

Envisioning 2030: AI and IoT-Driven Educational Projects

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Ramya Selvaraj

Lecturer, Preparatory Studies Centre

Mathematics and Computing Skills Unit

University of Technology and Applied Sciences, Sur, Sultanate of Oman

Abstract

By 2030, the world's education systems are projected to be on a new path, moving towards intelligent, data-driven learning landscapes, with the convergence of Artificial Intelligence (AI) and the Internet of Things (IoT). Recent advances in predictive analytics, intelligent tutoring systems, and AI-powered adaptive learning platforms enable the development of personalized learning journeys that dynamically respond to individual student needs and provide immediate feedback and early identification of students who may require more assistance. Meanwhile, IoT has facilitated the creation of smart classrooms, which include sensors, wearables, connected learning tools, and automated environmental controls, creating more interactive, effective, and secure learning spaces. These enhanced technologies are transforming the way the curriculum is delivered, are improving student support systems and are revolutionising institutional planning based on data-informed decision making.

But integrating IoT and AI presents as well difficult problems. Educators and legislators continue to be concerned about issues that involve data privacy and surveillance, expensive installation and maintenance costs, algorithmic prejudice, cybersecurity threats, and widening digital disparities. The benefits of these technologies need to be balanced with the protection of learner rights or institutional integrity, which is important when ensuring ethical, responsible and fair implementation of these technologies.

The goal of this article is to examine some new AI/IoT initiatives that are shaping the future of education in 2030, to provide scenario-based projections of likely intelligent learning environments, and to provide perspective for educators, institutional leaders, and policy makers to best leverage and integrate these learning-enhancing, technology-driven and inclusive tools to improve learning outcomes.

Keywords: Artificial Intelligence, Internet of Things, Smart Education, Adaptive Learning, Predictive Analytics, Educational Technology.

Introduction

In today's digital age, the global education landscape is experiencing a transformative shift as AI and IoT technologies become increasingly intertwined. From digitizing content and implementing learning management systems, to intelligent and data-driven educational ecosystems, the journey in this sector has been transformative. AI-enabled adaptive learning systems, predictive analytics, intelligent tutoring platforms, and generative assistants are becoming a part of IoT-powered smart classrooms, wearable devices, environment sensors, and connected learning infrastructures as institutions head toward 2030. These technologies are helping to transform the delivery, assessment and governance of knowledge and mark a shift from Education 4.0 to more human-centred, technologically-rich paradigms, commonly called Education 5.0.

AI in education (AIED) is not just a niche experiment anymore; recent scholarships have pointed to the systemic implementation of AI in education. Adaptive learning systems are based on machine learning algorithms that tailor instruction in real-time based on learner patterns of performance. Predictive analytics models use attendance, behavioral and academic data to determine who is at risk of failing early to implement early intervention strategies. Intelligent tutoring systems scale aspects of “one to one mentorship,” and generative AI tools are more and more being used to automate feedback, content creation, and student support. AI’s impact in primary and higher education has shown positive results in improving engagement, personalisation, and achievement when it is used pedagogically (Bagdonaite & Dagiene, 2025; Elbasi et al., 2025). Meanwhile, writers point out that predictive and adaptive systems can completely change the nature of instructional decision-making, from one solely based on human judgment to one that is algorithmically assisted.

Along with the advancement of AI, IoT sensors are shaping physical learning spaces into environments that are rich with data and responsive. Smart classrooms with motion sensors, environmental monitors, face recognition systems, wearables, and connected boards produce streams of contextual data at all times. These infrastructures can help to automate lighting and climate control, attendance tracking, safety monitoring and real-time behavioural analytics. The pedagogical architectures of the Internet of Things (IoT) go beyond classrooms into “smart campuses” that combine security systems, facility management, and student services onto a single digital platform (Adel, 2024; Rojek et al., 2025). Importantly, IoT doesn’t just digitise infrastructure it creates the data fabric on which AI analytics draw. This cyclical interplay of AI and IoT creates a continuous feedback loop: multimodal data is gathered from sensors, AI models uncover patterns, and adaptive systems take action based on the interpretation, whether that be on an individual or institutional level.

