AI-Driven Engineering Framework for Smart Technology Management, Behavioural Analysis, and Inclusive Education in Autism Support

Ibrahim O. Isiaka [1]

[1] University of Houston-Clear Lake
2700 Bay Area Blvd, Houston, TX 77058-1002, USA

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Corresponding Author:
Ibrahim O. Isiaka

Abstract. Researchers increasingly recognise Artificial Intelligence (AI) as an innovative technology that supports inclusive education for individuals with Autism Spectrum Disorder (ASD). This paper presents a holistic AI-driven engineering and smart technology management framework that integrates machine learning (ML), computer vision, Internet of Things (IoT), wearable biosensors, robotics, virtual reality (VR), and privacy-preserving artificial intelligence into a unified socio-technical architecture for behavioural analysis and personalised educational support. Rather than reporting a completed implementation, the proposed framework synthesises existing evidence to show how these technologies can integrate to support future intelligent classroom environments.

The proposed framework aims to integrate multimodal sensing and AI-assisted decision support to facilitate continuous behavioural monitoring, adaptive instructional recommendations, and personalised intervention strategies while maintaining teacher autonomy and promoting responsible AI governance. Prior work shows that computer vision, wearable sensing, robotics, and VR each offer useful capabilities to enhance behavioural understanding, social engagement, and individualised learning experiences for autistic learners.

The framework also calls for participatory design, ethical governance, transparency, and collaboration with autistic people, educators, families, and clinicians to help ensure future applications are neurodiversity-affirming. This work provides a practical foundation for future implementation, empirical validation, and continued innovation in AI-enabled inclusive education by integrating independently validated technologies into a single engineering blueprint.

Keywords: Artificial Intelligence; Autism Spectrum Disorder; Smart Technology Management; Machine Learning; Computer Vision; Wearable Sensors; Internet of Things; Inclusive Education.

INTRODUCTION

Autism spectrum disorder (ASD) is a heterogeneous syndrome of abnormal development that is lifelong and typically presents in early childhood. It is characterised by abnormalities in social communication and interactions, restricted interests, repetitive behaviours, and different patterns of sensory and cognitive functioning. These traits often clash with traditional classroom culture, limiting participation even when ability is high [1]. Historically, educational responses have relied on human observation, static accommodations, and episodic assessments that are difficult to scale, highly variable across settings, and only partially responsive to moment-to-moment shifts in a learner's state. At the same time, a growing literature is emerging on how digital technologies, from AI and sensing systems to interactive media, can support learning, communication, and engagement among autistic children and youth [2–5]. The convergence of ASD, inclusive education and smart technologies points to a new engineering goal: AI-guided smart technology management systems that continually modify the educational environment based on ongoing behavioural and contextual data.

Traditionally, machine-learning models (MLs) based on moderate amounts of behavioural and background features have distinguished autistic from non-autistic individuals at very high classification rates, suggesting a role for automated screening and risk stratification to complement clinical judgment and potentially reduce time to support [4, 6, 7]. At the same time, some systematic reviews point to conceptual and implementation problems like biased data sets, opaque behaviour of standard ML models and potential opportunities to incorporate external data to improve generalizability that currently hinder clinical rollout [4, 7]. We propose an engineering management agenda in which AI is not a replacement for expert assessment but part of wider socio-technical systems that must be resilient, interpretable, and ethically regulated.

Computer-vision reviews on ASD show that researchers have used visual analysis to assess gaze patterns, facial expressions, motor behaviour, and social attention for diagnosis and therapy [8–11]. Meanwhile, related efforts on automatic emotion recognition in autistic children have shown that multimodal classifiers can detect emotions from facial, vocal, and physiological signals with encouraging performance. Still, they also show significant variation in data-collection methods and labelling criteria [12]. Deep-learning models based on joint-attention behaviour in brief video segments have also shown that even fine-grained, social-attentional responses can predict ASD and symptom severity, demonstrating the link between carefully designed elicitation tasks and scalable, AI-based behavioural measurement [13, 14].

At the same time, wearable and environmental sensing have emerged as key technologies for AI-enabled behavioural analysis. Similarly, a systematic literature review on wearables for engagement detection in learning environments suggests that psychophysiological and emotional features can serve as proxies for cognitive and affective engagement. Still, only a few systems have been designed specifically for autistic learners [15]. Researchers have uniquely applied wearable biosensing to predict imminent aggressive behaviour in psychiatric inpatient youths with ASD. Heart rate and electrodermal activity models provided alerts 3 min before violent episodes, demonstrating the potential for proactive sensor-based intervention [16]. A parallel review of wearable sensors for ensuring the sports safety of children with ASD indicates that accelerometers, inertial measurement units, and physiological sensors can monitor abnormal movement patterns, stress responses, and potential injury risks in dynamic community settings [17].

Beyond passive monitoring, AI-infused systems increasingly aim to shape learners' experiences through adaptive interventions. Tablet communication, or augmentative and alternative communication (AAC) apps, for non-verbal autistic children can open accessible, visually structured lines of self-expression, often through an iterative process that values the individual's perspective [18]. This principle is now being applied to social-cognitive interventions in Virtual-reality (VR) systems, as an increasing number of randomised and quasi-experimental studies show that VR interventions can increase emotion recognition, conversational skills, and theory-of-mind-related performance through programs that engage participants with immersive yet highly predictable simulations of common social situations [19, 20]. These representations show how designed environments with appropriate sensing and analysis capabilities can serve as both training grounds and rich data sources for improving adaptive algorithms.

Social and educational robots are another form of AI-powered support. One of the first studies on using robots to research autism found that socially assistive robots can produce novel social behaviours and increase engagement, partly because their predictable, repeated interaction patterns are less stressful than those with human partners for some children with autism [21]. Recent systematic reviews suggest that robot-mediated interventions may scaffold many skills and processes involved in social communication, joint attention, and emotional understanding, but also warn that many existing studies were small and short-term [22, 23]. Building on this work, researchers are considering emotion recognition capabilities for educational robots as classroom tools that can attend to learners' affective states and provide graduated cues or practice opportunities in social-emotional competencies [21]. From an engineering-management view, such systems present orchestration challenges: when to schedule and trigger robotic interventions, and how to integrate them with teacher practices and other technologies in ways that reinforce rather than fragment inclusive classroom routines.

