POLITECNICO DI TORINO
Repository ISTITUZIONALE

AI-enhanced human-machine collaboration for supporting workers with mathematical learning difficulties

Original
AI-enhanced human-machine collaboration for supporting workers with mathematical learning difficulties / Fan, Y., Bonello, A., Simeone, A., Antonelli, D., Priarone, P.C., Settineri, L., Francalanza, E.. - In: CIRP - JOURNAL OF MANUFACTURING SCIENCE AND TECHNOLOGY. - ISSN 1755-5817. - ELETTRONICO. - 67:(2026), pp. 193-205. [10.1016/j.cirpj.2026.03.009]

Availability:
This version is available at: 11583/3011448 since: 2026-05-27T08:10:01Z

Publisher:
Elsevier B.V.

Published
DOI:10.1016/j.cirpj.2026.03.009

Terms of use:

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

Publisher copyright

(Article begins on next page)

19 November 2026

CIRP Journal of Manufacturing Science and Technology 67 (2026) 193–205

Contents lists available at ScienceDirect

CIRP Journal of Manufacturing Science and Technology

journal homepage: www.elsevier.com/locate/cirpj

AI-enhanced human-machine collaboration for supporting workers with mathematical learning difficulties

Yuchen Fan [a], Amberlynn Bonello [b], Alessandro Simeone [a,*], Dario Antonelli [a], Paolo C. Priarone [a], Luca Settineri [a], Emmanuel Francalanza [b]

[a] Department of Management and Production Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, Torino 10129, Italy
[b] Department of Industrial and Manufacturing Engineering, Faculty of Engineering, University of Malta, Msida MSD2080, Malta

ARTICLE INFO

Keywords:
Human-machine collaboration
Computer vision
Generative AI
Inclusive manufacturing
Assistive technology

ABSTRACT

Enhancing inclusivity in manufacturing environments is critical for addressing workforce diversity and improving overall productivity, particularly for operators with cognitive challenges such as dyscalculia. Operators with mathematical learning difficulties frequently encounter challenges in manufacturing tasks requiring precise numerical interpretation and measurement, which can limit their effective participation in complex workflows. This study presents a human-machine collaboration approach, specifically tailored to support inclusive manufacturing environments, by integrating computer vision, collaborative robotics, and generative AI technologies. The developed system provides targeted assistance across four key stages of a cable cutting and connector assembly process, utilising image-to-robot coordinate transformation and a natural language interface for intuitive voice interaction. The primary methodological contribution of this work is the innovative combination of AI-driven communication and robotic assistance designed to support the alleviation of cognitive burdens associated with numerical processing tasks. Laboratory-scale testing suggests that the system can enhance usability, efficiency, and accuracy, indicating the potential of advanced human-machine collaborative solutions to promote inclusivity and improve operator support in modern manufacturing environments.

1. Introduction

Mathematical challenges represent significant barriers to performance in modern manufacturing environments, where high levels of precision, spatial reasoning, and real-time numerical decision-making are essential for efficiency, quality, and safety [1]. For instance, among these challenges, developmental dyscalculia is a specific learning difficulty that impairs the ability to understand, process, and apply numerical information [2,3]. In manufacturing environments, individuals with dyscalculia often face challenges related to measurement interpretation, sequential processing, spatial estimation, and symbolic reasoning. Recent neurocognitive evidence confirms that adults with dyscalculia exhibit significant deficits in magnitude estimation and visuospatial grouping, which undermine accurate quantity representation and affect real-world numerical tasks [4]. Additionally, neuroimaging studies have identified structural differences in brain regions associated with spatial and sequential processing, such as reduced white matter integrity in the superior longitudinal fasciculus and anterior thalamic radiation, which correlate with lower mathematical performance [5]. From a neurocognitive perspective, developmental dyscalculia is associated with atypical activity in the parietal and prefrontal regions of the brain [6]. Further studies indicate that numerical cognition involves both domain-specific processes, like magnitude estimation in the intraparietal sulcus, and domain-general functions, such as working memory and inhibition controlled by the prefrontal cortex [7]. These atypical neural mechanisms contribute to difficulties with sequencing, estimation, and spatial organisation, which are all challenges that are common in industrial tasks involving tool operation, inspection, and assembly. Such cognitive constraints directly inform the types of functional limitations that must be considered when designing support mechanisms for operators in modern manufacturing settings.

To address these challenges, adaptive and assistive cognitive systems have been introduced, which provide task-specific support and, in some cases, adjust assistance based on user needs or performance indicators. Research on reciprocal learning frameworks suggests that adapting instructional content to short-term fluctuations in cognitive load can

* Corresponding author.
E-mail address: alessandro.simeone@polito.it (A. Simeone).

https://doi.org/10.1016/j.cirpj.2026.03.009
Received 8 October 2025; Received in revised form 12 March 2026; Accepted 22 March 2026
Available online 28 March 2026
1755-5817/© 2026 The Authors. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

improve performance and engagement [8]. Such approaches align with the goals of Industry 5.0, which focuses on making manufacturing more inclusive, human-centred, and resilient [9]. Advances in assistive technology have also improved opportunities for individuals with learning disabilities in industrial workplaces. Such tools not only allow workers to carry out tasks independently but also provide compensatory and remedial support where needed [10,11]. Reported examples include specialised calculators, voice recognition software, and mathematical support applications [12]. In parallel, human-machine collaboration has become an important direction in manufacturing research and practice. By combining the strengths of human workers with those of robotic systems [13,14], production can be accelerated and idle time reduced, in some cases by as much as 85% compared with all human teams [15]. Collaborative robots are designed to operate in close proximity to people, incorporating rounded surfaces and proximity sensors that allow safe interaction without the need for protective barriers [16]. However, the present generation of collaborative robots is still limited to relatively simple production processes. This limitation can affect operator confidence, particularly in situations that demand rapid or critical decisions [17].

Computer vision technology has revolutionised quality control and automation in manufacturing environments [18]. These systems offer enhanced productivity and accuracy while reducing operational costs, providing capabilities that may surpass traditional human inspection methods [19]. Artificial intelligence (AI)-powered defect inspection systems can analyse thousands of products per minute, identifying defects invisible to human inspection using machine learning and neural networks [20]. However, current computer vision applications in manufacturing focus primarily on defect detection and quality control, with limited consideration for supporting human operators with mathematical processing difficulties [19]. Research shows that machine vision can count tablets and capsules before packaging, inspect each item for accurate shape and size, identify damages in packages, and validate labelling, but these capabilities are not typically integrated to provide mathematical assistance to operators [18]. The potential for computer vision systems to provide real-time mathematical assistance, such as measurement verification and spatial guidance, remains largely unexplored in manufacturing contexts. Generative AI and speech recognition technologies are transforming industrial applications. Generative AI uses pattern learning to produce data and optimise processes, demonstrating 70% faster time to value compared to traditional approaches [21,22]. In manufacturing, generative AI enables artificial mapping of potential fault types before they occur, addressing insufficient training data challenges for defect detection systems [23]. Speech recognition technology [24], integrating with generative AI capabilities, enables natural language interfaces for manufacturing systems [25,26]. However, industrial applications of speech recognition face distinctive challenges, particularly regarding performance degradation due to industrial noise and environmental factors that affect recognition accuracy and user acceptance [27,28]. Despite significant advances in assistive technologies, human-machine collaboration, computer vision, and generative AI, substantial gaps remain in addressing the specific needs of workers with mathematical learning difficulties in manufacturing environments [29]. Current assistive technology solutions primarily focus on educational contexts rather than industrial applications, leaving manufacturing operators with dyscalculia without adequate technological support [30]. The integration of multiple advanced technologies to create comprehensive assistive systems for manufacturing workers represents an underexplored research area [14]. While individual technologies such as cobots, computer vision, and speech recognition have demonstrated effectiveness in manufacturing contexts, their coordinated application to support workers with specific learning disabilities remains limited [31].

Existing human-machine collaboration systems typically assume uniform cognitive abilities among human operators. Although features of learning disabilities in math vary from person to person, common characteristics include difficulty with counting, learning number facts and doing math calculations, difficulty with measurement, telling time, counting money, estimating number quantities, mental math, and problem-solving strategies. An employee who works in a manufacturing environment with a learning disability had difficulty remembering task sequences, requiring accommodations such as written instructions with colour-coded sub-tasks [11]. Manufacturing environments require specialised support systems that can accommodate these diverse cognitive profiles while maintaining production efficiency and quality standards. Although numerous technological solutions exist, ranging from traditional assistive tools to collaborative robotics, computer vision, and speech-based interfaces, their applications remain largely fragmented with respect to supporting operators with mathematical learning difficulties. Most tools target educational settings, focus primarily on quality control, or assume homogeneous cognitive profiles among operators, leaving a lack of integrated, real-time mathematical assistance in manufacturing environments. This set of limitations defines the specific problem addressed in this work. Table 1 summarises the principal categories of existing technologies, their typical manufacturing applications, and the specific limitations that hinder their use for supporting operators with mathematical learning difficulties. Quantitative metrics are listed only where explicitly reported in the referenced studies; differences in task context and evaluation protocols limit direct numerical comparability.

This research addresses these specific limitations by proposing an integrated system to provide assistance for manufacturing operators with mathematical learning difficulties. The proposed approach offers a coordinated framework designed to contribute to the support of cognitive diversity in industrial environments. The system integrates a collaborative robot, an industrial vision system, laser-based marking devices, and precision-controlled hardware within a modular software architecture. It delivers task-specific assistance for typical mathematical operations encountered in production workflows: centre point identification, equal division, length marking, and length measurement. This work presents two main contributions. First, it introduces a task-oriented cognitive support strategy to address fundamental mathematical challenges in manufacturing through assistive automation. Second, it develops a modular system architecture that integrates collaborative robotics, image processing, and AI into a configurable platform, including modules for calibration, task parameter extraction, hardware control, and user assistance. The system is tested in a laboratory-scale environment designed to mimic industrial conditions, assessing its feasibility in reducing cognitive load while maintaining process accuracy and task completion time. By embedding targeted mathematical assistance within a real-time production framework, this research aims to contribute to extending the scope of human-machine interaction to support cognitive accessibility, in line with Industry 5.0 objectives. The remainder of this manuscript is organised as follows: Section 2 presents the methodological framework and the cable assembly case study exemplifying the system implementation; Section 3 describes the experimental activities; Section 4 presents empirical results evaluating task completion time, accuracy improvements, and cognitive load variations using the NASA Task Load Index (NASA-TLX), followed by conclusions and outlook in Section 5.