This convergence is in line with the policy trends taking place in the world. Learner agency, adaptability and use of data for decisions are key elements of frameworks like OECD Learning Compass 2030. Education 5.0 models support innovation, sustainability and an ethical integration of technological elements for human purposes. In these conceptual frameworks, AI and IoT are not just about efficiency, but about achieving inclusive, lifelong and competency-based education as enablers. Research into the future of digital education systems predicts that by 2030, intelligent platforms will enable personalized curricula pathways, real-time formative assessment and institutional planning based on predictive modeling (Samadhiya et al., 2025). The change is a reconfiguration of educational ecosystems to socio-technical systems that are interrelated.

There are, however, also challenges identified in the literature with regard to the transformative potential. The use of AI and IoT brings into sharp focus issues of data privacy, surveillance, algorithmic bias, cyber vulnerabilities, and digital inequality. Without adequate governance protection, the monitoring of sensors and biometric tracking of learners can undermine learner autonomy. If training data are reflective of structural inequalities, this can perpetuate those inequalities in algorithmic decisions (Nguyen et al., 2023; Bulut et al., 2024). Furthermore, the economic and technological requirements of smart campuses with IoT can exacerbate inequalities between resource-rich and resource-poor campuses. The importance of transparency, explainability, human oversight and fairness in the responsible use of AI in education is increasingly highlighted by ethical frameworks.

While there is an increasing number of studies exploring AI and IoT separately in the field of education, very few studies have explored the combined effects of AI and IoT towards 2030. The current literature is mostly devoted to the pedagogical personalization enabled by AI or to the infrastructural optimization enabled by IoT, neglecting the impact of their joint use on governance, curriculum delivery, institutional planning and learner experience. It would be desirable to have a forward-looking, scenario based and holistic investigation that integrates technological, ethical and strategic aspects as a comprehensive vision of intelligent learning ecosystems.

This article aims to fill that void by exploring some of the new projects in education that are leveraging AI and IoT to influence the path to 2030. It creates scenario-based outlook for intelligent learning environment, discusses ethical and governance aspects, and offers strategic suggestions for teachers, institutional leaders, and policy makers. The main goal of the study is to inform the design of inclusive, responsible and sustainable smart education systems, which will improve learning outcomes and protect fundamental rights by putting the technological innovation in context of socio-technical and policy contexts. With the speed of digital transformation in education systems globally, it is crucial for everyone to understand the interplay between AI and IoT to imagine the potential of learning in the future – and build it safely.

Artificial Intelligence in Education

Over the last 10 years, Artificial Intelligence in Education (AIED) has progressed significantly from experimental prototypes to aswimmingly scalable institutional systems. According to recent systematic reviews (Bagdonaite & Dagiene, 2025; Elbasi et al., 2025), AI currently has a wide range of applications in primary education, secondary education, and higher education, focusing on the elements of personalization, accuracy of measurements, and ethical governance. The most significant applications are adaptive learning systems, intelligent tutoring systems, predictive analytics, learning analytics dashboards, and generative AI assistants.

Adaptive Learning Systems

Adaptive learning systems adapt the learning content, pace, and assessment to the learner by employing machine learning algorithms. These systems continuously monitor performance data (including accuracy of answers, time spent on task, and error patterns) to model the student's knowledge state and then modify subsequent learning activities. Estimation of mastery levels is often done using techniques like Bayesian knowledge tracing, reinforcement learning, and neural network-based classifiers.

Bagdonaite and Dagiene (2025) have found adaptive platforms to be very promising in primary education contexts, especially in mathematics and language learning. Adaptive systems can close the achievement gap and keep learners engaged by providing personalized pathways. Importantly, these systems can offer immediate feedback in the form of formative, which allows students to correct their misconceptions in real time.

Adaptive systems, however, make parts of the pedagogical control over to algorithmic decision making. Concerns are raised about obscurity in the recommendation process, the risk of reinforcing biases from training sets, and the maintenance of teacher autonomy. So, adaptive learning is beneficial for efficiency and personalization, but needs to be managed by humans.

