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Procedia CIRP 135 (2025) 1119–1124

www.elsevier.com/locate/procedia

32nd CIRP Conference on Life Cycle Engineering (LCE 2025)

A logic-assisted assembly support system to promote the inclusion of neurodiverse operators in manufacturing

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Abstract

Inclusive manufacturing fosters social sustainability and equal opportunities for diverse cognitive profiles, achievable through Industry 4.0/5.0 technologies. A logic-assisted assembly support (LoAS) system to guide neurodiverse operators with logic-related assembly challenges is proposed in this research. The system uses a deep learning paradigm for intelligent object recognition to verify the correct completion of critical steps and to identify assembly errors and incorrect sequences. The operational logic is modelled through a dynamic flowchart automatically generated by a large language model (LLM) based on feedback from the vision system. This flowchart shows each step, along with the tools and components required, and is updated in real time to inform operators of their next steps and current location within the process. The system also includes a step-by-step verification mechanism with detailed completion diagrams to ensure accuracy. Interactive instructions provide personalised step-by-step guidance, visual identification and immediate feedback to correct errors and guide the operator through the assembly sequence. The efficiency and effectiveness of LoAS have been verified at a proof-of-concept lab scale on an industrial workpiece. The results suggest the potential of those tools to foster inclusiveness in manufacturing environments.

Keywords: Social sustainability; Inclusive manufacturing; Neurodiverse workforce; Industry 5.0; Assembly processes

1. Introduction

The increasing emphasis on social sustainability in manufacturing has highlighted the need for inclusive workforce practices [1]. In particular, supporting individuals with neurodiverse cognitive profiles is critical to ensuring equal opportunities and improving productivity in industrial environments [2]. In this context, Industry 5.0 has emerged as a critical paradigm shift, focusing on human-centric processes integrating advanced technologies. Industry 5.0 represents a human-centric approach to manufacturing, where advanced technologies such as artificial intelligence, robotics, and smart systems are employed to enhance collaboration between humans and machines. It prioritises sustainability, adaptability, and the integration of human skills into the production process, fostering a balance between technological innovation and human well-being [3]. This shift addresses neurodiverse needs, encompassing conditions like autism, attention-deficit/ hyperactivity disorder (ADHD), and dyslexia, which can often present unique challenges in assembly tasks [4, 5].

People with these conditions often have unique strengths and challenges in different settings, including the workplace [6]. In manufacturing environments, particularly during assembly tasks, neurodiverse individuals may encounter specific logical issues that can affect their performance [1, 7]. Logical issues in this context involve challenges with sequences, complex instructions, or tasks requiring linear thinking and pattern recognition [8]. For example, people with autism may excel at repetitive tasks but struggle with unexpected changes or the need to adapt to new sequences [9].

10.1016/j.procir.2024.12.110

Similarly, people with ADHD may find it difficult to maintain focus across multiple steps, leading to errors in task performance [5]. Dyslexia can also contribute to difficulties in processing written instructions, making it harder to follow assembly procedures correctly. These logical challenges may manifest in a variety of ways during assembly tasks. An operator may skip steps, misinterpret the order of operations, or have difficulty identifying errors in the sequence of tasks [4]. This can result in incomplete assemblies, incorrect installations or the need for frequent rework, which ultimately affects the productivity and quality of manufacturing processes [10].

Current solutions in manufacturing largely rely on 'standardised' processes that may not account for the varied cognitive abilities within the workforce [11]. For instance, such workflows may assume a linear task execution style or rely heavily on detailed written instructions, which can pose challenges for operators with ADHD or dyslexia. While assistive technologies like augmented reality overlays [12], error-checking tools, and guided assembly systems exist [13, 14], they are typically designed for general-purpose use and lack the adaptability needed to address the unique challenges of neurodiverse operators, thus failing to offer real-time, personalised guidance, limiting their effectiveness in supporting diverse cognitive need. To address these issues, it is necessary to create assistive systems that can accommodate different cognitive profiles [15]. Industry 5.0 technologies can provide intelligent systems that deliver real-time feedback, customised guidance, and adaptive support, enabling neurodiverse workers to better handle the cognitive demands of assembly tasks [15–17]. These systems can potentially improve task accuracy and efficiency, fostering an inclusive work environment where individuals with diverse cognitive abilities can thrive [14]. Additionally, by reducing errors and minimising rework, such technologies contribute to sustainable manufacturing practices and boost overall productivity [18]. This research focuses on developing and evaluating a logic-assisted assembly support (LoAS) system, designed to deliver personalised, real-time guidance and adaptive assistance making it particularly beneficial for operators with neurodiverse cognitive profiles.