Recent work has also identified engagement as a key design goal for smart educational systems. Engagement is a multidimensional construct (behavioural, emotional, and cognitive) and is especially hard to observe reliably. For example, the Engagnition dataset was developed by collecting physiological and behavioural signals of autistic children during their engagement with a serious game and labelling their engagement levels based on the trainers' expertise to support the design of AI models that can detect whether the patients are engaged or disengaged with the gaming applications while facilitating real-time interventions [24]. This research area is very close to classroom realities, where teachers often say the important question is not whether a student has a diagnosis, but whether and how to teach them in the moment: Is the student ready to learn? Are they overwhelmed or understimulated? Engineering AI-based systems that can predict engagement in real time, and without explicit awareness, is of high practical value.

Developers, educators, and policymakers must support these evolving systems with an essential, non-negotiable ethical framework that respects both neurodiversity and inclusivity. The use of pervasive sensing and AI analytics in educational contexts intensifies our already grave concerns about privacy, data sovereignty, algorithmic bias, and technologies that could be weaponised to enforce rigidly neurotypical behaviours. Repositioning Autism and Technology, amongst other thinking, sets out a new way of thinking about the relationship of the autistic individual to technology as a move away from "fixing" the individual to "design[ing] technologies that 'recognise' and support multiple ways of being in the world" [25]. This philosophy also calls for participatory design approaches, where autistic people, families, and educators are not only research participants but co-designers involved throughout the design process. Projects such as Developing IDEAS e-Innovations Supporting Inclusion show that children with autism can participate and contribute positively to design teams, creating technologies that better reflect their needs, preferences, and experiences [3]. This way, the resulting systems are not only technically sophisticated but also humane, effective, and empowering.

Despite significant improvements, critical challenges remain for AI, engineering systems, and inclusive education. Most of the AI and sensing studies are in close laboratory or clinical settings such that the actual complexity of environments like classrooms is not fully considered-noise levels, concurrent activities, diverse student populations, lack of technical assistance and teachers' need for understanding. Technical work is often limited to narrow tasks (e.g., binary classification of ASD vs non-ASD, detection of a small set of emotions) that do not integrate outputs into larger management frameworks, including sequencing interventions, coordinating across multiple devices (robots, wearables, displays), and aligning with curricular goals. Moreover, ethical and human-centred design concerns remain under-specified, and research on long-term sustainability, maintainability, and policy integration is limited.

This study closes these gaps by conceptualising AI-based engineering and smart technology management systems as interactions among socio-technical layers in inclusive education systems for autistic learners. Rather than viewing individual machine-learning models, robots, wearables, or VR platforms as isolated tools, the proposed framework treats these technologies as interacting components of a managed educational environment.

a) Continuously integrates multimodal information from student behaviours, physiological signals, and classroom conditions, and

b) Applies AI and data-analytics pipelines to produce meaningful indicators of engagement, stress, and learning progress to support the decision-making of educators.

The proposed framework is grounded in empirical evidence from machine learning, sensing, robotics, and educational technology research on Autism Spectrum Disorder. It represents a non-medical engineering agenda focused on systems design, data governance, and participatory innovation for inclusive, neurodiversity-affirming educational environments.

This paper's main contribution is to propose a unified AI-driven engineering framework that integrates advances in machine learning, multimodal sensing, wearable technologies, IoT, robotics, virtual reality, federated learning, and human-centred design into a single smart technology management architecture for inclusive autism education. Unlike previous work that has largely treated these technologies in isolation, this paper integrates them into a broad engineering framework to guide future implementation, empirical validation, and ethical adoption of AI in authentic educational contexts.

Literature Review

Machine Learning and Computer Vision for Automated Behavioural Analysis. More recent deep-learning models on social cues push this frontier further. Authors [26] used attention-based neural networks on short videos of young children responding to joint-attention prompts. Using these behavioural patterns alone, they successfully dichotomised ASD versus typical development and estimated clinical severity categories. The study also applied visualisation techniques, such as class-activation maps, to identify the most informative video segments, providing interpretability that was uncommon in earlier machine-learning work.

These results demonstrate the potential of machine-learning and computer-vision approaches to extract structured behavioural information, but their translation into inclusive educational environments is less established. More generally, recent work on integrating artificial intelligence with assistive technologies for autism suggests considerable potential for individualised support while also flagging ongoing challenges in ethical deployment, privacy, accessibility, and the maturity of AI-enabled assistive systems [27]. These limitations reinforce the need for context-aware architectures that integrate automated behavioural indicators with other educational and environmental information, rather than using them as standalone classification outputs.

IoT and Wearable Sensors: Architecting Adaptive Learning Environments. One example of a smart classroom involves IoT technologies and wearable biosensors. Individualised, sensor-embedded classrooms are increasingly becoming a reality through IoT-enabled environments and distributed sensing technologies that enable two-way, real-time feedback loops between students and instruction systems. Authors [15] investigated wearable technologies to detect engagement in educational environments. They found that physiological signals (heart rate, electrodermal activity, skin temperature, respiration, oxygen saturation, blood pressure, and ECG) combined with visual information (facial expressions, posture, and gaze) offer more comprehensive and reliable indicators of affective, behavioural, and cognitive engagement than teacher observation alone.

Authors [27] concretise these ideas with a sensor- and machine learning-based sensory management recommendation system for children with ASD. They combine environmental and wearable sensor information to identify distracting and anxious classroom situations, and use a fuzzy-logic strategy module to deliver alerts and suggest sensory management strategies to teachers and caregivers. The assessment showed improved class performance and positive feedback on the system's usability. The authors described the tool as an 'intelligent companion' linking detected environmental conditions to personalised sensory strategies [27]. It is a concrete manifestation of the "smart" technology management layer. The system not only classifies states but also suggests context-aware interventions that support attention and self-regulation.

Researchers have also studied wearable sensing for more physically demanding applications. Authors [17] conducted a comprehensive review of wearable sensors for sports safety in children with ASD. They note that physiological and biomechanical sensors can provide early warning of distress, anxiety or risk of injury while participating in sports. In these environments, people are prone to sensory overload and variations in motor coordination. The review highlights the promise of these devices but also points to challenges in device wearability and acceptability, data privacy and security, and the lack of real-world, community-based evaluations [17].

Embodied AI: Robotics and Virtual Reality for Social and Cognitive Intervention. AI-enabled engineering also takes the form of embodied devices – social robots, immersive VR, in addition to ambient sensing. They also provide regular, consistent opportunities to practice skills that people with autism may struggle with, such as social-communicative domains [28].