Intelligent Tutoring Systems (ITS)

Intelligent Tutoring Systems are an extension of adaptive learning that are more interactive. ITS platforms emulate one-to-one tutoring through the combination of domain modeling, student modeling, and pedagogical strategies. They offer contextual clues, scaffolding and remediation based on misconceptions identified.

With the advancement of technology, modern ITS are increasingly equipped with natural language processing (NLP) and conversational AI features that enable learners to participate in dialogue-based interactions. Elbasi et al. (2025) point out that these systems are especially useful in STEM education where there are clear and well-defined tasks for problem solving that enable the accurate modelling of learners' thinking processes. Recent improvements in deep learning have contributed to the improvement of ITS to understand open-ended responses and provide personalized explanations.

New research also focuses on the coupling of the robotics and ITS, where we have the idea of an embodied AI tutor that interacts socially and physically in smart classrooms. Such integration is consistent

with the broader smart education initiatives that Adel (2024) mentions, where AI-powered tutoring systems communicate with IoT devices within the learning environment.

Despite the benefits, there are challenges with scalability, explainability, and ethical evaluation of ITS. The fairness, unbiased and pedagogically well-designed feedback mechanism is a fundamental research task.

Predictive Analytics

Predictive analytics uses machine learning models to predict learning outcomes, including the likelihood of dropping out, not finishing courses, and the chance of learning success. Historical data and attendance trends, combined with the academic performance of students and indicators of engagement, can be used to identify students who are at risk and initiate interventions.

Bulut et al. (2024) point out that predictive modelling has advanced to a greater degree of sophistication, including the use of ensemble methods and explainable AI approaches, which enhance accuracy and interpretability. These systems enable proactive advising and resource allocation, adding to the efficiency and success of institutions.

Predictive systems are fraught with ethics concerns, however. Relying on the term “high-risk” can have the unintended effect of stigmatizing pupils and/or causing teachers to have lowered expectations for them. Inequalities can be further intensified by algorithmic bias and data imbalance. Transparent governance frameworks, bias auditing and ongoing monitoring are all necessary for responsible deployment.

Learning Analytics Dashboards

Learning analytics dashboards convert complex data into visual information that educators and administrators can easily understand. These dashboards combine real-time and historical data, such as assessment performance, participation patterns and engagement metrics, into interactive visualizations.

Classroom and institutional data-informed decision making is improved with dashboards. Individual progress can be monitored by teachers and systemic progress trends can be monitored by school administrators. Dashboards, combined with predictive models, are very powerful tools for strategic planning.

However, effectively utilising it requires educator data literacy. If not trained properly, dashboard information could be misinterpreted or ineffective. Therefore, the process of technological implementation should come alongside professional development programs to get the most out of technology.

Generative AI Assistants

Generative AI is the latest development in AIED. LLMs and multimodal AI systems can create instructional material, give feedback on writing, summarize texts, and act as a Socratic dialogue. Such tools serve as helpmates for students and teachers alike.

Generative AI opens up new possibilities in education by generating content and providing highly contextualized feedback, as mentioned by Elbasi et al. (2025). Students get instant explanations of material based on their abilities and teachers can quickly create lesson plans for students of varying skill levels.

But generative AI comes with its own set of challenges: hallucination of information, plagiarism and authenticity issues, and authorship ambiguity. Ethical deployment requires well-defined limits of use, transparency and validation procedures.

IoT in Smart Education

AI offers analytical intelligence, and IoT creates the physical frameworks that can enable real-time data gathering and environmental responsiveness. Education is an application of IoT, where sensors, devices, and platforms are connected to create interactive, data-rich classrooms.

Sensor-Enabled Classrooms

Sensor equipped classrooms uses motion detectors, occupancy sensors, environmental sensors and interactive boards. Data is gathered from these devices about attendance, spatial utilization, lighting, temperature, and engagement indicators.

Rojek et al. (2025) explains how smart environments with the help of IoT can help to improve energy efficiency and classroom comfort whilst creating behavioral analytics. Real-time monitoring of air quality and lighting, for instance can enhance cognitive performance and well-being. But, the worry for constant monitoring is the danger of surveillance and data protection, which calls for robust cybersecurity procedures.

