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Inclusive manufacturing: A contribution to assembly processes with human-machine reciprocal learning

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ABSTRACT

This study explores the potential synergy between neurodiversity and advanced technology within Industry 5.0, focusing on the integration of neurodiverse individuals in the workforce through Human-Machine Collaboration and Reciprocal Learning (RL). A cognitive load (CL) assessment procedure is developed using fuzzy logic inference across the dimensions of attention, memory, language, math, logic, and reading. A case study evaluates the effectiveness of RL in assisting assembly tasks. Different error-handling scenarios are compared. Experimental results show how RL can reduce the CL while improving assembly tasks efficiency, underscoring the value of intelligent systems in inclusive manufacturing, enhancing productivity and facilitating the integration of neurodiverse workers.

1. Introduction

In the context of Industry 5.0, the manufacturing paradigm extends beyond the scope of automation, emphasising a synergistic integration of human expertise and intelligent technological systems [1,2]. Despite the growing emphasis on diversity, equity, and inclusion in the workforce, the integration of neurodiverse individuals (e.g., those affected by conditions such as autism spectrum disorder, attention deficit hyperactivity disorder, and dyslexia) remains under-addressed, resulting in their higher underemployment rates and the fact that research on their workforce development and integration is still in its early stages [3]. The integration of neurodiverse individuals could be successfully supported by the implementation of Human-Machine Collaboration (HMC) and Reciprocal Learning (RL), the latter referring to the process by which humans and artificial intelligence systems learn from each other through iterative interactions [4]. These technologies are not merely assistive, but transformative in nature [5,6], facilitating the optimal employment of the strengths of the neurodiverse workforce in manufacturing. The HMC enables an environment in which diverse cognitive approaches can be effectively utilised, while RL fosters a bi-directional learning paradigm, allowing for the continuous adaptation and advancement of both human workers and machines through iterative feedback mechanisms. To address the pending research gaps, this study explores inclusive manufacturing strategies, enhanced by HMC and RL, to potentially include neurodiverse individuals in assembly processes.

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2. Framework and methodology

The proposed framework outlines a comprehensive approach towards the integration of medically-identified neurodiverse individuals into the workforce. The framework, shown in Fig. 1, uses real-time data acquisition of operator behaviour, physiology, workplace settings and process characteristics, which is fed into a fuzzy logic system that normalises and fuzzifies such data for cognitive load (CL) assessment, which is carried out across relevant CL domains. Cognitive thresholds are used to match these results to inform decision-making in suitability, support, and medical aid, guiding the selection of support strategies such as workspace design, digital enhancement, as well as RL, and ultimately leading to the implementation of these strategies.

2.1. Cognitive load assessment

In manufacturing, the CL strongly influences operator performance, which is heightened by task complexity and error correction. High CL can overload working memory, causing more errors and stress, influenced by environmental factors and task design. The limited presence of neurodiverse workers in industry is attributed to these challenging conditions. Traditional CL assessment methods – subjective scales, performance metrics, physiological monitoring – are intrusive and not ideal for industry [7]. Current research is focusing on automated, industry-appropriate CL assessment systems that incorporate attention, environmental factors, workspace design, task difficulty, and behavioural stressors. Yet, their adoption in industry and with neurodiverse workers is constrained by the unwieldiness of necessary technologies and limited interpretability [8]. The literature survey highlights the need for novel, seamless, non-intrusive CL assessment tools in industrial settings that are specifically designed

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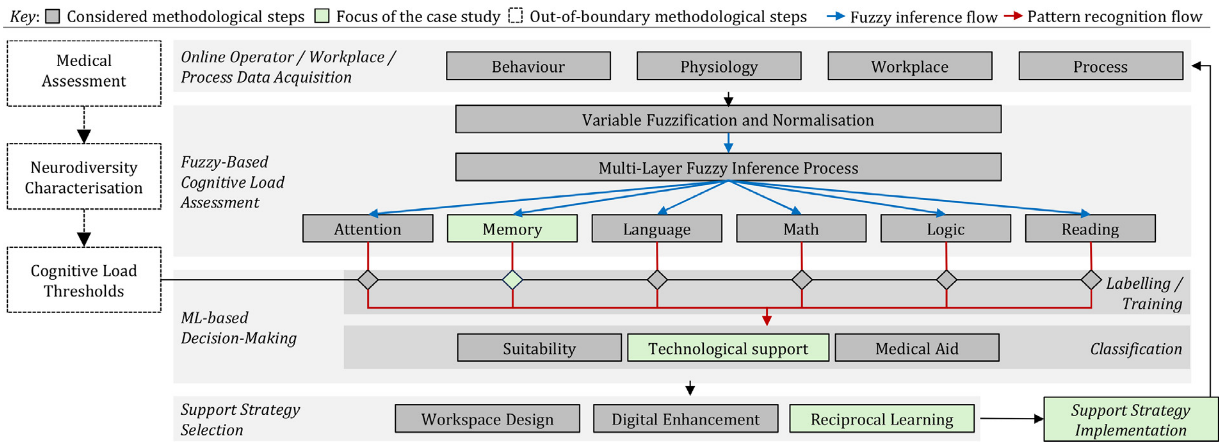

