

CONTINUOUS, ADAPTIVE, AND LEARNER-CENTRED EVALUATION

John Oji^{1*} & Caroline Ochuko Alordiah²

^{1,2}Department of Educational Foundations, University of Delta Agbor, Delta State, Nigeria

*john.oji@unidel.edu.ng

ABSTRACT: This paper explores the emergence of continuous assessment in the age of artificial intelligence (AI) and the creation of adaptive, personalised and data-driven assessment. Continuous assessment has been acknowledged for its formative and learning-monitoring features, but practice is often constrained by a range of issues, including timely feedback, personalised assessment, teacher load, and assessment subjectivity. The paper draws on constructivist learning, mastery learning and assessment for learning to develop the use of artificial intelligence (AI) technologies, including machine learning, learning analytics and automatic feedback, to address these issues. The study demonstrates the development of an AI-Driven Adaptive Continuous Assessment Model (AIDACAM), which involves learner data collection, data analysis, adaptive assessment tasks, personalised feedback, and data dashboards for teachers. The model facilitates timely feedback, adaptive assessment and data-driven learning practises. Moreover, the research explores the potential of AI-based assessment, including the benefits of efficiency, feedback and learning outcomes, as well as ethical considerations around data privacy, algorithmic bias and fairness. In all, the authors conclude that the application of AI technologies has the potential to enhance continuous assessment practises if applied with pedagogically and ethically sound approaches.

Keywords: Artificial Intelligence, Continuous Assessment, Adaptive Assessment, Personalised Learning, Learning Analytics, Automated Feedback, Educational Assessment

INTRODUCTION

Assessment remains an important element of the teaching and learning process as it provides systematic evidence of the extent to which learning outcomes are achieved. Learning outcome measurement is not the only aim of assessment in the educational context; it also provides a basis for informing teaching and learning practises, the development and implementation of curricula, and institutional policymaking (Calderon et al., 2023). Amongst the many forms of educational assessment, continuous assessment has gained popularity in recent years as a form of assessment which integrates assessment into the teaching-learning process and not just through final exams. Continuous assessment is often used to describe the practise of regular assignments, tests, projects, classroom activities, and other forms of formative assessment that measure students' learning over time and influence teaching and learning practises (Calderon et al., 2023). In this way, continuous assessment intends to better inform the learning and development of learners over a period of time and over different phases of their educational careers.

Although continuous assessment is a good idea in principle, in practice, continuous assessment has been shown to be problematic in many educational contexts. Some of the observations made of the shortcomings of traditional continuous assessment practices include: bias in assessment, lack of timely feedback, lack of personalised assessment opportunities and the use of standardised assessment practises that may not align with the needs of learners' progress and pace (Fynn & Mashile, 2022). As such, questions have been raised regarding the role of conventional continuous assessment in promoting learning and authentic assessment in a rapidly evolving world.

Recent advances in artificial intelligence (AI) have opened up opportunities to address these challenges in educational assessment. The emergence of new artificial intelligence technologies such as machine learning, intelligent tutoring systems, learning analytics and automated feedback systems is being incorporated into education in an attempt to support data-driven educational practises (Xia et al., 2024). In assessment, AI has the potential to analyse large volumes of data, detect learning patterns, offer feedback, automate some aspects of the assessment process and tailor assessment tasks to the individual learner's needs and preferences. This could make continuous assessment more flexible, adaptive and personalised.

However, the increasing use of learning systems enabled by AI technologies has implications for educational assessment. Students are already collaborating with AI machines to create written work and solve problems, and receiving explanations while undertaking learning tasks that potentially impact the validity and authenticity of assessment (Francis et al., 2025). In turn, educationalists and academics will need to re-conceive how continuous assessment is designed to be relevant, valid and provide measures of learning in technology-based learning environments.

With this in mind, this conceptual paper considers the opportunity to re-think the concept of continuous assessment by harnessing artificial intelligence technologies to develop adaptive and personalised assessment strategies that can optimise learning outcomes in educational settings.

Conceptual Clarifications

The Concept of Continuous Assessment

Continuous assessment is a systematic, ongoing evaluation of students' learning through tasks conducted over time. Rather than opting for a summative assessment, where testing and examinations are conducted at the end of a semester or course, continuous assessment is embedded within the learning and teaching process, enabling teachers to track students' learning progress. It focuses on gathering evidence of students' learning over time, rather than relying only on a major examination to determine students' performance (Sanchez-Ruiz et al., 2021).

Continuous assessment follows a formative assessment philosophy, where assessment tasks are seen as activities to encourage learning rather than to assess academic performance. Through continuous assessment, teachers can identify learning difficulties, offer feedback, and adjust teaching methods to improve students' learning of course content (Vahed et al., 2021). Thus,

continuous assessment is known as student-focused assessment, which motivates students and promotes learning.

Continuous assessment is different from exams in several ways. First through continuous assessment of student learning throughout the teaching and learning process. Second, it involves a range of assessment strategies for assessing different aspects of student learning. Third, it is integrated into the teaching and learning process, and the assessment results can inform teaching. Finally, continuous assessment focuses on providing feedback known to improve student performance (Okunbor & Alordiah, 2025).

Consequently, continuous assessment can include using different assessment strategies to measure different aspects of student learning. These include quizzes and tests that assess knowledge, assignments and projects that assess analysis and research skills, presentations that assess speaking skills, practical activities that assess procedural knowledge and class participation that assesses engagement in learning activities. The use of these different tools and techniques is in an effort to evaluate the whole student's learning and development (Rincón et al., 2024).

Artificial Intelligence in Education

Artificial Intelligence (AI) in education refers to the use of computer technologies that are capable of performing tasks that have previously been considered the exclusive domain of human intelligence, such as, for instance, decision-making, reasoning, understanding and processing human language and pattern recognition. In recent years, there has been a rise in the use of AI to support learning, teaching and assessment (Bahroun et al., 2023).

There are different forms of AI technologies used in education. These technologies include machine learning to recognise patterns in data sets, natural language processing to understand written and spoken language, intelligent tutoring systems to personalise teaching and learning, predictive analytics to predict student learning outcomes, and automated assessment systems to grade and provide feedback to students. AIs are able to process large amounts of data on learners using these technologies to provide insights for evidence-based practice in education (Hamal et al., 2022).

Adaptive Assessment

Adaptive assessment is a type of assessment in which the difficulty of the tasks is determined by the learner's ability level. In adaptive assessment systems, the difficulty of questions is based on the learner's success with them. If a learner is successful, it may then provide more difficult tasks; if unsuccessful, less (more appropriate for the level of ability) difficult tasks (Choi & McClenen, 2020).