2. Materials and methods

This section introduces the methodological framework designed to support operators with mathematical learning difficulties, showing its application step-by-step through a case study. The research problem addressed in this work is related to the difficulty experienced by operators when performing numerically demanding tasks in manufacturing contexts. A cable assembly task (Fig. 1) was selected as representative of challenges encountered in industrial environments. The chosen case study involves preparing and assembling a four-conductor cable connector, a common operation in electrical manufacturing that

Table 1
Overview of existing technologies and their limitations.

Technology category	Key capabilities	Quantitative metrics	Manufacturing applications	Limitations	References
Traditional assistive technologies	Calculators, text-to-speech, visual aids	Learning improvement rates, task performance improvement indicators	Basic mathematical support	Educational focus, limited industrial integration, no real-time assistance	[10–12, 32–34]
Human-robot collaboration	Shared workspace interaction, adaptive assistance	Task completion time, process efficiency indicators, safety and interaction performance metrics	Assembly, handling, precision tasks	Assume uniform cognitive abilities, limited mathematical support functions	[13–17,29]
Computer vision	Defect detection, quality control, measurement	Measurement accuracy, detection and localisation error metrics, dimensional deviation indicators	Automated inspection, dimensional verification	Quality control focus, no cognitive assistance, requires manual interpretation	[18–20,35]
Generative AI + Speech recognition	Natural language processing, adaptive responses	Speech recognition accuracy metrics (e.g. error rates), performance variation under different noise conditions, cognitive workload indicators (NASA-TLX)	Documentation, training, interface control	Lack of manufacturing-specific mathematical assistance, noise sensitivity in industrial environments	[21,23–28]
Proposed integrated system	Integrated CV, robotics, and AI with task-specific mathematical assistance modules	Task accuracy metrics (accuracy rate, deviation-based measures), task completion time metrics, cognitive workload metrics (NASA-TLX), user experience indicators	Real-time measurement, precision marking, division support, voice-guided assistance	Addresses specific mathematical-related challenges in manufacturing	Present work

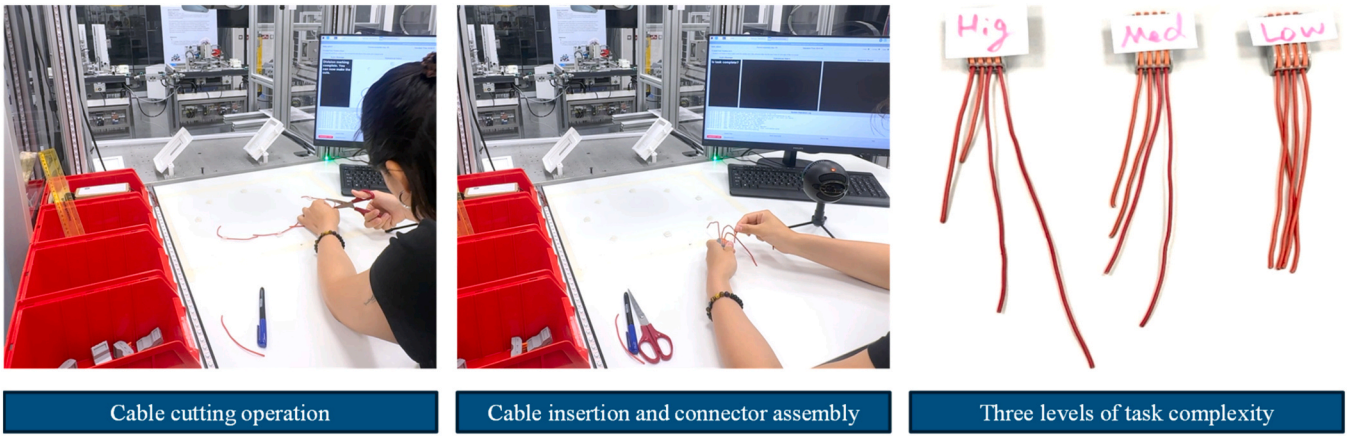


Fig. 1. Cable assembly case study illustrating the workflow and the three levels of mathematical task complexity.

requires precise measurements and spatial reasoning. The cable assembly process includes mathematical operations such as measurement interpretation, division, proportional reasoning, percentage calculations, fraction operations, and spatial orientation. Three distinct experimental conditions were designed to evaluate the applicability of the system across tasks of varying mathematical complexity. All

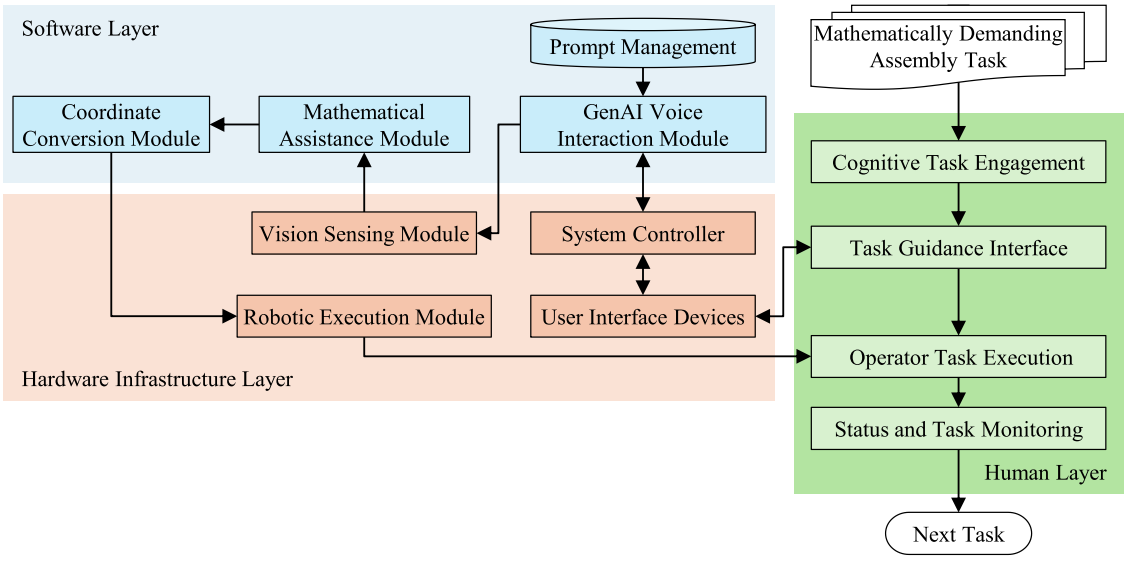


Fig. 2. Conceptual system framework highlighting the interaction between hardware, software, and human layers.

experimental conditions follow an identical five-step assembly process, with key differences situated in the cable division task.

2.1. Research framework

The proposed framework comprises three interconnected layers: (*i*) hardware infrastructure, (*ii*) software, and (*iii*) human, as illustrated in Fig. 2. This multi-layered design allows integration of technological components and task-specific support mechanisms. The integration of cobot, advanced computer vision, and generative AI technologies enables the system to offer targeted support for diverse manufacturing operations. The architecture facilitates mathematical interventions while upholding a user-centric approach that is expected to mitigate cognitive load and enhance task performance [10].

2.2. Hardware infrastructure layer

The hardware infrastructure layer defines the architectural principles for integrating actuation, perception, human-machine interaction, and safety subsystems in the collaborative assembly environment. It sets out the functional requirements and design considerations for deploying physical components in tasks such as spatial measurement, guided manipulation, and operator assistance. The actuation subsystem consists of a collaborative robotic manipulator with a constrained workspace, designed to allow safe operation in close proximity to the human operator. Perception is achieved through an overhead vision module that handles spatial measurement, object localisation, and geometric interpretation. Task-specific motion planning is generated from these visual inputs using embedded control logic [36]. Computational tasks are distributed across edge processing units, which coordinate sensor input, actuator control, and feedback delivery. Multimodal interaction is provided through audio input for voice commands, graphical interfaces for task guidance, and visual indicators for process status. Safety is addressed through hardware redundancy, configurable emergency stop logic, and adherence to industrial safety protocols. Together, these elements allow for synchronised control, perception, and interaction, forming the physical foundation of the collaborative assistance framework [37].

2.2.1. Hardware setup and configuration

The implemented setup is shown in Fig. 3 and Fig. 4. A UR3 robotic arm is operated through its dedicated controller, which communicates with a Raspberry Pi 5 managing the GPIO-connected peripherals. A Basler camera provides real-time visual input, while operator interaction is supported through a GUI with monitor and speaker for natural language processing [38]. System communication is established through Ethernet and USB/HDMI connections, coordinated by an OMRON industrial Ethernet switch. Digital outputs are configured so that DO0–0 and DO0–1 control the end effector LED lights (off/on), while DO1–0 and DO1–1 drive the laser pointer (off/on). Visual feedback is given by LED strips. Emergency control relies on two stop buttons, one integrated with the cobot and another independent, both linked via the UR3 safety I/O. A teach pendant is also available for programming and manual operation of the robot. Coordination between the UR3 controller and the Raspberry Pi is implemented using an event-driven, state-based communication scheme rather than fixed-cycle synchronisation. The Raspberry Pi monitors robot state variables and digital I/O events exposed by the UR controller and triggers peripheral actions and software routines upon detected state transitions. This asynchronous approach eliminates the need to align sampling rates across heterogeneous devices, avoids timing conflicts associated with fixed-cycle polling, and allows for stable task sequencing within the experimental workflow.

