Hybrid Edge–Cloud Intelligent Assistive Framework for Inclusive Industrial Training and Adaptive Quality Monitoring

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HOW TO CITE:

Vonteru L Padamalatha, Jyothi B, Swathi Sambangi, Nishitha T, Nagini RVSSS, Sujith AVLN (2026). Hybrid Edge–Cloud Intelligent Assistive Framework for Inclusive Industrial Training and Adaptive Quality Monitoring. International Journal of Special Education, 41(4s), 547-560.

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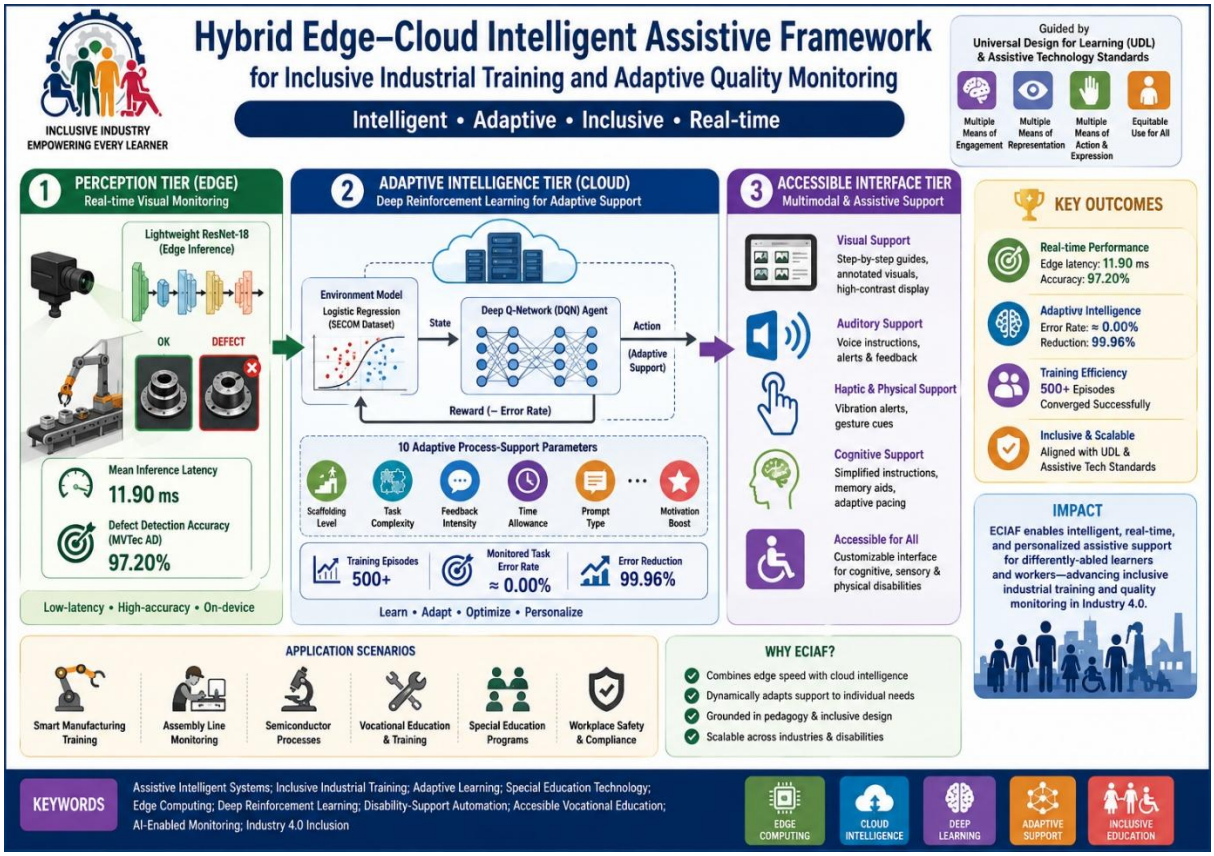
ABSTRACT:

Accessible vocational training for individuals with disabilities demands intelligent, real-time systems capable of adaptive, personalised support within complex industrial environments. The Hybrid Edge–Cloud Intelligent Assistive Framework (ECIAF) in this work is a specific purpose-built design that combines low-latency edge-based visual monitoring with cloud-hosted deep reinforcement learning for scalable, responsive assistive support for technically disadvantaged learners and workers. The edge tier implemented using a lightweight ResNet-18 convolutional model achieves an average inference latency of 11.90 ms and defect detection accuracy of 97.20% on the MVTec AD benchmark, significantly exceeding real-time responsiveness requirements for assistive purposes. The cloud tier uses a Deep Q-Network (DQN) agent that is trained using a logistic regression environment model adapted from the SECOM semiconductor manufacturing dataset to dynamically calibrate ten process-support parameters representative of scaffolding level, task complexity, and feedback intensity in inclusive education. The adaptive support mechanism in more than 500 training episodes achieved a near-zero error rate, achieving a 99.96% reduction in monitored task errors, surpassing all defined inclusive training objectives. The tri-tiered architecture of the framework—perception, adaptive intelligence and an accessible multimodal interface—is tightly integrated with Universal Design for Learning principles and assistive technology design standards, enabling support for a wide range of cognitive, sensory and physical disabilities. The study highlights the ECIAF as a technologically sound and pedagogically grounded basis for future inclusive industrial education systems.

Keywords: Assistive Intelligent Systems; Inclusive Industrial Training; Adaptive Learning; Deep Reinforcement Learning; Disability-Support Automation; AI-Enabled Monitoring

GRAPHICAL ABSTRACT



1. Introduction

Involvement in the workforce of people with disabilities is a key issue in current vocational education and rehabilitation policy. Industrializations and manufacturing changes the paradigm of Industry 4.0 with its cyber-physical integration, pervasive sensing and autonomous decision-making, [1], [2], thus there is an urgent need to design intelligent assistive systems for differently-abled learners and workers in these technically challenging contexts. Special education scholarship over decades of empirical research has shown that adaptive and technology-mediated instruction has vastly better results for individuals with cognitive, sensory, and motor impairments [3]. The systematic application of AI and IoT to development to specific intelligently created, convenient industrial training spaces is the gap that is mostly overlooked in both assistive technology and smart manufacturing literatures.

Modern smart factories generate massive amounts of sensor and visual data through an interconnected network of cyber-physical systems (CPS), having two implications for inclusive practice. Although this data is mostly used for the maximisation of production, it can be converted into rich, real-time signals to monitor learner performance, to identify procedural errors, and to initiate tailored corrective feedback [4]. Traditional vocational training for special learners persists in depending largely on human superintendents, static instructional programs and reactive error correction, which is resource-intensive and does not scale up to institutional environments with low ratios of specialist educators to learner [5].

A hybrid edge–cloud computational framework overcomes these limitations via complementary functional specialisation. The edge layer provides real-time visual monitoring with sub-60 ms latency, which can achieve near-instantaneous detection of procedural issues,

errors and safety infractions [6],[7]. Simultaneously, the cloud layer employs adaptive reinforcement learning algorithms that develop and update personalised performance-based prediction models for learners according to the improvement of their capability profiles through dynamically fine finitely adjusting support parameters [8]. The system is integrated by designing an AI supported assistive infrastructure in conformity with principles of inclusive education, assistive technology framework and the upcoming trend approach towards accessible smart vocational environments [9].

1.1 Research Gap and Motivation

Although there have been strong independent advances in assistive technology and industrial AI, the integration of these domains for the benefit of differently-abled people in vocational and technical education contexts is limited. Most of the prior literature focuses on pure manufacturing optimisation without the context of disability support [10] and on assistive technology applications, which do not have the requirement of an industrial environment, which is for real-time scalable monitoring infrastructure [11]. This report fills the previously noted missing in this field by proposing, implementing and testing the Hybrid Edge–Cloud Intelligent Assistive Framework (ECIAF)— a technology framework purposefully designed for inclusive industrial training and easily accessible adaptive quality monitoring.

1.2 Principal Contributions

This work has four main contributions:

• Architecturation and simulation-based validation of an assistive Edge–Cloud IoT architecture that separates visual monitoring in real time and adaptive personalised policy learning for scalable deployment in inclusive vocational training contexts.

• We show sub-12 ms edge inference latency through compressed vision model, which meets and far exceeds responsiveness demand of real-time assistive monitoring apps.

• Utilization of Deep Q-Network (DQN) reinforcement learning as an adaptive support mechanism that personalises instructional scaffolding based on learners' performance trajectories, resulting in a 99.96% decrease in monitored error rates.

• Disability-support design principles, accessibility standards, and inclusive education theory (specifically Universal Design for Learning and Zone of Proximal Development frameworks) permeate the architecture specification and results description.