Adaptive assessment is used to ensure the difficulty of the tasks and to understand the learner's knowledge. Adaptive assessment can increase the effectiveness of the assessment measurements, as well as the satisfaction of learners during the assessment process, by adapting the level of difficulty of the assessment tasks to the level of performance of the learner. Adaptive assessment is

supported by artificial intelligence, as AI algorithms can process the performance of learners in real time and select appropriate questions.

Personalized Assessment

Personalised assessment is the flexibility of assessment practises to meet the different learning needs, skills and traits of learners. Personalised assessment is an alternative to standardised assessment practises, which use uniform assessment processes to evaluate learners (Halkiopoulou & Gkintoni, 2024).

Personalised assessment can take different forms, such as offering individualised feedback to learners, providing different assessment options, offering different assessment tasks, and offering flexible time limits for assessment tasks so learners can complete them at their own pace. In this way, personalised assessment is considered an effort to provide positive assessment environments for learning.

Artificial intelligence helps personalise assessment, AI analyse big data generated by students' learning, and detects patterns in student learning. This information helps the learning platform provide the learner with feedback and make recommendations for learning resources and assessment tasks that are aligned with the learner's needs (Topping et al., 2025). So, AI-powered personalised assessment is an emerging trend in assessment that brings it in line with student-centred learning.

Theoretical Foundations

Understanding the change of continuous assessment in the age of artificial intelligence must place the discussion into a context of pertinent theories of learning and assessment. Several theoretical perspectives offer important insights into how assessment systems can be useful for supporting meaningful learning. Among the greatest frameworks that are related to AI-supported assessment are constructivist learning theory, mastery learning theory, and assessment for learning theory. These perspectives are in total focus on the idea of learner-centred evaluation, continuous feedback, and individual learning pathways.

The Theory of Constructivist Learning

The constructivist theory of learning holds that knowledge is not received passively but is actively constructed by learners through their interactions with their environment and engagement in meaningful learning tasks. Rooted in the works of scholars such as Piaget and Vygotsky, constructivism holds that learning occurs when people interpret new information in light of their prior knowledge and experiences (Mishra, 2025). From this perspective, assessment should go beyond the measurement of factual recall and evaluate learners' capacity to apply, analyse, synthesise and evaluate knowledge in authentic contexts.

Constructivist-oriented assessment, therefore, focuses on problem-solving, project-based activities, reflective learning, and collaborative engagement in which learners are given opportunities to demonstrate greater conceptual understanding. In contrast to traditional approaches to testing that emphasise correct answers, in constructivist assessment, it is the reasoning processes and conceptual development involved in learners' answers that are being examined.

Artificial intelligence has the potential to reinforce constructivist-oriented evaluation through more interactive and authentic assessment experiences. AI-supported learning environments can be used to simulate real-world scenarios, create adaptive problem-solving tasks, and offer personalised feedback based on student responses. Through the use of technologies such as intelligent tutoring systems and learning analytics platforms, AI can analyse learner interactions and help detect patterns in the conceptual understanding of students, which can then be used to assess the knowledge construction processes in a more meaningful way [Kaldaras et al., 2024]. Consequently, AI-based assessment systems align well with the principles of constructivism by promoting dynamic, interactive, and learner-centred evaluation practises.

Mastery Learning Theory

The premise of mastery learning theory, commonly linked to the work of Benjamin Bloom, is that a very large proportion of learners can develop a high level of understanding if they are given the right learning conditions and allowed a substantial amount of time to master instructional objectives. According to this theory, instruction should be structured in clearly defined learning units, and students should demonstrate mastery of each learning unit before moving on to more advanced content (Winget, M., & Persky, 2022).

Within frameworks of mastery learning, incessant evaluation plays a key role in the identification of whether learners have achieved the expected degree of competence. Frequent formative assessments help educators diagnose learning difficulties and provide corrective instruction as well as ensure that students have mastered before moving on. This approach is in contrast to the traditional instructional models, where all learners are moving at the same pace regardless of differences in comprehension levels.

Artificial intelligence technologies can play a major role in the implementation of the principles of mastery learning. AI-driven adaptive learning platforms can analyse students' performance data and adapt instructional content accordingly. When learners show they have mastered a certain concept, the system can present more advanced material; and, when learners have trouble, the system can offer them extra practise activities or other explanations. By fostering individualised pacing and targeted feedback, artificial intelligence (AI)-powered adaptive assessment systems generate conditions that come close to the tenets of mastery learning (Alvarez et al., 2025).

The Theory of Assessment for Learning

Assessment for learning is a formative approach in which the purpose is to use assessment as a tool to support and enhance learning, rather than simply certifying achievement. Within this framework,

assessment activities are embedded in the instructional process and designed to provide feedback to help students understand their learning progress and identify areas for improvement (Van Orman et al., 2024).

Key features of assessment for learning are continuous feedback, student participation in assessment, clear learning goals and use of assessment information to make decisions about instruction. Teachers use assessment results to make changes in teaching strategies, whereas students use feedback to self-regulate their own learning behaviours (Alordiah, 2025).

Artificial intelligence technologies, in particular, hold the potential to greatly enhance assessment-for-learning practices. AI-enabled systems can provide immediate feedback, in-depth performance analytics, and personalised learning recommendations based on students' responses to assessment tasks. Such capabilities enable learners to receive immediate guidance on their performance, increasing opportunities to improve learning outcomes in a timely manner. In addition, learning analytics tools can detect patterns in student engagement and achievement, which can then help educators intervene more effectively when learners encounter difficulties (Mao et al., 2023).

Limitations to Traditional Continuous Assessment

Despite their theoretical benefits, traditional systems of continuous assessment are often constrained by practical limitations that limit their ability to contribute to meaningful learning. These limitations have become more apparent as educational environments have become more complex, as well as technologically mediated.

Lack of Personalisation

One major disadvantage with traditional continuous evaluation is the lack of personalisation in evaluation practises. In many educational settings, assessment tasks are standard and used for all students irrespective of differences in learning abilities, cognitive styles and academic backgrounds. Such approaches to uniform evaluation may not accurately reflect the learning progress of individual learners and may disadvantage those learners who need differentiated approaches to instructional support (Manoharan, 2019).

