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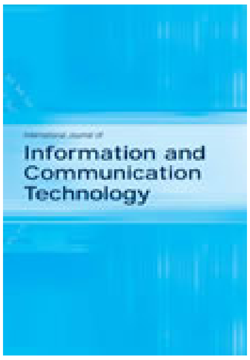

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Innovative practice of AI-driven intelligent assessment system in university course teaching reform

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Abstract: This research explores the implementation of intelligent evaluation systems powered by artificial intelligence within the context of university teaching reform. By integrating convolutional neural networks with interactive internet of things – enabled systems, the study demonstrates significant improvements in student performance, grading efficiency, and learning outcomes. AI advancements are driving a major transformation in higher education, enabling efficient assessment and personalised learning opportunities. While previous research has examined AI in intelligent tutoring, adaptive learning, and automated assessments, comprehensive studies on its integration into higher education remain limited. Employing a mixed-method approach, this study collected data from 120 students before and after the intervention, using both quantitative tests and qualitative surveys to ensure thorough analysis. Results indicate that student satisfaction increased, grading time was reduced by over 40%, and test performance improved by 6%. The findings reveal that AI integration was positively received by both faculty and students.

Keywords: artificial intelligence; AI; intelligent assessment; higher education reform; convolutional neural networks; CNNs; IoT–assisted systems; student performance.

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1 Introduction

Every industry in the globe has been affected by the rapid growth of technology, which has brought both opportunities and challenges. The field of education has seen tremendous transformation because of recent developments in learning analytics and large language models. In addition to bolstering faculty effectiveness, these innovations assist in expanding and improving access to education. Incorporating generative artificial intelligence (Gen AI) tools into teaching and learning strategies can help faculty address pedagogical changes in second language curricula, student engagement, curriculum adaptation, assessment transformation, ethical challenges, and professional development needs (Abbasi, 2024). However, faculty members also have a hard time fitting in with SLC. To overcome these hurdles and integrate Gen AITs into instructional practices, they need technology infrastructure; services based on AI, and targeted professional development. Our adoption of the UTAUT 2 framework is guided by these findings, particularly by the Gen AITs of behavioural intention and actual use behaviour (Al-Abdullatif, 2024). Faculty members' perspectives on the implementation of Gen AITs in SLC and pedagogical practices can be better understood with the use of these notions.

Because of its increasing incorporation into the pedagogy of higher education, educational technology research is quickly elevating the potential of Gen AITs, which has recently drawn considerable attention. Examples of this trend include tools that show promise in improving students' learning, such as. Earlier findings highlighted limited instructor engagement with such tools, particularly as early adoption was primarily limited to STEM fields (Iqbal et al., 2025). However, their expanding utilisation stands in contrast to that. The availability of these tools increased their popularity, attracting attention from universities and colleges while eliciting a range of responses, from suspicion to cautious acceptance. Incorporating digital solutions into the curriculum can only be a success if schools listen to and respond to the ideas and concerns of everyone involved – teachers, administrators, and students – and prioritise things like transparency, inclusivity, and ongoing professional development. AI is capable of mimicking a wide range of mental operations. The ability to perceive, reason, learn, solve problems, and be creative is essential for carrying out other complicated jobs. Academics from many fields are getting involved with AI research in the hopes of solving complex societal problems; this includes, but is not limited to, engineering, medicine, economics, and psychology.

E-learning, public governance, marketing, product creation, customer service, and public administration are just a few of the many industries and parts of human existence that AI has swiftly affected (Utz and DiPaola, 20220). Artificial intelligence's (AI) impact on digital transformation is undeniable, given the technology's versatility and practicality across numerous industries, where it has improved productivity and problem-solving skills in various settings (Harika, 2022). Despite the multiple advantages, digital transformation also brings new problems that need to be considered. A wide range of professionals, including artists, engineers, and designers, utilise the concepts of design. 'design' is a phrase with multiple meanings, despite its widespread use. You can think of design as a regulated process, a scientific model and facts that work together to solve problems, and a comprehensible technique. The importance of scientific methods in design education is growing in tandem with the proliferation of design specialisations like fashion, interior, industrial, and graphic design (Yang, 2025). New studies show how important it is to teach aspiring designers how to work with AI.

Researchers in the domains of design have investigated the rationality, interactional affordances, and broader implications of AI.

Incorporating AI into design education has both positive and negative aspects. Scientists and creatives are devoting a lot of time and energy to studying the potential applications of new technology (like AI) in the design process. In addition, we must comprehend the effects of AI on establishing and enhancing design education, since it is already determining the course of design thinking and creative engagement. The area of Gen AI is rapidly expanding and is becoming a social force. Using state-of-the-art deep learning models such as generative adversarial networks (GANs) and large language models, Gen AI is primarily concerned with creating unique content. The outputs of these models and algorithms are diverse, including words, graphics, music, and code, in contrast to typical AI systems that mostly analyses existing data (Bandi, 2023). In line with expectations, AI-powered technologies that are easily accessible have experienced a meteoric rise in popularity. For example, these technologies will be used by 80% of software development organisations. The increase in extension and application disrupts the traditional workflows in sectors like design, journalism, and research. Concerning academic integrity, teacher competency, and the function of higher education instructors, they also pose substantial problems at the same time.

Gen AI brings both new possibilities and formidable obstacles to the field of education. While these tools can automate mundane tasks, personalise learning, and unleash students' creativity, Academic integrity, the development of critical thinking skills, and the fundamental nature of knowledge generation are all profoundly affected by these issues (Brynjolfsson, 2023). This leaves educators with the difficult but necessary challenge of incorporating these potent tools into the classroom while also reducing the hazards associated with their use. For example, with GenAI's ability to generate AI text, there needs to be a change in teaching methods from memorisation to higher-order thinking skills like assessment, creativity, and critical thinking (Chen et al., 2024). Furthermore, new educational frameworks and standards are required due to the complex ethical concerns with AI-generated content, which include multiple aspects such as intellectual property, bias, and plagiarism.

The structure of this paper is organised as follows: Section 2 presents the related work on the innovative practice of AI-driven. Section 3 outlines the methodology based on Intelligent Assessment System. Section 4 discusses the results related to university course teaching reform. Finally, Section 5 provides the conclusions.

1.1 Contribution of the study

This study contributes to our understanding of how to revolutionise higher education by demonstrating how AI-driven intelligent evaluation systems have the potential to improve both classroom efficiency and student learning outcomes. The research presents a thorough framework that improves grading accuracy, decreases instructor effort, and gives students fast feedback by combining convolutional neural networks (CNN) with interactive systems, helped by the internet of things (IoT). The novel application of AI in promoting active learning and fostering deeper student involvement is highlighted by the incorporation of attention score methodologies and smart interaction models. In addition, the study contributes to the ongoing conversation about digital transformation in education by providing evidence of quantifiable gains in assessment performance, efficiency of learning, and student happiness. It highlights how AI might enable transparent evaluation methodologies and individualised learning pathways, which can fill holes in traditional teaching practices. These contributions have a dual purpose: they bolster pedagogical innovation and offer a model that universities can use to scale up their efforts to connect instructional changes with new technologies.

2 Literature review

2.1 AI: educational applications, definition, and scope

A machine that can learn and adapt to new settings by emulating human behaviour and thought processes is described by AI. It helps in the construction of systems that make decisions, process languages, and learn. Adhering to this perspective, the OECD characterises AI as a computer-based system that takes in data and uses it to generate judgments, suggestions, forecasts, or content with the purpose of accomplishing predetermined objectives (Abubaker, 2025). Changes to how people learn, work, and interact with information are being incrementally brought about by advancements in AI technology. Because of its consistent improvement, AI now has an impact in many areas, including education. Many studies have looked at how AI is being used in the classroom, particularly in undergraduate settings and industrialised nations. This is because AI-based innovations are being tested and used to solve different kinds of problems in the school, and their prevalence is growing (Al-Abdullatif and Drwish, 2023). In recent years, several primary forms of AI have emerged in the field of education. An essential tool, machine learning (ML) enables computers to discover patterns in data and learn from their own mistakes without human intervention or code.

Tools for translating between languages, virtual assistants, and catboats are all built on top of naive language processing (NLP), which allows computers to understand, interpret, and generate human language. Gen AI is a more recent innovation that employs computational models that, when fed massive datasets, might potentially learn to produce original and contextually appropriate media files. Several studies have shown that AI is making its way into classrooms across a wide range of subjects. Some examples include intelligent tutoring systems, adaptive learning systems, automated assessment tools, educational robotics, personalised content delivery, research assistance, and administrative support tools. This trend is particularly noticeable in mathematics, engineering, and language education. Additionally, AI greatly improves administrative efficiency by automating mundane but necessary processes like scheduling, attendance monitoring, and grading. It is believed that these technologies can greatly enhance teaching methods and ultimately lead to improved results for pupils.