2. Framework and methodology

The proposed LoAS system, shown in Fig. 1, is designed to support operators in assembly tasks by leveraging both deep learning for real-time error detection and large language models (LLMs) for dynamic instruction generation. The system comprises three main modules: (*i*) the Vision System Module, (*ii*) the Instructions Development Module, and (*iii*) the Instructions Feedback Module. These modules work together to detect, classify and correct assembly errors, providing personalised guidance and ensuring task accuracy through a continuous feedback loop.

2.1. Vision System Module

The Vision System Module is the first element of the LoAS framework, designed to monitor both the completion and correctness of each assembly step.

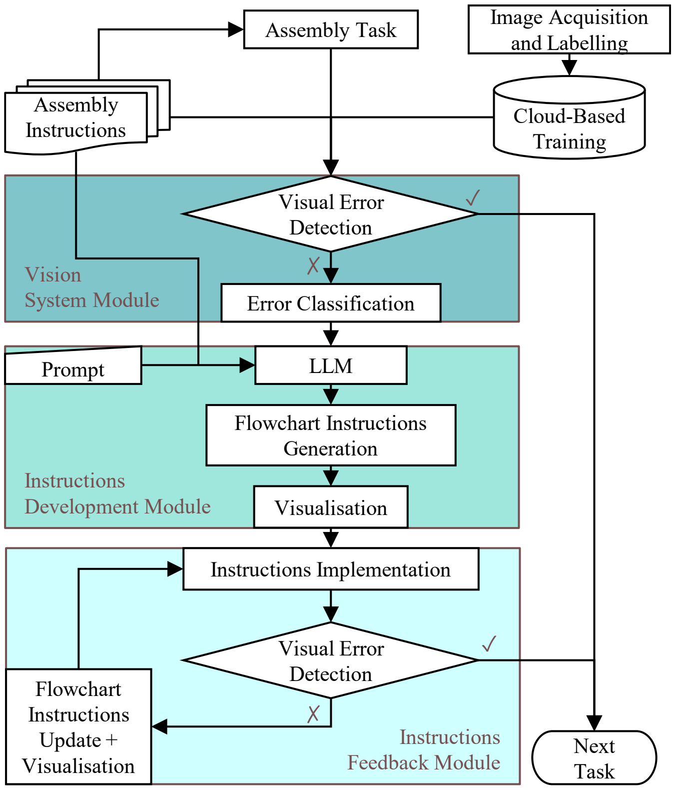

Fig. 1. Overall LoAS framework flowchart.

It utilises a convolutional neural network (CNN) [1], a deep learning model that mimics human vision to extract spatial features from images. Unlike traditional machine learning algorithms, CNNs handle complex visual data directly without extensive feature engineering [19], enabling real-time detection, classification, and error feedback to ensure correct assembly steps.

The system detects errors by evaluating recognised objects and their relationships, ensuring that each critical step is completed correctly. Detected configurations are compared against predefined ones, with discrepancies classified via a confusion matrix from the model output. Errors may involve incorrect sequences, or missing or incorrect components or tools. When an error is identified, the system activates the subsequent modules to provide corrective instructions based on the error classification. In case of misclassification, a reciprocal learning-based approach [1] can be employed, leveraging human feedback to refine classification accuracy and improve error detection performances.