Delayed Feedback

Another challenge related to traditional continuous assessment is the lapse of time for offering feedback to learners. In traditional classroom settings, it often takes teachers a long time to grade assignments, tests and projects. As a result, students may not receive feedback on an assessment task for several days or weeks after completing the task. This delay decreases the effectiveness of feedback as a learning tool because students may not remember the reason behind the response or may have already moved on to new topics (Ding et al., 2024).

Teacher Workload

Continuous assessment can also create significant pressure on the workload for educators. Evaluating many assignments, quizzes, and projects for large numbers of students takes a lot of time and effort. Too many grading responsibilities may restrict educators' abilities to give specific feedback or construct innovative assessment behaviours, subsequently diminishing the general quality of the evaluation procedure (Creagh et al., 2023).

Subjectivity in Evaluation

Human evaluation processes sometimes introduce subjectivity and bias into evaluation outcomes, especially in evaluations that require open-ended responses, such as essays, reports, and presentations. Differences in teachers' expectations, grading standards, and the interpretation of students' responses can result in inconsistent scoring, thereby affecting the reliability and fairness of assessment results (Hauer et al., 2023).

Limited Data Utilisation

Traditional continuous assessment systems are also plagued by a lack of use of learner performance data. Although a lot of information is produced by quizzes, assignments, and classroom activities, it is rarely systematically analysed to identify patterns in student learning. Consequently, meaningful intelligence that can be used to feed into instruction improvement and individual support is often underused (Broughan & Prinsloo 2019).



Figure 1: Comparison Between Traditional Continuous Assessment and AI-Driven Continuous Assessment

Figure 1 compares the traditional and AI-based continuous assessment approaches. Traditional assessment is based on standardised fixed tests; feedback is provided manually and takes time; there is limited ability to customise; there is a large workload in grading; scores are often subjective; and basic tracking. It is mostly teacher-centred and oriented to the end results. In contrast, AI-powered assessment is adaptive and dynamic, providing instant automated feedback, personalised assessment, and automated grading. It relies on advanced analytics to create data-driven insights for more consistent, objective scoring. This approach is interactive, engaging, and learner-centred, improving both teaching efficiency and students' learning experiences through continuous, real-time improvement and better understanding of individual progress.

Artificial Intelligence and Changing the Nature of Continuous Assessment

The rapid development of technologies in artificial intelligence (AI) has had a major impact on the design and implementation of educational assessment systems. In the modern learning environments, AI enables powerful tools for improving the efficiency, accuracy and responsiveness of continuous assessment. By combining the power of machine learning, data analytics, and automated decision-making capabilities, AI has made it possible to create more dynamic and learner-centric evaluation processes that can adapt to the learning needs of students in real-time (Kooli & Yusuf, 2024).

AI-Supported Automated Grading

One of the most widely known uses of AI in assessing education is automated grading. AI-powered assessment systems can assess objective, structured responses such as multiple-choice questions, short answers, and some written responses with high accuracy. Natural language processing technologies enable AI systems to process natural-language submissions and create initial evaluations based on preset scoring criteria. Automated grading is a major game-changer in the process of continuous assessment, saving educators much time and work tied to it to focus on instructional tasks and personalised student support (Deepshikha, 2025).

Real Time Learning Analytics

AI technologies also make it easy to use learning analytics as a way of monitoring student progress. AI-driven educational platforms can monitor the learners' interactions with the digital educational environments, analyse patterns in the learners' engagement and performance, and pinpoint areas where the students might need additional support. Real-time learning analytics allow educators to gain insights into students' strengths and weaknesses for timely instruction and intervention, as well as better educational decision-making (Leong, 2025).

Proactive Intelligent Feedback Systems

Another revolutionary power of AI when it comes to continuous assessment is intelligent feedback. Traditional assessment systems provide little timely feedback due to the time taken to grade the test. In contrast, AI-powered systems can have immediate feedback as learners submit their work, and highlight mistakes, explain them, and suggest learning resources. Immediate feedback helps students reflect on their mistakes and deepen their understanding during the learning process (Xavier et al., 2025).

Mechanisms of Adapting the Test

AI-based adaptive testing systems adjust the difficulty of test questions based on the learner's performance. When a student answers questions correctly, the system asks harder ones, and when errors are made, it introduces easier ones. This is an adaptive mechanism that enables assessment

tasks to be appropriately challenging and enhances measurement accuracy (Mahamuni & Tonpe, 2024).

Prognostic Models for Assessments

AI technologies are also being used to develop predictive assessment models that look at past learning data and predict how a student will perform in the future. By analysing patterns in past assessments, participation levels, and learning behaviours, AI systems can identify students at risk of difficulties in certain subjects and suggest interventions (Jiao et al., 2022). Such predictive capabilities allow educators to implement proactive strategies that will boost student success.

Proposed Conceptual Framework: Artificial Intelligence-Based Adaptive Continuous Assessment Model

To address the shortcomings of traditional Continuous Assessment and explore the possibilities of artificial intelligence, this paper introduces a conceptual framework called the AI-Driven Adaptive Continuous Assessment Model (AIDACAM). The model conceptualises continuous assessment as a dynamic, data-driven process in which data about learners are collected, analysed, and used to create adaptive assessment tasks and personalised feedback on an ongoing basis. The framework incorporates artificial intelligence, learning analytics, and instructional decision-making into a single framework that supports both student learning and teacher effectiveness.

The model comprises five interrelated components: Learner Data Collection, Learning Analytics Engine, Adaptive Assessment System, Personalised Feedback Mechanism, and Instructor Dashboard.