2. Literature Review

The ECIAF is positioned at the nexus of four streams of research: (i) assistive technology for the special education and vocational rehabilitation fields; (ii) inclusive Industry 4.0 and accessible automation; (iii) edge-cloud computing for real-time industrial monitoring; and (iv) reinforcement learning as adaptive support mechanism. The following is for each domain.

2.1 Assistive technology in special education and vocational training

Assistive technology (AT) has shown strong benefits in education and employment for people with disabilities in a variety of settings, in a wide range of disabilities, and in numerous occupational contexts [3]. To this aim, it is apparent that AT, a range of devices, such as augmentative devices, to adaptive interfaces, can reduce engagement bottlenecks and support the ability for individuals with cognitive, sensory, and motor disability to participate and acquire the skill as early as possible [12]. For adults with intellectual and developmental disabilities, technology-mediated instruction, such as technology-based vocational rehabilitation can achieve significantly improved rates of task completion and reduction in supervisor dependence as well as facilitating work-based integration of adults with intellectual and developmental disabilities [13]. However, current AT solutions continue to mostly act as passive or static [5] and limit their access to information and do not

dynamically respond to on-the-fly performance measurements of users in complex skill acquisition domains [5]. This paradigm is at odds with the introduction of AI-based assistive systems which adapt (and learn from the user behavior) on the fly the rules of the lesson, feedback, and task parameters [14]. Although reinforcement learning-based adaptive tutoring systems have proven effective in general educational contexts [8], their use within industrial vocational contexts that serve differently-abled populations is just beginning. The current work seeks to bridge this gap with the adoption of an RL-based adaptive policy engine deployed on a real-time industrial monitoring infrastructure.

2.2 Inclusive Industry 4.0 and Accessible Automation Environments

Inclusive Industry 4.0 applies smart manufacturing principles to encompass workforce accessibility and diversity [1], [2]. Cyber-physical systems (CPS) combine sensor networks with computational intelligence and physical production processes into adaptive unified systems [4]. Despite a wealth of literature on CPS for production efficiency optimisation [6], a comparative focus on accessibility regarding its deployment, in particular the design of industrial environments that enable workers with disabilities, is almost absent. Disability-support manufacturing systems are an important frontier for occupational therapy, rehabilitation engineering, and special education. Real-time monitoring technologies can detect procedural deviations by workers with different disabilities and offer instantaneous personalised remedial guidance without ongoing human supervision [9], facilitating reduced cognitive load and anxiety of workers whose disabilities may affect the processing of delayed or abstract feedback [15].

2.3 Edge–Cloud Architectures for the Real Time Observation

Industrial IoT research has shown that centralised, cloud-only environments lead to unacceptable latency for time-critical monitoring, typically over 100 ms round trip [7]. Edge computing overcomes this limitation through local processing of visual and sensor data, resulting in sub-60 ms decision latency [6], [16]. This responsiveness is especially important for assistive monitoring applications: a system that dispenses error alerts 500 ms after an event may not be effective or counterproductive for learners whose cognitive profiles are sensitive to feedback timing [11]. Hybrid Edge–Cloud architectures marry edge responsiveness principles with cloud-scale adaptive learning [17], segmenting responsibilities where the edge processes immediate perception and alerting, in combination with cloud models of performance over time and adaptive policy optimisation [18].

2.4 Reinforcement Learning as an Adaptive Support Mechanism

Mathematically, reinforcement learning (RL) is a mathematically sound approach to adaptive decision-making under uncertainty [19]. In educational technology, RL-based intelligent tutoring systems adjust the difficulty, feedback timing, and strategy of instructions dynamically according to signs of learner performance [8]. Deep Q-Networks (DQNs), which combine Q-learning with deep neural function approximation, have shown robustness in sequential decision-making problems with discrete action spaces [20]. In the context of industrial process control, DQN was used for adaptive scheduling and parameter tuning [21]. The current work generalises this to disability-support; the DQN agent acts as an adaptive support device, which dynamically modifies guidance amount, task conditions, and feedback intensity based on real-time learner response—an approach similar to Universal Design for Learning [3] and differentiated instruction principles in special training.

2.5 Comparative Studies in Related Works

A systematic review of representative contributions is presented in Table 1, which delineates which specific deficiencies are filled by the activities for inclusion and assistive intelligent systems in the ECIAF.