Ensure that wearables and Student Tracking are in place.

Smart bands and biometric sensors attached to clothing allow monitoring of physiological measurements like stress and heart rate. Choubey et al. (2026) introduce the concept of wearable systems that can be nested into adaptive learning platforms to make system-level adjustments according to cognitive load or emotional states.

These technologies provide on-demand wellness guidance, but they raise even more questions about consent, control of data and how it might be misused or misinterpreted for biometric information. Data policies need to clearly establish boundaries of data use to protect the rights of the student.

Environmental Automation

By using IoT infrastructures, lights, ventilation and safety systems can be automated. Optimized learning conditions and improved comfort and sustainability through environmental automation. Adel (2024) emphasizes that smart city education has given rise to the integration of the IoT, robotics and intelligent tutoring systems, highlighting how the planning of institutions is becoming more and more dependent on technological ecosystems.

However, the high cost of installation and maintenance could create an increasing gap between well-resourced and under-resourced institutions.

Incorporating AI and Edge Computing. Integrating AI and Edge Computing

Edge computing combined with IoT provides greater scalability and data privacy. The processing of data on edge devices instead of centralized cloud servers helps decrease latency and lowers privacy risks for institutions. With Edge-AI architectures, feedback is possible in real-time, without a considerable amount of data being transmitted, inside classrooms.

This distributed intelligence framework is a significant step towards a more secure integration of AI and IoT, enabling proactive and resilient smart learning environments.

AI-IoT Convergence: Intelligent Learning Ecosystems

The cross-cutting between Artificial Intelligence (AI) and the Internet of Things (IoT) is the conceptual basis of the next generation of smart education. AI offers cognitive services, such as prediction, personalization, and decision-making assistance, while IoT brings the sensory and infrastructural elements that gather real-time information about the environment and individual behavior. These technologies together form closed-loop intelligent learning ecosystems which are capable of continual adaptation on both the individual and institutional level. This convergence represents a structural transformation from digitized education systems to dynamically responsive education systems based on learning data, in line with the Learner-centred, adaptive education systems imagined by the OECD Learning Compass 2030.

The Real-Time Data Loop: From Sensors to Personalised Response

The key to AI-IoT convergence is the real-time feedback. Multimodal data is gathered by embedded sensors in classrooms about attendance, movement, engagement, environmental parameters (temperature,

lighting, air quality), and how users interact with the devices. Wearable technologies can also provide physiological data like stress or activity.

This continuous data stream is fed into AI analytics engines, which are capable of processing structured and unstructured data, using a machine learning and predictive modeling approach. Algorithms identify patterns, predict risks, measure cognitive load and measure engagement shifts. The analytical layer creates personalized or systemic interventions to adapt learning content, instructional pacing, classroom environment, or to alert early warnings.

For instance, if the engagement data decreases in a session, it can suggest an interactive activity or change the lighting conditions. Predictive analytics can be used to trigger interventions for mentoring that can be given to students if there is an increased risk of dropping out. This closed-loop configuration allows classrooms to become adaptive environments and not just teaching spaces.

This approach is consistent with the view of Qudrat-Ullah (2024), who argues that educational leaders in the era of AI need to use analytics-driven feedback systems that facilitate evidence-based leadership decisions. The integration of AI and IoT technologies into institutional governance introduces new layers of continuous feedback and learning, which improves the personalization of learning and strategic planning on both the micro (individual learner) and macro (institutional) levels.

Digital Twin Classrooms

The idea of digital twin classrooms is another step forward in the AI–IoT integration. A digital twin is a virtual representation of a physical system, updated in real-time with sensor data that is borrowed from the industrial and smart city sector.

In educational settings, digital twins are used to simulate classroom spaces, student interactions, and resource usage. These virtual representations enable the administrators and educators to test pedagogical strategies, environmental changes, and/or policy interventions without having to do so in real life. Institutional leaders, for instance, could pilot program changes in the schedule or curriculum in a virtual setting and evaluate the anticipated learning results.