Conceptual Structure of the Framework

AI-Driven Adaptive Continuous Assessment Model

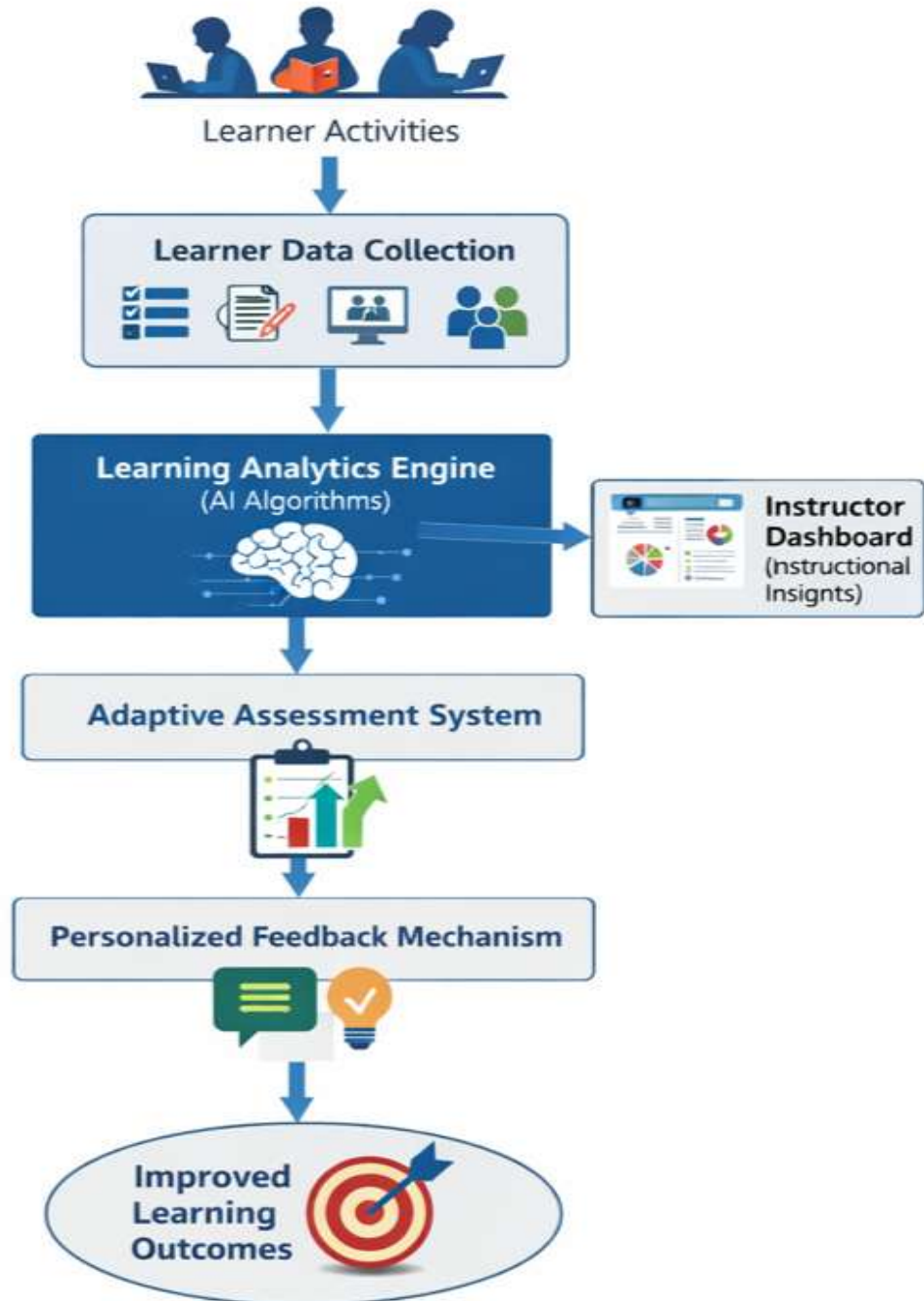


Figure 2: Conceptual framework of the AI-Driven Adaptive Continuous Assessment Model (AIDACAM)

Learner Data Collection

The first component of the model in Figure 2 is the systematic collection of learner data that are generated during instructional and assessment activities. Modern digital learning environments generate vast quantities of data that can be used to gain insights into students' learning behaviours. Data sources can include quiz performance, assignment turn-in, interaction with learning management systems, involvement in collaborative learning activities, and time spent working on instructional tasks. These data serve as the basis for the analysis and decision-making process based on artificial intelligence (Lopez-Meneses et al., 2025).

Learning Analytics Engine

The second part of the framework is the learning analytics engine, which is the core artificial intelligence system that is responsible for processing and interpreting learner data. Machine learning algorithms take student performance, engagement, and learning behaviour patterns to understand the strengths, weaknesses and possible gaps in learning. Through predictive analytics and pattern recognition, the system can generate insights that inform both the design of assessments and the delivery of instruction (Kasneci et al., 2023).

Adaptive Assessment System

The adaptive assessment system uses the information that the learning analytics engine produces to dynamically modify assessment tasks based on the competence level of students. Instead of giving all learners the same assessment tasks, the system adjusts the difficulty of the questions, the complexity of the tasks, and the assessment pathways based on the performance of each learner. This approach to assessment is an adaptive mechanism that should ensure that it is appropriately challenging while providing more accurate measurement of student learning (Van der Linden & Glas, 2023).

Individualised Feedback Mechanism

Another important part of the model is the personalised feedback mechanism. Based on the analysis of the learner performance data, the system creates individualised feedback aimed at learning improvement. Feedback may include explanations of incorrect responses, suggestions for further learning resources, suggestions for practise activities, and suggestions for areas that need further attention. Immediate and targeted feedback helps to increase the metacognitive awareness of the students and facilitates self-regulated learning (Rudolph, Tan, & Tan, 2024).

Instructor Dashboard

The last element in the framework is the instructor dashboard, which gives educators visualised analytics about the learning progress of students. Through interactive data dashboards, teachers have access to information including performance trends, engagement levels, learning gaps and

predictive risk indicators. These insights help educators to make informed instructional decisions, tailor interventions and offer extra help to learners who need it.

Overall, the AI-Driven Adaptive Continuous Assessment Model describes assessment as an intelligent, data-supported ecosystem that continually links learner performance, analytics, feedback and instructional decision-making. By integrating artificial intelligence in continuous assessment systems, educational institutions have the opportunity to shift towards more responsive, personalised, and effective assessment practises that are able to improve the learning outcomes of students in different educational levels.

Opportunities Offered by Continuous Assessment Based on AI

The implementation of artificial intelligence (AI) in continuous assessment systems has presented major opportunities for revolutionising the way student learning is assessed and supported. AI technologies enable assessment processes to become more dynamic, responsive and learner-centred by using large amounts of data on education to inform decision-making. Rather than being mere instruments of grading, AI-enabled assessment systems are becoming increasingly important tools that can be converted into intelligent learning support mechanisms with the ability to improve the quality of feedback and instruction and facilitate greater engagement in learning (Chen et al., 2024). Several important opportunities are created by adoption of AI-driven continuous assessment in education environments.