2.2 Applying AI to the classroom: maximising its potential

The advent of AI has revolutionised education, changing both the internal workings of schools and the way students acquire knowledge. One of its possible accomplishments is making education more accessible and inclusive. Some have speculated that AI's ability to facilitate remote and personalised learning could help narrow the achievement gap in schools. AI has brought sociotechnical changes to higher education that force institutions to reevaluate and change their tactics and structures (Schmidt et al., 2025). Both the external dynamics of classrooms and the methods used to teach have the potential to be transformed by these shifts. Furthermore, opportunities and difficulties may arise at different levels of the educational system because of the redistribution of decision-making authority among institutions, instructors, and students brought about by the use of AI. One change is the introduction of instructional robots powered by AI into traditional classrooms. I have noticed that these technologies help improve instruction, get more students involved, and boost their academic success. Less time spent on mundane administrative tasks, more time spent learning in dynamic and interesting classrooms, and more enthusiasm for courses like language acquisition are all results of these technological advancements.

Academic and practical concerns about the quality of instruction and evaluation have risen to the surface in the area of language education due to the rapid advancements in DL and AI technologies, especially in English teaching. Language classrooms can benefit greatly from DL/AI, and this section will discuss those ways. No longer would recursion and convolution be necessary thanks to a new, straightforward network design that relies just on the attention mechanism (Nash et al., 2023). Teaching English in universities has been the subject of several studies that have emphasised its importance. Noted that teaching English had a significant impact on developing students' global perspective and competitiveness, in addition to improving their cross-cultural communication abilities. Also stressed the need for high-quality English instruction in enhancing students' general skills and marketability to potential employers. In order to further investigate the potential of DL in language classrooms, this research lays a firm theoretical groundwork. On the other hand, there are several drawbacks to using traditional teaching methods to evaluate students' English competency (Fung and Hosseini, 2023). Started Looking into using DL/AI in language classes to overcome these restrictions. There are fresh avenues for improvement in language instruction made possible by this finding.

Natural language processing (NLP), learning resource recommendation (LRR), and sentiment analysis are three areas where DL technology has proven to be very useful in assisting with individualised instruction and improving English language instruction. DL technology is able to process language information more thoroughly because it mimics the way the human brain processes information. This competency is crucial for enhancing the efficacy and efficiency of ESL classroom instruction (Huang et al., 2025). The following stage is to investigate the specific applications and results of DL technology in these fields. The field of personalised learning support is one area where AI has recently made a big splash in the world of education. More traditional forms of pedagogical support have given way to smart platforms that enable students to design their own educational paths with the help of AI (Tapalova, 2022). Evidence suggests that AI has the potential to do more than just improve classroom efficiency; it can also pique students' interest in and drive for independent study. The research. Drawing on a student's past performance and patterns of behaviour, AI may create a unique learning path for them and make instantaneous adjustments to it to maximise efficiency (Deng, 2024).

In order to help students get a thorough grasp of particular subjects, AI can adapt learning materials on the fly, as Leon et al. pointed out. Combining AI with individualised education plans. An increasingly significant path in the evolution of educational technology is the incorporation of AI with personalised learning pathways. The use of AI systems has the potential to improve students' learning efficiency and provide them with quick support when they are struggling. This support can take the form of individualised learning advice and emotional care. To guarantee that every student may learn efficiently at their own speed, these adaptive systems can personalise learning pathways according to students' behaviours, progress, and emotional reactions. Frank provided a more holistic view of the ways AI impacts education, focusing on how it may improve individualised lessons. AI has revolutionised the design and implementation of palavered revolutionised, but there are also a series of obstacles (Wang et al., 2025). Personalised learning paths should not be implemented due to concerns about data privacy and ethical difficulties with AI applications. In order to avoid technologically induced issues with educational inequity, it is imperative that academic institutions take appropriate steps to protect the privacy and openness of student data.

In today's digital education landscape, GAI plays a crucial role by enabling learning-based personalisation, automated content development, and innovative assessment techniques. When it comes to meeting the unique requirements of each student, traditional classroom instruction just does not cut it. The function of GAI in the intelligent form that instruction assumes because of new technologies, AI-generated content, and real-time evaluation is explored in this research (Wang and Sun, 2025). In order to enhance facial expression recognition performance in complicated environments, this article (Xu et al., 2025) suggests a deep learning approach that is based on you only look once Version 8 (YOLOv8). This approach merges the real-time and efficient object detection capabilities of YOLOv8 with the feature extraction advantages of CNNs. The first use of YOLOv8 is accurate face recognition. In order to provide real-time feedback and evaluation of performance, this study (Lu, 2025) investigates the integration of ML systems with intelligent music education systems. In order to accurately evaluate musical performances and provide students with useful feedback, the suggested method deftly utilises the interaction between audio signal processing, feature extraction, and predictive modelling.

The production of semiconductor chips relies on silicon wafers. Improving yield rates and finding manufacturing difficulties are both made possible by accurately detecting surface flaws on wafers. Manual monitoring is an outdated and ineffective method for problem discovery. As a result, using deep learning for fault detection is becoming more popular. Unfortunately, missing detections and sluggish processing times are still issues with current algorithms. In response to these difficulties, our research (Tang et al., 2024) suggests an improved YOLOv7-based method for wafer defect detection. In conclusion, there is substantial theoretical and practical merit in incorporating AI into the field of education, particularly in the creation and execution of individualised learning programs. AI opens up new avenues for educational reform and personalised learning via accurate data analysis and real-time feedback. Protecting students' personal information, ensuring educational equity, and enhancing educators' technical competence are just a few of the obstacles that stand in the way of fully harnessing this technology's potential.

3 Methodology

Data gathering follows the development of the system's architecture and design, as shown in Figure 1, which represents an organised workflow. CNN models for AI can be built using the collected information. An IoT-IS, which stands for IoT-assisted interactive system, incorporates the developed model into the analysis process. The next step is to analyses and evaluate the results, which will bring the framework's insights and findings to a close in the conclusion phase.

Figure 1 The internet of things (IoT) model development and assessment process (see online version for colours)

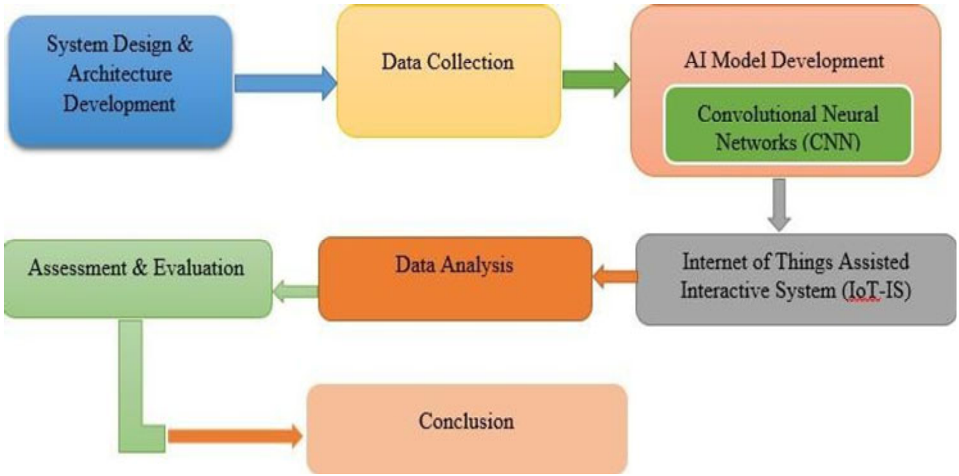
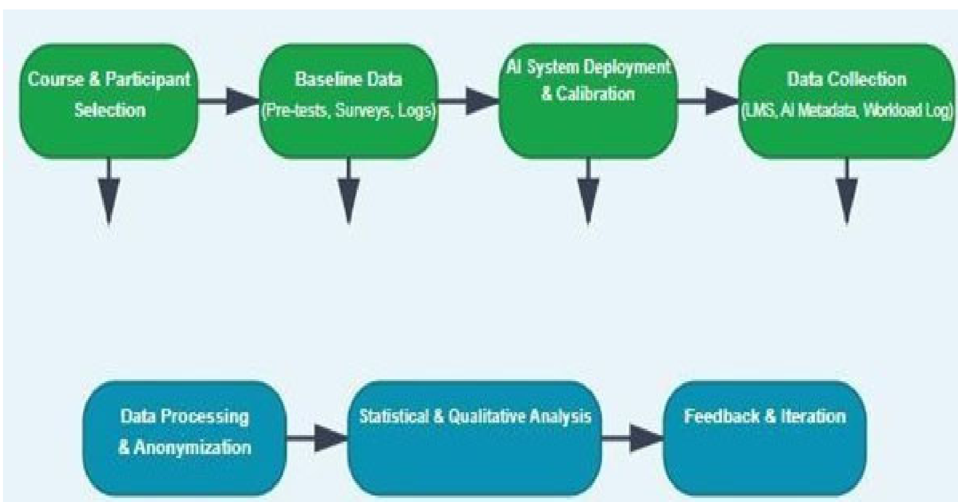