2.3. Computer vision-based software layer

The computer vision-based software layer defines the methodology for translating visual input into robotic actuation through an embedded coordinate transformation process. This layer supports image-guided tasks under constrained collaborative scenarios, particularly those requiring spatial referencing and precision measurement. The underlying approach is based on a calibration-driven transformation from image space to joint space, in which a finite set of reference points defines the mapping between pixel coordinates and robot joint angles. This regression-based method is designed to balance computational simplicity with sufficient spatial accuracy for semi-structured manufacturing environments. It removes the need for iterative inverse kinematics and supports near real-time execution on edge-processing hardware. The transformation logic is divided into three stages: (*i*) image acquisition and target localisation, (*ii*) coordinate transformation using polynomial regression, and (*iii*) robot actuation and visual confirmation. This architecture ensures repeatable behaviour under constrained conditions, aligning with inclusive manufacturing objectives [39]. Second-order polynomial regression was selected due to its ability to model non-linear relationships between image coordinates and joint angles (θ_{wrist1} and θ_{wrist2}) while remaining computationally

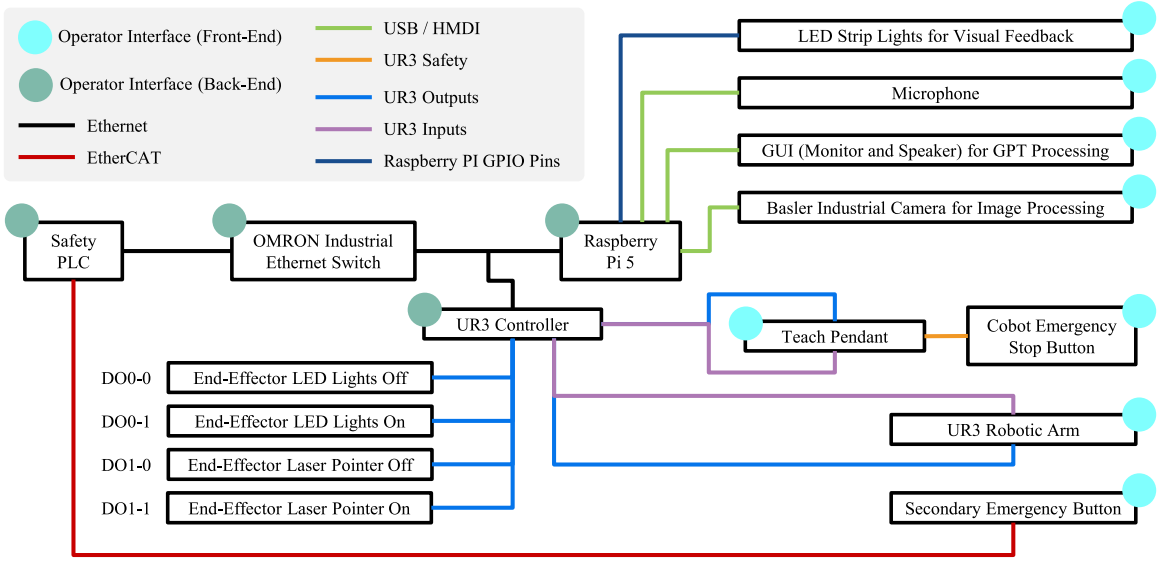


Fig. 3. Hardware connection diagram.

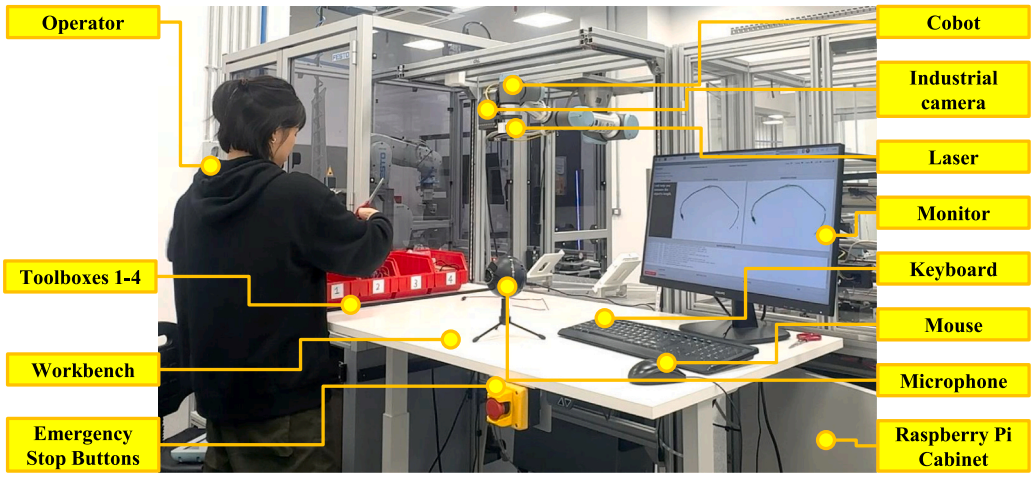


Fig. 4. Laboratory-scale experimental workbench (Digital and Industrial Automation Lab, University of Malta).

lightweight. The fitted equations, presented as Eqs. (1) and (2), take the form:

$$\theta_{wrist1} = a_0 + a_1x + a_2y + a_3x^2 + a_4xy + a_5y^2 \quad (1)$$

$$\theta_{wrist2} = b_0 + b_1x + b_2y + b_3x^2 + b_4xy + b_5y^2 \quad (2)$$

where (x, y) are the pixel coordinates in the image plane, and $a_0, \ldots, a_5$, $b_0, \ldots, b_5$ are the model coefficients determined through calibration. Although the polynomial mapping defined in Eqs. (1) and (2) was primarily selected to ensure low computational latency and real-time responsiveness, its positional accuracy was explicitly addressed through calibration and empirical validation, as detailed in Section 2.3.1. This approach is expected to offer four main advantages [40]:

- *Enhanced operational safety:* the movement is restricted to only two joints (W1 and W2), with all other joints fixed at predetermined positions, as shown in Fig. 5. This constraint reduces the risk of unintended contact in shared workspaces;
- *Reduced computational overhead:* the use of a polynomial model avoids the need for iterative inverse kinematics in the considered workspace, allowing faster response times and lower system latency;
- *Improved responsiveness*: the simplified transformation pipeline allows for near real-time coordinate conversion, enhancing system interactivity;
- *Reliable positioning accuracy*: the regression-based model captures the non-linear spatial mapping with sufficient precision for the constrained workspace, ensuring consistent task execution without external sensors or feedback control.

2.3.1. Coordinate conversion and implementation

The coordinate conversion system was calibrated after hardware configuration using 12 manually-selected reference points distributed across the workspace. At each point, pixel coordinates extracted from overhead images were paired with the corresponding joint angles of Wrist 1 and Wrist 2, while the remaining joints were fixed to predefined values for safety (Joint 1: −1.0°, Joint 2: −17.6°, Joint 3: −182.7°, Joint 4: 46.7°). Regression models were embedded in the control software, enabling direct mapping of image-plane targets to joint commands without predefined trajectories. During operation, the camera acquires a live image, pixel coordinates are extracted, and the wrist joints move the end effector to the computed target position [41]. A laser module mounted on the end effector provides visual confirmation of the calculated target location. The calibration and transformation process is illustrated in Fig. 5, and the corresponding regression coefficients are reported in Table 2. The transformation was calibrated and validated over an area of 46 × 35 cm, corresponding to the camera field of view covering the workbench surface, with a camera-to-workplane distance

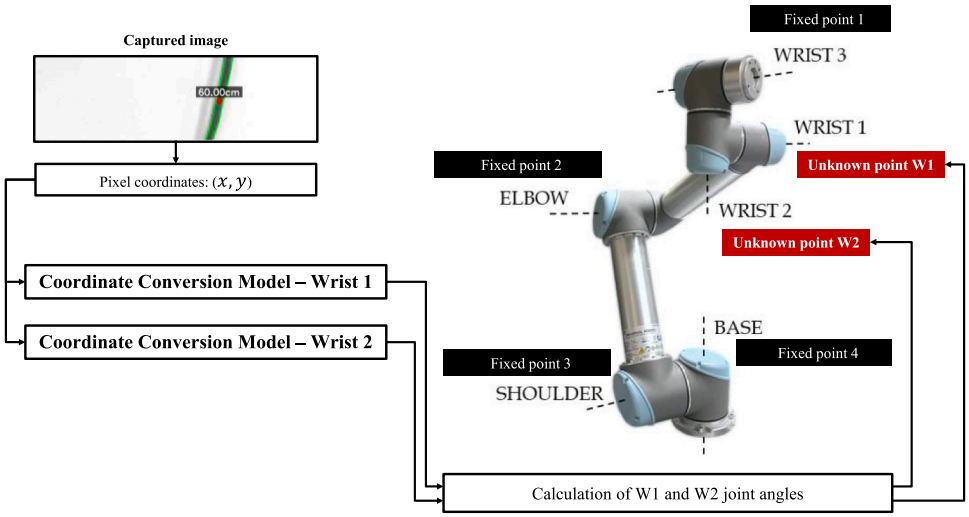


Fig. 5. Schematic diagram of pixel-to-joint coordinate conversion for Wrist 1 and Wrist 2.

Table 2
Polynomial regression coefficients for the pixel-to-joint coordinate transformation, specific to the calibrated workspace and camera-robot configuration.

Coefficient	Wrist1 model (θ_{wrist1})	Wrist2 model (θ_{wrist2})
Intercept (a_0, b_0)	-5.351×10^{1}	-1.125×10^{2}
x(a_1, b_1)	9.332×10^{-4}	1.252×10^{-2}
y(a_2, b_2)	-1.313×10^{-2}	8.727×10^{-4}
x^2(a_3, b_3)	2.068×10^{-9}	3.297×10^{-7}
xy(a_4, b_4)	-3.233×10^{-7}	-4.600×10^{-7}
y^2(a_5, b_5)	1.950×10^{-7}	2.013×10^{-7}

of approximately 70 cm. Validation was performed through repeated positioning tests ($\geq$ 20 trials) using the laser pointer, which consistently aligned with the intended image-based targets across the calibrated workspace, indicating stable and repeatable mapping performance, with a mean positional deviation of 2.1 ± 1.3 mm across the calibrated workspace under typical operating conditions. Although the proposed transformation is not intended for metrology-grade positioning, its accuracy was sufficient for the supported marking and measurement tasks, which require centimetre- and sub-centimetre-level tolerances. The polynomial regression model assumes a fixed spatial relationship between the camera frame and the robot workspace, which is valid under stable mounting conditions. Consequently, transformation accuracy is sensitive to changes such as camera displacement or joint drift. In the present implementation, these effects are mitigated through explicit calibration and by constraining robot motion to a limited set of joints within a fixed workspace. This design choice is expected to be appropriate for semi-structured manufacturing tasks and laboratory-scale deployments. A basic online check can further support active drift detection: at system start-up, the laser pointer targets a fixed reference marker at a known position; if the measured offset exceeds the sub-centimetre task tolerance, recalibration is triggered before operation resumes.