Enhanced Feedback Systems

One of the most important benefits of AI-based continuous assessment is the ability to provide improved and timely feedback to learners. In traditional assessment environments, feedback often reaches students long after task completion due to the time spent grading and evaluating. AI-powered assessment systems can analyse student responses in real time and provide automated feedback, highlighting errors, explaining them, and suggesting learning resources for improvement. Immediate feedback is an important component in supporting formative learning because it helps students to identify their misconceptions and adjust their learning strategies in real time (Alordiah & Okoro, 2018; Ajogbeje, 2023). Furthermore, AI systems can also be used to give more detailed feedback than traditional grading methods by analysing patterns across multiple learning activities and identifying recurring conceptual challenges.

Data-Driven Instruction

Another large opportunity linked to AI-supported continuous assessment is the encouragement of data-driven instructional decision-making. AI systems have the ability to gather and process large amounts of data about learners generated by quizzes, assignments, digital learning platforms, and in-class interactions. Through the application of learning analytics techniques, these systems can identify patterns in students' performance, engagement, and learning behaviours. The insights obtained from such analyses provide teachers with very useful information about areas where students have difficulties and topics that require additional teaching attention (Bhandari &

Kshetree, 2024). By helping educators make instructional choices based on empirical evidence instead of intuition alone, AI-supported analytics are part of more targeted and effective teaching strategies.

Personalised Learning Experiences

AI-driven continuous assessment also facilitates the creation of personalised learning experiences that accommodate the diversity in the ability, learning styles, and academic requirements of the learners. Traditional assessment approaches often use one-size-fits-all evaluation tasks, and the teacher is not sensitive to each student's learning journey. In contrast, AI systems can analyse individual performance patterns and customise assessment activities accordingly. Adaptive assessment mechanisms adjust the difficulty of questions and learning paths, as well as feedback recommendations, to each learner's progress. Such personalisation helps to make assessment tasks sufficiently challenging without being meaningless or unchallenging in terms of the opportunities it offers for growth (Naseer et al., 2024). Personalisation of assessment systems also fosters learner autonomy in that students take on self-regulated learning processes.

Increased Efficiency of Assessment

AI technologies are a major factor in increasing the efficiency of continuous assessment systems. Automated grading tools save time and effort spent grading assignments, tests, and quizzes, reducing the burden on teachers, who often need to grade large volumes of work. Natural language processing technologies can evaluate some written responses, while machine learning algorithms can process structured responses with high accuracy. As a result, educators can focus more on designing meaningful learning activities, offering mentorship, and supporting student development (Botelho et al., 2023). Increased efficiency also allows educational institutions to carry out continuous assessment on a larger scale without sacrificing the quality of the evaluation.

Improved Learning Outcomes

The combination of timely feedback, personalised learning pathways and data-informed instruction ultimately contributes to improved learning outcomes. AI-supported continuous assessment systems establish learning environments in which students receive ongoing guidance and opportunities for improvement. When learners receive immediate feedback and receive adaptive support, they are also more likely to correct their misunderstandings in time and gain deeper conceptual understanding. Empirical studies in AI-supported education environments suggest that adaptive assessment technologies can help improve student engagement, motivation and academic performance (Oji & Alordiah, 2024; Yaseen et al., 2025). Consequently, AI-based continuous assessment has significant potential to enhance the effectiveness of education across multiple levels of schooling.

AI Assessment Tools and Their Educational Implications

- Automated Grading Systems**
 - Grading quizzes and assignments
 - ▶ Faster feedback & consistent grading
- Learning Analytics Platforms**
 - Monitoring student engagement
 - ▶ Early identification of struggling learners
- Adaptive Testing Systems**
 - Personalized assessments
 - ▶ Accurate skill measurement
- Intelligent Feedback Systems**
 - Instant feedback & suggestions
 - ▶ Improved student learning
- Predictive Analytics Models**
 - Identifying at-risk students
 - ▶ Early intervention & support
- Content Recommendation Systems**
 - Targeted learning resources
 - ▶ Personalized learning pathways



Enhancing Education with AI-Powered Assessment Tools

Figure 3: AI Assessment Tools and Their Educational Implications

Figure 3 gives a brief look at some of the important AI assessment tools and their implications for education, and how such technologies could revolutionise teaching and learning. Automated Grading Systems Automated grading systems take advantage of machine learning algorithms to grade a structured response, which will allow faster, more consistent grading, freeing up teachers to focus on higher-order instruction tasks. Learning analytics platforms are used to collect data and analyse the students' data to understand the engagement patterns and performance trends of the students, enabling educators to take data-driven interventions and give support to students who may be struggling with their studies. Adaptive testing systems adjust difficulty levels based on the system's assessment of the student's performance and ensure that testing is appropriately challenging and accurately reflects student competence. Intelligent feedback systems provide instant and tailored feedback, resulting in continuous improvement and reinforcement of learning. Predictive analytics models help identify students who are at risk of failing and can then be seen to intervene with in order to increase retention and success. Finally, content recommendation systems aided with AI foster personalised learning content and allow students to follow unique learning paths leading to mastery while fostering more effective, self-directed learning experiences. This table shows a visualisation of the integration of AI in education, both evaluative and instructional, which includes the potential of AI to improve learning outcomes.

Challenges and Ethical Issues

Despite the great opportunities that come with AI-based continuous assessment, the process of incorporating artificial intelligence into educational assessment systems also brings along a number of challenges and ethical issues. Addressing these issues is critical to ensuring that AI technologies are used to support equitable, transparent, and responsible assessment practices.

Algorithmic Bias

One key challenge is the potential for bias in algorithmic AI assessment systems. Machine learning algorithms are trained on historical datasets, and if these datasets are biased or disproportionate, the resulting AI models may be biased. In educational contexts, biased algorithms may disadvantage some groups of students by making inaccurate predictions about their performance or unfair decisions about their grades (Boateng & Boateng, 2025). Ensuring fairness and transparency in AI algorithms and in AI-based assessment systems, therefore, becomes a key issue in the development of such systems.

Data Privacy and Security

AI-supported continuous assessment relies to a large extent on the collection and analysis of large volumes of learner data. These datasets often contain sensitive information related to students' academic performance, behavioural patterns and engagement levels. Without the right safeguards, the storage and processing of such data could lead to privacy violation concerns and unauthorised

access. Educational institutions must therefore have robust data protection measures in place to ensure that student information is kept confidential and secure (Folorunso et al., 2024).

Over-reliance on Technology

Another potential challenge with AI-ordered assessment systems is the threat of excessive reliance on technology. While AI can be used to assist in the evaluation process of education, over-reliance on automated systems may diminish the importance of professional judgment in evaluation processes. Teachers are key to interpreting student performance, understanding the contextual elements of learning, and providing emotional support that technological systems cannot replicate in detail. Maintaining an appropriate balance between the power of human expertise and the aid of technology is therefore key to effective educational evaluation.