Fig. 1. Overall framework.

to accommodate neurodiverse workers, thereby boosting both productivity and overall occupational well-being. In this respect, the CL assessment methodology proposed here involves a fuzzy inference-based data fusion method that converts simple input variables into complex CL descriptors for industrial settings. The input variables should be acquired by wearable and nearable sensing units to reduce the intrusiveness. This analysis requires a diverse array of data, encompassing task-specific details and broader environmental and human health conditions. Process data accounts for assembly complexity, tool usage, workstation design, number of components, and information load. Workplace assessments include spatial configuration and environmental factors like noise, lighting, and temperature.

Physiological metrics, essential for well-being and performance assessment, monitor heart rate, respiratory rate, and body temperature. Behavioural monitoring, necessary for crisis prediction and mental health oversight, uses non-intrusive camera tracking. Ethical and legal considerations, beyond the scope of this study, are recognised. The implementation phase must integrate data privacy protocols and develop solutions that respect individual differences, ensuring adaptability to evolving ethical and legal standards. The acquired data is then subjected to a pre-processing and normalisation procedure for all the variables belonging to the input categories: (*i*) physiology, (*ii*) behaviour, (*iii*) workplace settings, and (*iv*) process characteristics, where the raw data are converted to a common range $\in [0, 1]$ based on intervals suggested by relevant literature and guidelines. Subsequently, the analytical procedure evaluates the dynamic interactions amongst the aforementioned variables. Each fusion step uses a fuzzy logic methodology [9], which encompasses the fuzzification of the normalised variables into three designated membership classes (low, medium, and high). This categorisation is followed by the application of a set of fuzzy inference rules, leading to a defuzzification process that results in a normalised output value, again within the range of [0,1]. The ensemble of these processes forms a layered, hierarchical structure, iteratively synthesising the input data into six distinct CL descriptors: (*i*) attention, (*ii*) memory, (*iii*) language, (*iv*) math, (*v*) logic, and (*vi*) reading [8]. These descriptors are chosen to cover a wide range of occupational mental stressors that affect psychological well-being. The whole fusion process is underpinned by expert knowledge in occupational health, neurodiversity and process engineering translated into fuzzy inference rules, as detailed in the Supplementary material. The output of this procedure is a set of dynamic charts that display fluctuations in each CL component over time, aligned with the corresponding assembly task, providing a temporal visualisation of the cognitive demands placed on the operator by the manufacturing environment.

2.2. ML-based decision-making on the status of the operator

The inputs from the fuzzy-based CL assessment are then processed to quantify the CLs across the six dimensions, which are evaluated against predetermined CL thresholds established by medical assessments (integrating guidelines and expert medical knowledge [10]). Such evaluation is required to label the normalised and defuzzified CL outputs. Subsequently, the module utilises Machine Learning (ML) algorithms for pattern classification. The module relies on a classifier pre-trained on labelled CL data using techniques such as Support Vector Machines, Neural Networks, and Decision Trees, all of which are recognised for their effectiveness and robustness in classification tasks [11]. This setup ensures the accurate and consistent classification of new CL instances in real time. Specifically, the classification process of the Decision-Making module stratifies CL status of the operator into three categories: (*i*) a *Suitability* class, in which operators are considered capable of performing the tasks without restrictions; (*ii*) a *Medical Aid* class, which requires the intervention of healthcare professionals; and (*iii*) a *Technological Support* class, which prompts the selection of appropriate support strategies.

In the case of a *Technological Support* classification, the module guides the selection of CL mitigation strategies. These are tailored to the assessed needs of the individual and may include workplace design optimisations, such as adjusting lighting levels or reconfiguring the layout to reduce cognitive strain [8]. In addition, multimedia support strategies are considered, including the deployment of augmented reality and virtual reality-based tools, as well as the delivery of instructions through monitors or auditory devices to improve task comprehension and execution [12].