An influential review on robots for autism research found that socially assistive robots effectively elicit social behaviours that are hard to evoke in human-human interactions, perhaps because a robot's behaviour is more predictable, less socially complex, and easier to process [29]. Recent randomised and quasi-experimental studies have also shown how exposure to humanoid robots can support some components of social cognition such as theory of mind and joint attention (e.g., improved performance on tasks requiring an understanding of others' mental states). Recent meta-analyses support improvements in joint attention, emotion recognition and adaptive behaviour in robot-assisted interventions, especially when robots are combined with AI-driven feedback and fine-grained sensing [22, 23].

Authors [30] provide a comprehensive review on educational and social robots in autism-targeted learning contexts. They state that educational robotics is a "new frontier for learning," which enables the recognition of inclusive environments where both autistic and non-autistic students belong. Robots could serve as social intermediaries, playmates, and peer-interaction scaffolding devices to reduce social isolation and provide structured opportunities to practice communication skills and emotional understanding. A concrete example is the Emorobot Project, which will implement an open-source social robot able to recognise emotions and help autistic children develop social skills (with teachers designing individualised activities, then extending them for whole-class contexts) [30]. This work shows a teacher-centred orchestration model in which robots are not standalone "therapists", but part of an instructional ecosystem.

Virtual reality offers a complementary path. A physiologically based VR social-communication system demonstrated that immersive environments can simulate realistic social interactions (e.g., classroom, playground) and monitor anxiety arousal via physiological measures to dynamically adapt the simulation in real time, keeping the participant within a sensitive learning zone [19, 31]. Building on this idea, recent VR social-cognition training systems provide scaffolded practice in interpreting social cues and understanding emotions, with apparent gains in social-cognitive performance with repeated exposure [20, 32, 33]. The biggest strength of VR is that it can create "Goldilocks" environments that are realistic enough to generalise to the real world, but controlled enough not to be overly stimulating for the learner.

However, the evidence base for immersive technologies is still heterogeneous. A scoping review of 49 virtual- and augmented-reality studies in autism reported promising applications for social-skills interventions, but also found generally small participant samples, underrepresentation of female participants, and a need for more rigorous study designs using established intervention strategies [34]. Readers should not interpret evidence that a virtual environment can support a given social or cognitive skill as evidence of universal effectiveness or suitability for all autistic learners.

Ethical Imperatives and Participatory Design. As technology continues to evolve, addressing ethics and human-centred design becomes even more important. Deploying pervasive sensing and AI analytics in learning environments also carries risks around privacy, consent, data sovereignty, and algorithmic bias (and the subsequent loss of accountability), with worrying potential to enforce conformity to neurotypical norms rather than support individual needs and neurodiversity.

In Rethinking Autism and Technology, authors [25] argue for a shift from deficit-orientation toward a "dialectical" approach where "technologies are co-constructed together with autistic individuals but also other stakeholders". In this sense, technology should not be used to 'fix' the person, but to mediate relationships between people, environments and expectations in ways that protect the autonomy, dignity and meaning of their lives. This positioning has much in common with participatory design (PD) approaches where users – autistic children, their families and educators – are involved throughout the design process.

For instance, the developing IDEAS project has shown that autistic children can work in design teams to co-create ideas and preferences and to critique the technology that emerged [35]. These PD efforts increase the possibility that systems will be sensitive to the real needs of users and avoid imposing an external understanding of "normality". In the process, they highlight subtle yet important user experience issues (e.g., sensory acceptability of devices and interaction pace) that technology-driven designs may neglect.

More recent participatory-design work reinforces this concern. Project PHoENIX was developed in response to the lack of autistic representation in extended-reality design, applying participatory design principles to involve autistic individuals in developing the learning experience and the technology-development process [36]. This further supports the argument that designers and developers should incorporate accessibility and neurodiversity-affirming principles into system requirements from the outset, rather than evaluate them only after developing the technology.

AI-system engineers and managers must incorporate these ethical considerations into governance structures by embedding explicit policies, consent procedures, data retention practices, and mechanisms for transparency and accountability as core design elements rather than add-on features.

Synthesis, Gaps, and Directions for Smart Technology Management. Several cross-cutting themes that characterise affective computing, wearables, smart environments, diagnostic modelling, robotics and VR, combine to guide the design of AI-powered engineering and smart technology management systems supporting autism education:

Multimodal sensing is an important design requirement. Systems for emotion recognition [12], wearable-based engagement monitoring [15], or sensor-based sensory-management recommendation systems [27] show that one modality alone is not enough: strong inference relies on combining facial, vocal, physiological, and environmental signals.

Value is added through adaptive intervention and orchestration. Systems such as the sensory recommender [27] and Emorobot [30] go beyond classification by recommending or applying a particular intervention at the appropriate time; this calls for orchestration engines that can also sequence and coordinate supports such as lighting changes, break prompts, robot activities or communication "scaffolds" to fit classroom schedules.

Scalability, privacy and governance are non-trivial limitations. Holistic ML research projects and federated learning approaches explore the possibility of training high-performance models under realistic data constraints, but emphasise the importance of broad sample representation, external validation, and privacy-preserving infrastructure [35, 37].

Technological advances have been substantial, but important questions remain. Overall, the literature provides more evidence for individual assistive and intelligent technologies than for their coordinated implementation in complete educational systems. A recent systematic review of assistive technologies for students with special educational needs and disabilities found promising educational applications, including for autistic learners, but also highlighted the limited evidence base, variability across studies, and the importance of combining technology with effective teaching practices rather than relying on technology alone [38]. This distinction is relevant to the proposed framework: the open challenge is not only whether individual technologies are feasible, but how to combine sensing, AI analysis, assistive tools, privacy protections, and teacher decision-making into a sustainable classroom architecture. Most existing artificial intelligence systems for ASD address isolated challenges such as behavioural classification, emotion recognition, wearable sensing, robotics, or virtual reality interventions. Few studies have proposed an integrated engineering framework to coordinate these technologies in a unified smart technology management architecture suitable for inclusive education settings. Moreover, little attention has been given to the engineering challenges of long-term deployment, interoperability, governance, privacy-preserving AI, and participatory design as interconnected issues. These limitations drive the unified framework proposed in this paper.

METHODS

Research Design and Framework Development Approach. This study developed an AI-driven smart technology management framework for autism support in inclusive educational environments, based on a conceptual, evidence-informed engineering design approach. The researchers developed the framework by analysing technical, educational, and ethical evidence from the existing literature and translating it into an integrated socio-technical system architecture.

Four objectives guided the framework development process:

1) To identify relevant AI-enabled technologies that can support autism,

2) To identify how these technologies can serve as components of interconnected systems,

3) To identify the decision-support functions needed in inclusive classrooms, and

4) To incorporate principles of privacy, transparency, teacher autonomy, and neurodiversity-affirming design into the proposed architecture.