Equity and Access to AI Tools

The implementation of technologies that support AI-based assessment might also cause concerns about equity and access. Educational institutions with limited technological infrastructure may have a hard time implementing sophisticated AI systems, which could also lead to a widening disparity between well-resourced and under-resourced educational institutions. Students living in areas of the world with limited internet access or digital resources may be disadvantaged in AI-supported learning environments (Kim & Danilina, 2025). Addressing these inequalities requires policy interventions that aim at providing equitable access to digital technologies.

Teacher Digital Competence

The effective use of AI-driven assessment systems certainly relies heavily on the digital competence of the teachers. Educators will need the skills needed to interpret learning analytics data, manage AI-supported platforms, and incorporate the technology tools into instructional practice. Without proper training, it may be challenging for teachers to make the most out of the capabilities of AI-based assessment systems. Professional development programs focused on improving teachers' digital literacy are thus a necessary part of the successful integration of AI in education.

Step-by-Step Guide for Implementing the AI-Driven Adaptive Continuous Assessment Model

Table 3: Step-by-Step Implementation of the AI-Driven Adaptive Continuous Assessment Model (AIDACAM)

Implementation Stage	Key Activities	Expected Educational Outcomes	Potential Challenges	Strategies for Overcoming Challenges
1. Establish Digital	Teachers adopt learning management systems	Creation of a digital ecosystem where learning	Limited technological infrastructure,	Begin with simple platforms, provide institutional ICT

Assessment Infrastructure	(e.g., Moodle, Canvas, Google Classroom) and AI-supported learning platforms to host instructional materials, assessments, and student interactions.	activities and assessment data can be automatically recorded and analysed.	lack of institutional support, and inadequate teacher digital skills.	support, organize teacher professional development workshops on digital assessment tools.
2. Design Continuous Digital Assessment Activities	Teachers develop frequent formative assessments such as quizzes, assignments, reflective journals, projects, and peer assessments aligned with learning objectives.	Continuous monitoring of student progress and improved alignment between assessment and learning outcomes.	Increased workload in developing multiple assessment tasks and maintaining assessment quality.	Utilise AI-generated question banks, reuse existing assessment materials, and apply automated grading tools for objective assessments.
3. Implement Learner Data Collection	Student interactions with learning systems are captured through quiz scores, assignment submissions, participation levels, time spent on learning tasks, and engagement with digital materials.	Generation of comprehensive learner performance datasets that enable detailed learning analysis.	Concerns regarding data privacy, data misuse, and ethical management of student information.	Use secure institutional platforms, establish data protection policies, inform students about data usage, and ensure compliance with ethical research standards.
4. Utilise AI-Based Learning Analytics	AI algorithms analyse collected data to identify patterns in student learning behaviour, engagement levels, and conceptual difficulties.	Teachers obtain actionable insights into student learning progress and instructional effectiveness.	Difficulty interpreting complex analytics dashboards and limited teacher data literacy.	Provide training on learning analytics interpretation and encourage collaboration with instructional technology experts.
5. Introduce Adaptive Assessment Mechanisms	AI-supported systems dynamically adjust the difficulty level of assessment questions according to student performance.	More accurate measurement of student competence and improved personalisation of assessment experiences.	Potential algorithmic bias and overreliance on automated assessment decisions.	Maintain teacher oversight, periodically review automated results, and ensure fairness in algorithmic evaluation processes.

6. Provide Personalised Feedback	AI-generated feedback offers individualised guidance, highlighting errors, suggesting learning resources, and recommending improvement strategies.	Faster learning improvement through immediate and targeted feedback.	Risk that automated feedback may lack contextual depth or reduce teacher-student interaction.	Combine AI-generated feedback with teacher commentary and encourage reflective dialogue between teachers and learners.
7. Use Instructor Dashboards for Decision-Making	Teachers analyse visualised learning analytics to monitor class performance, identify struggling learners, and modify teaching strategies accordingly.	Data-driven instructional practices that enhance learning effectiveness and early intervention for at-risk students.	Teachers may feel overwhelmed by large volumes of analytics data.	Focus on key indicators initially and provide professional training in educational data interpretation.
8. Promote Responsible AI Use Among Students	Teachers educate students on the ethical use of AI, academic integrity, and responsible engagement with AI-assisted learning tools.	Development of responsible digital learners capable of using AI technologies ethically.	Risk of academic dishonesty and excessive reliance on AI tools for completing academic tasks.	Introduce AI literacy education and establish institutional policies regarding ethical AI use in learning environments.
9. Evaluate and Improve the Assessment System	Teachers continuously review assessment outcomes, gather student feedback, and refine AI-supported assessment practices.	Continuous improvement of the assessment system and enhanced alignment with educational goals.	Resistance to change and limited institutional support for innovation.	Promote collaborative professional learning communities and institutional policies supporting educational innovation.

The successful implementation of the AI-Driven Adaptive Continuous Assessment Model requires balancing technological innovation and good pedagogy. While the use of artificial intelligence provides a whole range of powerful tools to improve the efficiency, personalisation, and data-driven approach of assessment and instruction, human judgment is fundamental to ensuring fairness, ethical responsibility, and meaningful learning experiences.

When teachers take a gradual and reflective approach to implementation, artificial intelligence-driven promotions for continuous assessment can dramatically improve how we evaluate education by turning assessment into a continuous process that supports learning, rather than simply judging learning.

Implications of Educational Practice

The transformation of continuous assessment through artificial intelligence has important implications for educators, curriculum developers, policymakers and students. This required teachers to develop digital assessment literacy that will help them make good use of AI-based tools for monitoring student learning. This involves understanding learning analytics, interpreting performance data, and using adaptive assessment platforms to support instructional decision-making. Curriculum developers must include strategies for integrating AI into the assessment framework. Learning outcomes should focus on competencies such as critical thinking, problem solving, or digital literacy, which can be properly assessed in AI-supported assessment systems. Educational policymakers need to set the regulatory structures for the ethical and responsible use of artificial intelligence in assessment. Policies should cover issues such as data protection, algorithm transparency, and equitable access to AI technologies. Students must be led to use AI technologies responsibly and ethically. Educational institutions, on their part, should encourage digital ethics, academic integrity, and critical awareness of AI tools so that learners make use of these technologies as supports to their learning, rather than as shortcuts to academic work.