Another aspect emphasized by Khan et al. (2025) in their study on AI-supported sustainable university development is the role of digital twins in supporting sustainability initiatives. Incorporating environmental sensor information with predictive analytics can help institutions improve energy usage, space usage, and operational efficiency. So, digital twin classrooms transcend pedagogy to institutional resilience and sustainability.

But the development of digital twins comes with data governance challenges. When physical and virtual systems have to be synchronised continuously, architectures need to be established in a secure way to guarantee that no unauthorized access or misuse of the systems can take place.

Provide privacy protection by using Federated Learning. Implement Federated Learning for privacy protection.

However, with the significant data collection required for AI–IoT ecosystems, privacy concerns are heightened. The solution is promising with Federated learning. In federated learning, machine learning models are trained locally on edge devices and then only model parameters or gradients are sent to the central servers. This way, data is kept local and can still be improved together.

In the context of smart campus, the federated architecture can make it possible to improve predictive models across classrooms, departments or institutions without sharing the sensitive student information. Decentralized learning models are in line with new regulatory needs and ethical standards that focus on privacy-by-design.

Federated learning also facilitates fair data governance. Institutions can keep control on locally produced data and enjoy benefits of the shared performance improvement of the model. This distributed intelligence approach reduces the risk of surveillance and boosts trust among stakeholders.

Edge AI for Smart Campuses

Edge AI also enhances the convergence architecture with real-time analytics at or near the data source. Edge computing can be used in conjunction with cloud-based processing, with a device embedded in the classroom processing sensor data locally. This helps to minimize latency, increase responsiveness, and improve data security.

For example, edge devices can analyze facial recognition or engagement data in real time and make instant adjustment to instruction without sending the biometric data out to an external source. Edge AI further enables system resilience in low connectivity environments, enabling smart education solutions to be more scaled across different institutional contexts.

Edge AI can help with sustainability by reducing data transmission, which helps conserve energy. The use of integrated digital infrastructures to optimize operational resources while also improving educational quality is becoming a prerequisite for sustainable development in universities as Khan et al. (2025) put it.

Conceptual Model: Intelligent Learning Ecosystem Architecture

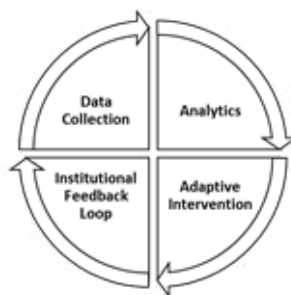
The convergence of AI and IoT can be conceptualized as a cyclical, multi-layered system:

Data Collection (IoT) → Analytics (AI) → Adaptive Intervention → Institutional Feedback Loop

1. Data Collection (IoT Layer): Environment, behavior, and performance data are collected from sensors, wearables and connected devices.
2. Analytics (AI Layer): Machine learning models analyze patterns, make predictions and detect intervention points.
3. Adaptive Intervention (Application Layer): Individual learning modifications, environment modifications, or supports are implemented.
4. Institutional Feedback Loop (Governance Layer): Compiled feedback is used for policy-making, curriculum planning, resource planning and strategic planning.

This cyclical model is based on the OECD framework Learning Compass 2030, which highlights the importance of learner agency, adaptability and the rigorous systemisation of the curriculum, pedagogy and institutional strategy. Data on multiple levels is used throughout intelligent learning ecosystems to inform decision making, leading to responsiveness and resilience.

Figure Intelligent Learning Ecosystem Architecture



Toward Integrated, Human-Centered Ecosystems

AI-IoT convergence is a paradigm shift from the individual use of technological tools to the use of socio-technical ecosystems. The real-time data loop increases personalization, digital twins provide simulation and strategic foresight, federated learning safeguards privacy and edge AI is designed to be responsive and sustainable.

But, technology integration needs to be grounded in human-centred principles. As put by Qudrat-Ullah (2024), in educational leadership, there is a need to strike a balance between efficiency and moral

responsibility. Intelligent ecosystems can exacerbate inequality and undermine trust without transparent governance frameworks, strong cybersecurity protocols, and fair access planning.

The future of education powered by AI and IoT will not only rely on the sophistication of the technology, but the capacity of educational institutions to develop innovation which is inclusive, sustainable and ethically guided. Pedagogical objectives, which are about empowering learners, supporting teachers and enhancing institutional resilience in a data-driven world, are at the heart of intelligent learning ecosystems.