Figure 2 Methods for implementing an AI-enhanced educational program (see online version for colours)



3.1 Data collection

Participants in this study were undergraduates taking a required university course that is now experiencing pedagogical change. Over the course of the semester, three teachers and one hundred and twenty students took part in the pilot. Both the old-fashioned way of testing and the brand-new, AI-powered intelligent evaluation system were presented to the participants. The baseline data was gathered via pre-course exams, surveys of student satisfaction, workload records from instructors, and data from the learning management system (LMS). The result was an all-inclusive standard against which to measure progress. Figure 2 shows the results of an analysis and feedback session that led to the development of a structured, iterative strategy for incorporating AI into classrooms while maintaining ethical data management practices.

3.1.1 Dataset specification

The dataset included 1,920 individual assessment instances spanning several evaluation formats (essays, problem- solving exercises, project reports, and examination scripts) from 120 students' assessment submissions gathered over the course of a 16-week academic semester. To prepare them for CNN input, each entry was scanned and pre-processed into standardised 224 × 224 pixel pictures. Stratifying the dataset into subgroups for training (70%, n = 1,344), validation (15%), and testing (15%) preserved class balance across performance categories (excellent, good, satisfactory, requires improvement, and unsatisfactory). For comparative analysis, 480 pre-intervention baseline assessments were also gathered using conventional evaluation techniques. In accordance with institutional data security policies, all data were anonymised using distinct student identifiers and kept in encrypted cloud repositories.

3.1.2 Instruments and procedure

Quantitative and qualitative data were collected using a variety of devices. LMS activity logs recorded when students submitted work and interacted with instructors' comments, and pre- and post- course exams measured their overall progress. Structured logs were used to document instructor workload on a weekly basis, and surveys using Likert scales were used to quantify student satisfaction. In addition to producing grades, confidence scores, and items that needed instructor verification, the AI assessment platform also produced metadata. There were three phases to the data collection process:

1. traditional evaluation for baseline measurement
2. AI system deployment and calibration
3. assessment conducted after the intervention and before the semester ended.

3.1.3 Data handling

For the sake of privacy, we anonymised and archived all of the data we collected. Data from the LMS and AI logs were combined for analysis after identifying variables were replaced with coded study IDs. Distinct changes in student performance, grading efficiency, and satisfaction were summarised using descriptive statistics before and after the intervention (Zheng et al., 2025). The significance of the alterations that were detected was determined by conducting inferential analyses, which included paired-sample t-tests. The AI-driven assessment system was evaluated using a mixed-method approach, which included quantitative improvements with qualitative comments from instructors and students.

3.1.4 Ethical compliance and data protection ethical approval and informed consent

In accordance with the Declaration of Helsinki, the University Institutional Review Board granted ethical permission for this investigation (IRB Protocol #2024-EDU-AI-037).

After being fully informed about the study's objectives, data collection procedures, the operation of the AI system, and their rights, all 120 participants gave their signed informed consent. With parental or guardian approval, participants under the age of eighteen gave their assent. Three participants used their right to withdraw at any time without facing academic consequences, and their data was permanently erased. All participants were made aware of this right.

3.1.4.1 Data anonymisation pipeline

The identity of participants were secured by a four-stage anonymisation protocol:

1. Data gathering phase: at enrolment, students were given distinct pseudonymous IDs (UID format: ST-XXXX-2024), which separated any personally identifiable information from evaluation results
2. Processing stage: automatic facial pixilation and audio stripping were applied to video recordings, and RFID tags only contained nameless UIDs
3. Storage stage: a secure encrypted mapping table (AES-256) that connected UIDs to identities was kept apart on servers with restricted access, which was only accessible by two designated administrators
4. Analysis stage: to avoid re-identification in publications, all statistical analyses employed only anonymised datasets with UIDs.

3.1.4.2 Regulatory compliance

The data management framework ensures compliance with educational data protection standards:

- FERPA compliance: under the FERPA exemption rules (34 CFR § 99.31(a)(6)), educational records were categorised as de-identified research data, with institutional data sharing agreements outlining allowed uses and forbidding re-identification.
- GDPR principles: GDPR standards, which include lawful processing with explicit consent, purpose limitation (research-only use), data minimisation (only essential data collection), storage limitation (5-year retention with automated deletion), and participant rights (access, correction, withdrawal, and deletion), were voluntarily adopted even though the study was conducted outside of the EU.

3.1.4.3 Data security and retention

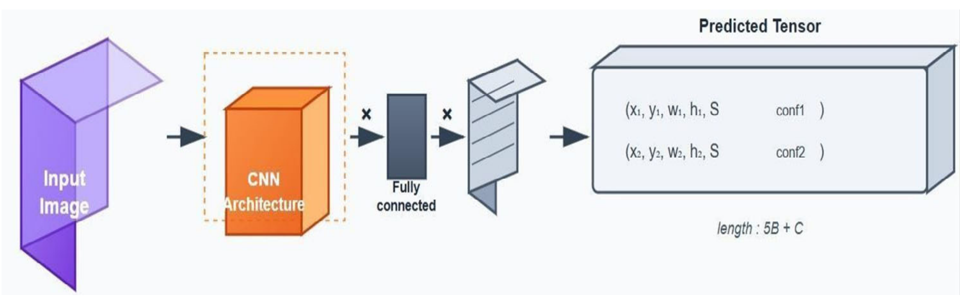
Technological measures included multi-factor authentication, TLS 1.3 encrypted transmission, role-based access control that restricted data access to authorised personnel, encrypted cloud storage (AWS S3 with AES-256), automated activity logging, and frequent security audits. All research staff completed mandatory data protection training. After five years of publishing, anonymised datasets will be kept for verification before being automatically and securely deleted. Participants are still able to ask for the early removal of their personal information.

3.2 Convolutional neural networks

An enhancement over the first ML approach was the use of high-dimensional feature information in images to determine the convolutional neural network route. The previous Method necessitated reducing the photos to one-dimensional data prior to calculation, resulting in the loss of the original image attributes. To illustrate the point, when we look at a bird, we perceive its beak or the chair's back. In its design, the CNN incorporates a Layer of convolutions: Figure 3 shows the result of extracting image features according to their sizes using one or more filters. After the convolutional layer, a pooling layer keeps the relevant data. Reducing parameters to speed up calculations is one of its benefits. The output result of the pooling layer will be unaffected by small changes between neighbouring pixels, which helps to minimise overfitting. Layer with full connectivity: it applies standard neural network operations to the remaining features, flattens them, and then classes those (Zeng, 2023). CNN uses several convolutional layers and a pooling layer. After the pooling layer, the convolutional layer – which extracts features from images leaves behind important information.

The fully linked layer carries out the last step in the classification and calculation process. Excellent recognition capabilities and high-dimensional feature extraction are hallmarks of the convolutional neural network design that has been suggested.