Conclusion

The introduction of artificial intelligence for continuous assessment systems is a radical change in the evaluation of education. AI technologies provide opportunities to create adaptive, personalised, and data-driven assessment environments that can improve the quality of feedback delivery, facilitate instructional decision-making, and support learning improvement. At the same time, attention must be paid to ethical issues, technology equity, and the professional development of educators to ensure the successful implementation of AI-based assessment. By embracing balanced strategies that integrate technological innovation with sound pedagogical principles, educational institutions can unlock the potential of artificial intelligence to develop more responsive and effective assessment systems to shape the future of learning.

Recommendations

- i. Integrate AI-based assessment tools gradually within existing educational systems.
- ii. Provide continuous professional development to enhance teachers' digital and data literacy.
- iii. Establish clear ethical guidelines addressing data privacy, security, and algorithmic fairness.
- iv. Combine AI-driven assessment with human judgment to maintain validity and contextual understanding.
- v. Invest in digital infrastructure to ensure equitable access to AI-supported learning environments.
- vi. Promote the use of adaptive and personalized assessment strategies to support diverse learners.
- vii. Encourage the use of learning analytics for data-driven instructional decision-making.
- viii. Develop institutional policies that support responsible and transparent AI implementation.
- ix. Foster student awareness of ethical AI use and academic integrity.

- x. Support ongoing research to evaluate the effectiveness and impact of AI-driven assessment systems.

Reference

- Ajogbeje, O. (2023). Enhancing Classroom Learning Outcomes: The Power of Immediate Feedback Strategy. *International Journal of Disabilities Sports and Health Sciences*. <https://doi.org/10.33438/ijdsbs.1323080>.
- Álvarez, C., Falkner, N., Kinnunen, P., Savelka, J., & Zhang, L. (2025). Show Me the Mastery Learning! Obstacles to Adoption and Opportunities for New Solutions. *Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education V. 1*. <https://doi.org/10.1145/3724363.3729104>.
- Alordiah, C. (2025). Enhancing Learning Outcomes through Formative Assessments in Africa: A Systematic Review of Practices, Challenges, and Opportunities. *E-Kafkas Journal of Educational Research*, 12(2), 592-615. <https://doi.org/10.30900/kafkasegt.1630814>
- Alordiah, C. O., & Okoro, F. O. (2018). Formative Assessment: A catalyst for effective learning during classroom instruction. *African Journal of Curriculum and Instructional technology (AJCIT)*, 2(1), 52-60.
- Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming Education: A Comprehensive Review of Generative Artificial Intelligence in Educational Settings through Bibliometric and Content Analysis. *Sustainability*. <https://doi.org/10.3390/su151712983>.
- Boateng, O., & Boateng, B. (2025). Algorithmic bias in educational systems: Examining the impact of AI-driven decision making in modern education. *World Journal of Advanced Research and Reviews*. <https://doi.org/10.30574/wjarr.2025.25.1.0253>.
- Botelho, A., Baral, S., Erickson, J., Benachamardi, P., & Heffernan, N. (2023). Leveraging natural language processing to support automated assessment and feedback for student open responses in mathematics. *J. Comput. Assist. Learn.*, 39, 823-840. <https://doi.org/10.1111/jcal.12793>.
- Broughan, C., & Prinsloo, P. (2019). (Re)centring students in learning analytics: in conversation with Paulo Freire. *Assessment & Evaluation in Higher Education*, 45, 617 - 628. <https://doi.org/10.1080/02602938.2019.1679716>.
- Calderon, K., Serrano, N., Blanco, C., & Gutierrez, I. (2023). Automated and continuous assessment implementation in a programming course. *Computer Applications in Engineering Education*, 32. <https://doi.org/10.1002/cae.22681>.

- Chen, A., Zhang, Y., Jia, J., Liang, M., Cha, Y., & Lim, C. (2024). A systematic review and meta-analysis of AI-enabled assessment in language learning: Design, implementation, and effectiveness. *J. Comput. Assist. Learn.*, 41. <https://doi.org/10.1111/jcal.13064>.
- Choi, Y., & McClenen, C. (2020). Development of Adaptive Formative Assessment System Using Computerized Adaptive Testing and Dynamic Bayesian Networks. *Applied Sciences*. <https://doi.org/10.3390/app10228196>.
- Creagh, S., Thompson, G., Mockler, N., Stacey, M., & Hogan, A. (2023). Workload, work intensification and time poverty for teachers and school leaders: a systematic research synthesis. *Educational Review*, 77, 661 - 680. <https://doi.org/10.1080/00131911.2023.2196607>.
- Deepshikha, D. (2025). A systematic review on the future of educational assessment: AI-driven grading and personalised feedback in higher education. *Artificial Intelligence in Education*. <https://doi.org/10.1108/aiie-03-2025-0036>.
- Ding, G., Li, M., Li, S., & Wu, H. (2024). Exploring the impact of feedback timing on student performance in online testing. *Asia Pacific Education Review*, 26, 303 - 315. <https://doi.org/10.1007/s12564-024-10024-z>.
- Folorunso, A., Adewumi, T., Adewa, A., Okonkwo, R., & Olawumi, T. (2024). Impact of AI on cybersecurity and security compliance. *Global Journal of Engineering and Technology Advances*. <https://doi.org/10.30574/gjeta.2024.21.1.0193>.
- Francis, N., Jones, S., & Smith, D. (2025). Generative AI in Higher Education: Balancing Innovation and Integrity. *British Journal of Biomedical Science*, 81. <https://doi.org/10.3389/bjbs.2024.14048>.
- Fynn, A., & Mashile, E. (2022). Continuous Online Assessment at a South African Open Distance and e-Learning Institution. , 7. <https://doi.org/10.3389/feduc.2022.791271>.
- Halkiopoulos, C., & Gkintoni, E. (2024). Leveraging AI in E-Learning: Personalized Learning and Adaptive Assessment through Cognitive Neuropsychology—A Systematic Analysis. *Electronics*. <https://doi.org/10.3390/electronics13183762>.
- Hamal, O., Faddouli, N., Harouni, M., & Lu, J. (2022). Artificial Intelligent in Education. *Sustainability*. <https://doi.org/10.3390/su14052862>.
- Hauer, K., Park, Y., Bullock, J., & Tekian, A. (2023). “My Assessments Are Biased!” Measurement and Sociocultural Approaches to Achieve Fairness in Assessment in Medical Education. *Academic Medicine*, 98, S16 - S27. <https://doi.org/10.1097/acm.0000000000005245>.