2.3. Mitigation strategy – reciprocal learning

To narrow the research scope and fill the identified gaps, this study focuses on the implementation of RL strategies, an approach which incorporates iterative feedback mechanisms and peer-to-peer learning opportunities, that have been shown to effectively reduce CL and improve task performance [13]. Within a Human-Robot Collaboration (HRC) assembly system, an RL approach is used for CL reduction, as illustrated in Fig. 2. This strategy integrates an ML model, a collaborative robot, and the human operator to facilitate human-machine RL [14]. The system is based on two primary loops: Human in the Loop (HITL), where humans provide feedback on the machine outputs (e.g., object recognition and manipulation), and Machine in the Loop (MITL), where the machine offers real-time feedback to humans (e.g., on assembly tasks sequence errors). Such loops are here combined for optimal learning and efficiency. This synergy in human-machine RL leverages the strengths of both humans and machines, enhancing task efficiency and reducing weaknesses in the HRC system. As regards the human-machine communication protocols, various techniques could be adopted, from standard interfaces to tailored solutions like vocal synthesis, audio instructions, and visual aids, to address specific neurodiversity challenges such as writing, reading, attention, language, and logic issues.

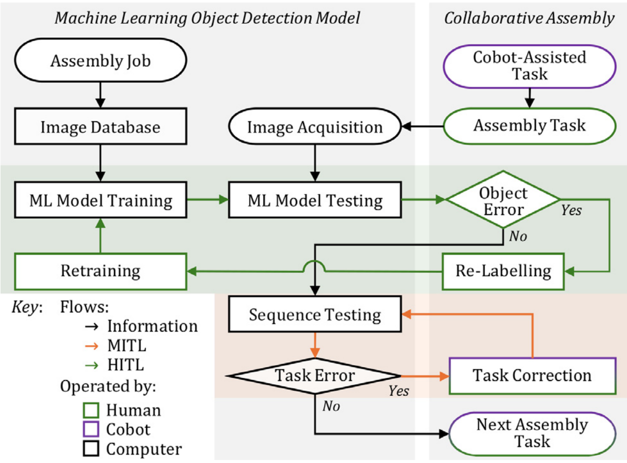

Fig. 2. RL paradigm adapted to the research framework.

3. Case study

To validate the applicability of the proposed framework, a case study is reported in this section. An assembly process was considered because it is a typical example of human-machine interaction and a potential source of stress for operators, as it involves repetitive operations with tight and predetermined timing. To simulate relevant neurodiversity conditions, the CL assessment was artificially forced to provide different scenarios with warning values for the memory components for specific assembly tasks. In addition to recording physiological data in the field (using commercially available smartwatches), the actual task duration was artificially delayed relative to the nominal duration to simulate memory problems, sometimes resulting in induced assembly errors. Given the simplified case study, behavioural and work environment data were set to produce non-warning CL values. The decision-making process suggests that the CL profile is suitable for technological support, and the subsequent strategy identification leads to the adoption of the RL approach as a mitigating measure. Fig. 3 shows the experimental setup, based on an OMRON TM5-900 robot, assisting the human operator. A camera streams real-time activity to the HRC system for analysis. An adjustable fixed light ensures that the camera captures detailed images of industrial components. A control box manages the robot operations, including motion and system monitoring. Lastly, TMflow™ software enables graphical programming of robot tasks. The joystick controls the robot functions and emergency protocols. Two screws, two gears (labelled as unit #45 and unit #40), and six nuts are assembled on a base unit. The assembly process is divided into two phases: Phase 1, which is entirely manual, and Phase 2, which is partially assisted by the robot, according to the sequence in Fig. 4. Table 1 lists the assembly steps and the related standard times. To apply the proposed framework, a series of memory-related manufacturing task errors have been introduced during the assembly process: (*i*) Error 1: in step #2, the operator uses the wrong part, which has not been identified by the system, and (*ii*) Error 2: in step #6, the operator performs the wrong sequence. The case study examines three scenarios, i.e., (*a*) no error, (*b*) error with manual correction, and (*c*) error with RL correction:

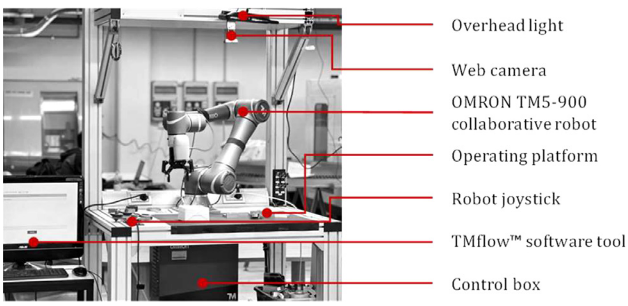

Fig. 3. Experimental setup.