2.4. Mathematical assistance module

The mathematical assistance module builds upon the computer vision layer to enable real-time dimensional analysis during measurement-driven operations. It interfaces directly with the coordinate transformation module and the generative AI voice interface, supporting operator interaction and reducing cognitive load associated with manual numerical reasoning [7]. The module follows an object-oriented design comprising a modular class hierarchy. A core 'Measurement class' encapsulates the image processing pipeline, which includes: (*i*) image preprocessing, (*ii*) object segmentation, (*iii*) geometric feature extraction, (*iv*) centreline computation, and (*v*) coordinate transformation for robot control. This structure ensures methodological consistency across tasks and facilitates subclassing for specialised operations [42]. Preprocessing operations involve bilateral filtering for noise reduction and edge preservation, followed by contrast normalisation and adaptive thresholding for object segmentation. Morphological filters are applied to enhance contour continuity, enabling reliable extraction of geometric primitives and centrelines. Subsequently, image coordinates are transformed into robot coordinates using the calibrated model described in Section 2.3.1 [43]. Measurement-specific functionalities are implemented via subclasses of the 'Measurement class', which include four functional modules:

- *Centre detection*: computes centroids of symmetric or bounded features;
- *Object division*: segments objects based on equal or proportional intervals;
- *Length marking*: identifies fixed-length intervals from a defined origin;
- *Measurement validation*: assesses conformity against predefined tolerances.

The module establishes a task-level closed loop between visual sensing and robotic execution, supporting consistent coordinate mapping across tasks and robust operation under varying workspace conditions. It provides the computational basis for subsequent modules addressing numerical reasoning and operator interaction.

2.4.1. Task-specific implementation

In the cable assembly scenario, the mathematical assistance module was tailored to automate length-based operations involving flexible cables, integrating seamlessly into the larger system pipeline shown in Fig. 1. The task-specific software builds on the Measurement base class by defining image-to-length estimation for curved structures. The algorithm begins with bilateral filtering (diameter = 5, sigmaColour = 50, sigmaSpace = 50) to suppress noise, followed by brightness ($\alpha = 1.5$) and contrast ($\beta = 3$) enhancement. Adaptive Gaussian thresholding (block size = 25, constant = 12) is used to segment cable structures under varying lighting. The full processing sequence implemented in this task is illustrated in Fig. 6. Contours are filtered based on area (>50 pixels), circularity (<0.9), and aspect ratio (> 1.2), isolating the cable path. Morphological dilation (~45 pixels) and erosion (kernel ~1/4 dilation size) are applied to form a coherent mask. Skeletonisation then yields the centreline, and length estimation is performed by summing Euclidean distances between consecutive pixels, scaled using a calibrated pixel-to-centimetre ratio.

The system implements three specialised subclasses inheriting from the base 'Measurement class':

- *Cable centre finder*: traverses the cable centreline to identify the cable midpoint by accumulating distances until half the total length is reached. Results are provided in both image and world coordinates for precise midpoint marking or robotic cutting;
- *Cable equal divider*: calculates positions of user-defined equally spaced division points along the cable by dividing the total centreline length and mapping corresponding positions. Critical for equal interval marking or cutting operations;
- *Cable length marker*: locates points at specific lengths from the cable starting point by accumulating distances along the centreline until target length is reached, enabling precise marking at arbitrary positions regardless of cable shape.

Error sources in measurement and segmentation tasks are mitigated through stabilisation mechanisms embedded in the image-processing pipeline. Segmentation robustness is achieved using bilateral filtering, adaptive thresholding, and morphological refinement, while contour selection and skeletonisation reduce artefacts due to local noise, incomplete edges, and thickness variations. Minor occlusions are handled through morphological dilation-erosion and a union-find-based path reconstruction strategy, enabling recovery of fragmented cable segments. Geometric measurements are performed on skeletonised centrelines and scaled using a calibrated pixel-to-centimetre ratio obtained under operational conditions. Under correct cable placement, deviations were consistently within sub-centimetre-level tolerances across the calibrated workspace. All computed target positions undergo laser-based visual verification prior to robot actuation. These measures constrain residual image-processing errors within the tolerances required for the supported measurement and segmentation operations.

2.5. Gen-AI powered voice processing module

The GenAI-based voice processing module enables non-intrusive voice interaction to support mathematical tasks within collaborative manufacturing environments. This module brings together speech recognition, natural language understanding, and speech synthesis in a

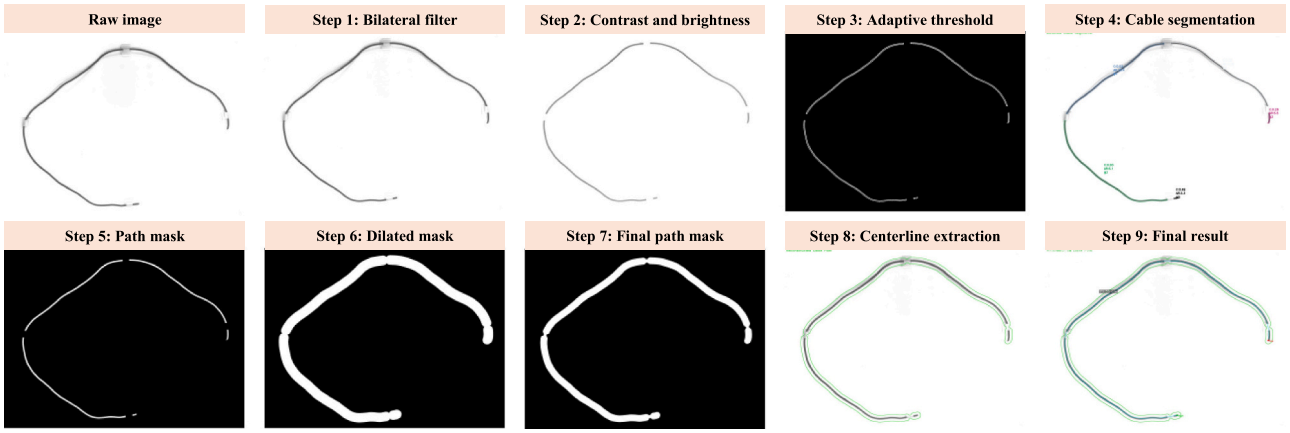


Fig. 6. Processing pipeline for cable length estimation, illustrating preprocessing, segmentation, morphological refinement, skeletonisation, and centreline-based length computation for flexible cables.

unified interface. Its architecture features two main stages: first, converting spoken language into actionable intent (speech-to-intent processing); and second, generating spoken feedback (text-to-speech response). In this workflow, the voice interface also issues an activation signal to the vision sensing module whenever the operator confirms a request for mathematical assistance, thereby triggering the corresponding vision-based computation rather than transferring visual data. To improve the resilience of the speech recognition stage under intermittent connectivity, the system employs a dual-layer approach. The Google Speech Recognition API serves as the primary engine, with automatic fallback to a local CMU Sphinx model if needed. Techniques such as adaptive energy thresholding, ambient noise calibration, and pause detection are used to segment speech input accurately. Recognised speech is analysed by a large language model, which is guided by a custom system prompt to focus solely on task-relevant queries. The system currently supports four types of mathematical assistance: centre detection, object division, length marking, and general computation. Task execution is managed through a bidirectional confirmation loop. When a task is correctly interpreted, the system generates and executes a structured JSON command; if not, it requests clarification from the user. Output feedback is delivered using Google Text-to-Speech (gTTS), with a mutual exclusion lock ensuring that recognition and synthesis processes do not overlap. Mathematical expressions are reformatted for clear and effective speech delivery. The full interaction workflow, including voice input, intent recognition, task execution, and feedback, is depicted in Fig. 7.

2.5.1. *Voice interface implementation*

The voice module implementation consists of two components: (*i*) the Voice GPT System, responsible for recognition and intent extraction, and (*ii*) the Voice TTS module for synthesised speech feedback. Task recognition relies on a structured prompt that constrains the language model to predefined categories and expected response formats. The complete system prompt is detailed in Fig. 8.

Real-time operation is enabled by the speech recognition library with a 300-level energy threshold, 0.3-second noise calibration, and a 0.5-second speech segmentation pause. Prior to synthesis, mathematical expressions are standardised to enhance clarity (e.g., converting 'cm' to 'centimetres' or 'π' to 'pi'). Recognised tasks are structured in JSON format for consistent downstream integration. The TTS response is generated using gTTS, and audio playback is handled via the *pygame* library to ensure synchronised and intelligible feedback delivery. Thread-based exclusion (*tts_lock*) prevents audio overlap. Confirmation is managed by the *wait_for_confirmation* method, which employs a continuous listening loop with a configurable timeout (default 100 s) and interprets a broad set of affirmative and negative phrases to ensure reliable user validation. The module exports standardised JSON commands to the execution controller. Prior to execution, each JSON