2.2. Instructions Development Module

The Instructions Development Module is responsible for generating dynamic, personalised flowchart-based instructions in response to errors detected by the Vision System Module. Errors identified by the Vision System, represented as confusion matrix results, are encapsulated into JavaScript Object Notation (JSON)-formatted prompts and sent to a Large Language Model (LLM) via a Python-based interface. Specifically, the GPT-4.0 API is used to process these prompts, generating corrective instructions that are extracted and transformed into graphical flowcharts using Mermaid GPT

[20]. Once an error is classified, the LLM processes the prompt, which contains essential details such as the error type, the current assembly state, and the necessary corrective actions, along with relevant technical information about the tools, components, and steps involved.

The system dynamically generates flowcharts by interpreting real-time data from the Vision System, translating it into step-by-step corrective instructions. The flowcharts rendering combines prompt-defined inputs and automated outputs from Mermaid GPT. The prompts specify the content, connections, and styles of nodes (e.g., colours, icons), while Mermaid algorithm automatically generate the layout and visual arrangement, ensuring clear and accessible diagrams. These flowcharts outline required tools and components, highlight critical actions with visual markers, and clearly indicate errors to be corrected, enabling operators to follow the correct sequence with minimal confusion. The flowchart is displayed to the operator in real time, providing detailed guidance at each step to ensure accurate task execution. The system supports step-by-step verification, enabling operators to confirm progress after each corrective action and ensuring errors are resolved efficiently before resuming the task.

2.3. Instructions Feedback Module

The Instructions Feedback Module evaluates the effectiveness of corrective instructions and ensures the overall accuracy of the assembly process. It re-engages the Vision System Module after instructions are implemented, creating a continuous feedback loop. Once the operator follows the flowchart-based instructions, the Vision System Module re-scans the assembly to verify if the corrective actions resolved the error. If the errors have been rectified and the assembly step is correct, the task proceeds. However, if further issues are detected, the system updates the instructions accordingly, refining the flowchart and guidance based on the latest feedback. In cases where new or recurring errors are identified, the LLM regenerates an updated flowchart based on the newly classified errors.

This iterative process enables quick refinement of the instructions and helps accommodate any ongoing logical challenges faced by the operator.

3. Case study

To demonstrate the applicability of the LoAS, a case study was conducted on the assembly of a horizontal centrifugal pump (Fig. 2). The study evaluated the LoAS ability to reduce error resolution time, improve accuracy, and enhance operator independence compared to a human-supervised baseline. Three operators (A, B, and C) participated, with error detection and correction tested across three assembly steps, i.e., Steps 10, 11, and 12 (see Table 1). The tests featured two scenarios: supervisor assistance and LoAS. In the supervisor-assisted scenario, operators paused work upon detecting an error and received guidance from the supervisor. In the LoAS scenario, the system automatically detected errors and provided step-by-step corrective instructions. Each operator completed the task under both scenarios, resulting in two tests per operator.

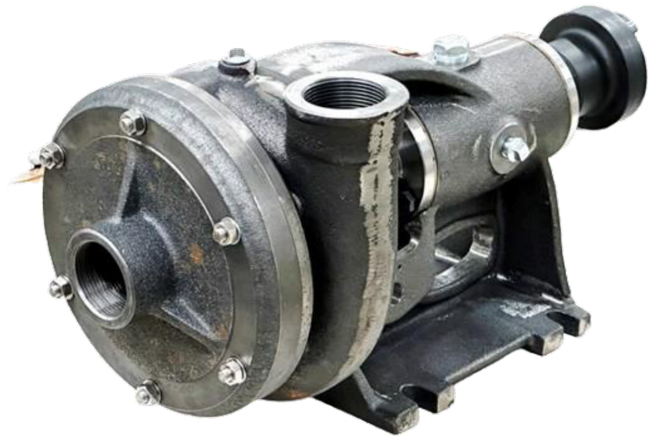

Fig. 2. Centrifugal pump (courtesy of Aldo Barbera srl).

To mitigate the memory effect, the tasks were performed with a one-week interval between each scenario for each operator. It is important to clarify that the three operators involved in the study are not neurodiverse. To account for neurodiverse conditions, the system was calibrated by simulating common cognitive challenges, such as logical sequencing errors and difficulties with tool or component identification. Typical errors, such as incorrect task sequencing, wrong tool selection, and misuse of components were introduced. Such errors were designed to mimic the cognitive challenges often experienced by neurodiverse individuals. This allowed the system to be tested on detecting and correcting mistakes common among neurodiverse individuals, enhancing its ability to provide tailored real-time guidance. Since this was a controlled lab test and not an industrial validation, the limitations are addressed in Section 4.