Readers should view the developed framework as an engineering blueprint for future implementation and empirical validation, not as a completed or experimentally tested system.

Evidence-Informed Requirements Identification. The technical and functional requirements of the proposed framework are derived from a narrative synthesis of literature in several related areas. These included automatic emotion recognition in autistic learners [12], wearable-based engagement detection in educational environments [15], sensor- and machine-learning-based sensory-management systems [27], computer-vision and joint-attention analysis [13, 26], federated learning for privacy-preserving AI [38], and robot- or virtual-reality-mediated interventions [19, 21, 23, 39].

The researchers identified the literature through targeted searches of scholarly databases and academic search platforms using combinations of terms related to autism spectrum disorder, artificial intelligence, machine learning, computer vision, wearable sensors, engagement detection, physiological monitoring, Internet of Things technologies, virtual reality, social robotics, federated learning, assistive technology, and inclusive education. We also identified additional publications relevant to the technological components considered in the framework by searching the reference lists of relevant review articles and primary studies.

Studies were included if they: addressed one or more technological, educational, behavioural, privacy or human-computer interaction components relevant to the proposed framework; were related to autism-related applications or technologies transferable to inclusive educational environments; and provided sufficient methodological or conceptual information to inform system requirements. The researchers surveyed empirical studies and relevant review articles to identify established capabilities, design requirements, and implementation challenges across multiple technology domains. We excluded studies irrelevant to autism support or educationally relevant assistive technologies; those focused only on biomedical or genetic diagnosis without implications for the proposed system architecture; those lacking information relevant to framework development; and non-scholarly sources. Because the review aims to inform framework development rather than estimate pooled treatment effects, we conducted study selection and synthesis narratively and thematically, rather than using a systematic-review or meta-analytic protocol.

We thematically reviewed the literature to identify recurring technological capabilities, implementation limitations, ethical concerns, and classroom-management requirements. The main themes identified were:

a) The need for multimodal rather than single-source behavioural information;

b) The importance of low-latency data processing and interpretable recommendations;

c) The requirement for teacher-controlled rather than fully automated intervention;

d) The need for privacy-preserving and decentralised data-management mechanisms;

e) The importance of interoperability among sensing, analytics, and intervention technologies; and

f) The need to involve autistic individuals, families, educators, and other stakeholders in future system design and evaluation.

We conceptually drew on participatory design principles in neurodiversity-affirming and human-centred technology research [3, 25, 35, 40]. These principles guided the framework's standards for transparency, accessibility, voluntary participation, stakeholder control, and safeguards against using AI for behavioural normalisation.

Proposed System Architecture. The proposed framework comprises a modular, multilayer socio-technical architecture consisting of:

a) A sensing and data-acquisition layer;

b) A data-fusion and communication layer;

c) An AI and decision-support layer; and

d) An intervention and human-machine interaction layer.

Figure 1 shows the overall four-layer architecture of the proposed AI-driven Smart Technology Management System for Autism Support in Inclusive Classrooms.

This layered structure allows you to introduce, replace, or remove individual technologies without redesigning the entire system. It also supports implementation at different levels of technological readiness and institutional capacity.

1) Sensing and Data-Acquisition Layer. The sensing layer determines the types of information that can support context-aware educational decisions. Possible data sources include non-intrusive computer vision, wearable biosensors, classroom environmental sensors, and interactions in digital learning platforms.

Computer-vision components may extract non-identifying behavioural features such as body posture, head orientation, movement patterns, and signs of task engagement. Wearable devices may provide physiological measures like heart rate, heart-rate variability, electrodermal activity, and movement intensity. Environmental Internet of Things sensors can measure classroom conditions such as noise, lighting, temperature, and air quality.

The framework does not require each learner to use every sensing modality. We propose a modular configuration so that students who cannot or do not want to wear a device can still get educational support from environmental information, teacher observations, learning platform interactions, or other non-wearable inputs. This fallback structure is especially important for autistic learners who may experience discomfort or sensory distress when wearing biosensors.

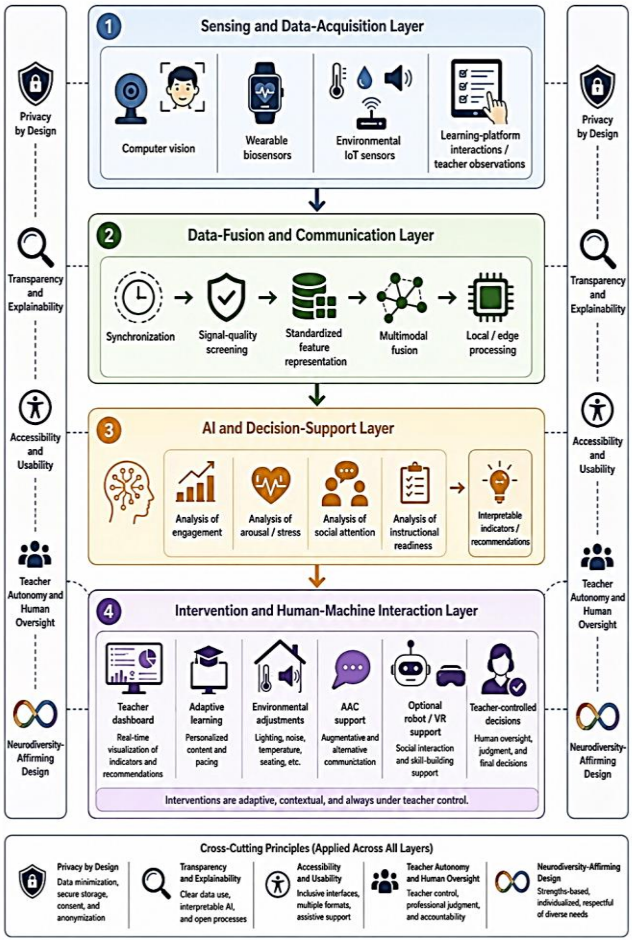

Figure 1 – Shows Overall Four-Layer Architecture of the Proposed AI-Driven Smart Technology Management System for Autism Support in Inclusive Classrooms

2) Data-Fusion and Communication Layer. The data-fusion layer organises information from various sensing modalities and prepares it for AI-assisted analysis. In the proposed architecture, the system associates sensor observations with synchronised timestamps and organises them into well-defined observation windows.

The conceptual data-fusion process includes:

a) Synchronising physiological, behavioural, educational, and environmental observations;

b) Screening inputs for missing, unreliable, or low-quality signals;

c) Transforming each data source into a standardised feature representation;

d) Combining available features into a multimodal representation of the classroom context; and

e) Transmitting only the minimum information required by the AI decision-support layer.