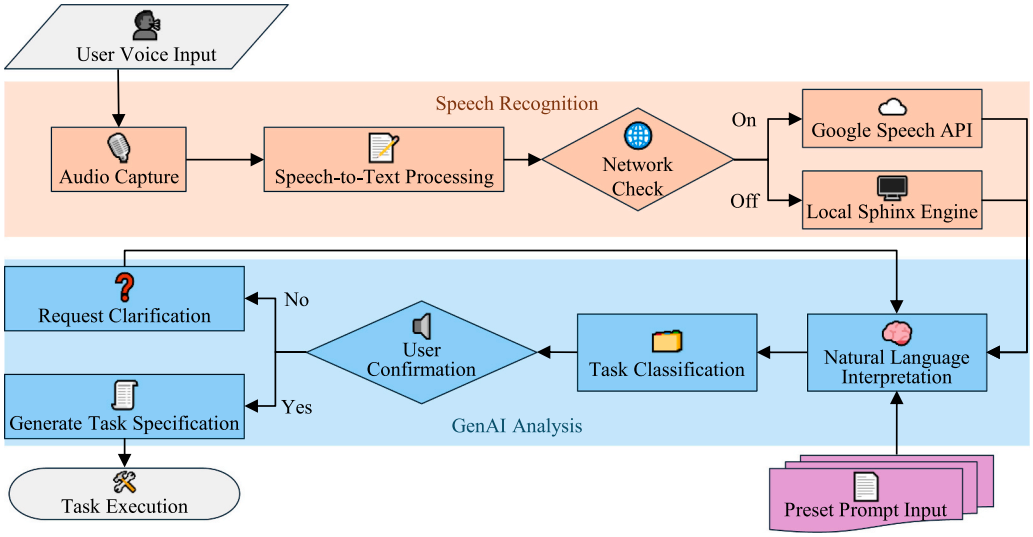


Fig. 7. Process architecture of the GenAI-based voice interaction module.

```
You are a friendly math assistant that helps with calculations and measurements. You can:
1. Find centre points of objects (centre_finder)
2. Divide objects into equal or unequal parts (equal_divider)
3. Mark specific lengths (length_marker)
4. Measure object lengths (length_measure)

For these four specific tasks:
- First confirm if you understand the user's intent
- If user confirms, output the task in JSON format and end conversation
- If user denies, ask for clarification

For division tasks, support the following approaches:
- Specify exact segment lengths: Directly provide the length of each segment in cm
- Equal division: Simply specify how many equal parts to divide into
- For non-equal division patterns (like geometric progression, specific proportions),
  calculate the exact segment lengths and provide them directly

For general math calculations:
- Provide direct calculation results and explanations

Always keep responses concise and brief. Use simple, direct language.

Please respond in JSON format:
{
    "command": "centre_finder/equal_divider/length_marker/length_measure/calculation",
    "is_task_command": boolean,  # True for the four specific tasks, False for calculations
    "needs_confirmation": boolean,  # True if need to confirm task understanding
    "parameters": {
        "length": value,  # For length_marker
        "unit": "unit",   # For length_marker
        "position": "position",  # For marking position
        "divisions": value,  # Number of divisions
        "division_type": "equal|geometric|specific|proportional|mixed",  # Division type for equal_divider
        "segment_lengths_cm": [value1, value2, ...],  # Array of segment lengths in cm (PREFERRED method)
        "object_to_measure": "description"  # For length_measure
    },
    "response": "concise response to user"
}
```

Fig. 8. Structured prompt used for task recognition from user voice input.

command could be validated against a fixed schema: only commands matching the four predefined task types with parameters within operational bounds are forwarded to the robot controller. Commands failing this check are discarded and the user is prompted to repeat the input. Additional features include GUI display of recognised speech, support for complex mathematical input (e.g., proportional division), and a testing interface for validation.

2.6. Human operation layer

The interaction modules are designed to minimise cognitive and physical interference during numerically-demanding assembly tasks. The voice interaction module enables hands-free communication during tool handling, reducing visual attention shifts and manual interface navigation during measurement and segmentation operations. To avoid workflow disruption, voice interaction is implemented as an on-demand, non-intrusive interface that provides brief confirmations rather than continuous guidance, thereby supporting operational

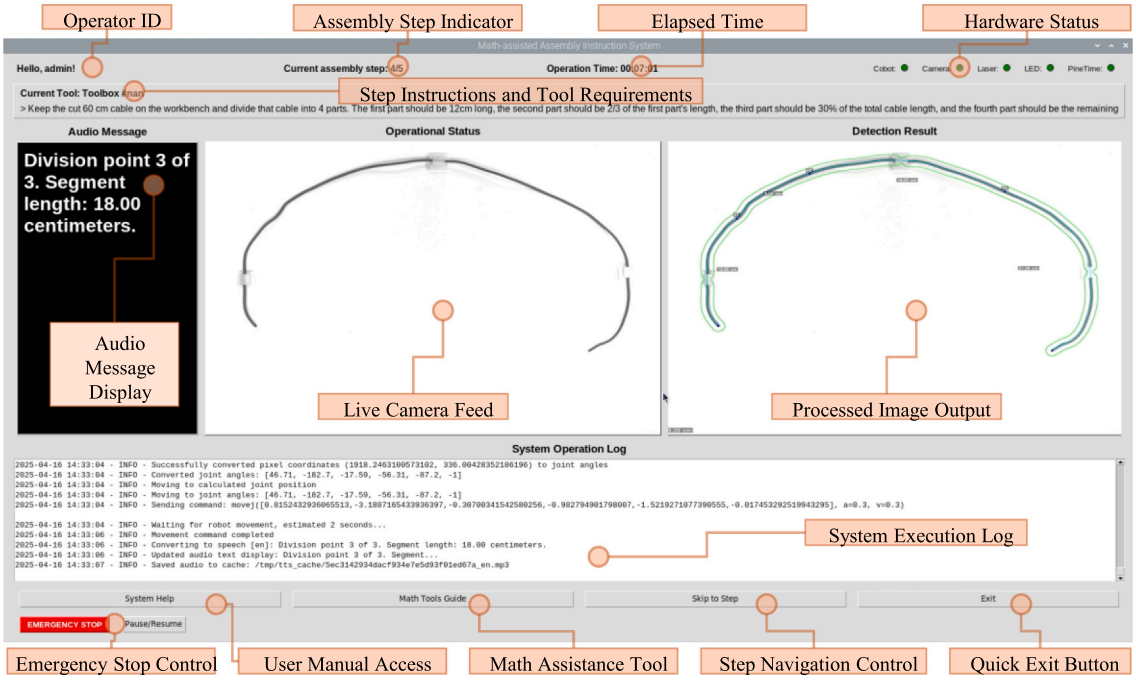


Fig. 9. User interface of the math-assisted assembly system.

efficiency while maintaining operator focus on the physical task. The human operation layer regulates operator-system interaction during task execution (Fig. 2). Four stages are defined: (*i*) cognitive engagement, (*ii*) guidance interface, (*iii*) execution, and (*iv*) monitoring. The structure supports demanding operations while preserving autonomy. Assistance may be requested according to task difficulty or confidence. Intervention remains selective and context dependent. The interface (Fig. 9) integrates visual feedback, audio interaction, and logs. Feedback is multimodal: transcribed and spoken messages, overlays, and interactive controls. A status bar shows step number, elapsed time, and hardware indicators. Dedicated regions display the camera feed and processed output. Logs provide continuous traceability. Critical functions (such as emergency stop, step navigation, mathematical assistance) are directly accessible to ensure continuity and safety.

2.6.1. Human-system interaction implementation

The human operation layer was deployed in the cable assembly scenario as illustrated in Fig. 10. The process begins with cognitive task engagement, where the operator identifies the required task and determines whether mathematical support is needed. Upon activation, the system synchronises hardware configuration, GUI layout, and voice interaction protocols. The operator progresses through five predefined steps: cable preparation, length measurement, cutting, segmentation, and connector assembly. When a mathematically intensive step is encountered, the system prompts for assistance using the voice interface. If confirmed, one of the assistance modules is selected based on the task type. These modules handle measurement, segmentation, centre estimation, and symbolic calculation. Visual confirmation and guidance are then provided through the interface, enabling informed and accurate operator execution. The system monitors task progression, providing feedback on action correctness and completion. This process ensures timely coordination across the human, software, and hardware layers of the framework. Accurate measurement requires the cable to be laid flat within the workspace. Substantial occlusions, such as an operator's hands covering the cable, temporarily degrade detection; therefore, the system prompts the operator to clear the workspace prior to image acquisition.

3. Exploratory feasibility study

This section describes the exploratory feasibility study conducted to examine how the proposed human-machine collaboration system performs when applied to cable assembly tasks involving varying levels of mathematical complexity. Rather than aiming to draw definitive conclusions about effectiveness, the study was intended to provide preliminary insights into the potential of the system to support task execution and mitigate cognitive demands under controlled laboratory conditions. The experimental procedure followed a five-step cable assembly workflow. Steps 1, 2, 3, and 5 were identical across trials, whereas Step 4 introduced a condition-dependent mathematical task (Table 3), enabling the evaluation of three levels of numerical complexity (Table 4):

- *Condition A (Equal division)*. Participants were asked to divide the 60 cm cable into four equal parts by solving the equation: $4 \cdot x = 60$, yielding $x = 15$ cm per segment. This represents a baseline level of computational difficulty;
- *Condition B (Proportional division)*. The task required dividing the cable into segments following a geometric ratio, with the constraint $x + 1.2 \cdot x + 1.44 \cdot x + 1.728 \cdot x = 60$. Solving for $x = 11.2$, yields segment lengths of approximately 11.2 cm, 13.4 cm, 16.1 cm, and 19.3 cm, introducing proportional reasoning and increasing mathematical complexity;
- *Condition C (Specification-based division)*. The task combined heterogeneous numerical operations: a fixed first segment (12 cm), a second segment defined as two-thirds of the first (8 cm), a third segment equal to 30% of the total cable length (18 cm), and a final remainder

Table 3
Cable assembly instructions (tool numbering refers to Fig. 10).