An intelligent vision system employing a YOLOv10 [21] convolutional neural network with a 640×640 pixel input was used, trained over 300 epochs with a batch size of 16. The dataset comprised 252 images of assembly components, including 12 types of tools and components (e.g., T-type wrench, Allen key, pump housing, bolts) and four assembly step states, i.e., Steps 10, 11, and 12 (see Table 1).

These images were captured using a C101 webcam (1280×960 pixels) under uniform LED lighting. Data augmentation [22] via Roboflow [23] generated three additional variations per image through rotation, cropping, and adjustments to saturation, brightness, and exposure, expanding the dataset to 1,008 images. The dataset was then split into 882 images for training, 84 for validation, and 42 for testing.

The LLM utilized in this research was ChatGPT 4.0, and the prompt used is shown in Fig. 3. If an error is detected, the system generates a correction message using the OpenAI GPT-4.0 API, based on predefined prompts and step information. GPT-4 then generates the syntax for the error correction flowchart in Mermaid, a JavaScript-based diagramming tool used to create visual representations like flowcharts, Gantt charts, and sequence diagrams from text-based descriptions. This Mermaid syntax is subsequently processed by the Mermaid renderer to produce the final flowchart image.

Table 1. Assembly instructions for the relevant steps.

	Instruction	Components	Tool	Operation	Result
Step 10	**10.1:** Take the components ID2 and ID23. **10.2:** Take the tool T7. **10.3:** Thread the short head of the 4 short stud bolts (ID23) into the pump housing (ID2). Start threading the bolts (ID23) by hand, then tighten them using the T-type wrench (T7).	 ID2  ID23	 T7		
Step 11	**11.1:** Take the components ID24. **11.2:** Take the tool T7. **11.3:** Turn the pump housing (ID2) upside down and thread the short head of the 6 long stud bolts (ID24). Start threading the bolts (ID24) by hand, then tighten them using the T-type wrench (T7).	 ID2  ID24	 T7		
Step 12	**12.1:** Take the components ID17, ID18 and ID1. **12.2:** Take the tool T6. **12.3:** Place the pump housing (ID2) onto the shaft (ID5), aligning the 4 short stud bolts (ID23) with the holes in the support (ID1). Attach the 4 washers (ID17) and 4 nuts (ID18) onto the bolts (ID23). Hand-tighten the nuts (ID18), then use a 13 mm wrench (T6) to tighten them in a crisscross pattern for even pressure.	 ID2  ID17  ID18  ID1	 T6		

```
Flowchart_prompt = f"""
Your task:
1. Analyse the user's error: {error_description}
2. Compare with correct step: {step_data}
3. Create a simple, clear flowchart for error correction
with 5-6 main nodes.
Flowchart requirements:
1. Use a top-down (TD) layout.
2. Use simple icons or emoticons at the start of each
node.
3. Keep each node EXTREMELY brief and action-oriented,
max 3-5 words per node.
4. Use everyday language, avoid technical terms.
5. Highlight the error and correct action with different
colours.
Use the following Mermaid flowchart syntax:
```mermaid
%%{{init: {{'theme': 'base', 'themeVariables': {{
'fontSize': '24px', 'fontFamily': 'Arial' }}}}}}%%
flowchart TD
A["🚫 Error: \n2-3 words"]
B["🔍 Reason: \n3-5 words"]
D1["🛠️ Fix 1: \n3-5 words"]
D2["🛠️ Fix 2: \n3-5 words"]
D3["🛠️ Fix 3: \n3-5 words"]
E["✅ Re-check: \n2-3 words"]
A --> B --> D1 --> D2 --> D3 --> E
```
Instructions:
- For 'Error', use only 2-3 words to summarise the
error.
- For 'Reason', use 3-5 words to explain the core reason
for the error.
- For each 'Fix' step, use 3-5 words to describe a
specific, actionable step.
- For 'Re-check', use 2-3 words to remind of
verification.
- If fewer than 3 fix steps are needed, remove
unnecessary nodes.
- Prioritise clarity and brevity over completeness.
- Use only the most essential words to convey each
point.
- Avoid articles (a, an, the) and other non-essential
words. Capitalise each word.
"""
```

Fig. 3. Prompt for the LLM-based corrective flowchart instructions.