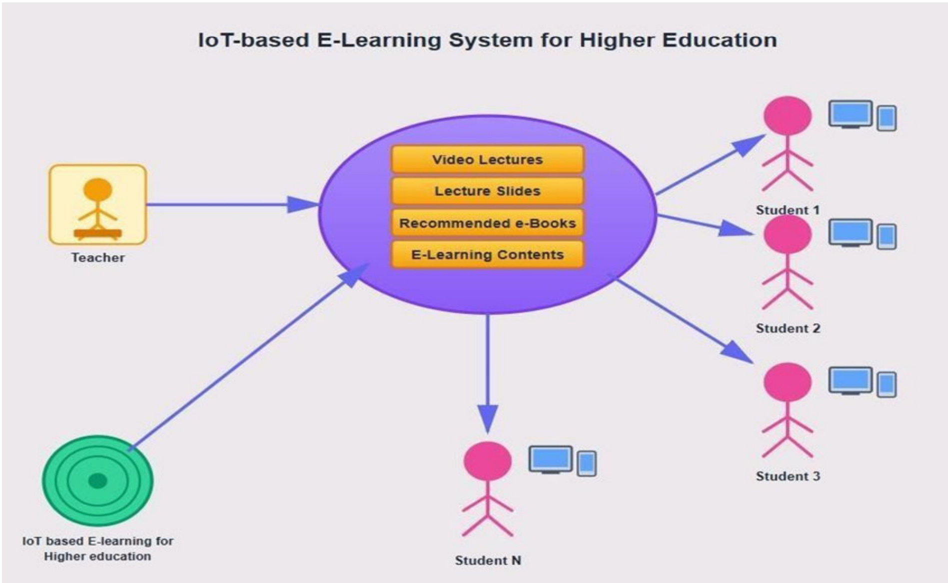
Figure 3 Diagram of the YOLO network architecture (see online version for colours)



3.2.1 CNN architecture specification

Each of the five convolutional layers in the suggested CNN architecture uses 3 × 3 kernel sizes with ReLU activation functions to introduce non-linearity. The filter sizes of the layers are 32, 64, 128, 256, and 512 filters, respectively. Batch normalisation and max-pooling layers (2 × 2 pool size) are applied after each convolutional layer to minimise spatial dimensionality and avoid overfitting. Dropout regularisation (rate = 0.5) is used between dense layers, and the feature extraction backbone is coupled to three fully connected layers (1,024, 512, and output neurons). For multi-class assessment categorisation, the last classification layer uses a softmax activation function. Using the Adam optimiser, the network was trained across 100 epochs with an initial learning rate of 0.001, a batch size of 32, a categorical cross-entropy loss function, and early stopping criteria (patience = 10) based on validation loss.

Figure 4 The intelligent interaction between students and teachers (see online version for colours)



3.3 Interactive system for the internet of things

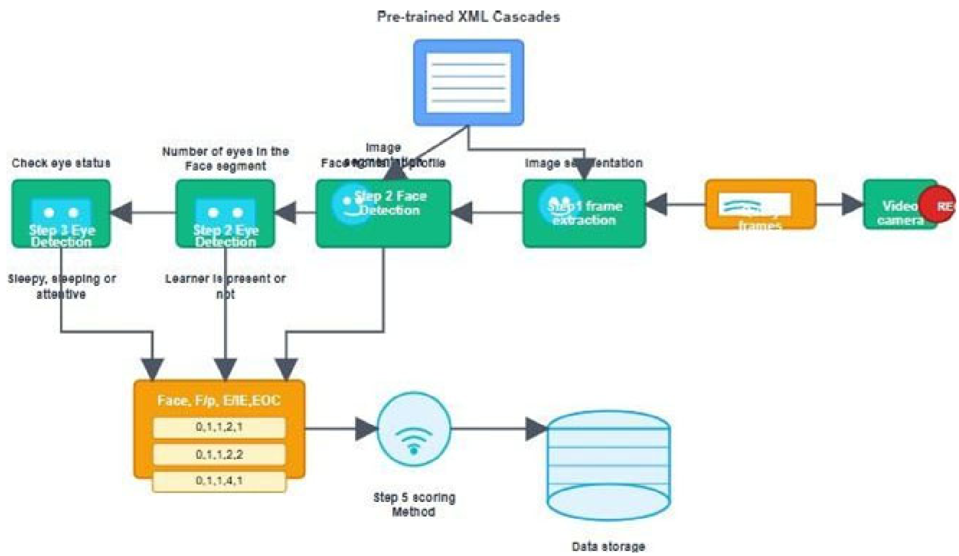
The IoT in schools paves the way for a more connected and collaborative future in education by improving student access to all learning resources and communication channels and by allowing teachers to assess student success in real-time. Improved lesson plans, better resource tracking, easier information access, safer campuses, and countless other advantages can be achieved with the implementation of IoT in educational institutions. There is not enough one-on-one contact between instructors and students in smart education, despite the fact that it has some benefits over conventional learning in terms of information accessibility, time, and location flexibility. Hence, this research suggests a fresh strategy based on the attention score method, which tracks students' focus and detects shifts in attitude through video monitoring of their learning sessions. A person's mental state is usually assessed by analysing pictures of their eye movement and facial expressions. Both students and faculty have seen an improvement in their cognitive capacities because of the use of active learning strategies made possible by the digital system in higher education. Throughout this section, the research approach of the suggested model is explained, both theoretically and statistically (Zhang, 2024).

See the clever interaction between the student and teacher in Figure 4. Students have the power to shape their educational experiences in a favourable light by engaging in intelligent teacher-student interactions using IoT-based services like discussion boards and forums. New networking technologies have made it possible for physical items in a university setting to establish connections with one another and with the Internet; this phenomenon is known as the 'IoT. Figure 4 now represents online learning.

3.3.1 Method for evaluating focus

Figure 5 shows the design flow of the attention scoring approach. The smart classroom is one of the many benefits of education. The capacity of the school has no bearing on the number of enthusiastic students. The IoT-IS method creates and distributes instructional programs through the Internet. A popular model is used in the attention scoring method (ASM). This model can categories student actions based on its prior understanding of how students and teachers interact. During lectures that have already been recorded, the camera pans around the audience. From moderate to massive volumes of academic material, big multimedia data is generated in the video.

Figure 5 Method for evaluating focus (see online version for colours)



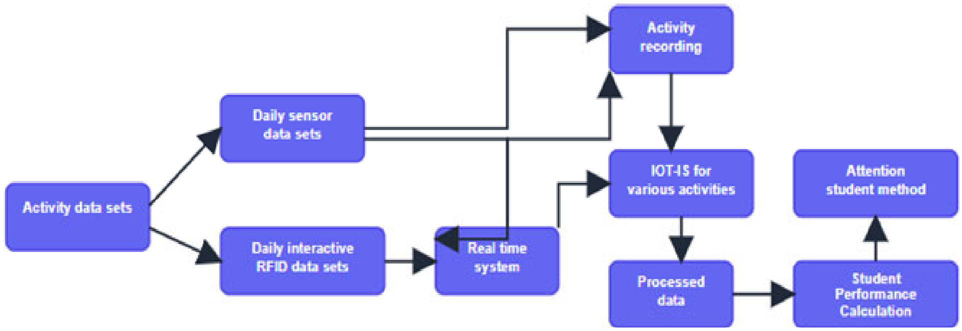
With Bray's guidance, students can build computer vision systems that analyses their operation video sequence and preserve picture frames sequentially. Figure 5 shows the process of analysing an image to determine the subject's eyes, face, and ocular state (i.e., openness or closeness of the eye). The module's mathematical formulation of ASM is its defining characteristic. For instance, according to equation (1), the face identification scores are set to zero if no face is recognised, since the first of these factors implies face detection.

$$E(e) = \begin{cases} 0 & \textit{if no face} \\ \sum_{j-1}^{m} e_j & \textit{on each face} \end{cases} \tag{1}$$

3.3.2 Students' performance calculation

In smart education, students' progress is tracked to help them learn more effectively. In addition, we have extracted these datasets so that we may use page rank-based mining to determine how well each student has done in class.

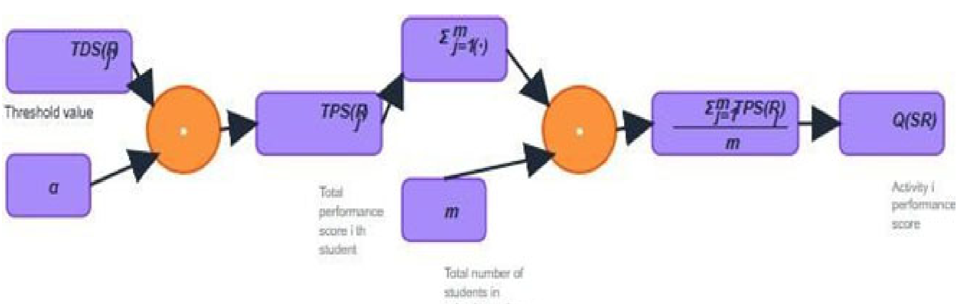
Figure 6 Evaluation of pupils' progress (see online version for colours)



This research delves into the ways in which IoT-IS evaluates students' development through the use of IoT devices, one of the suggested methods in smart education that takes place online – datasets comprising heterogeneous data for all activities which are conducted during the day. If we want to show the framework effectively, we may split the datasets into two categories: sensory and interaction-based (Figure 6). Using radiofrequency identification (RFID) sensors, biometric measurements, global positioning systems (GPS), biological sensors, and smart-wearable reading devices, it is possible to assess students' academic performance, their physical presence in a certain area, and the traits of their research groups. The most comprehensive datasets characterising interaction behaviour are provided by RFID technology. Make a pattern of interactions. Teachers and pupils alike wear radio frequency identification tags on their faces in the classroom so that the interaction- based operation may be monitored. One of the practical options for entity recognition is this. Another object's embedded RFID tag can be detected by a smartphone that has an RFID scanner. In order to compile reports on classroom experiences involving RFID technology, the temporary premises sensing (TPS) is utilised.