Step ID	Instructions	Math-related	Math-assist tool
1	Select a cable from the box indicated by the green light, lay it flat, and secure it using the wire holder	No	No
2	Measure the length of the cable	Yes	Tool 1
3	Cut the cable to a length of 60 cm	Yes	Tool 2
4	Cable segmentation task (see Table 4 for specific instructions)	Yes	Tool 4
5	Select a connector from the box indicated by the green light, and insert the four split cables into the connector	No	No

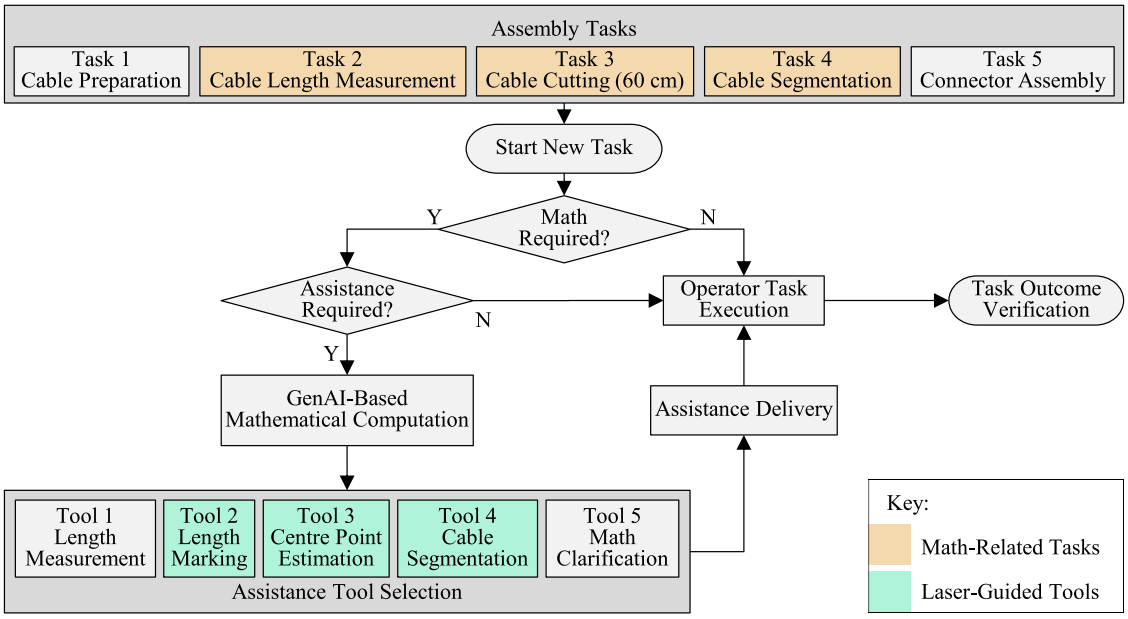


Fig. 10. Experimental workflow illustrating task execution and on-demand mathematical assistance.

Table 4
Step 4: variations across experimental conditions.

Condition	Task description	Difficulty	Mathematical operations required
A: Equal division	Divide the 60 cm cable into 4 equal parts	Low	Basic division
B: Proportional division	Divide the cable into 4 parts, where each part is 1.2 times longer than the previous one	Medium	Geometric progression
C: Specification-based division	First part: 12 cm; Second part: 2/3 of first part length; Third part: 30% of total length; Fourth part: remaining length	High	Mixed operations

segment (22 cm). This condition simulates a set of mixed mathematical requirements that may pose challenges for individuals with numerical processing difficulties.

The proof-of-concept study employed a between-subjects quasi-experimental comparison involving eight participants (aged 20–45), equally divided into two groups. The first group (labelled *Group 1*) comprised individuals who self-reported persistent difficulties with mathematical tasks in workplace or educational contexts, including tasks involving numerical processing, spatial reasoning, and basic calculation. No formal diagnostic assessment was administered; therefore, *Group 1* should not be interpreted as representing clinically-defined mathematical learning difficulties. This limitation is consistent with the exploratory objectives of the study, which was not targeted to establish population-level inferences. The second group (*Group 2*) included individuals who did not report such difficulties. All participants had normal manual dexterity, provided informed consent, and were unaware of the research hypotheses. Each participant completed the cable assembly workflow under two conditions: (*i*) a standard condition using conventional manual tools (ruler, tape measure, and marker), and (*ii*) an assisted condition using the collaborative system with voice guidance, computer vision, robotic assistance, and laser-based visual cues. To minimise potential order effects (i.e., biases introduced by the sequence in which the experimental conditions were performed), the order of the standard and assisted conditions was counterbalanced across participants. Rest intervals of 5–10 min were provided between trials to reduce fatigue and carryover effects. Immediately after each trial, participants completed the NASA-TLX questionnaire to assess subjective workload [44]. The NASA-TLX evaluates six dimensions (mental demand, physical demand, temporal demand, performance, effort, and frustration), each rated on a 21-point scale ranging from 0 to 100 (in increments of 5). Scores were recorded digitally and examined descriptively at both composite and dimensional levels to characterise the perceived cognitive and emotional demands under the two conditions. An overall workload score was computed as the sum of the six subscales, yielding a total score in the range 0–120.

4. Preliminary results and discussion

The assessment of system performance incorporated both objective and subjective measures. Objective data included task completion times recorded automatically by the system, precision indicators related to length measurement and segmentation consistency, and observations of task execution correctness. Subjective evaluation employed the NASA-TLX to assess perceived workload across six dimensions. In addition, semi-structured interviews provided qualitative insights and suggestions for improvement. A custom-designed questionnaire captured perceived usability, operational efficiency, confidence in performing mathematical tasks, satisfaction, and stress using 5-point Likert scales. Given the small sample size and the quasi-experimental allocation to groups, the statistical power and generalisability of the findings are limited. For this reason, the analyses presented in this section are intended as descriptive observations of feasibility and trend-level patterns rather than definitive inferential conclusions.

4.1. Task completion time by difficulty level

Fig. 11*a* shows the distribution of task completion times (for the 5 steps defined in Table 3) across the three difficulty levels under both standard and assisted conditions. The box plots highlight the variability observed within each group and condition, as well as the presence of individual differences. Overall, the assisted condition produced shorter and more consistent completion times compared with the standard condition in both groups. Under standard conditions, completion times exhibited substantial variability, particularly at the medium and high difficulty levels. In contrast, assisted trials showed a more stable pattern, with times tending to cluster within a narrower range. This trend was especially visible in *Group 1*, whose members had self-reported difficulties with numerical reasoning. The reduced spread of completion times in the assisted condition suggests that the system may help normalise performance across individuals, mitigating the variability associated with tasks requiring mathematical processing. It is also notable that completion times for *Group 1* did not increase markedly as the mathematical complexity of the task increased in the assisted condition. This pattern is consistent with the design of the assistive system, in which numerically demanding operations are offloaded to automated computational and visual tools, while the physical manipulation of the cable remains comparable across difficulty levels. Nevertheless, given the small sample and the absence of stratification by prior experience, these observations must be interpreted with caution. Individual familiarity with manual operations or learning effects across trials may have influenced the observed patterns. Overall, these results provide preliminary evidence that the assistive system can attenuate (though not necessarily eliminate) the time penalties typically associated with increasing mathematical complexity, particularly for participants reporting difficulties with numerical reasoning. Larger and more diverse samples will be required to confirm the robustness and generalisability of these trends.

4.2. Precision and accuracy observations

To assess how the assistive system influenced segmentation precision, deviations between the produced segment lengths (L_i) and the intended target values (L_{ref}) were examined using the Average Absolute Deviation (*AAD*) [45], defined in Eq. (3):

$$AAD = \frac{1}{n}\sum_{i=1}^{n}\left|L_i - L_{ref}\right| \tag{3}$$

The *AAD* provides a general indication of the magnitude of deviation from reference values. A related metric, the Improvement Rate (*IR*) [46], shown in Eq. (4), can be used to express the proportional reduction in deviation between unaided and assisted trials:

$$IR = \left(\frac{AAD_{standard} - AAD_{assisted}}{AAD_{standard}}\right) \times 100\% \tag{4}$$

Although the *IR* can support quantitative comparisons in larger studies, the present exploratory experiment reports only qualitative trends.

Under standard conditions, both groups displayed noticeable variability in segmentation accuracy, with deviations increasing as the mathematical complexity of the task increased. *Group 1* exhibited a broader range of deviations in unaided trials, typically spanning several centimetres (approximately 3–13 cm), and showed occasional proportional inconsistencies in the medium-difficulty condition. *Group 2* generally showed smaller deviations (typically below 4 cm), reflecting

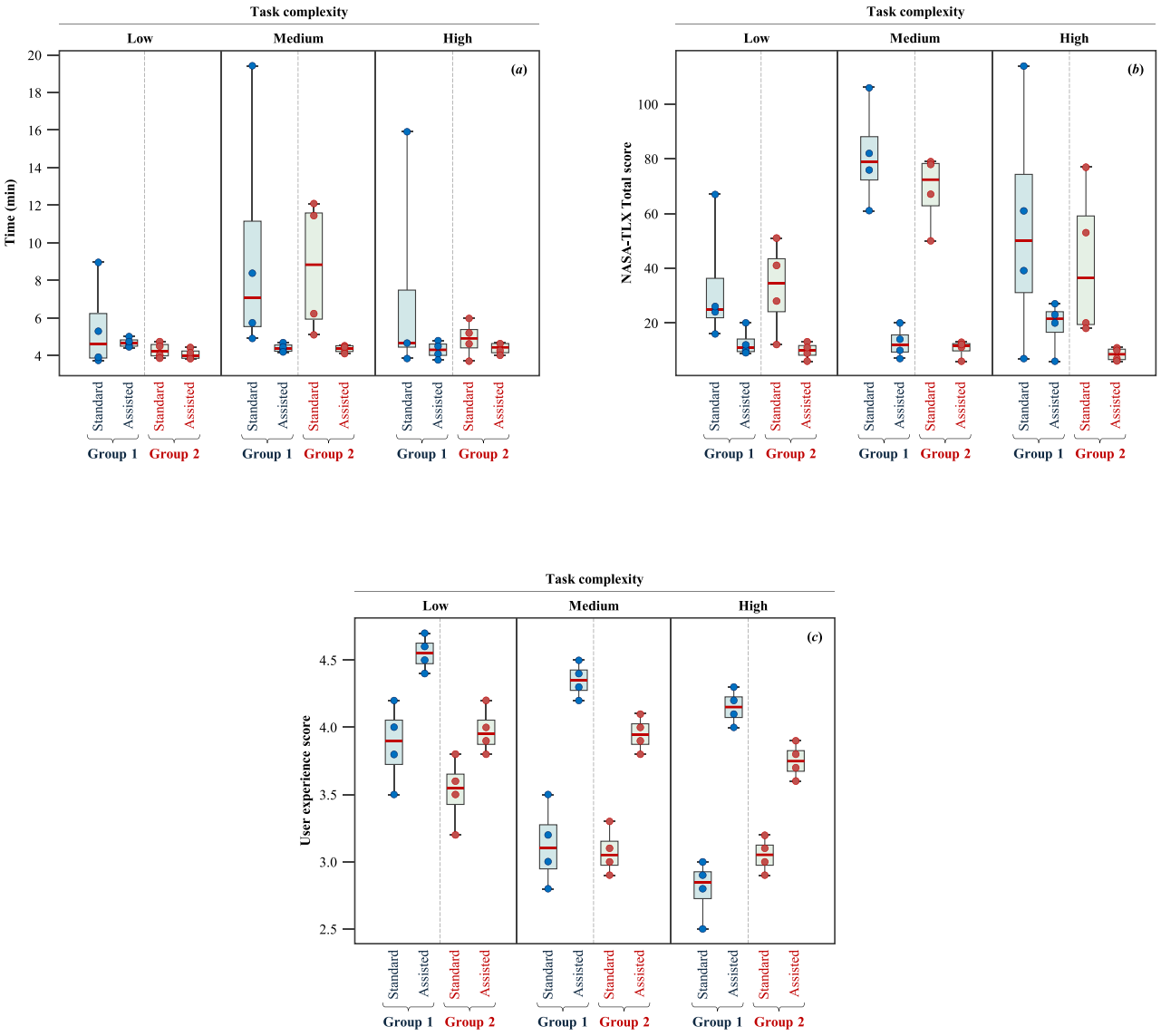


Fig. 11. Results for task completion time (*a*), NASA-TLX total score (*b*), and user experience score (*c*).