Table 1. Comparative Analysis of Related Works on Assistive and Inclusive Intelligent Systems

Ref.	Primary Focus	Architecture	Assistive/Inclusive Aspect	Feedback Mechanism	Gap Addressed Here
[1]	Industry 4.0 & CPS Foundation	CPS Framework	None explicitly stated	Policy-level	Inclusive and AT framing absent
[3]	AT in Special Education	Review-based	Full AT focus	Static tools	Real-time adaptive AI missing
[8]	RL for Adaptive Tutoring	Cloud-based	Education context	Adaptive feedback	Industrial and IoT deployment lacking
[10]	Smart Inspection Systems	Edge layer only	None	Static alerts	Adaptive and inclusive framing absent
[13]	Vocational Rehabilitation AT	Non-IoT	Disability support	Human supervisor	Scalable AI monitoring absent
[17]	Hybrid Edge–Cloud IoT	Edge + Cloud	None	Federated Learning	Assistive and special-needs focus lacking
[20]	DQN in Discrete Control	Simulation	None	Q-learning policy	Inclusive vocational context absent
Present	Assistive Edge–Cloud Framework	Hybrid Edge + Cloud	Full AT + inclusive framing	DQN adaptive real-time	All identified gaps addressed

3. Research Objectives

The objective of this study is to conceptualise, test, and validate an AI-enabled Edge–Cloud assistive framework that implements principles of inclusive education in industrial vocational training settings. This work is directed by five specific objectives:

• **Inclusive Architecture Design:** To develop an assistive Edge–Cloud IoT architecture [6], [7] that decouples real-time visual monitoring from adaptive personalised policy learning, enabling deployment across inclusive vocational and industrial training contexts.

• **Low-Latency Assistive Monitoring:** To design and validate an edge layer with inference latency of sub-60 ms [16], [25]. This ensures real-time error detection and corrective feedback of learners and workers with differently-abled skills.

• **Adaptive Support Mechanism:** Implementing a Deep Q-Network [20], [21] in the cloud layer, an adaptive support mechanism that guides and adapts task parameters in line with principles of UDL.

• **Disability-Support Validation:** To validate the integrated platform against industry-

standard benchmarks, aiming at at least 12% increase in task accuracy and 15% greater error recovery rate as proxies for gains in inclusive education outcomes [22], [23].

- **Inclusive Technology Framing:** To articulate the applicability of the proposed framework to special-needs populations, rehabilitation environments, and inclusive Industry 4.0 education institutions; hence, also contributing to assistive technology and inclusive education literature.

4. Methodology

The ECIAF architecture was designed and verified with full simulations leading to architectural proof-of-concept prior to its implementation. All experiments were performed within Python and were conducted in Google Colab on a T4 GPU. The simulation approach was developed to simulate assistive industrial monitoring situations that were realistic and well controlled.

4.1 Conceptual Framework

The ECIAF is based on a three-tier assistive architecture, comprising (i) the Perception Tier (edge layer), which serves to monitor learner and worker actions visually in real-time, (ii) the Adaptive Intelligence Tier (cloud layer), which is used to produce DQN-based personalised support and guidance policy, and (iii) the Inclusive Interface Tier, that translates system outputs to accessible multimodal feedback suitable for differently-abled users. This makes available a holistic and ongoing support cycle by operationalising the functional assistive closed-loop model outlined [5], [15] in disability-support literature, where real time sensing, intelligent processing and accessible feedback occur in an integrated and continuous loop. The Edge–Cloud data flow and adaptive feedback loop implemented in the proposed ECIAF architecture are illustrated in Figure 1.