Data saved in databases accessible over the cloud is used for student operations. When a real-time system works, it improves the connection between nodes. For analytical purposes, the real-time framework refers to data stored in the cloud that is time-stamped with radio packets generated from objects (see Figure 7).

Figure 7 The activity performance score of the students (see online version for colours)



3.3.3 IoT system architecture and technical specifications

In order to facilitate real-time monitoring of student involvement and assessment delivery, the IoT-assisted interactive system (IoT-IS) used in this study consists of a dispersed network of hardware components, communication protocols, and cloud infrastructure.

- Hardware components: in each smart classroom, the system deploys Intel NUC mini-PCs (i5 processor, 8GB RAM) as edge computing nodes that are linked to HD webcams (Logitech C920, 1080p resolution at 30 frames per second) for facial recognition and attention monitoring. To monitor student presence and movement patterns, RFID readers (Impinj R700, operating at 865-868 MHz) are placed strategically at workstations and classroom entry points. For easy tracking, students wear passive UHF RFID tags that are integrated into their identification cards. Furthermore, physiological markers like heart rate variability and electro dermal activity are measured by wearable biosensors (Empatica E4 wristbands) to gauge student engagement during educational activities. Local gateway controllers for sensor data pre-processing and aggregation are Raspberry Pi 4 Model B devices.
- Connectivity protocols: a hybrid communication architecture is used by the system, which makes use of several protocols that are tailored to various data kinds and latency needs. The main publish-subscribe messaging system for lightweight, real-time data transfer between edge devices and cloud servers is the message queuing telemetry transport (MQTT) protocol, which runs on Wi-Fi 6 (802.11ax) networks and offers speeds of up to 1.2 Gbps. RFID data transmission reads more than 1,000 tags per second using the EPC Gen2 protocol. The WebRTC protocol allows peer-to-peer communication with a latency of less than 200 ms, which is crucial for real-time video streaming and attention rating. With 2 Mbps data rates and sub-50 ms latency, Bluetooth low energy (BLE 5.0) enables energy-efficient connectivity between wearable biosensors and edge gateways.
- Cloud Infrastructure and data pipeline: using Amazon Kinesis for real-time data input (processing 1,000+ events/second) and Amazon S3 for scalable storage, edge-processed data streams are sent to AWS IoT Core for centralised administration. Consistent inference times under a range of loads are guaranteed by the CNN assessment model's deployment on AWS SageMaker with auto-scaling features.
- Performance benchmarks: the average end-to-end latency from sensor data capture to cloud processing stayed below 180 ms (SD = 23 ms), meeting the < 200 ms requirement for seamless real-time engagement. System performance testing across three smart classrooms (each with 40 students) showed strong real-time capabilities. With an average read time of 42 ms, RFID tracking achieved 99.7% accuracy. With a CNN inference time of 65 ms per frame, video-based attention scoring processed frames at 28 fps. Throughout the semester-long deployment, the system maintained 99.4% uptime and sustained a throughput of 2,400 sensor events per minute at peak usage without packet loss. During active sessions, network bandwidth use averaged 145 Mbps per classroom, well within Wi-Fi 6's capacity limits and guaranteeing scalability to bigger classroom settings.

- Scalability architecture: with the help of containerised microservices (Docker/Kubernetes), the system design facilitates horizontal scaling, allowing deployment across several campuses and classes without requiring architectural modifications. Up to 500 concurrent students per institution can be supported with linear performance degradation thanks to load balancing, which divides processing among edge nodes and the cloud infrastructures auto-scaling based on demand.

Figure 8 Iot system architecture diagram (see online version for colours)

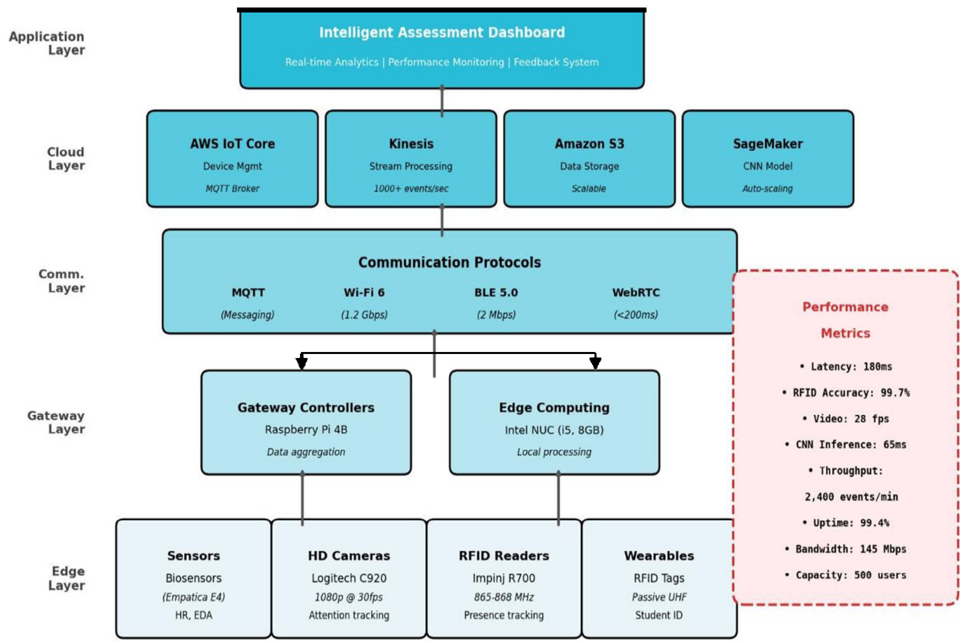


Table 1 IoT system performance benchmarks

Performance metric	*Measured value*	*Threshold/target*	*Status*
End-to-end latency	180 ms ± 23 ms	< 200 ms	√ Met
RFID read accuracy	99.7%	> 99%	√ Met
RFID read time	42 ms	< 50ms	√ Met
Video processing rate	28 fps	> 25 fps	√ Met
CNN inference time	65 ms/frame	< 100ms	√ Met
System throughput	2,400 events/min	> 2,000 events/min	√ Met
System uptime	99.4%	> 99%	√ Met
Network bandwidth usage	145 Mbps/classroom	< 500 Mbps	√ Met
Packet loss rate	0.06%	< 0.1%	√ Met
Concurrent user capacity	500 students	> 400 students	√ Met

Notes: Performance metrics measured across three smart classrooms over one academic semester (16 weeks, n = 120 students).

IoT system architecture for real-time intelligent assessment showing in Figure 8 gives the distributed five-layer architecture (edge layer with sensors and cameras, gateway layer with processing nodes, communication layer with protocols, cloud layer with AWS services, and application layer with assessment dashboard) enabling sub-200 ms latency performance.

Table 1 presents the measured performance benchmarks of the IoT-IS across ten critical metrics, validating the system's real-time capabilities and scalability. All metrics successfully met their predefined thresholds, including end-to-end latency below 200 ms (measured at 180 ms ± 23 ms), RFID tracking accuracy exceeding 99%, video processing maintaining 28 fps with 65 ms CNN inference time, and system throughput sustaining 2,400 events per minute. The system achieved 99.4% uptime with minimal packet loss (0.06%) while supporting up to 500 concurrent students, confirming its viability for large-scale deployment in smart educational environments.