Scenario-Based Projections for 2030

The future of education powered by AI and IoT involves stepping away from simple prediction and into structured foresight approaches. Foresight is a blend of trend analysis (which extrapolates current trends) and scenario planning (which considers various possible futures based on technological, regulatory, economic and ethical factors). Scenarios are not a prediction for what will happen, but a strategic exercise that gives decision-makers a sense of uncertainty and trade-offs.

To protect against new risks, new inflection points, and new governance gaps when they materialize into real systemic issues, foresight in AI and IoT research is vital, Mohammadzadeh (2025) points out. Likewise, Raman et al. (2025) state that “predicting the future of advanced AI, such as Artificial General Intelligence (AGI), should be aligned with sustainable development goals and institutional resilience. In the field of education, scenario planning can help policymakers to consider how the education ecosystem might look in 2030, given different visions for governance and equity, as AI and IoT converge.

Based on the current trends, this part outlines three probable scenarios for what intelligent education in 2030 might look like: (1) Hyper-Personalized Global Classroom, (2) Regulated Smart Campuses, and (3) Digital Divide 2.0.

Optimistic Future – “Hyper-Personalized Global Classroom” – the best possible outcome scenario. The best possible outcome scenario – Scenario 1: Optimistic Future – Hyper-Personalized Global Classroom.

In this case, AI and IoT are growing up in concert with effective ethics governance and fair access programs. Widespread adoption of intelligent learning ecosystems is possible thanks to universally available broadband infrastructure, inexpensive devices, and international cooperation.

Universal Access & Inclusion

Digital equity is a priority for governments and global bodies, aiming to provide rural and under-served communities with AI-powered platforms. Personalized learning support across geographies with cloud based adaptive systems and multilingual generative AI tutors. Learning is connected globally and collaborative learning across borders can be achieved in immersive virtual learning spaces.

Real-Time Support and Lifelong Learning

In an IoT classroom, all the data captured by the classroom sensors and the wearables is fed into these AI analytics engines and is used to make adjustments to teaching and learning in real time. Predictive analytics detect gaps in learning or skills, which then can be addressed with targeted interventions. The 24/7 generative AI assistants offer contextual explanations, personalized study plans, and formative feedback to benefit students.

Learning changes from linear, standardized progression to learning based on competence, with a focus on the OECD Learning Compass 2030 on learner agency, flexibility and all-around skills. Sentiment analysis and adaptive engagement tools are other applications of AI that can benefit SEL.

Ethical Governance and Trust

Regulatory frameworks are strong, ensuring transparency, fairness and accountability of AI systems. Federated learning architectures help to preserve data privacy, and bias auditing mechanisms minimize

discriminatory outcomes. Schools implement participatory governance structures with students, teachers, technologists and policy makers.

In this positive outlook, AI–IoT convergence fosters inclusivity, sustainability and collaboration across the world, helping to build equitable knowledge societies by the year 2030.

In this scenario, the government will regulate controlled innovation. In this scenario, controlled innovation will be governed by the government, “Regulated Smart Campuses”.

This is a more conservative scenario in which AI–IoT development takes place incrementally with careful oversight and compliance with regulations. Risk mitigation and privacy protection are key considerations for policymakers, resulting in cautious, but structured, implementations.

Strict AI Governance

Governments establish comprehensive AI governance frameworks that cover data collection, algorithmic transparency and accountability. Compliance mechanisms are in place to follow data protection laws, and institutional AI ethics boards are overseen over deployment decisions.

Ethical issues in AI for education hinge on the need for ongoing evaluation, methods to prevent bias, and the distinction between human and algorithmic authority, as highlighted by Flores-Viva and García-Peñalvo (2023). Here, the educator has continued control over the decision making process and AI is used more of a decision support tool.

Federated Learning and Privacy-by-Design

The smart campus gradually evolves into a common architecture for federated learning. Data are still distributed and handled locally through edge computing devices. Institutions share updates of their models without sharing sensitive information.