4. Results and discussion

This section evaluates the performance of the two scenarios, i.e., supervisor assistance and the LoAS, by analysing task completion times and error correction efficiency. The comparison provides insights into how the use of intelligent, automatically generated instructions affects process efficiency, with particular emphasis on the potential benefits for operators, especially those facing challenges with logical sequencing.

The improvements in task completion time and error correction efficiency are illustrated in the bar charts in Fig. 4. In terms of task completion time, the LoAS scenario consistently outperformed the supervisor-assisted scenario. For all operators, the time required to complete the assembly was significantly reduced with the use of intelligent instructions. The bar charts show a substantial reduction in downtime across all operators. Regarding error correction times, the LoAS scenario also demonstrated better performance compared to the supervisor-assisted setup. In the traditional scenario, operators had to wait for supervisory input when errors were detected, causing delays. In contrast, the LoAS provided immediate feedback, allowing operators to address errors more swiftly. This is evident in the bar charts (Fig. 4), where error correction times are significantly shorter in the LoAS scenario.

The system ability to automatically detect errors and deliver real-time corrective instructions, reported in Fig. 5 for the three types of error, minimised task disruption, demonstrating how the intelligent flowchart-based instructions were a key factor in driving such improvements. In the LoAS scenario, operators received structured, step-by-step guidance immediately after an error was detected. This process reduced waiting times and enabled continuous task execution, unlike the supervisor-assisted approach, where operators frequently paused to seek guidance. The YOLOv10 model yielded high object classification accuracy, generally reaching 100%. A nominal misclassification rate of 12% between the 'nut' and 'washer' categories was observed during training, probably due to their visual similarity. Notably, no misclassifications occurred during testing, suggesting the reliability of the model in practical applications.