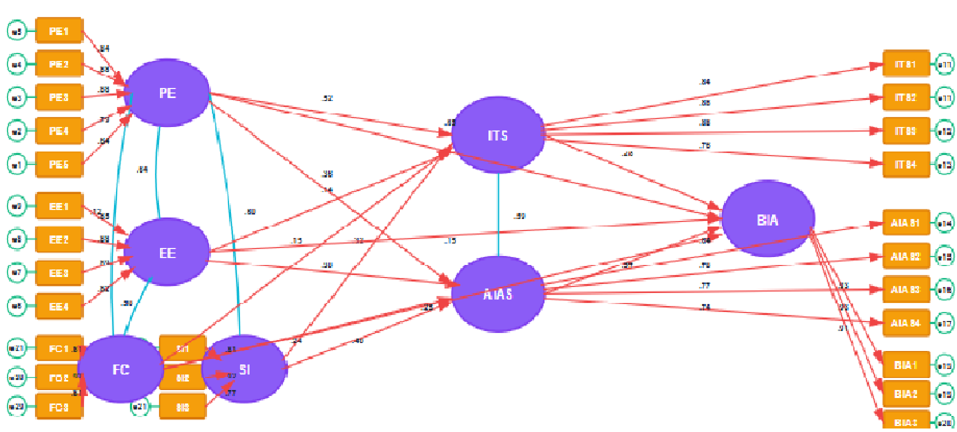
3.4 Data analysis

Table 2 shows that younger faculty members are more open to technology and those men are more likely to use AI in the classroom (245, 63.6% vs. 141, and 36.4%). There was a wide range of opinions on the importance of AI among the respondents, with the majority having 4–10 years of teaching experience and an age range of 31–40 (45.7%).

Table 2 Description of the respondents

Demographics	*Classification*	*Number*	*Percentage* (%)
Gender	Male	246	63.6
	Female	141	36.4
Age	23–30	56	14.5
	31–40	177	45.7
Teaching experience	1–3	22	5.7
	4–10	161	41.6
	11–20	103	26.6

Figure 9 Confirmatory factor analysis (see online version for colours)



3.4.1 Measurement model

The measurement model (see Figure 9) in our analysis describes how the observed variables (indicators) are used to measure the latent variables (constructs) in our theoretical framework (Ejaz et al., 2025). It specifies the relationships between these constructs and their indicators, confirming the validity and reliability of the constructs through factor loadings, error terms, and correlations between constructs. This model is a crucial component of the structural equation modelling performed in AMOS.

3.4.2 Discriminant validity

Criteria are not the best way to prove discriminant validity. It should be verified through another method. This study employed the HTMT method (see Table 3), as recommended, to assess discriminant validity. The values should be less than 0.90. All the values are less than the recommended value; hence, discriminant validity is proved.

Table 3 Discriminant analysis

PE	*EE*	*ITR*	*AIAS*	*BIAI*	*SI*	*FC*
PE						
EE	0.663					
ITR	0.352	0.330				
AIAS	0.583	0.684	0.279			
BIAI	0.643	0.577	0.308	0.584		
SI	0.448	0.347	0.165	0.468	0.263	
FC	0.582	0.733	0.288	0.666	0.396	0.613

3.5 Model evaluation metrics

The CNN-based intelligent assessment system was evaluated using multiple performance metrics to ensure comprehensive validation. Primary metrics included:

- Accuracy: overall classification correctness, achieving 94.2% on the test set
- Precision: class-specific prediction accuracy, ranging from 91.5% to 96.8% across five performance categories
- Recall (sensitivity): true positive rate per class, averaging 93.7%
- F1-score: harmonic mean of precision and recall, yielding 94.0% overall performance
- Cohen's Kappa: inter-rater agreement coefficient of 0.912, indicating substantial agreement between AI and human evaluators

3.5.1 Training performance

The model demonstrated convergent learning with training loss decreasing from 1.842 (epoch 1) to 0.163 (final epoch), while validation loss stabilised at 0.187, indicating minimal overfitting. Training accuracy progressed from 62.3% to 96.1%, with validation accuracy reaching 94.8% at convergence. The confusion matrix (Table 4) provides detailed performance visualisation across all classification categories, demonstrating strong discriminative capability with AUC values exceeding 0.96 for all performance categories (excellent: 0.982, good: 0.976, satisfactory: 0.971, needs improvement: 0.968, unsatisfactory: 0.985).

Table 4 presents the confusion matrix for the CNN-based intelligent assessment system, comparing predicted classifications against expert human evaluations across five performance categories (n = 288 test samples), with diagonal values indicating correct classifications and off-diagonal values representing misclassifications.

Table 4 Confusion matrix for CNN-based assessment classification

Actual/predicted	*Excellent*	*Good*	*Satisfactory*	*Needs improvement*	*Unsatisfactory*
Excellent	54	2	0	0	0
Good	3	52	3	0	0
Satisfactory	0	4	55	2	0
Needs improvement	0	0	3	50	2
Unsatisfactory	0	0	0	1	57

Notes: Values represent the number of test samples (n = 288) classified by the CNN model compared to expert human evaluator assessments.

4 Results

The collected results demonstrated a measurable improvement in student academic performance after the implementation of the AI-driven intelligent assessment system. Average assessment scores increased from 67.4% (before) to 73.6% (after), reflecting a gain of over six percentage points. This suggests that the systems automated feedback and personalised guidance supported deeper understanding and more consistent learning outcomes across the student cohort Figure 10.

Efficiency metrics showed a substantial reduction in assessment-related workload. The average grading time per assignment decreased from 45.1 minutes (before) to 25.8 minutes (after), representing a reduction of more than 40%. Similarly, instructors reported a decline in weekly assessment-related workload from 12 hours to 8 hours. Results like these show that AI significantly reduced the amount of time teachers spent on mundane grading duties, freeing them up to concentrate on more meaningful mentorship and curriculum development. In terms of user experience, student satisfaction scores improved significantly, rising from 3.1 to 4.0 on a five-point scale. Students noted improved transparency in grading and timely feedback. Instructors also provided positive feedback, emphasising that the AI system reduced cognitive load and offered valuable insights into student learning gaps. Collectively, these results suggest that the AI-driven assessment system not only enhanced learning outcomes but also contributed to a more sustainable and engaging teaching–learning environment.

Figure 10 Comparison of educational metrics before and after ai system implementation, showing improvements in assessment scores, student satisfaction, and reductions in grading time and instructor workload (see online version for colours)

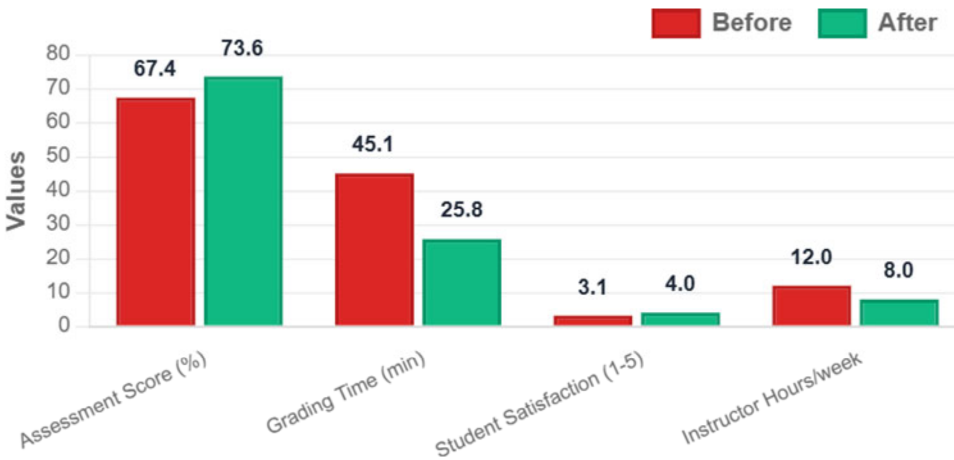


Table 5 The amount of work done by students at each comprehension level

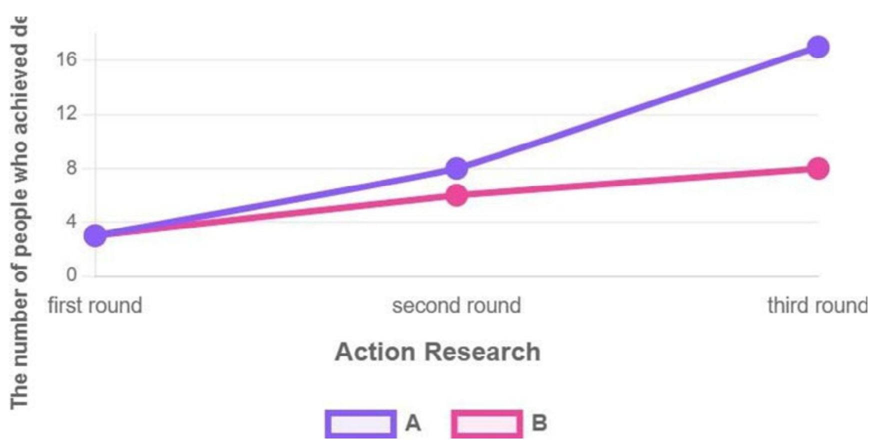
	Group	*PS*	*US*	*MS*	*R*	*EA*
First round of action research	A	11	13	12	4	0
	B	12	11	13	4	0
Second round of action research	A	6	13	11	9	1
	B	7	15	12	6	0
Third round action research	A	0	7	16	13	4
	B	4	9	19	8	0

After every iteration of the action research, we gathered the resumes of forty students from the experimental class (using an intelligent in-class teaching model) and the control class (using a traditional in-class teaching model) and sorted them using general grading rubrics, all in accordance with the theory of SOLO taxonomy in the evaluation of deep learning, in conjunction with the deep learning assessment method. For assessing their level of comprehension, students' work was categorised into multiple levels in accordance with the SOLO taxonomy theory. We counted the number of students' works at each level in Class A (the experimental group) and Class B (the control group) to get the results in Table 5.