- Jiao, P., Fan, O., Zhang, Q., & Alavi, A. (2022). Artificial intelligence-enabled prediction model of student academic performance in online engineering education. *Artificial Intelligence Review*, 55, 6321 - 6344. <https://doi.org/10.1007/s10462-022-10155-y>.
- Kaldaras, L., Haudek, K., & Krajcik, J. (2024). Employing automatic analysis tools aligned to learning progressions to assess knowledge application and support learning in STEM. *International Journal of STEM Education*, 11. <https://doi.org/10.1186/s40594-024-00516-0>.
- Kim, J., & Danilina, E. (2025). Towards inclusive and equitable assessment practices in the age of GenAI: Revisiting academic literacies for multilingual students in academic writing. *Innovations in Education and Teaching International*, 62, 1593 - 1597. <https://doi.org/10.1080/14703297.2025.2456223>.
- Kooli, C., & Yusuf, N. (2024). Transforming Educational Assessment: Insights Into the Use of ChatGPT and Large Language Models in Grading. *International Journal of Human-Computer Interaction*, 41, 3388 - 3399. <https://doi.org/10.1080/10447318.2024.2338330>.
- Leong, W. (2025). AI-Powered Classroom Monitoring: Enhancing Learning Environments. *2025 IEEE International Conference on Consumer Electronics - Taiwan (ICCE-Taiwan)*, 251-252. <https://doi.org/10.1109/icce-taiwan66881.2025.11207887>.
- López-Meneses, E., López-Catalán, L., Pelicano-Piris, N., & Mellado-Moreno, P. (2025). Artificial Intelligence in Educational Data Mining and Human-in-the-Loop Machine Learning and Machine Teaching: Analysis of Scientific Knowledge. *Applied Sciences*. <https://doi.org/10.3390/app15020772>.
- Mahamuni, A., P., & Tonpe, S. (2024). Enhancing Educational Assessment with Artificial Intelligence: Challenges and Opportunities. *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, 1, 1-5. <https://doi.org/10.1109/ickecs61492.2024.10616620>.
- Manoharan, S. (2019). Cheat-resistant multiple-choice examinations using personalization. *Comput. Educ.*, 130, 139-151. <https://doi.org/10.1016/j.compedu.2018.11.007>.
- Mao, J., Chen, B., & Liu, J. (2023). Generative Artificial Intelligence in Education and Its Implications for Assessment. *TechTrends*, 68, 58 - 66. <https://doi.org/10.1007/s11528-023-00911-4>.
- Mishra, N. (2023). Constructivist Approach to Learning: An Analysis of Pedagogical Models of Social Constructivist Learning Theory. *Journal of Research and Development*. <https://doi.org/10.3126/jrdn.v6i01.55227>.

- Naseer, F., Khan, M., Tahir, M., Addas, A., & Aejaz, S. (2024). Integrating deep learning techniques for personalized learning pathways in higher education. *Heliyon*, 10. <https://doi.org/10.1016/j.heliyon.2024.e32628>.
- Oji, J., & Alordiah, C. O. (2024). Developing the Innovation and Creativity Assessment Model (ICAM): A Framework for Enhancing Entrepreneurial Studies. *NIGERIAN JOURNAL OF PSYCHOLOGY*, 24(2), 1-15. <https://npa-journals.org/wp-content/uploads/2024/10/NJP-2024-Vol-24-Issue-2-Formatted-Unidel-1-Developing-the-Innovation-and-Creativity-Assessment-Model-ICAM-1.pdf>
- Okunbor, D., & Alordiah, C. (2025). Toward a Critical Pedagogy of Music Assessment in Nigeria: Unpacking the Hegemonic Structures of Music Education and their Implications for Assessment. *NIU Journal Of Humanities*, 10(2), 215-226. <https://doi.org/10.58709/niujhu.v10i2.2221>
- Rincón, Y., Munárriz, A., & Ruiz, A. (2024). A new approach to continuous assessment: Moving from a stressful sum of grades to meaningful learning through self-reflection. *The International Journal of Management Education*. <https://doi.org/10.1016/j.ijme.2024.101072>.
- Sánchez-Ruiz, L., Moll-López, S., Morano-Fernández, J., & Roselló, M. (2021). Dynamical Continuous Discrete Assessment of Competencies Achievement: An Approach to Continuous Assessment. *Mathematics*. <https://doi.org/10.3390/math9172082>.
- Topping, K., Gehringer, E., Khosravi, H., Gudipati, S., Jadhav, K., & Susarla, S. (2025). Enhancing peer assessment with artificial intelligence. *International Journal of Educational Technology in Higher Education*, 22. <https://doi.org/10.1186/s41239-024-00501-1>.
- Vahed, A., Walters, M., & Ross, A. (2021). Continuous assessment fit for purpose? Analysing the experiences of academics from a South African university of technology. *Education Inquiry*, 14, 267 - 283. <https://doi.org/10.1080/20004508.2021.1994687>.
- Van Orman, D., Gotch, C., & Carbonneau, K. (2024). Preparing Teacher Candidates to Assess for Learning: A Systematic Review. *Review of Educational Research*, 95, 427 - 463. <https://doi.org/10.3102/00346543241233015>.
- Winget, M., & Persky, A. (2022). A Practical Review of Mastery Learning. *American Journal of Pharmaceutical Education*, 86. <https://doi.org/10.5688/ajpe8906>.
- Xavier, C., Rodrigues, L., Costa, N., Neto, R., Alves, G., Falcão, T., Gašević, D., & Mello, R. (2025). Empowering Instructors With AI: Evaluating the Impact of an AI-Driven Feedback Tool in Learning Analytics. *IEEE Transactions on Learning Technologies*, 18, 498-512. <https://doi.org/10.1109/tlt.2025.3562379>.

Xia, Q., Weng, X., Fan, O., Lin, T., & Chiu, T. (2024). A scoping review on how generative artificial intelligence transforms assessment in higher education. *International Journal of Educational Technology in Higher Education*, 21, 1-22. <https://doi.org/10.1186/s41239-024-00468-z>.

Yaseen, H., Mohammad, A., Ashal, N., Abusaimh, H., Ali, A., & Sharabati, A. (2025). The Impact of Adaptive Learning Technologies, Personalized Feedback, and Interactive AI Tools on Student Engagement: The Moderating Role of Digital Literacy. *Sustainability*. <https://doi.org/10.3390/su17031133>.