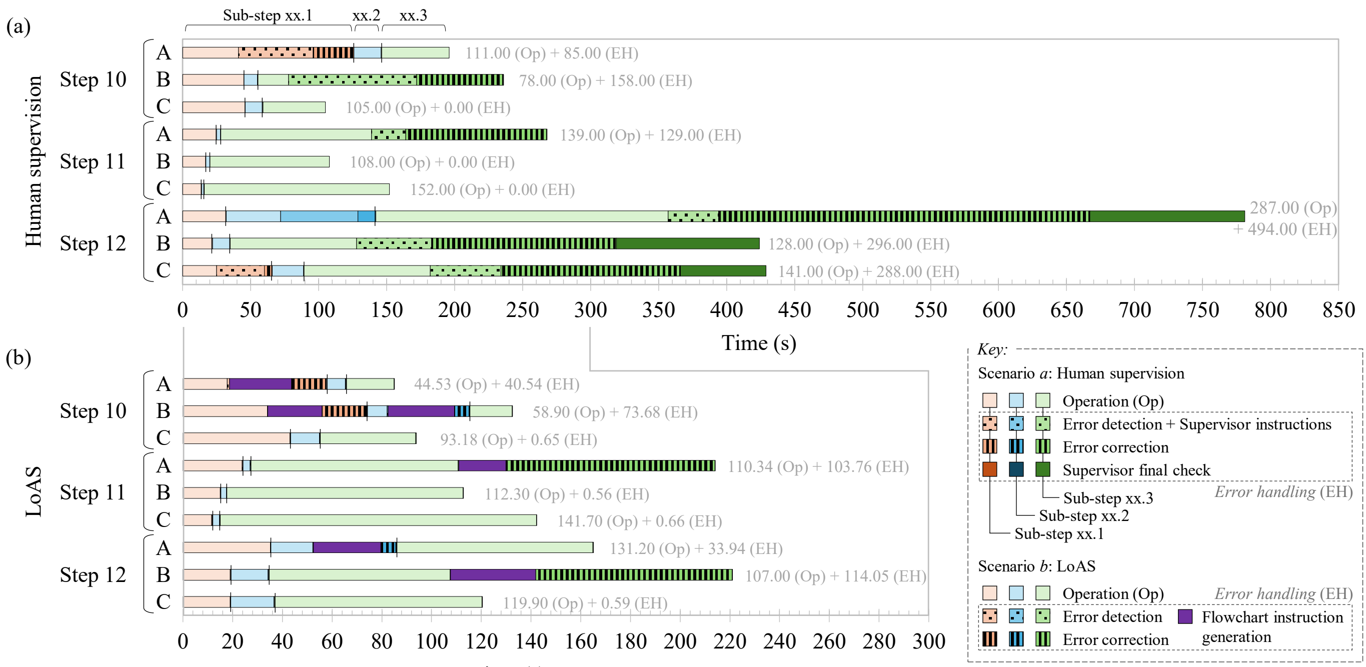

Fig. 4. Assembly time results: (a) Human supervisor; (b) LoAS.

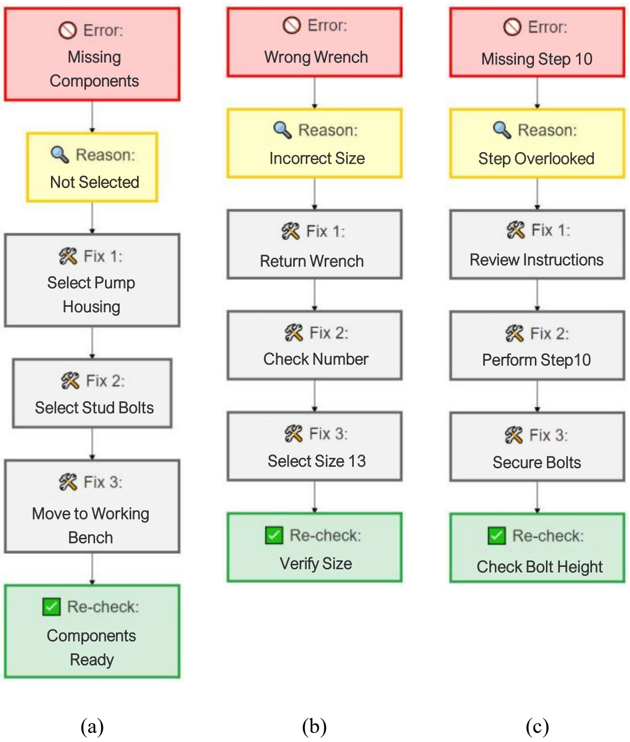

Fig. 5. Digital instructions flowchart (a) missing component, (b) wrong tool, (c) wrong operation.

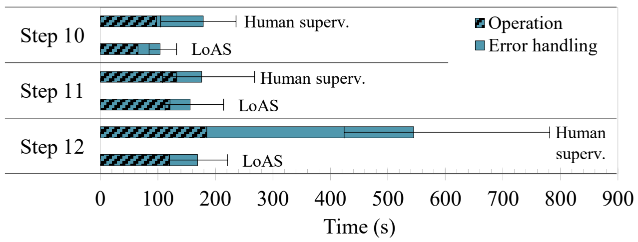

Fig. 6. Average total assembly and error-handling times.