greater baseline consistency. When the assistive system was used, deviations tended to decrease across participants and difficulty levels. Visual inspection of the segmentation outputs showed more regular spacing and fewer incorrect subdivisions, with *AAD* values generally falling well below 1 cm for both groups. Reductions in deviations were generally larger in *Group 1* than in *Group 2*, consistent with the fact that *Group 1* started from a broader range of unaided performance. Relative improvements were observed across all difficulty levels, with the most pronounced differences occurring in tasks requiring proportional or mixed reasoning. These results suggest that the assistive system may help stabilise performance in tasks involving measurement accuracy and proportional subdivision, particularly for individuals reporting difficulties with numerical reasoning. Their interpretation remains tentative until validated in broader experimental settings.

4.3. NASA-TLX based cognitive load observations

Fig. 11*b* illustrates the distribution of NASA-TLX total scores across the three difficulty levels. Under standard conditions, perceived workload varied widely, especially in the medium- and high-difficulty tasks. In *Group 1*, scores ranged from approximately 15–70 in the low-difficulty task, from around 60–105 in the medium task, and 5–115 in the high-difficulty task. *Group 2* also showed increased workload with task complexity, with scores ranging approximately 10–50 (low), 50–80 (medium), and 20–80 (high). In contrast, assisted trials exhibited lower and more consistent workload levels in both groups. Scores tended to cluster within a narrower range, typically around 10–25 for *Group 1* and approximately 5–15 for *Group 2*, regardless of task difficulty. This reduced dispersion suggests a more stable and predictable user experience in the assisted condition. The differences between standard and assisted conditions were most pronounced for *Group 1*. Participants in this group appeared to particularly benefit from the automation of measurement and subdivision processes, which reduced the mental effort normally associated with proportioning and multi-step numerical tasks. *Group 2* also exhibited reductions in perceived workload under assisted conditions, although baseline variability in the standard condition was smaller than in *Group 1*. A qualitative inspection of the six NASA-TLX subscales indicated reductions across cognitive, physical, and affective-related dimensions, with the largest changes typically observed in mental demand, effort, and frustration. These trends are consistent with the intended function of the system in offloading numerically intensive operations and providing structured visual

guidance during task execution. As participants differed in their prior experience with manual assembly tasks and familiarity with digital tools, individual factors may have contributed to the variability observed under standard conditions. These aspects were not systematically controlled and should be considered when interpreting the workload patterns.

4.4. User experience observations

Fig. 11*c* summarises the user experience ratings across the three difficulty levels. Overall, participants reported more positive experiences in the assisted condition than in the standard one. For *Group 1*, improvements were evident across multiple dimensions, including perceived confidence in performing mathematical tasks, perceived efficiency, ease of use, and task satisfaction. Stress levels tended to decrease in the assisted condition, and several participants expressed a greater willingness to use the system again in similar tasks. These trends suggest that the assistive system may contribute to a more supportive and less demanding user experience for individuals reporting difficulties with numerical reasoning. *Group 2* also showed increases in positive user experience ratings under the assisted condition. Participants in this group frequently rated ease of use, satisfaction, and willingness to repeat the experience at the upper end of the scale, reflecting generally favourable perceptions of the system regardless of task difficulty. Taken together, these observations indicate that the assistive system was well received by participants in both groups, with the most noticeable benefits reported by those who identified challenges with mathematical or visuospatial aspects of the task.

5. Conclusions and outlook

This research presented a modular human-machine collaboration system designed to support operators in manufacturing environments who experience difficulties with mathematical reasoning. The system integrates computer vision, collaborative robotics, and voice interaction into a configurable architecture that provides four types of mathematical assistance: centre point detection, equal division marking, length marking, and length measurement. These functions are enabled by a coordinate conversion methodology that allows visual-robotic alignment under predefined safety constraints. Findings from this proof-of-concept study, conducted with a small participant cohort, suggest that the system has the potential to alleviate key challenges associated with numerically demanding assembly tasks. Participants reporting difficulties with numerical reasoning tended to show the most pronounced improvements in task completion time, segmentation accuracy, and performance consistency. Reductions in perceived workload were also observed, with decreases spanning cognitive, physical, and affective dimensions of the NASA-TLX. Qualitative feedback highlighted the value of visual guidance and automated support in reducing stress and enhancing confidence and task satisfaction. These results should be interpreted cautiously, as participants with self-reported mathematical difficulties were not assessed using formal diagnostic tools, and the small sample limits generalisability. Robustness depends on stable lighting conditions and accurate calibration, while background noise can compromise speech recognition. Hardware requirements may restrict adoption in resource-constrained settings. The current implementation is domain-specific and has only been tested in a laboratory-scale environment. As a proof-of-concept, the present study provides suggestions rather than conclusive outcomes, and further validation under industrial conditions is required. In addition, the present study did not include a systematic quantitative evaluation of speech recognition accuracy under simulated or real industrial noise conditions. The dual-layer voice architecture, combining a cloud-based recogniser with an offline fallback, was introduced as a robustness-oriented design choice to mitigate sensitivity to ambient noise rather than to optimise recognition accuracy under high-noise environments. Within the proof-of-concept scope of this work, speech interaction performance was therefore characterised qualitatively. Controlled noise-level testing and quantitative accuracy assessment should be addressed in future studies targeting industrial deployment. The experimental validation was conducted under controlled lighting conditions. To maintain segmentation robustness under variable ambient light, the image-processing pipeline employs adaptive thresholding, which adjusts locally to illumination gradients rather than relying on a fixed global threshold. For industrial deployment, supplementary localised illumination such as LED lighting or partially enclosed workstations would further stabilise performance. In industrial deployments, vision-based robustness can be achieved through localised and task-specific illumination, such as LED lighting or partially enclosed workstations, which are widely adopted in manufacturing environments and involve limited additional cost. Similarly, speech interaction can be supported using commercially available directional or noise-cancelling microphones designed for industrial use, without requiring invasive changes to the workstation. These adaptations would allow the proposed system to operate under realistic shop-floor conditions while preserving its core functionality. Dynamic changes in the camera-robot configuration, such as long-term mechanical drift or reconfiguration of the workspace, would require recalibration to maintain transformation accuracy. Future work should therefore investigate periodic or automated recalibration strategies to support long-term operation and deployment in evolving industrial environments, as well as extend testing to industrial contexts with higher variability and complexity. Studies with larger and more diverse participant groups are required to confirm generalisability. Longitudinal investigations could determine whether extended use fosters mathematical competence or functions mainly as compensatory support. Further research should also explore transferability to other manufacturing domains involving measurement, division, or spatial estimation, and assess scalability in full production environments.

CRediT authorship contribution statement

Yuchen Fan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Amberlynn Bonello:** Writing – original draft, Visualization, Software, Investigation, Formal analysis, Data curation. **Alessandro Simeone:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Dario Antonelli:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Paolo C. Priarone:** Writing – review & editing, Visualization, Validation, Supervision, Methodology. **Luca Settineri:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Emmanuel Francalanza:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used ChatGPT and DEEPL in order to improve syntax and grammar. After using these tools, the authors reviewed and edited the content as needed and assume full responsibility for the content of the publication.

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.

Acknowledgments

This research was developed within the framework of LEONARDO project, funded by the European Commission under the

Erasmus+programme KA−220 Cooperation Partnerships for Higher Education - No. 2023-1-IT02-KA220-HED-000164699.

References

[1] Da Silva Soares R, Ramirez-Chavez KL, Tufanoglu A, Barreto C, Sato JR, Ayaz H. Cognitive effort during visuospatial problem solving in physical real world, on computer screen, and in virtual reality. Sensors 2024;24(3):977. https://doi.org/10.3390/s24030977.

[2] Maulida L, Nurossobah P, Aura BA, Nengsih ED, Rasilah. Improving the effectiveness of mathematics learning through artificial intelligence: literature review. J Gen Educ Humanit 2024;3(4):323–38. https://doi.org/10.58421/gehu.v3i4.267.

[3] Ferrie B. What is dyscalculia and how can it be spotted and supported in children and adults? Natl Numer 2022. Available at: ⟨https://www.nationalnumeracy.org.uk/news/what-dyscalculia-and-how-can-it-be-spotted-and-supported-children-and-adults⟩.

[4] Gilstron M, Hadad B-S, Rubinsten O. Weaker groupitizing abilities in magnitude perception in dyscalculia. Learn Individ Differ 2024;113:102491. https://doi.org/10.1016/j.lindif.2024.102491.

[5] Ayyıldız N, Beyer F, Üstün S, Kale EH, Mançe Çalışır Ö, Uran P, Öner Ö, Olkun S, Anwander A, Witte AV, Villringer A, Çiçek M. Changes in the superior longitudinal fasciculus and anterior thalamic radiation in the left brain are associated with developmental dyscalculia. Front Hum Neurosci 2023;17:1147352. https://doi.org/10.3389/fnhum.2023.1147352.

[6] De Freitas E, Sinclair N. The cognitive labour of mathematics dis/ability: neurocognitive approaches to number sense. Int J Educ Res 2016;79:222–30. https://doi.org/10.1016/j.ijer.2015.10.008.