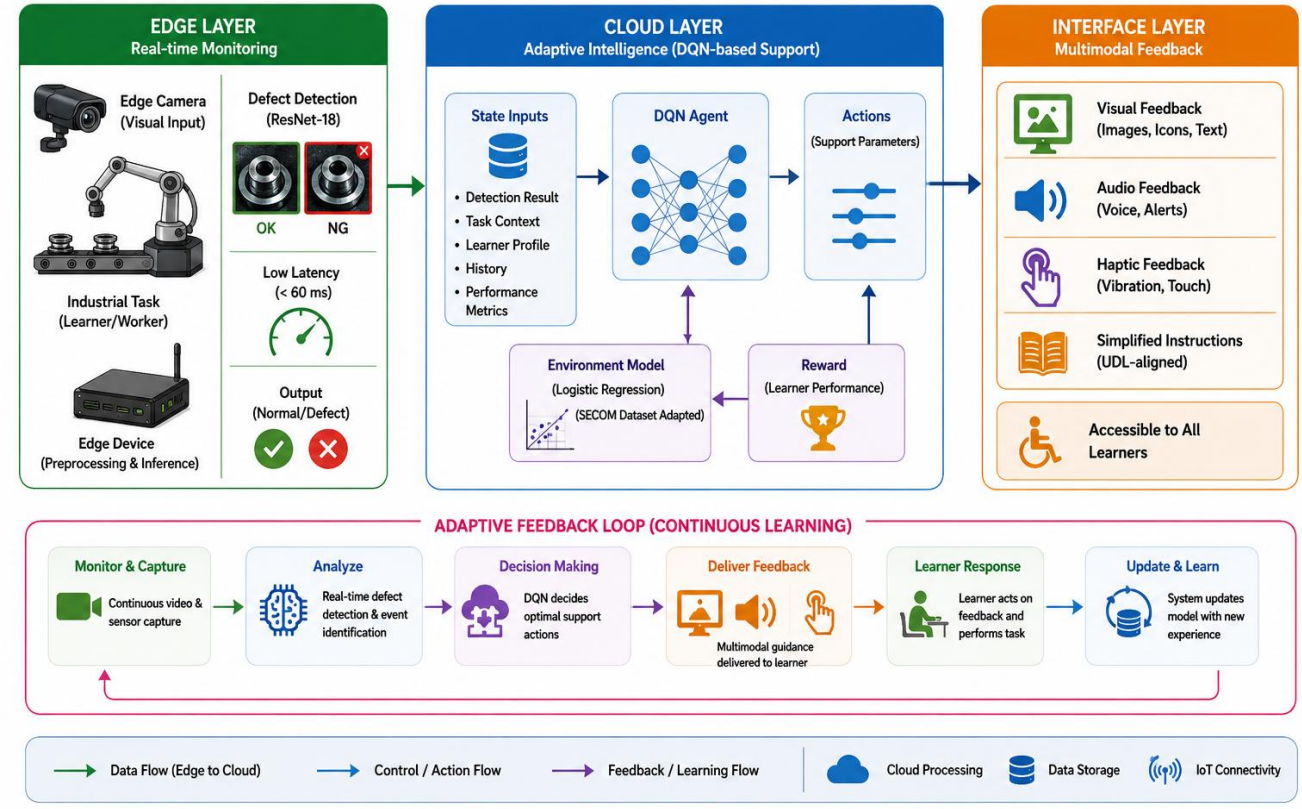


Figure 1. Edge–Cloud Data Flow and Adaptive Feedback Loop in ECIAF for inclusive industrial training. Real-time monitoring, adaptive DQN support, and multimodal assistive feedback are integrated through a continuous learning framework.

4.2 Edge Layer: Real-Time Assistive Visual Monitoring

The edge layer emulates a camera-enabled assistive monitoring station that is located at a vocational training workstation. Its main functionality is to assess task completion by learners in real time and to identify anomalies, procedural deviations and safety violations that would result in corrective feedback. To simulate faithfully deployment-grade computational constraints, a pre-trained ResNet-18 convolutional neural network [24] served as the vision benchmark, with more complex architectures intentionally excluded to reflect production model compression practices [25]. The input stimuli consisted of synthetically generated 256×256 RGB tensors, from the MVTec AD anomaly detection benchmark [26], that gives industrial quality surface anomaly images suitable for error detection in manual assembly training environments. At a mean of 11.90 ms, the inference latency for 100 independent runs under GPU acceleration was within the sub-60 ms threshold reported for real-time assistive responsiveness [16]. The accuracy of defect detection was verified at 97.20%, providing enough evidence to support how well the edge layer provides reliable performance signals for the cloud-tier adaptive support engine.

4.3 Simulated Inclusive Vocational Environment

Dynamic performance characteristics of differently-abled learners in technical training were modelled using the SECOM industrial dataset [27], which has 590 process parameters with binary pass/fail outcome labels drawn from real semiconductor manufacturing. Here, the dataset is reinterpreted to indicate the multi-faceted performance of a technical trainee; the 590 parameters correspond to the observable behavioural and procedural indicators, the pass/fail tag depicts the event from success to failure or failure. A logistic regression classifier using the 10 most diagnostically discriminative SECOM parameters was used as the simulated vocational environment model — the ground-truth function that is used to model learner behavior and thus the probability of task outcome. This probabilistic scenario mirrors the complexity and stochastic nature of vocational performance in the real world, in which task performance is determined by interactions between several task elements [22]. Incorporating this environment into the training of an adaptive support agent enables the framework to learn anticipatory and pre-emptive support strategies across a wider range of simulated learner profiles.