Fig. 6 summarises the average total assembly operation and error-handling times for the three operators and for Steps 10, 11, and 12 in both the supervisor-assisted and LoAS scenarios. In the supervisor-assisted scenario, error handling included error detection, supervisor instructions, error correction, and a final supervisor check. In contrast, the LoAS scenario included error detection, flowchart instruction generation and error correction. On average, LoAS reduced error handling times by 19% to 86% and total assembly times by 11% to 69% compared to the supervisor-assisted setup. The benefits were more pronounced for complex tasks such as step 12, where delays due to manual intervention were significantly reduced. By standardising task execution and providing structured flowchart-based guidance, LoAS reduced the variability related to the differences in operator skill or experience, as shown by the error bars in Fig. 6. One limitation of this study is the small sample size of operators and the focus on a sub-set of assembly tasks. Further research with a broader range of tasks and a more diverse operator group would provide more comprehensive insights into the generalisability of these findings. Additionally, the controlled environment in which this study was conducted may not fully represent the complexity of real-world industrial settings, where other variables may influence the system performance. The practical implications of these findings extend beyond this specific case study. Intelligent, automatically generated instruction systems like LoAS have the potential to enhance operational efficiency across various industries by reducing cognitive load on operators and enabling faster task completion [1]. By supporting neurodiverse employees, such systems also promote a more inclusive approach to workforce management. Implementing these systems in industrial settings could reduce dependence on human supervision, improve process consistency, and offer scalability in precision tasks where error minimisation is essential [24]. In the LoAS scenario, error detection and correction were enhanced as the system automatically identified errors and generated corrective instructions in real time. This visual, step-by-step approach to corrections simplified complex error resolutions and reduced the likelihood of repeated mistakes. Especially for neurodiverse operators, this kind of structured guidance could improve their ability to understand and recover from errors more quickly, promoting a smoother and more efficient workflow. Although this research work primarily reports results in terms of task completion and error correction times, future studies could explore how these metrics relate to cognitive load. Faster error correction may reflect a reduced cognitive burden, as operators rely on the system to resolve issues promptly. Similarly, shorter task completion times could indicate less mental effort required to identify next steps or correct errors independently.

5. Conclusions

This research conceptualised a logic-assisted assembly support (LoAS) system and demonstrated its effectiveness in improving task completion times and error correction efficiency using a lab-scale industrial workpiece under simulated neurodiverse conditions. The system employs intelligent, auto-generated flowchart-based instructions, enhancing operator independence and consistency while reducing reliance on supervision. LoAS structured, step-by-step guidance aids individuals with challenges in logical sequencing and task execution. Its intelligent error detection and correction features minimise downtime and repeated errors, increasing operational efficiency and accuracy. Whilst the findings suggest that LoAS can enhance productivity and foster a more inclusive manufacturing environment, its effectiveness with neurodiverse operators still needs to be experimentally quantified and fully understood. A deeper focus on error recurrence and classification is needed, requiring larger sample sizes and extended observation periods to better understand error development and persistence. Incorporating more diverse error scenarios and exploring a broader range of task complexities will provide further clarity on how LoAS manages various challenges. In addition, assessing long-term operator performance, along with cognitive load and user feedback, could provide further insights to this research field.

Acknowledgements

The authors sincerely thank Aldo Barbera srl (Brandizzo, Torino, Italy) for supplying the resources for the case study.

References

[1] Simeone, A., Fan, Y., Antonelli, D., Catalano, A.R., Priarone, P.C., and Settineri, L., 2024. Inclusive manufacturing: A contribution to assembly processes with human-machine reciprocal learning. *CIRP Annals - Manufacturing Technology*. 73 (1), 5–8.

[2] Thompson, E. and Miller, J., 2024. Neuroinclusion at Work. Survey report. London: Chartered Institute of Personnel and Development.

[3] Rijwani, T., Kumari, S., Srinivas, R., Abhishek, K., Iyer, G., Vara, H., et al., 2024. Industry 5.0: a review of emerging trends and transformative technologies in the next industrial revolution. *International Journal on Interactive Design and Manufacturing*.

[4] Harris, L.N., Creed, B., Perfetti, C.A., and Rickles, B.B., 2022. The role of word knowledge in error detection: a challenge to the broken error monitor account of dyslexia. *Annals of Dyslexia*. 72 (2), 384–402.

[5] Rollnik-Sadowska, E. and Grabińska, V., 2024. Managing Neurodiversity in Workplaces: A Review and Future Research Agenda for Sustainable Human Resource Management. *Sustainability*. 16 (15), 6594.

[6] Doyle, N., 2020. Neurodiversity at work: a biopsychosocial model and the impact on working adults. *British Medical Bulletin*. 135 (1), 108–125.

[7] Volpone, S.D., Avery, D.R., and Wayne, J.H., 2022. Shaping Organizational Climates to Develop and Leverage Workforce Neurodiversity. in: Neurodiversity in the Workplace, Routledge, New York. 16–59.