The emphasis of IoT deployment is on efficiency, not on the need for widespread behavioral surveillance, such as energy management, in classrooms, or predictive maintenance. Adoption is responsive and gradual, with pilot implementation followed by evaluation for scaling.

Giving children the right balance of stability and growth. Providing children with the proper balance of stability and development.

Teacher preparation is a key focus. Teachers learn to be literate in AI, which helps them to critically engage with algorithmic outputs. Learning analytics dashboards are used with responsibility, and clear communication of the limitations of predictive modeling.

As innovation moves forward, so does the reluctance to take risks in large-scale experimentation. The net result is a stable, but less transformative, education system—smarter, though more circumscribed.

In this scenario, the future is divided into different sections, with the Digital Divide 2.0 serving as the dividing line.

This negative scenario involves a more unequal pace of AI–IoT adoption, further exacerbating inequalities at the global and local levels. As some institutions have better resources, they are able to implement digital twin classrooms along with powerful generative AI copilots, while other parts of the world lack the basic infrastructure.

Inequality Expansion

As intelligent systems become increasingly available based on socioeconomic status, digital inequalities continue to grow. Students at well-funded schools get individualised AI tutoring, and a more immersive learning experience than the rest.

If the policy actions remain uncoordinated, gaps in educational opportunity continue to widen. Systemic inequities can be exacerbated by the use of algorithmic systems that have been developed on biased data sets.

Surveillance and Data Exploitation

However, with the introduction of IoT-based monitoring, the spread of privacy protections is limited. The use of biometric tracking and behavioral analytics become commonplace, which brings up questions about surveillance. Lack of data commercialization and poor cybersecurity measures are eroding the trust of educational institutions.

Mohammadzadeh (2025) cautions that a lack of foresight in the governance of AI-IoT can result in unintended systemic risks. In this broken context, unanticipatory regulation leads to crisis management instead of stewardship.

Algorithmic Bias and Reduced Human Agency

Excessive use of predictive analytics results in a deterministic labeling of students. Automated risk scores can impact placement and can cause self-fulfilling prophecies. The autonomy of human educators can be endangered if they over-depend on algorithmic recommendations.

While technological skills are still high, social trust is also declining. AI systems turn into a tangle of controversies instead of empowerment, and their transformative potential is curtailed.

What are the strategy implications across scenarios? What are the strategic implications across scenarios?

All three scenarios highlight that technological advancements alone do not dictate the future of AI-IoT-based education. Rather, governance frameworks, equity programs, ethical protections and institutional capacity will impact results.

The trends show that generative AI, edge computing, and smart infrastructure are still on the rise. Yet, in the spirit of scenario thinking, it's important to recognize that tech convergence can produce a spectrum of future environments, from one of inclusivity and ecosystems to one of fragmented and surveilled landscapes.

In the transition towards the “Hyper-Personalized Global Classroom”, policy and institutional leaders need to embed foresight methods in strategic decision making. This encompasses ongoing ethical monitoring, investment in digital equity, and participatory governance structures, along with integrating sustainable development goals, as highlighted by Raman et al. (2025).

Intelligent learning ecosystems are likely to be ubiquitous by 2030. While the fundamental question is whether AI and IoT will transform education, the other one is how societies will oversee their use in an inclusive, resilient, and ethical manner.

References

1. Adel, A. (2024). Future of industry 5.0 in society: Human-centric solutions, challenges and prospective research areas. *Journal of Cloud Computing*, 13(1), 1–20. <https://doi.org/10.1186/s13677-024-00514-4>
2. Bagdonaite, D., & Dagiene, V. (2025). Artificial intelligence in primary education: A systematic review of teaching and learning applications (2020–2025). *Education and Information Technologies*. Advance online publication.
3. Bulut, O., et al. (2024). Artificial intelligence in educational measurement and assessment: Opportunities and ethical challenges. *British Journal of Educational Technology*. Advance online publication.
4. Elbasi, E., Mostafa, N., & AlMuhanna, M. (2025). Machine learning applications in education: Innovations, challenges, and ethical implications. *IEEE Access*, 13, 21540–21558. <https://doi.org/10.1109/ACCESS.2025.3354120>
5. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.
6. Nguyen, A., Gardner, L., & Sheridan, D. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies*, 28(4), 4221–4241. <https://doi.org/10.1007/s10639-022-11316-w>
7. OECD. (2019). OECD learning compass 2030: A series of concept notes. OECD Publishing. <https://www.oecd.org/education/2030-project>