The design draws inspiration from multimodal engagement datasets such as Engagnition [24] and previous work that combines behavioural and contextual information for autism-related analysis. The proposed architecture focuses on local or edge processing, avoiding continuous transfer of raw video and sensitive physiological data to an external cloud platform.

When using computer vision, the system should locally convert raw images into non-identifying features such as skeletal keypoints or movement descriptors. Raw video generally should not be retained, except as required for a future study that has been specifically approved and is covered by informed consent, data-retention rules, and institutional oversight.

3) AI and Decision-Support Layer. Figure 2 illustrates the AI decision-making pipeline that transforms multimodal sensor data into personalised intervention recommendations.

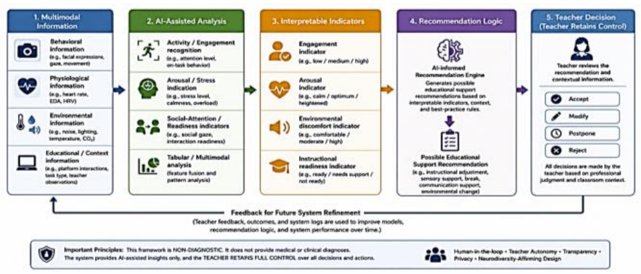

Figure 2 – Illustrates the AI decision-making pipeline used to transform multimodal sensor data into personalised intervention recommendations

The AI and decision-support layer provides the framework's analytical capabilities but does not diagnose autism or autonomously manage classroom activities. Instead, it aims to transform available multimodal information into interpretable indicators that can help teachers understand engagement, arousal, environmental discomfort, and readiness for instruction.

Potential analytical functions include:

Activity and engagement recognition: Pose, movement, gaze and learning-platform interaction features can be analysed using computer-vision or temporal-learning approaches based on previous activity-recognition and joint-attention research [13, 26, 41].

Arousal and stress signal: Physiological and environmental features can be combined to detect trends that may indicate increased arousal or sensory discomfort. Existing biosensing and emotion-recognition research has demonstrated such multimodal analysis [12, 16].

Non-diagnostic estimates of social attention and readiness: Gaze direction, head orientation, response timing, and interaction patterns may indicate social attention and readiness to engage in an activity. Readers should not consider these indicators as measures of learner value, compliance, or clinical severity.

Table and multimodal analysis: Tree-based models may suit structured context variables, while temporal or deep-learning models may suit high-dimensional time series and visual data [39].

Figure 3 presents the multimodal data fusion architecture for the proposed system.

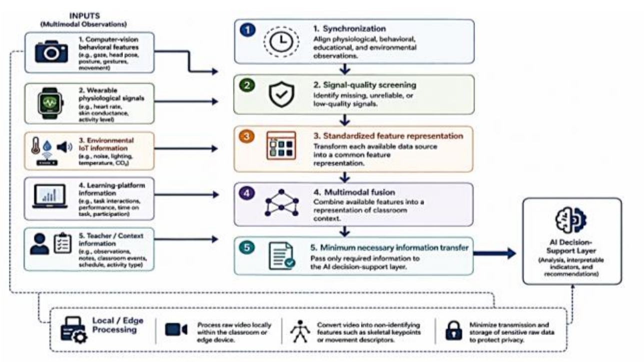

Figure 3 – Shows the multimodal data fusion architecture for the proposed system

The framework does not propose a final algorithm because the researchers have not yet implemented the system. The choice of models will depend on the available data, institutional resources, the need for interpretability, fairness evaluation, and the needs and desires of participating stakeholders.

4) Adaptive Recommendation Logic. The adaptive logic component explains how the AI-generated indicators translate into optional educational recommendations. Conceptually, this component draws on sensor- and machine-learning-based sensory-management systems that link environmental and behavioural observations to recommended support strategies [27].

Possible recommendations may include:

a) Offering a brief sensory or movement break;

b) Reducing environmental noise or adjusting lighting;

c) Changing the instructional format or task difficulty;

d) Offering visual rather than text-heavy material;

e) Delaying a demanding activity;

f) Providing an alternative communication method; or

g) Recommending an available robot- or VR-supported activity when appropriate [19, 21, 33, 39, 42].

Recommendations are meant to be advisory. Each recommendation is subject to acceptance, modification, postponement or rejection by the teacher. The system should also provide the rationale for a recommendation (e.g., high noise levels, sustained shifts in engagement metrics) rather than making automated decisions without explanation.

Future implementations may investigate reinforcement learning to refine recommendations based on observed outcomes. But adapting the system in this way would require careful safeguarding against rewarding conformity, suppressing harmless autistic behaviour, or optimising only for classroom convenience.

5) Privacy-Preserving Collaborative Learning. The framework supports federated learning to facilitate model development across multiple educational institutions without centralising raw student data. This approach would let institutions retain local control over their data, sharing only protected model updates for aggregation [38].

Federated learning does not remove privacy risk. Future implementation would therefore require secure aggregation, access control, update auditing, data-minimisation procedures, and measures to prevent reconstructing sensitive information from model parameters. Schools and families should also be able to withdraw data and stop participation without reducing the educational support provided to a student.

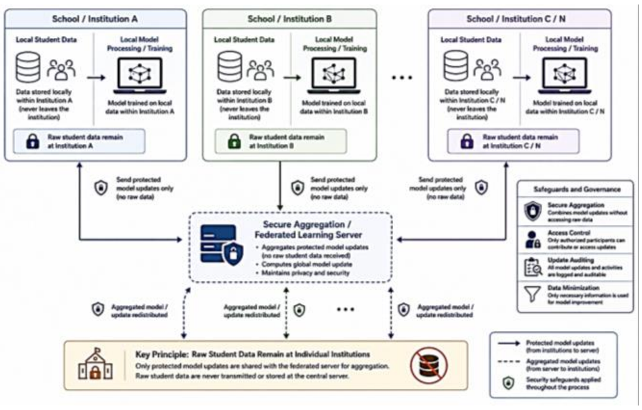

Figure 4 – Privacy-preserving federated learning structure across participating educational institutions

Intervention and Human-Machine Interaction Layer. The intervention layer defines how the proposed system communicates with educators and connects with available educational technologies.

Teacher dashboard: A secure dashboard could show simplified indicators related to engagement, arousal, environmental conditions, and system confidence. The interface should not display uncertain model estimates as facts. Each alert should contain a brief description and allow teachers to accept, change, dismiss, or provide feedback on the recommendation.