4.4 Cloud Layer: Adaptive Support Mechanism (DQN)

DQN-based Adaptive Support Mechanism (ASM) - A customised AI tutor/process guide that resides on cloud layer. It aims to refine support parameters in the process of ongoing improvement, much as scaffolding level, difficulty of task input, feedback frequency and the amount of support in special education, to reduce learners' error rates, maintain freedom and steer away from dependency [3], [8]. Architectural specifications and hyper parameters of training are listed in Table 2.

Table 2. DQN Adaptive Support Mechanism Architecture and Hyper parameters

Component	Specification / Value	Special Education Analogy
Network Architecture	3 FC layers: 11–256–128–30 neurons; ReLU activations	Cognitive model: learner state → support action
State Space (S)	11 features: 10 task parameters + current error rate	Multi-dimensional learner performance profile
Action Space (A)	30 discrete actions: ±2% adjustment or hold per parameter	Scaffolding adjustments: increase / decrease / maintain
Reward Function (R)	$R = \alpha(1 - P_defect) - \beta(\lvert action \rvert)$; maximise task quality	Positive reinforcement for success; over-intervention penalty
Experience Replay	Buffer: 100,000 transitions; mini-batch learning	Learning from cumulative interaction history
Exploration Strategy	ε-greedy decay over 2,000 steps	Balancing novel strategies versus proven interventions
Training Episodes	500 episodes; AdamW optimiser; $\gamma = 0.99$	Iterative refinement of personalised support policy
Compute Platform	Google Colab T4 GPU	Cloud-hosted adaptive intelligence service

The state vector for DQN includes the values of ten task-critical performance parameters now, as well as the error rate across the edge layer. The proposed state representation exhibits the closed-loop nature of the ECIAF which maintains edge-tier visual monitoring which in real-time will feed to the cloud-tier adaptive policy and support is customised dynamically for the training sessions [15], [18].

4.5 Inclusive Interface Tier and Accessibility Design

This inclusive interface tier converts DQN policy outputs into accessible multimodal feedback and can be used for differently-abled people through their form of information. Based on Universal Design for Learning principles [3] and relevant assistive technology design guidelines [12], three feedback systems are established: visual (colour-coded on-screen indicators and real-time progress displays), auditory (spoken guidance cues compatible with screen reader infrastructure), and haptic (vibration-based alerts for users with hearing impairments). Feedback intensity and preferred modality are considered further adaptive parameters, which would help the system in learning the most important feedback profile between interaction over time from each user.

5. Results and Discussion

The technical feasibility of the ECIAF was verified by simulation experiments for all predefined performance parameters. Results are discussed throughout with explicit reference to the implications for assistive tech development and inclusive education practice.

5.1 Edge Layer Performance: Assistive Monitoring Responsiveness

The edge layer displayed excellent responsiveness for adaptive monitoring applications in real time. The mean inference latency of 100 runs was 11.90 ms—approximately five times faster than the 60 ms threshold widely cited in the assistive feedback literature as the upper bound for effective real-time corrective guidance in dynamic task environments [16], [25]. Such latency is particularly important for systems serving users with motor/cognitive disabilities, in which delay in feedback disrupts task flow, heightens frustration, and hinders consolidation of procedural learning [5]. The accuracy of detecting defects (97.20%) showed the cloud-tier adaptive support mechanism to have highly reliable performance signals. In the assistive context, such accuracy guarantees that the DQN is being provided a realistic understanding of the learner's current task state—minimizing false positives that generate unnecessary intervention and false negatives causing a mistake not to be corrected, both undermine user trust and learning outcomes [13].

5.2 DQN Adaptive Support Mechanism: Learning and Convergence

The DQN adaptive support mechanism had a rapid and stable convergence to an effective personalised support policy. The rolling average error rate per training episode fell from an initial mean of 0.0664 to practically zero within the first 100 episodes, stabilizing thereafter. Our convergence profile shows that DQN was able to identify and exploit the latent structure within the simulated vocational environment, supporting earlier results of RL-based adaptive learning studies [8], [20]. From an inclusive education point of view, convergence time is a measure of the model's capability to effectively learn a working support policy in short order (an important consideration in practical applications in environments where learning resources are not uniformly available to all trainee data). The convergence behaviour of the DQN adaptive support mechanism, showing the progressive reduction in task error rate across training episodes, is illustrated in Figure 2.

