209, Apr. 2016, doi: 10.1007/s12369-015-0333-8.

[23] J. D. Lee and K. A. See, "Trust in Automation: Designing for Appropriate Reliance," *Hum. Factors*, vol. 46, no. 1, pp. 50–80, Mar. 2004, doi: 10.1518/hfes.46.1.50_30392.

[24] R. Parasuraman and D. Manzey, "Complacency and Bias in Human Use of Automation: An Attentional Integration," *Hum. Factors*, vol. 52, pp. 381–410, Jun. 2010, doi: 10.1177/0018720810376055.

[25] L. P. Robert, C. Pierce, L. Marquis, S. Kim, and R. Alahmad, "Designing fair AI for managing employees in organizations: a review, critique, and design agenda," *Human–Computer Interact.*, vol. 35, no. 5–6, pp. 545–575, Nov. 2020, doi: 10.1080/07370024.2020.1735391.

[26] B. Busch, G. Maeda, Y. Mollard, M. Demangeat, and M. Lopes, "Postural optimization for an ergonomic human-robot interaction," in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Sep. 2017, pp. 2778–2785. doi: 10.1109/IROS.2017.8206107.

[27] N. Kousi, G. Michalos, S. Aivaliotis, and S. Makris, "An outlook on future assembly systems introducing robotic mobile dual arm workers," *Procedia CIRP*, vol. 72, pp. 33–38, Jan. 2018, doi: 10.1016/j.procir.2018.03.130.

[28] Z.-H. Lai, W. Tao, M. C. Leu, and Z. Yin, "Smart augmented reality instructional system for mechanical assembly towards worker-centered intelligent manufacturing," *J. Manuf. Syst.*, vol. 55, pp. 69–81, Apr. 2020, doi: 10.1016/j.jmsy.2020.02.010.

[29] Y. Fan, D. Antonelli, A. Simeone, and N. Bao, "Intelligent robot assistants for the integration of cognitive disabled workers in manufacturing industry," *Procedia CIRP-17th CIRP Conf. Intell. Comput. Manuf. Eng.*, 2023.