[8] Piccinini, G. and Scarantino, A., 2011. Information processing, computation, and cognition. *Journal of Biological Physics*. 37 (1), 1–38.

[9] Krzeminska, A. and Hawse, S., 2020. Mainstreaming Neurodiversity for an Inclusive and Sustainable Future Workforce: Autism-Spectrum Employees. in: Industry and Higher Education, Springer Singapore, Singapore. 229–261.

[10] Li, J., Wang, S., Wang, G., Zhang, J., Feng, S., Xiao, Y., et al., 2024. The effects of complex assembly task type and assembly experience on users' demands for augmented reality instructions. *The International Journal of Advanced Manufacturing Technology*. 131 (3–4), 1479–1496.

[11] Rojas, M., Balderas, D.C., Maldonado, J., Ponce, P., Lopez-Bernal, D., and Molina, A., 2024. Lack of verified Inclusive Technology for Workers with disabilities in industry 4.0: a systematic review. *International Journal of Sustainable Engineering*. 17 (1), 1–21.

[12] Aivaliotis, S., Papavasileiou, A., Konstantinou, C., Anastasiou, T., Gkournelos, C., Koukas, S., et al., 2024. An interactive Augmented Reality based framework assisting operators in human-robot collaborative assembly operations. *Procedia CIRP*. 126 170–175.

[13] Moya, A., Bastida, L., Aguirrezabal, P., Pantano, M., and Abril-Jiménez, P., 2023. Augmented Reality for Supporting Workers in Human–Robot Collaboration. *Multimodal Technologies and Interaction*. 7 (4), 40.

[14] Wehmeyer, M.L., Davies, D.K., Stock, S.E., and Tanis, S., 2020. Applied Cognitive Technologies to Support the Autonomy of People with Intellectual and Developmental Disabilities. *Advances in Neurodevelopmental Disorders*. 4 (4), 389–399.

[15] Motti, V.G. and Evmenova, A., 2020. Designing Technologies for Neurodiverse Users: Considerations from Research Practice. in: R. and C.S. and C.A. Ahram Tareq and Taiar (Ed.), Human Interaction and Emerging Technologies, Springer International Publishing, Cham. 268–274.

[16] Adibi, S., Rajabifard, A., Shojaei, D., and Wickramasinghe, N., 2024. Enhancing Healthcare through Sensor-Enabled Digital Twins in Smart Environments: A Comprehensive Analysis. *Sensors*. 24 (9), 2793.

[17] Li, X., Nassehi, A., Wang, B., Hu, S.J., and Epureanu, B.I., 2023. Human-centric manufacturing for human-system coevolution in Industry 5.0. *CIRP Annals - Manufacturing Technology*. 72 (1), 393–396.

[18] Zheng, C., Wang, K., Gao, S., Yu, Y., Wang, Z., and Tang, Y., 2024. Design of multi-modal feedback channel of human–robot cognitive interface for teleoperation in manufacturing. *Journal of Intelligent Manufacturing*.

[19] Zhao, X., Wang, L., Zhang, Y., Han, X., Deveci, M., and Parmar, M., 2024. A review of convolutional neural networks in computer vision. *Artificial Intelligence Review*. 57 (4), 99.

[20] Mermaid, 2024. Diagramming and charting tool. https://mermaid.js.org/. Accessed December 2024.

[21] Hussain, M. and Khanam, R., 2024. In-Depth Review of YOLOv1 to YOLOv10 Variants for Enhanced Photovoltaic Defect Detection. *Solar*. 4 (3), 351–386.

[22] Shorten, C. and Khoshgoftaar, T.M., 2019. A survey on Image Data Augmentation for Deep Learning. *Journal of Big Data*. 6 (1), 60.

[23] Roboflow Inc., 2024. Roboflow: Computer vision tools for developers and enterprises.

[24] Ahmad, M.I., Keller, I., Robb, D.A., and Lohan, K.S., 2023. A framework to estimate cognitive load using physiological data. *Personal and Ubiquitous Computing*. 27 (6), 2027–2041.