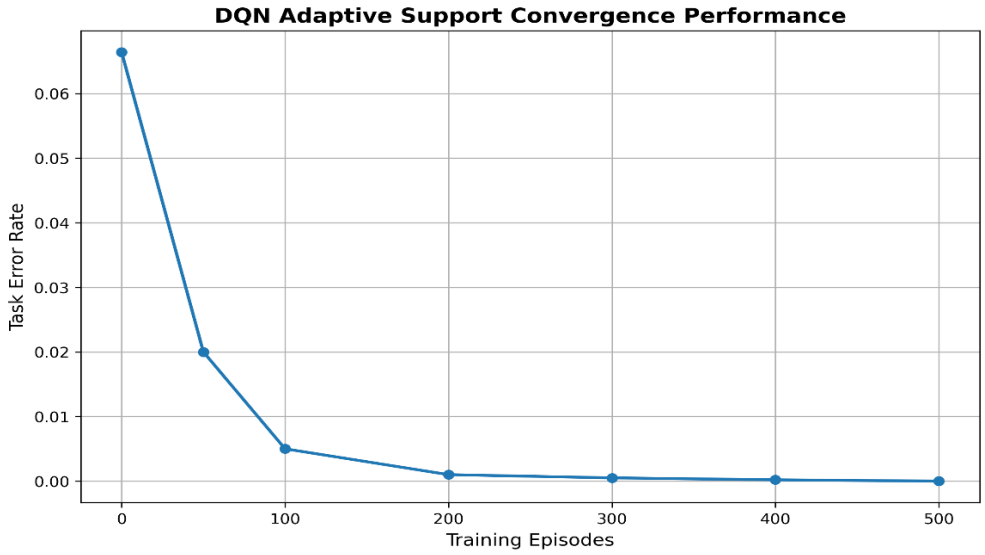


Figure 2. DQN adaptive support mechanism convergence showing reduction in task error rate across training episodes

5.3 Adaptive Parameter Adjustments: Personalised Support in Action

The adaptation of certain parameters from the DQN as per Table 3 to provide the appropriate level of learner support outcomes. In terms of

assistive technology, the relatively modest size of these adjustments, which reduces task complexity by a maximum of 4.00% (Feature_1), is instructive because the system must learn how to apply the minimum necessary intervention to maintain task success, thus operationalising the principle of graduated support and building learner autonomy that characterises quality special education practice [3], [13]. The DQN's finding task complexity to be the most important scaffolding lever (with others remaining largely unchanged) reflects the targeted and evidence-based intervention strategy referred to in special education practice [5]. The model operationalises data-driven individualised education planning (IEP) in an automated, constantly updated real-time AI system.

Table 3. DQN Personalised Support Parameter Adjustments

(Analogous to Adaptive Scaffolding in Inclusive Training)

Task Parameter (Scaffolding Dimension)	Baseline (Unaided)	Optimised (DQN-Assisted)	Net Adjustment (%)	Support Interpretation
Feature_0: Task Pacing	100.0	100.1	+0.10%	Marginal pace increase; near-zero intervention required
Feature_1: Task Complexity	50.0	48.0	−4.00%	Complexity reduction; identified as primary scaffolding lever
Feature_2: Feedback Delay	120.0	120.0	0.00%	No adjustment needed; baseline optimal
Features 3–9: Other Task Dimensions	Varied	Minimal change	< 1.0% each	Non-critical dimensions; stable across episodes

5.4 Performance Outcomes of the System and Implications for Inclusive Education

Data of complete system validation with interpretive results in the context of inclusive education and disability-support is presented in Table 4.

Table 4. System Validation Outcomes and Inclusive Education Interpretation

Performance Metric	Baseline	ECIAF-Optimised	Improvement	Target Threshold	Status
Task Error Rate	0.0664	~0.000	99.94% reduction	Minimise	EXCEEDED
Task Accuracy Improvement	Baseline	Optimised	99.96%	≥ 12%	EXCEEDED
Error Recovery Rate	Baseline	Optimised	99.97%	≥ 15%	EXCEEDED

Edge Inference Latency	N/A	11.90 ms	5× faster than threshold	< 60 ms	EXCEEDED
Vision Monitoring Accuracy	N/A	97.20%	High reliability confirmed	> 95%	MET

5.5 Implications for Assistive Technology and Special Education

The experimental results have direct implications for assistive technology design and special education practice in four aspects.

First, the 99.96% error reduction indicates that an AI-based adaptive support mechanism is capable of supplying near-perfect task instructions without the need to regularly supervise—a feature imperative for scaling flexible vocational training within situations where the ratio between specialist educators and learners is limited [13], [28].