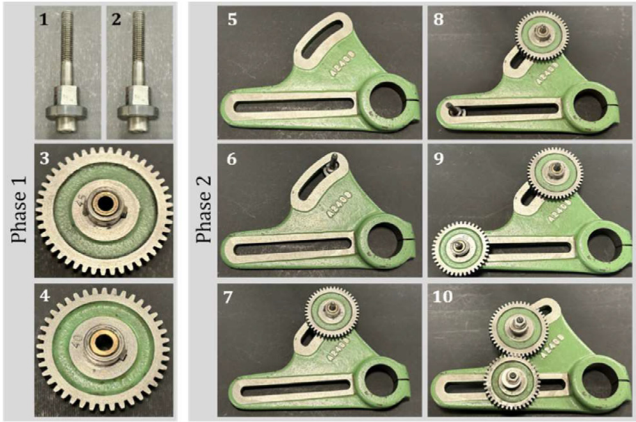

Fig. 4. Assembly sequence.

Table 1
Assembly time per task.

Phase	Step	Task	t_s (s)
Phase 1	1	Screw unit #1 assembly	15
	2	Screw unit #2 assembly	15
	3	Gear unit #45 assembly	19
	4	Gear unit #40 assembly	19
Phase 2	5	Base positioning	10
	6	Top-right screw unit #1 installation	16
	7	Placement of gear unit #45 in position	27
	8	Bottom-left screw unit #2 installation	16
	9	Placement of gear unit #40 in position	10
	10	Top screw assembly and gear integration	31

- Scenario (*a*) represents a baseline for benchmarking, where the operator makes no errors and the time required to complete the tasks corresponds to the nominal values. Here, each step time t_s from Table 1 includes a constant object selection time t_o = 5 s and a constant (manual) inspection time after each step t_i = 3 s;
- In Scenario (*b*), when an error occurs, this is identified by the operator within 5 s after the beginning of the next step, hence, this manual error detection time is t_{ed} = 5 s. After the error is detected, the operator calls the supervisor for a check, with a supervisor inspection time t_{si} = 10 s (this time includes the error diagnosis and correction instructions). The time required to reverse the error occurred in the task is given by: $t_{rev} = t_s - t_o - t_i$. Then, the operator has to re-perform the assembly task correctly, assuming $t_{rework} = t_{rev}$;
- In Scenario (*c*), the object detection time t_{od} = 1 s, the step time for Phase 1 is $t_{s1(RL)} = t_s - t_i + t_{od}$, while the step time for Phase 2 is $t_{s2(RL)} = t_s - t_o - t_i + t_{od}$ due to the robot handling object selection. For the robot-assisted tasks, the robot picks up the component and places it in the working area; t_r = 3 s is assigned to this task.

On the MITL side of RL, YOLOv7, a convolutional neural network, was used for the object detection, configuring the task into a classification problem. It predicts target boundary box positions and categories in a single forward pass [15]. The training dataset for Phase 1 contained 270 images of each component. The training dataset for Phase 2 contained 300 images across 6 categories, representing different assembly steps. Both datasets were divided into 82% samples for training and 18% for validation and testing, respectively. The models were trained for 300 epochs (≈ 2 h in total), with a batch size of 16 and image size of 640 × 640 px.

4. Results and discussion

This section presents and discusses the experimental outcomes in terms of CL and temporal efficiency to assess the MITL, while ML performance is used to evaluate the HITL. Specifically, the analysis is limited to the memory-related component of the CL, among all the CL components, due to its relevance. With reference to Fig. 5, the plotted data compare CL in assembly tasks across the scenarios. Normalised Memory Cognitive Load (NMCL) values were calculated following the procedure illustrated in Section 2.1 (and further detailed in the