Adaptive learning interfaces: Where appropriate digital-learning platforms are available, the framework may support teacher-approved changes to the pace, difficulty, format or presentation style of instruction.

Robotic and virtual-reality support: Educational robots and virtual-reality systems could be provided as optional tools, rather than as mandatory components. Learners should choose their use based on preference, educational purpose, institutional resources, and evidence from robot-assisted and VR-based autism research [19, 21, 23, 33, 39, 42].

Alternative and augmentative communication: Communication apps can offer alternative modes of expression to non-speaking learners or those who communicate better in visual or technology-assisted formats [18].

Figure 5 presents the proposed relationship among sensing devices, local processing, teacher-facing interfaces, and optional educational technologies.

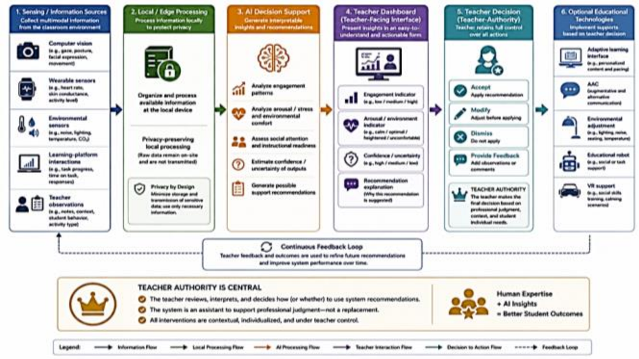

Figure 5 – Presents the proposed relationship among sensing devices, local processing, teacher-facing interfaces, and optional educational technologies

Figure 6 shows the conceptual workflow from observation through interpretable recommendation, teacher decision, and subsequent feedback.

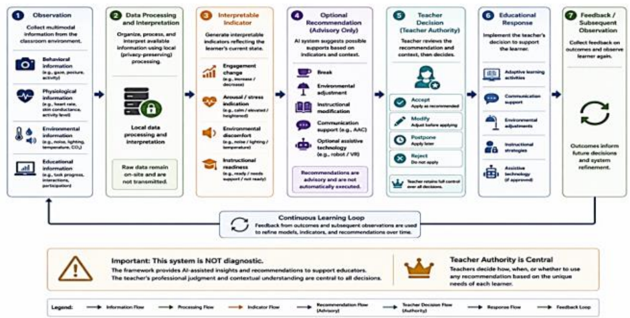

Figure 6 – Conceptual workflow from observation through interpretable recommendation, teacher decision, and subsequent feedback

Conceptual Implementation and Evaluation Plan. Because the researchers have not yet implemented the framework, this section outlines recommended evaluation stages rather than reporting results from a completed study.

1) Technical Feasibility Evaluation. Evaluate an initial prototype in a controlled setting before

deploying it in an authentic classroom. Technical evaluation should examine:

a) Sensor reliability and missing-data frequency;

b) System latency and computational-resource requirements;

c) Interoperability among devices and software components;

d) Model accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve where appropriate [16, 37];

e) Calibration and confidence of model outputs;

f) Differences in performance across student groups and environments;

g) Frequency of false alerts and missed events; and

h) System behaviour when users refuse, remove, or disconnect sensors, or when sensors become unavailable.

Researchers should not present the framework as suitable for real-time deployment until they have evaluated these technical and safety requirements.

2) Classroom Feasibility and Usability Evaluation. After completing technical validation, researchers could conduct a small-scale classroom feasibility study to determine whether the system can operate without disrupting instruction or increasing teachers' workload. Evaluation should also assess dashboard usability, alert frequency, teacher interpretation, student comfort, device acceptability, technical-support needs, and the practical cost of deployment.

The staged evaluation could start with silent observation, where the system doesn't make recommendations, followed by teacher-visible indicators, and then optional recommendations. Progression from one stage to the next should be based on safety, usability, and stakeholder acceptance, not a calendar schedule.

3) Educational and Behavioural Evaluation. Future evaluation should determine whether the framework supports meaningful outcomes identified by autistic learners, families, and educators. Outcomes should extend beyond task compliance or reductions in visible behaviour and may include:

a) Access to learning activities;

b) Communication and self-advocacy;

c) Comfort and sense of safety;

d) Participation and belonging;

e) Ability to request breaks or adjustments;

f) Teacher understanding of individual needs;

g) Student control over technology use; and

h) Reduction of avoidable environmental distress.

Where appropriate, researchers may combine observational measures, teacher assessments, system use records, and supported interviews. They may also inform future measurement procedures by drawing on existing research on engagement, sensory management, robot-assisted interventions, and virtual reality [15, 19, 27, 40, 42].

Ethical Governance and Design Safeguards. Ethical governance is a fundamental engineering requirement, not an extra compliance activity. The proposed framework is grounded in privacy-by-design, data minimisation, informed participation, explainability, accessibility, and neurodiversity-affirming principles [3, 25, 43].

Future implementation should include the following safeguards:

Informed and continuous participation: Parental or guardian consent should not replace the learner's assent. Students should be able to opt out of a wearable device, ask that sensing stop, or withdraw from an activity without losing access to regular instruction.

Data minimisation: Collect only the information directly necessary for an approved educational purpose. Whenever technically feasible, process raw video locally and convert it to non-identifying features.

Retention and deletion: Schools should have clear policies regarding what data are retained, for how long, who can access them, and how students or families can request deletion.

Protection of non-participants: Camera and audio systems must consider classmates, teachers, and visitors who have not agreed to participate. Where necessary, use masking, limited fields of view, edge processing, or non-visual alternatives.

Human supervision: AI recommendations should be reviewable and reversible. Teachers and students should be able to challenge, reject or correct system outputs.

Fairness and bias assessment: Future models should be evaluated for differences in performance across relevant demographic, communication, sensory and support-needs groups. Model evaluation should account for the consequences of false positives and false negatives, not just overall accuracy [12, 37].

Non-normalising use: Repetitive movements, reduced eye contact, non-speaking communication, or requests to withdraw should not automatically be classified as undesirable behaviour. The framework should identify support needs and environmental barriers, not prescribe neurotypical behaviour [25].

Participatory governance: Autistic people, families, educators, technologists, and other relevant support professionals should be involved in decisions about system goals, acceptable data use, intervention rules, evaluation results, and deployment limits [3, 43].

These safeguards outline the conditions under which researchers and practitioners can implement and evaluate the proposed framework responsibly. They do not reflect completed ethical approval, participant recruitment or data collection in the present study.