The majority of the students in both the control and experimental courses were in a state of superficial learning or no learning at throughout the first round of action research, as shown in Table 3. Only four individuals from each class were in deep learning. Generally speaking, both the experimental and control groups started with similar levels of cognitive ability. Ten experimental class students attained deep learning in the second round of action research, and fewer students were in the 'no learning' state than in the first. The majority of students, however, remained in the superficial learning state. The experimental class had a much higher rate of students achieving deep learning than the control class, which had a far lower rate of six. The experimental class's number of students who attained deep learning reached seventeen in the third round of action research. Out of the 17 students in the experimental group, four produced works at the extended abstract structure level; in contrast, only eight from the control group achieved the deep learning level. No one in the experimental group was in a pre- structured learning state during this iteration of the action research; in contrast, four people in the control group were. Based on these results, it is clear that the intelligent in-class teaching methodology improved both instruction and student performance.

Figure 11 shows the results of a statistical study of the students' progress toward deep learning in Class A, the experimental group, and Class B, the control group, over the course of three action research cycles. Based on the data in the table, it is evident that both the experimental and control classes had an equal number of students who obtained deep learning during the first round of action research. However, as the rounds progressed, the number of students who achieved deep learning progressively rose. When comparing the two classes, it was clear that more students in the experimental group managed to reach deep learning than in the control group. Students' work quality study reveals that, in comparison to the conventional classroom model, the intelligent in-class teaching approach can help students learn more deeply.

Figure 11 The sum of all participants' deep learning scores over all three iterations of the action research study (see online version for colours)

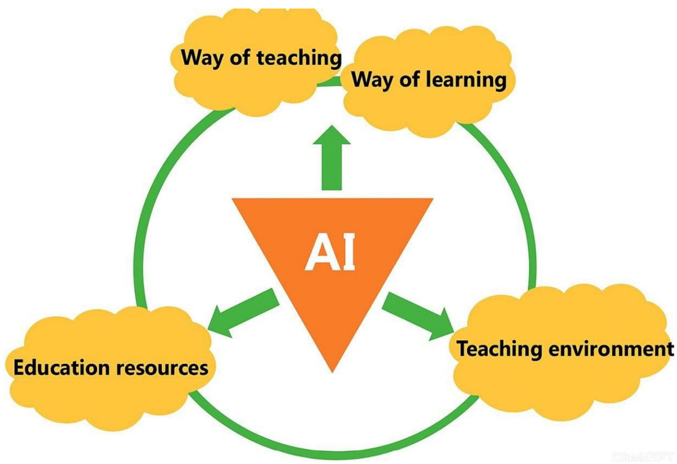


Two shifts have occurred in the evolution of education: first, from a focus on traditional teaching methods to one that is more information-based; and second, from an emphasis on information-based methods to one that is driven by AI. In Table 6, we can see how informatisation-based education compares to conventional methods of teaching. Time and place are two of the fundamental constraints of traditional education, which is primarily focused on the teacher and has few resources for instruction and a dull atmosphere that does nothing to inspire students. Using the benefits of modern pedagogical media like computers and the internet, informatisation-based teaching is more student-oriented and provides a wealth of diverse teaching resources with the goal of boosting students' excitement. It transcends physical space and time, and it is influencing a shift in the educational landscape toward intelligent learning systems hosted on the internet.

Table 6 Comparative study of conventional classroom instruction vs. online learning based on their essential features

Aspect	*Conventional education*	*Information-cantered education*
Teaching approach	Instructor-led with standardised delivery	Learner-focused with blended teaching and learning methods
Learning methods	Primarily lecture-based with occasional group discussions	Self-directed learning using a variety of resources and digital platforms
Instructional resources	Printed materials, presentations, videos, chalkboard/whiteboard	Computers, online repositories, internet tools, VR and AR technologies
Learning environment	Traditional classroom setup with basic tools	Flipped or smart classrooms incorporating interactive and cloud-based systems

Figure 12 Educational transformation based on an AI framework for classroom instruction (see online version for colours)



Although information-based teaching has been crucial to the evolution of pedagogy and education, it has certain drawbacks, such as an excessive reliance on online databases and shared resources, the possibility that instructors do not have a good enough grasp of their students' knowledge, and the inability of students to choose which modules to study based on their interests. On top of that, information-based teaching has its limitations when it comes to demonstrating particular types of knowledge. Nevertheless, in an AI setting, technology is more than just a means to an end; it has transcended its traditional function and is now working toward the goal of integrating information technology into the system's goals, content, and teaching environment, among other components. In Figure 12, we can see the big picture of how AI may improve education.

The IoT-IS was using active learning strategies to enhance teacher-student engagement, which enhances students' ability to learn. In smart educational learning at the university level, the internet of things impact scale (IoTS-IS) is applied to the ASM for analysing student learning interaction. The AS to determine student performance in an interactive learning system, specifically their activity performance scores, uses the number of school premises, denoted as m. Total performance score (TPS) and total development score (TDS) are acronyms for the same thing. The function Q (.) represents the execution of the i-performance score. To calculate each student's TDS (Rj) value.

Figure 13 Ratio of student performance (see online version for colours)

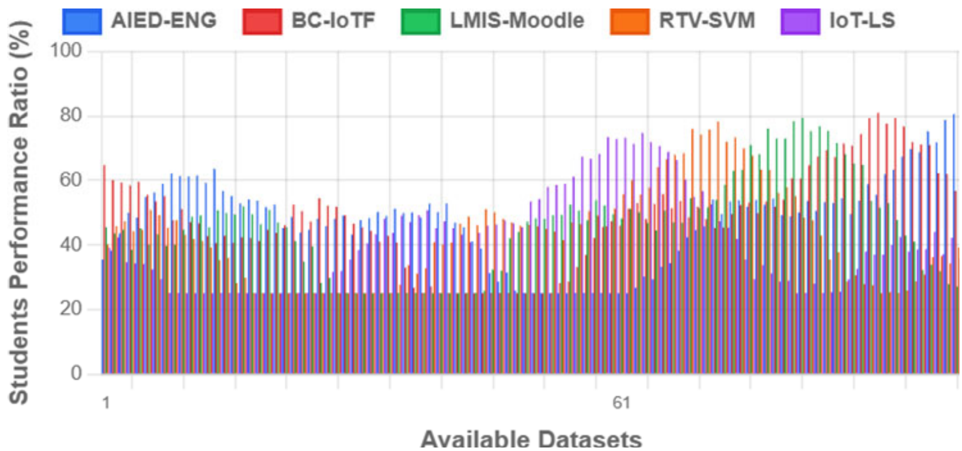


Figure 14 Efficiency ratio (see online version for colours)