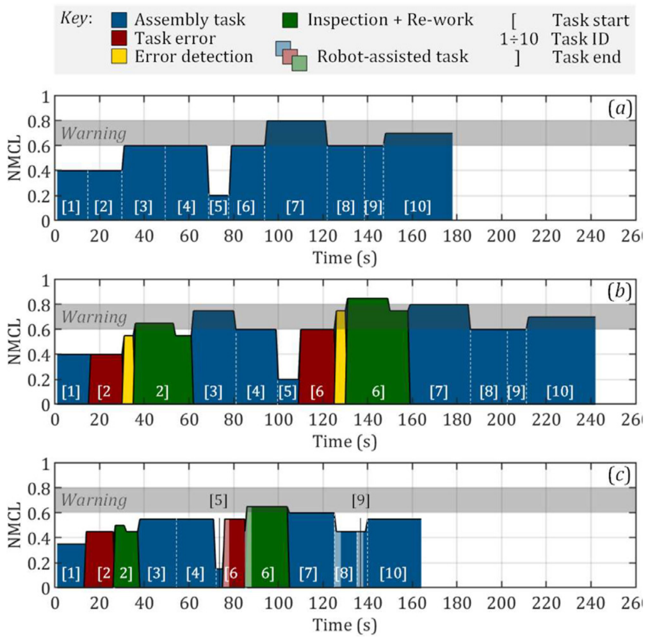

Fig. 5. Normalised Memory Cognitive Load vs Assembly time, in baseline (*a*), error + manual check (*b*), and error + RL (*c*) scenarios.

Supplementary material). Specifically, for each task reported in Table 1, the fuzzy-based fusion was applied taking into account the following manufacturing process variables: number of sub-tasks, task difficulty, number of items to be assembled, nominal and actual execution time for the sub-task. The physiological variables were the heart rate, body temperature and blood pressure, while the working environment was characterised by temperature and noise. The warning range for the NMCL was defined as [0.6–0.8] in this research. Scenario (*a*) shows the baseline NMCL indicating error-free task flow and reference cognitive demand (blue). Scenario (*b*) features a significant increase in the NMCL after error encounter (red) upon detection (yellow), followed by a sustained but reduced increase during error correction (green), suggesting a higher CL for error management than for routine tasks. The NMCL returns to baseline after error resolution, indicating recovery. Scenario (*c*), implementing RL, exhibits a less pronounced increase in NMCL during error detection and correction, demonstrating the effectiveness of the technique in reducing cognitive load. The quick return to baseline NMCL after correction proves efficient error management with minimal cognitive disruption. In terms of time, taking Scenario (*a*) as a reference, Scenario (*b*) shows that traditional error identification and correction methods are time consuming and cognitively demanding, while Scenario (*c*) demonstrates reduced time even compared to the baseline scenario due to the benefit of RL and collaborative robot in enhancing task efficiency and operator productivity. The results argue for proactive systems that reduce CL and improve operational efficiency, highlighting the importance of intelligent feedback in optimising manufacturing processes.

Regarding the results of the object classification using YOLOv7, for Phase 1, 100% recognition rates were achieved for most components, with the exception of a 9% error rate for the gear unit #40, which was confused with gear unit #45, due to their geometrical differences that are more easily detected by humans than by machines. The model achieved a confidence level of 0.837. Phase 2 training achieved 100% recognition rate and a confidence level of 0.985. The model classification performance was then improved using the HITL mechanism. After operator-induced labelling, the correctly labelled images were added to the training set, and after 6 epochs of re-training ($\approx$ 2.5 min in total), the classification error of gear unit #40 was reduced to 3%. This procedure improved the overall accuracy of the model.

5. Conclusions

The proposed framework and case study highlight the effectiveness of RL in reducing CL, particularly in error handling scenarios, suggesting potential for broader inclusion of neurodiverse workers by customising RL to each CL dimension. However, challenges remain in applying these technologies in diverse assembly environments and in capturing real data from neurodiverse operators. The CL assessment model, through its data fusion structure, is designed to indirectly detect fatigue once a steady state is achieved via system calibration and tuning. The study also highlights the need to refine the task complexity evaluation to better integrate operator skills. In addition, the study outlines strategies to reduce the operator learning effects in the experimental tests, recognising their complete elimination as a limitation. Future directions should include refining RL algorithms and enhancing system adaptability to support a wider range of neurodiverse conditions, contributing to a more sustainable and inclusive manufacturing ecosystem.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Alessandro Simeone: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft. **Yuchen Fan:** Data curation, Investigation, Software, Visualization, Writing – original draft. **Dario Antonelli:** Conceptualization, Investigation, Validation. **Angioletta R. Catalano:** Visualization, Writing – original draft, Writing – review & editing. **Paolo C. Priarone:** Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Luca Settineri:** Methodology, Resources, Supervision.

Supplementary materials

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.cirp.2024.03.005.

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