Conceptual Evaluation And Expected System Capabilities. This section does not present findings from a completed implementation. Instead, it benchmarks the proposed architecture against evidence reported in prior studies and characterises the framework's capabilities, limitations, and validation needs. The discussion therefore turns to the system's intended functions and the conditions researchers must meet before claiming effectiveness.

1) Technical Capabilities of the Proposed Framework. An AI-driven smart technology management framework comprises an integrated architecture to orchestrate multimodal sensing, machine learning, wearable biosensors, environmental Internet of Things devices, and privacy-preserving data processing techniques in inclusive educational environments. The main technical contribution of this work is integrating these technologies into a single system, rather than demonstrating a specific performance level.

The computer-vision module extracts non-identifying behavioural characteristics related to movement, posture, social attention, and task engagement. Previous work has suggested computer-vision and deep-learning approaches to facilitate activity recognition, engagement analysis, and joint-attention assessment in autism-related settings [13, 40, 41]. However, the proposed component has not been implemented or benchmarked; therefore, future testing is needed to determine its accuracy, reliability, and comparative performance.

The multimodal analysis section fuses visual, physiological, educational and environmental data where available and voluntarily provided. Combining multiple sensing modalities can provide a more complete representation of engagement and arousal than a single information source [15, 12]. Multimodal fusion is therefore an evidence-informed design strategy, and researchers need to evaluate its effectiveness under realistic classroom conditions.

Physiological sensing may offer additional information on changes associated with increased arousal or sensory discomfort. Previous biosensing research indicates that heart-rate and electrodermal-activity patterns may sometimes precede observable behavioural escalation [16].

Researchers do not consider these signals universally reliable, diagnostic, or appropriate for all students. Future validation will need to account for individual variability, sensor refusal, missing data, false alerts and the fact that similar physiological changes may have different causes.

The framework also supports local or edge processing to minimise the transmission and storage of sensitive information. One possible approach to building models across institutions without centralising raw student data is federated learning [35]. This architecture may reduce some privacy risks but does not eliminate them. In implementation, we need to consider communication efficiency, model security, computational requirements, and potential information leakage in model updates.

2) Support for Engagement and Self-Regulation. The framework helps educators recognise changes in engagement, environmental comfort, and instructional readiness by combining existing behavioural, physiological, educational, and classroom context information. It does not judge a student's behaviour as right or wrong or enforce continuous participation.

Studies of wearable engagement detection, sensory-management systems, and physiological monitoring indicate that technology-assisted observations may help educators detect changes that are difficult to observe reliably [15, 16, 27]. Based on this evidence, the framework may suggest earlier and more contextually relevant educational responses, such as taking a break, reducing environmental stimulation, modifying an activity or providing an alternative communication method.

How much you get out of these capabilities depends on the quality of the data available and the educator's interpretation of the recommendation. Interventions should not automatically trigger based on a change in movement, gaze, heart rate, or engagement. That same signal could indicate concentration, anxiety, fatigue, sensory discomfort, personal preference, or many other factors that an automated model cannot reliably distinguish.

Thus, the framework promotes enhanced situational awareness and responsive educational support instead of automatic behaviour reduction. Future evaluation should examine whether the system helps students access learning, communicate their needs, request adjustments, and participate according to their individual preferences.

3) Educational Adaptation and Personalisation. The architecture supports teacher-led personalisation of instructional activities. Possible adaptations may include changes in task difficulty, instructional pace, presentation format, sensory conditions, communication mode, or activity timing.

Research on virtual reality interventions and technology-supported social cognition training shows that structured, adaptable digital environments can support emotion recognition, communication practice, and social participation for some autistic learners [19, 20, 44]. These findings provide an evidence base for integrating adaptive educational interfaces into the framework, but do not prove that the complete proposed system will produce the same results.

Personalisation is provided through the optional use of recommendations rather than automatic control of instruction. Teachers remain responsible for educational decisions, but students should have meaningful opportunities to accept, refuse, or request alternatives to technology-supported activities.

The effectiveness of personalisation will depend on the individual's preferences and communication needs, classroom resources, the teacher's workload, the reliability of the system and the availability of appropriate alternatives when a particular technology is uncomfortable, inaccessible or inappropriate.

4) Classroom Feasibility and Teacher Interaction. For the framework to be practical, its outputs must be understandable and manageable within normal classroom routines. Therefore, the teacher dashboard we propose should show a few interpretable indicators, rather than continuous flows of raw sensor information.

A practical implementation should rank relevant recommendations, explain the reason for a recommendation, display uncertainty, and allow teachers to dismiss, modify or correct the system's interpretation. Classroom feasibility testing should examine whether the dashboard disrupts instruction, adds to cognitive workload, generates too many alerts, or requires levels of technical support that schools can't reasonably provide.

The modular architecture can also allow different levels of technology availability. Schools are not required to deploy cameras, wearable devices, robots, virtual-reality systems and environmental sensors simultaneously. Implementation can then begin with environmental sensing and teacher input or learning-platform information, and other components can be included only where they are relevant, affordable, acceptable, and evidence-based.

5) Stakeholder and Ethical Considerations. The framework is a collaborative decision-support architecture, not an autonomous surveillance or behaviour management system. Involving autistic learners, families, educators, school administrators, technologists, and other relevant support professionals is essential to successful implementation.

Participatory design research shows that involving autistic people and other stakeholders may make technology more relevant, accessible, and acceptable [3, 25, 43]. Future implementation should involve stakeholders in defining system objectives, acceptable sensing methods, data retention rules, intervention boundaries, interface features, and evaluation outcomes.

The architecture promotes transparency and user control by requiring privacy safeguards, informed participation, opt-out mechanisms, explainability, and human oversight. These protections must be instantiated as functional system requirements, not merely stated as vague ethical principles.

Students who refuse to wear wearable devices, video monitoring or other forms of sensing must still have access to regular instruction and educational support. Other inputs might include teacher observations, student self-reports, information from communication applications, environmental sensing, or learning-platform interaction data.

6) Benchmarks for Future Validation. Researchers can claim the framework's effectiveness only after evaluating it against technical, educational, practical, and ethical benchmarks.

Technical benchmarks should include:

a) Sensor reliability and missing-data rates;

b) Processing latency and computational requirements;

c) Model accuracy, calibration, false-positive rates, and false-negative rates;

d) Interoperability among sensing, analytical, and interface components;

e) Performance when one or more sensing modalities are unavailable;

f) Privacy and security risks associated with local and federated processing; and

g) Consistency of model performance across relevant learner groups and classroom conditions.