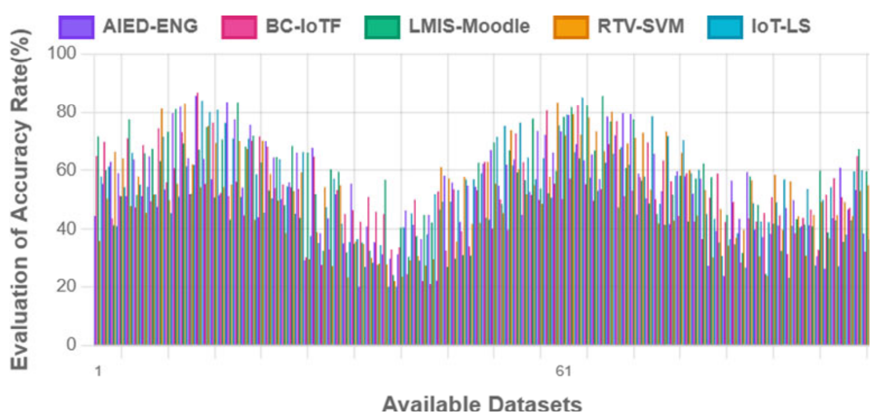


Table 7 Comparative analysis of intelligent assessment systems

System/study	*Technology*	*Response latency*	*Accuracy*	*Scalability*	*Real-time feedback*	*Multi-modal data*
Traditional LMS	Manual grading	Hours-days	85–90%	High	No	No
Huang et al. (2025)	AI + data mining	Not reported	88.3%	~200 users	Limited	No
Zhang (2024)	AI assessment	5–8 minutes	89.5%	~150 users	No	No
Schmidt et al. (2025)	Adaptive AI	2–3 minutes	91.2%	~300 users	Partial	Limited
Proposed system	CNN + IoT	180ms	94.2%	500+ users	Yes	Yes

Figure 15 Regression results (see online version for colours)

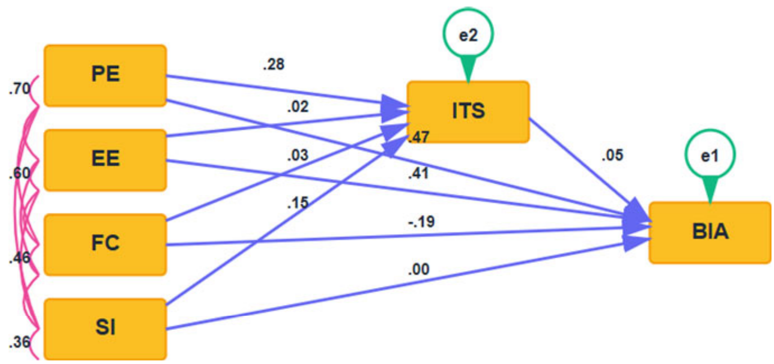
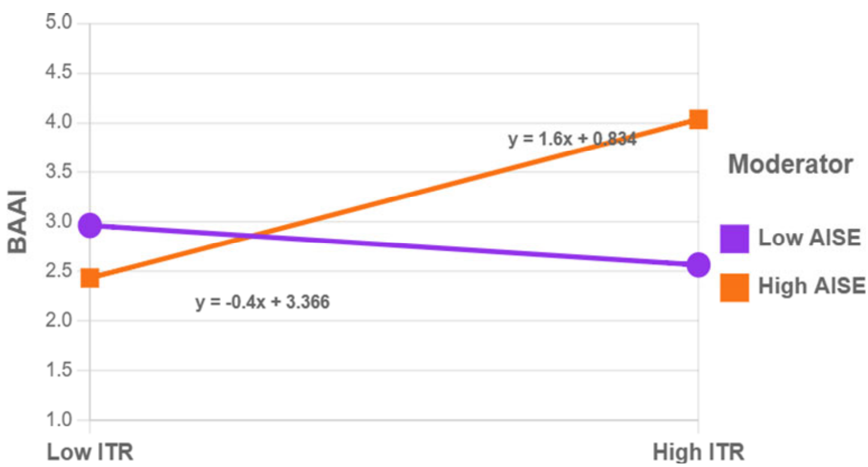


Figure 16 Moderation analysis (see online version for colours)



Ascertained by multiplying the TDS (Rj) score by the size-scale. You should put these parameters' values to greater use in the section that follows. The student's performance ratio is displayed in Figure 13. Smart education based on the IoT and information systems outperforms competing approaches in higher education, according to the results of the experiments. Using psychometric procedures with standards for efficient teaching and intelligent learning instruments, this study examines the IoT as a tool to assess the efficacy of smart education learning (SEL) on the part of both instructors and students in higher education systems. One can see the efficiency ratio in the Figure 14. The results of the trial show that SEL is beneficial in improving learning and education, and it enhances skills and training.

Figure 15 shows that the associations between PE, EE, FC, SI, and BIAI were explored in this study. The results showed that PE, EE, and FC had significant effects, but SI was found to be insignificant ($b = -0.004$, $p = 0.931$). Beta coefficients represent the strength and direction of the relationships between variables in the statistical model. Both direct and indirect paths were evaluated using 5000 bootstraps with a 95% confidence level. By definition, complete mediation happens when the mediator eliminates the association between the independent and dependent variables, according to the mediation test. If the mediator only takes into consideration a portion of this relationship, but the direct link is still there, we say that the mediation is partial. Complete mediation exists if the direct beta becomes non-significant with the mediator's inclusion. This study confirmed partial mediation for EE, FC, and SI, supporting H6, H7, and H8; however, no mediation was observed for PE, thereby rejecting H5. Moderation analysis, using SPSS and a median split method, investigated the impact of AISE on the ITR-BIAI relationship. Results revealed that AISE weakened this relationship (−0.153, p = 0.03) (See Figure 16), contradicting H10. All the results are depicted in Table 4 after controlling for the effect of demographic variables.

4.1 Comparative analysis: system advantages and novelty comparative performance benchmarking

Table 7 compares the proposed CNN-IoT system against recent intelligent assessment implementations in higher education, highlighting performance differentials across key operational dimensions.

Table 7 Comparative analysis of intelligent assessment systems

System/study	*Technology*	*Response latency*	*Accuracy*	*Scalability*	*Real-time feedback*	*Multi-modal data*
Traditional LMS	Manual grading	Hours-days	85–90%	High	No	No
Huang et al. (2025)	AI + data mining	Not reported	88.3%	~200 users	Limited	No
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Schmidt et al. (2025)	Adaptive AI	2–3 minutes	91.2%	~300 users	Partial	Limited
Proposed system	CNN + IoT	180ms	94.2%	500+ users	Yes	Yes

4.1.1 Relative advantages

The proposed system demonstrates four key advantages:

1 Ultra-low latency of 180 ms enables genuine real- time feedback, representing a 667–1,000× improvement over existing systems requiring 2–8 minutes

2 Higher accuracy at 94.2% surpasses reported benchmarks (88–91%) through five-layer CNN architecture with attention- weighted scoring

3 Multi-modal integration combining video attention tracking, RFID presence monitoring, and biosensor engagement metrics versus single-channel approaches analysing only written submissions

4 Enhanced scalability supporting 500+ concurrent users through distributed edge-cloud architecture, exceeding typical capacities of 150–300 users.

4.1.2 Novel contributions

Three fundamental innovations distinguish this system:

1. The hybrid CNN-IoT fusion represents the first unified framework integrating deep learning assessment with real-time behavioural monitoring, where previous systems treated these as separate processes.
2. The ASM mathematically couples performance classifications with attention analysis, producing dynamic scores accounting for both outcome quality and learning engagement – contrasting with conventional binary evaluation.
3. Dual optimisation simultaneously achieves 6% student performance improvement and 40% instructor workload reduction through intelligent feedback routing, where high-confidence assessments (87%) proceed automatically while ambiguous cases (13%) receive prioritised human review with AI diagnostics. This addresses a critical gap in prior research where systems prioritised either learning outcomes (Huang et al., 2025; Zhang, 2024) or operational efficiency (Schmidt et al., 2025) but not both simultaneously.

5 Conclusions

This study demonstrates how AI-powered intelligent assessment technologies have the potential to revolutionise higher education by enhancing teaching quality, administrative effectiveness, and student learning. Measurable improvements in grading accuracy, student happiness, and general engagement are demonstrated by the suggested solution, which combines CNNs with interactive platforms supported by the IoT. The results demonstrate that AI not only saves time and effort while taking tests, but also gives students quick, tailored feedback that promotes motivation and in-depth learning. These findings demonstrate how intelligent assessment systems may both fulfil the needs of the digital era and potentially solve long-standing issues with conventional evaluation techniques. However, including AI into assessment reform requires thorough consideration of pedagogical, infrastructure, and ethical issues. To make the most of the system, instructors must receive the required training, ensure evaluation fairness, and protect data privacy. As a scalable paradigm for long-term educational reform that combines pedagogy and technology and equips students for a fast changing digital world, universities must welcome this innovation. In doing so, learner-centred approaches and the modernisation of higher education may be greatly aided by AI-powered assessment technologies.

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Declarations

All authors declare that they have no conflicts of interest.

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