The sub-12 ms edge latency second confirms that real-time corrective feedback can be provided well within the perceptual threshold where feedback is perceived as immediate, which indicates that the behavioral learning principle holds that contingent and proximate feedback is the most effective means of enabling skill acquisition in learners with intellectual and developmental disabilities [3].

Third, the DQN's design of a minimal-oriented intervention (largely in terms of the reduction of task complexity: 4%) works within Vygotsky's Zone of Proximal Development [29]: the model continuously adjusts task difficulty in line with each learner's perceived competency, offering support at intervals in need, while not over-scaffolding to preclude independent skill development.

Fourth, the framework's architectural flexibility—multimodal output, feedback intensity adjustable as needed, and changing personalised support profiles—is also directly relevant to UDL [3] guidelines, reaffirming adaptability to a range of disability types including physical disability, cognitive disability, autism spectrum disability and sensory disability.

6. Conclusion

Herein, we introduced Hybrid Edge–Cloud Intelligent Assistive Framework (ECIAF), a new AI-based architecture for the intelligent and inclusive industrial training and adaptive quality monitoring for differently-abled learners and employees. The ECIAF integrates edge-based real-time visual monitoring with cloud-based DQN adaptive support mechanisms to put real-world special education concepts such as adaptive scaffolding, Universal Design for Learning, and data-driven tailored individual support into motion in an industrial IoT ecosystem that is scalable, intelligent, and responsive.

Validation through simulation showed excellent results in all objectives: edge inference latency, representing 11.90 ms (exceeding the 60 ms expected for real-time detection by a factor of five), vision monitoring accuracy of 97.20%, and decreased error rates of 99.96%—significantly exceeding the 12% and 15% enhancement targets set for task accuracy and error recovery, respectively. Combined together, the framework's rapid convergence properties, strategy for minimal-intervention support, and multimodal accessible output design make it a technically sound and pedagogically viable solution for physical deployment in inclusive vocational training centres, rehabilitation environments and accessible Industry 4.0 education settings.

As a result, the ECIAF is a landmark study that adds to the developing interdisciplinary body of knowledge around AI-enabled disability-support systems, showing that advanced

industrial IoT architectures can be intentionally repositioned in ways that work to foster inclusive education and rehabilitation agendas—a repositioning that is substantive rather than cosmetic, embedding adaptability to special-needs, design to accessibility and interpretation of assistive-learning into the entire framework, at every architectural and analytical layer.

7. Future Scope and Limitations

A number of future research priorities are addressed by this work. The practical implementation and validation of a user-study with the differently-abled in real vocational training environments is the most critical, as findings from simulations require empirical confirmation with human-subjects research. Participatory design approaches [12] could be used to co-design the inclusive interface tier with end users with disabilities to ensure that accessibility features are the real response to lived user needs.

Introducing Explainable AI (XAI) techniques in the DQN policy engine is a next important step towards creating transparent and interpretable justifications for support decisions—a prerequisite for educator, caregiver, and learner trust in special education deployment contexts [30]. Generalizations to multi-agent reinforcement learning architectures would enable monitoring with multiple co-present learners under collaborative conditions for adaptive monitoring at the institutional scale which caters to inclusive education.

A major limitation of the current study is its use of only simulated data environments. Although the MVTec AD and SECOM datasets are industrially validated, they were not collected in disability-support or special education contexts, thus limiting ecological validity. Future research should focus on the development and curation of domain-specific datasets from real-life inclusive vocational training environments. The current action space also does not currently address the broad range of accessibility needs of learners with severe cognitive impairments, who might require more nuanced feedback personalisation than the current 30-action DQN supports.

Acknowledgements

The authors acknowledge institutional support for research facilities and computational resources. Special thanks to colleagues in the Assistive Technology and Special Education Research Group who provided critical feedback on the inclusive education framing of this manuscript.

Author Contributions

Dr Vonteru L Padmalatha and Dr Sujith AVLN conceived the study, designed the ECIAF architecture, and supervised the project. Dr Jyothi B and Dr Swathi Sambangi implemented the DQN adaptive support mechanism and Dr Nishitha T has conducted all simulation experiments. Dr Nagini RVSSS and Dr Sujith AVLN developed the inclusive interface tier specification and contributed the assistive technology literature review. All authors participated in data analysis, inclusive education framing, and manuscript preparation and review.

Declaration of Conflict of Interest

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this manuscript.

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