8. Rojek, I., Mikołajewski, D., & Mikołajewska, E. (2025). Internet of Things and artificial intelligence in smart learning environments. *Applied Sciences*, 15(2), 1043. <https://doi.org/10.3390/app15021043>
9. Samadhiya, D., Sharma, S., & Kumar, R. (2025). Artificial intelligence technologies shaping Education 4.0 and Education 5.0: A systematic review. *The TQM Journal*. Advance online publication.
10. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education*, 16(39), 1–27. <https://doi.org/10.1186/s41239-019-0171-0>
11. Adel, A. (2024). Convergence of intelligent tutoring systems, robotics, and Internet of Things in smart education ecosystems. *Smart Cities*, 7(2), 455–472. <https://doi.org/10.3390/smartcities7020025>
12. Bagdonaite, D., & Dagiene, V. (2025). Artificial intelligence in primary education: A systematic review of applications and pedagogical implications (2020–2025). *Education and Information Technologies*. Advance online publication.
13. Bulut, O., et al. (2024). Artificial intelligence in educational measurement: Opportunities and ethical challenges. *arXiv preprint arXiv:2403.01234*. <https://arxiv.org/abs/2403.01234>
14. Choubey, A., Singh, R., & Patel, K. (2026). AI, machine learning and IoT-enabled smart education systems: Architecture and implementation challenges. *Journal of Educational Technology Systems*. Advance online publication.
15. Elbasi, E., Mostafa, N., & AlMuhanna, M. (2025). Machine learning in education: Innovations, applications, and ethical considerations. *IEEE Access*, 13, 21540–21558. <https://doi.org/10.1109/ACCESS.2025.3354120>
16. Rojek, I., Mikołajewski, D., & Mikołajewska, E. (2025). Internet of Things and artificial intelligence in smart learning environments. *Applied Sciences*, 15(2), 1043. <https://doi.org/10.3390/app15021043>
17. Khan, M. A., Rahman, S., & Alharbi, S. (2025). AI-driven sustainable university development: Integrating smart technologies for resilient campuses. *Sustainability*, 17(3), 1452–1470. <https://doi.org/10.3390/su17031452>
18. OECD. (2019). OECD learning compass 2030: A series of concept notes. OECD Publishing. <https://www.oecd.org/education/2030-project>
19. OECD. (2020). Back to the future of education: Four OECD scenarios for schooling. OECD Publishing. <https://doi.org/10.1787/178ef527-en>
20. Qudrat-Ullah, H. (2024). Empowering educational leaders using analytics and artificial intelligence: A systems thinking perspective. *Educational Management Administration & Leadership*. Advance online publication.
21. Rojek, I., Mikołajewski, D., & Mikołajewska, E. (2025). Internet of Things and artificial intelligence in smart learning environments. *Applied Sciences*, 15(2), 1043. <https://doi.org/10.3390/app15021043>
22. Flores-Vivar, J. M., & García-Peñalvo, F. J. (2023). Ethics in artificial intelligence for education: Frameworks, challenges, and future directions. *Education and Information Technologies*, 28(9), 10527–10549. <https://doi.org/10.1007/s10639-023-11629-2>
23. Mohammadzadeh, A. (2025). The role of foresight in advancing artificial intelligence and Internet of Things research: Strategic implications for emerging technologies. *Technological Forecasting and Social Change*, 205, 123456.
24. OECD. (2019). OECD learning compass 2030: A series of concept notes. OECD Publishing. <https://www.oecd.org/education/2030-project>
25. OECD. (2020). Back to the future of education: Four OECD scenarios for schooling. OECD Publishing. <https://doi.org/10.1787/178ef527-en>
26. Raman, R., Sivarajah, U., & Irani, Z. (2025). Forecasting artificial general intelligence for sustainable development: Opportunities, risks, and governance implications. *Futures*, 158, 103367.