Educational and usability benchmarks should include:

a) Student comfort and willingness to use the technology;

b) Teacher workload and dashboard usability;

c) Clarity and usefulness of system explanations;

d) Frequency with which teachers accept, modify, or reject recommendations;

e) Access to learning and communication;

f) Student agency, safety, participation, and belonging;

g) Availability of non-technological alternatives; and

h) Practical deployment costs and technical-support requirements.

These benchmarks establish the criteria for future implementation and evaluation. This study does not present them as findings from the current study.

7) Key Contribution of the Framework. The core contribution of this work is an integrated engineering blueprint that bridges multimodal sensing, AI-assisted analysis, privacy-preserving processing, teacher-facing decision support, and optional educational interventions into a single socio-technical architecture.

The framework does not claim that the proposed system improves engagement, predicts behavioural escalation, reduces teacher workload, or produces better educational outcomes. Rather, it shows how to coordinate technologies studied in isolation and highlights the technical, educational, practical and ethical conditions for responsible implementation.

Future research should assess the architecture's technical feasibility; its acceptability to autistic learners and educators; its sustainability in real educational environments; and the extent to which it enables meaningful outcomes without increasing surveillance, workload, or pressure to conform to neurotypical behavioural expectations.

This paper proposes an AI-driven engineering and smart technology management framework for behavioural analysis and inclusive education for learners with Autism Spectrum Disorder. Drawing on evidence from a synthesis of machine learning, computer vision, wearable sensing, IoT, robotics, virtual reality, and participatory design, the researchers developed a framework that integrates these technologies into a single socio-technical architecture for potential future deployment in inclusive classrooms. The proposed framework is not a report on a completed deployment, but an engineering blueprint to guide future system development, implementation, and empirical evaluation.

Educational impact and pedagogical integration. The proposed framework is expected to support inclusive educational practices by enabling adaptive instruction based on continuously monitored behavioural, physiological, and environmental information. Existing research suggests that AI-assisted personalisation, wearable sensing, and adaptive educational technologies can improve student engagement, support individualised learning, and help educators make more responsive instructional decisions. By integrating these capabilities into a unified engineering architecture, the proposed framework could strengthen inclusive classroom practices while preserving teacher autonomy and professional judgment.

Stakeholder engagement, ethics, and neurodiversity. The framework proposed emphasises ethical governance and stakeholder engagement in system design. The framework builds on participatory design principles and neurodiversity-affirming perspectives by highlighting transparency, informed consent, privacy protection, and ongoing collaboration with autistic individuals, families, educators, and clinicians in all future system development and deployment. The proposed architecture is intended to support autonomy, accessibility, and inclusive educational practices while ensuring that human decision-making remains central to classroom intervention, rather than seeing AI as a tool for normalising behaviour.

Theoretical and practical implications. The proposed framework contributes to the growing research advocating for AI-enabled, human-centred educational technologies for Autism Spectrum Disorder. By unifying machine learning, wearable sensing, computer vision, IoT, robotics, virtual reality and participatory design into a single engineering architecture, the framework provides a structured basis for future research and practical implementation. If adopted and validated, this approach could promote more adaptive, inclusive, and responsive educational environments while supporting the responsible adoption of AI in special and inclusive education.

Limitations and Future Directions. This work is not a report of a completed implementation or clinical evaluation, but a proposal for an engineering framework. Therefore, the expected technical performance, educational benefits, and stakeholder outcomes discussed in this paper are based on existing scientific evidence, not primary experimental data from the present study. Future work should apply the proposed framework in real classroom settings, validate technical performance, evaluate educational outcomes across different learner types, and assess long-term practicality, scalability, and ethical implications.

Future work should involve multi-site implementation studies, privacy-preserving federated learning across educational institutions, long-term classroom deployment, and comprehensive evaluations of educational, behavioural, ethical, and usability outcomes. Special attention should be paid to participatory systems development with autistic learners, educators, families and clinicians, to ensure future implementations align with neurodiversity-affirming principles while supporting responsible and transparent AI adoption in inclusive education.

CONCLUSIONS

This paper presents a comprehensive framework for engineering and smart technology management for inclusive education and behavioural analysis. Grounded in evidence from machine learning, computer vision, wearable sensing, IoT, robotics, virtual reality, federated learning, and participatory design, the proposed framework describes how to embed these technologies into a unified socio-technical architecture to support future implementation in inclusive educational environments. Rather than reporting results from a deployed system, this work provides an engineering blueprint for developing, implementing, and empirically validating future systems.

The evidence reviewed in this paper consistently supports the framework's technical feasibility. Prior work has shown that machine learning, multimodal sensing, wearable biosensors, adaptive learning technologies, educational robotics, and privacy-preserving AI architectures all offer useful capabilities to support autistic learners. The proposed system combines these independently validated technologies into a single engineering framework, providing a practical foundation for future intelligent classroom environments focused on personalisation, accessibility, ethical governance, and human-centred educational support. Ongoing professional development for teachers is critical: teachers will need help interpreting multimodal signals and guidance on how to incorporate recommendations into their lesson planning as well as to co-reflect on data with students – a finding consistent with previous work showing that, in deployments of sensory-management systems or robotics kits, teacher competence strongly mediated educational impact.

Schools and districts need to establish participatory governance structures that include (where appropriate) autistic students, families, educators, and technologists to build on participatory design principles in developing consent procedures, student opt-out mechanisms, policies for acceptable use of educational technologies, and evaluation frameworks for responsible AI deployment.

Future research should develop three main lines of inquiry. Researchers should conduct a longitudinal, multi-site evaluation to assess robustness, bias, and generalizability across different educational contexts using existing federated infrastructure, as demonstrated in previous clinical ASD modelling. Researchers should also expand outcome frameworks, in collaboration with autistic stakeholders, to ensure they capture not only engagement and incident reduction but also autonomy, sense of safety, belonging, and self-advocacy, since standard measures may favour classroom "smoothness" over student-led goals. The analytic scope should extend from detection of individual states to social interaction and peer dynamics, using existing research on joint attention and automated social-engagement detection to support cooperative learning, friendship development, and self-regulation.

Altogether, AI-based engineering and smart technology management systems could enable more responsive, accessible, and affirming classrooms for autistic learners, provided that educators, developers, and autistic communities treat them as socio-technical systems, respect neurodiversity, value human judgment, and co-govern their design and implementation. The most impactful interactive systems will combine technical excellence in multimodality analytics and orchestration with deep commitments (philosophical, creative, and ethical) to agency, transparency, and inclusion. If educators, developers, policymakers, and autistic communities can strike that balance, AI will not just make classrooms "smarter" but will help create educational environments in which autistic students can participate, learn, and grow on their own terms.

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