[7] Schliephake A, Bahnmueller J, Willmes K, Koch I, Moeller K. Influences of cognitive control on number processing: New evidence from switching between two numerical tasks. Q J Exp Psychol 2023;76(11):2514–23. https://doi.org/10.1177/17470218231154155.

[8] Simeone A, Fan Y, Antonelli D, Catalano AR, Priarone PC, Settineri L. Inclusive manufacturing: A contribution to assembly processes with human-machine reciprocal learning. CIRP Ann 2024;73(1):5–8. https://doi.org/10.1016/j.cirp.2024.03.005.

[9] Ghobakhloo M, Iranmanesh M, Foroughi B, Babaee Tirkolaee E, Asadi S, Amran A. Industry 5.0 implications for inclusive sustainable manufacturing: An evidence-knowledge-based strategic roadmap. J Clean Prod 2023;417:138023. https://doi.org/10.1016/j.jclepro.2023.138023.

[10] Bryant DP, Bryant BR, Ok MW. Assistive Technology for Individuals with Learning Disabilities. In: Lancioni G, Singh N, editors. Assistive Technologies for People with Diverse Abilities. Autism and Child Psychopathology Series. New York, NY: Springer; 2014. https://doi.org/10.1007/978-1-4899-8029-8_9.

[11] JAN, Job Accommodation Network. Learning Disability. Available at: ⟨https://askjan.org/disabilities/Learning-Disability.cfm⟩ (Last accessed Jan 7, 2026).

[12] JAN, Job Accommodation Network. Situations and solutions finder. Available at: ⟨https://askjan.org/sitsol/index.cfm⟩ (Last accessed Jan 7, 2026).

[13] Matheson E, Minto R, Zampieri EGG, Faccio M, Rosati G. Human–Robot Collaboration in Manufacturing Applications: A Review. Robotics 2019;8(4):100. https://doi.org/10.3390/robotics8040100.

[14] Montini E, Daniele F, Agbomemewa L, Confalonieri M, Cutrona V, Bettoni A, Rocco P, Ferrario A. Collaborative robotics: a survey from literature and practitioners perspectives. J Intell Robot Syst 2024;110(3):117. https://doi.org/10.1007/s10846-024-02141-z.

[15] Sobalvarro P. Here's why human-robot collaboration is the future of manufacturing. World Econ Forum 2020. Available at: ⟨https://www.weforum.org/stories/2020/08/here-s-how-robots-can-help-us-confront-covid/⟩.

[16] Dhanda M, Rogers BA, Hall S, Dekoninck E, Dhokia V. Reviewing human-robot collaboration in manufacturing: opportunities and challenges in the context of industry 5.0. Robot Comput-Integr Manuf 2025;93:102937. https://doi.org/10.1016/j.rcim.2024.102937.

[17] Othman U, Yang E. Human–Robot collaborations in smart manufacturing environments: review and outlook. Sensors 2023;23(12):5663. https://doi.org/10.3390/s23125663.

[18] Zhou L, Zhang L, Konz N. Computer vision techniques in manufacturing. IEEE Trans Syst Man Cyber Syst 2023;53(1):105–17. https://doi.org/10.1109/TSMC.2022.3166397.

[19] Ren Z, Fang F, Yan N, Wu Y. State of the art in defect detection based on machine vision. Int J Precis Eng Manuf-Green Technol 2022;9(2):661–91. https://doi.org/10.1007/s40684-021-00343-6.

[20] Ettalibi A, Elouadi A, Mansour A. AI and computer vision-based real-time quality control: a review of industrial applications. Procedia Comput Sci 2024;231:212–20. https://doi.org/10.1016/j.procs.2023.12.195.

[21] Roy S., Prasad S. 4 ways generative AI addresses manufacturing challenges. IBM. ⟨https://www.ibm.com/think/topics/generative-ai-for-manufacturing⟩. (Last accessed Jan 7, 2026).

[22] Rashidi HH, Pantanowitz J, Hanna MG, Tafti AP, Sanghani P, Buchinsky A, Fennell B, Deebajah M, Wheeler S, Pearce T, Abukhiran I, Robertson S, Palmer O, Gur M, Tran NK, Pantanowitz L. Introduction to Artificial intelligence and machine learning in pathology and medicine: generative and nongenerative artificial intelligence basics. Mod Pathol 2025;38(4):100688. https://doi.org/10.1016/j.modpat.2024.100688.

[23] BOSCH Global. Generative AI in manufacturing. Available at: ⟨https://www.bosch.com/stories/ai-image-recognition-production/⟩ (Last accessed Jan 7, 2026).

[24] Al-Fraihat D, Sharrab Y, Alzyoud F, Qahmash A, Maaita A. Speech recognition utilizing deep learning: a systematic review of the latest developments. Hum-Centr Comput Inf Sci 2024;14:15. https://doi.org/10.22967/HCIS.2024.14.015.

[25] NVIDIA. Glossary: What is Speech AI? Available at: ⟨https://www.nvidia.com/en-us/glossary/speech-ai/⟩ (Last accessed Jan 7, 2026).

[26] Kheddar H, Hemis M, Himeur Y. Automatic speech recognition using advanced deep learning approaches: a survey. Inf Fusion 2024;109:102422. https://doi.org/10.1016/j.inffus.2024.102422.

[27] Vajpai J, Bora A. Industrial applications of automatic speech recognition systems. Int J Eng Res Appl 2016;6(3):88–95.

[28] Rosilius M, Spiertz M, Wirsing B, Geuen M, Bräutigam V, Ludwig B. Impact of industrial noise on speech interaction performance and user acceptance when using the MS HoloLens 2. Multimodal Technol Interact 2024;8(2):8. https://doi.org/10.3390/mti8020008.

[29] Keshvarparast A, Battini D, Battaia O, Pirayesh A. Collaborative robots in manufacturing and assembly systems: literature review and future research agenda. J Intell Manuf 2024;35(5):2065–118. https://doi.org/10.1007/s10845-023-02137-w.

[30] Rajkumar R., Hema G. Assistive technology for mathematics learning disabilities (Dyscalculia). In: Sujathamalini J., Solayan M. (Eds). Recent Trends in Special Education, 2016. ISBN: 978-81-920462-1-7.

[31] Puttero S, Verna E, Genta G, Galetto M. Collaborative robots for quality control: an overview of recent studies and emerging trends. J Intell Manuf 2025:1–37. https://doi.org/10.1007/s10845-025-02600-w.

[32] Poobrasert O, Gestubtim W. Development of assistive technology for students with dyscalculia. 2013 s International Conference on E-Learning and E-Technologies in Education (ICEEE). Poland: Lodz; 2013. p. 60–3. https://doi.org/10.1109/ICeLeTE.2013.6644348.

[33] Mutlu Y. Effects of dyscalculia on personal, social, academic, professional and daily life: a case study. Int Electron J Elem Educ 2024;17(1):89–101. https://doi.org/10.26822/iejee.2024.365.

[34] Salisbury L. How can you manage dyscalculia in the workplace? Individ 2023. Available at: ⟨https://exceptionalindividuals.com/about-us/blog/how-can-you-manage-dyscalculia-in-the-workplace/⟩ (Last accessed Jan 7, 2026).

[35] Emergent Vision Technologies Inc. Utilizing machine vision for manufacturing defect detection and prevention. Available at: ⟨https://emergentvisiontec.com/applications/inspection-and-automation/defect-detection-and-prevention/⟩ (Last accessed Jan 7, 2026).

[36] Vicentini F. Collaborative robotics: a survey. J Mech Des 2021;143(4):040802. https://doi.org/10.1115/1.4046238.

[37] Sidiropoulos A, Dimeas F, Papageorgiou D, Semetzidis TP, Doulgeri Z, Zanella A, Grella F, Sagar K, Jilich M, Albini A, Cannata G, Zoppi M. Safe and effective collaboration with a high-payload robot: a framework integrating novel hardware and software modules. IEEE Robot & Autom Mag 2024;31(3):38–47. https://doi.org/10.1109/MRA.2023.3283331.

[38] Chebotareva E, Mustafin M, Safin R, Tsoy T, Martinez-García EA, Li H, Magid E. Camera-based safety system for collaborative assembly. J Intell Manuf 2024;36(8):5593–611. https://doi.org/10.1007/s10845-024-02533-w.

[39] Zhu L, Cheng H, Yin X, Zhang K, Liu S, Zhang X. A vision-based simultaneous calibration method for dual-robot collaborative system. IEEE Trans Ind Inform 2024;20(11):13396–405. https://doi.org/10.1109/TII.2024.3435546.

[40] Terras N, Pereira F, Ramos Silva A, Santos AA, Lopes AM, Silva AFD, Cartal LA, Apostolescu TC, Badea F, Machado J. Integration of deep learning vision systems in collaborative robotics for real-time applications. Appl Sci 2025;15(3):1336. https://doi.org/10.3390/app15031336.

[41] Wu L, Zang X, Ding G, Wang C, Zhang X, Liu Y, Zhao J. Joint calibration method for robot measurement systems. Sensors 2023;23(17):7447. https://doi.org/10.3390/s23177447.

[42] Magaña A, Vlaeyen M, Haitjema H, Bauer P, Schmucker B, Reinhart G. Viewpoint planning for range sensors using feature cluster constrained spaces for robot vision systems. Sensors 2023;23(18):7964. https://doi.org/10.3390/s23187964.

[43] Yan S, Tao X, Xu D. High-precision robotic assembly system using three-dimensional vision. Int J Adv Robot Syst 2021;18(3):1–12. https://doi.org/10.1177/17298814211027029.

[44] Hermansyah MSA, Handayani NU. NASA-TLX assessment of mental workload in manufacturing industry. Spektrum Ind 2022;20(2):1–14. https://doi.org/10.12928/si.v20i2.43.

[45] Burati JL, Weed RM. Accuracy and precision of typical quality measures. Transp Res Rec J Transp Res Board 2006;1946(1):82–91. https://doi.org/10.1177/0361198106194600110.

[46] Cohen J. Statistical Power Analysis for the Behavioral Sciences, 2nd Edition. Routledge, New York. DOI:⟨10.4324/9780203771587⟩.