Integrating Artificial Intelligence to support Online Assessment in Higher Education: Opportunities and Challenges for Cognitive and Practical Learning

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Abstract. Artificial intelligence (AI) has profoundly transformed online assessment systems in higher education by making assessment practices more personalized, adaptive, and contextual. This article highlights the opportunities and challenges presented by AI-based online assessment, focusing on two complementary dimensions: cognitive assessment and authentic assessment. The first dimension focuses on modeling learners' mental processes through the analysis of responses, learning traces, and interaction patterns, enabling adaptive systems to generate personalized feedback, support metacognitive regulation, and ensure timely remediation. The authentic dimension emphasizes the assessment of skills in realistic or simulated professional contexts, where learners' actions and decisions provide rich evidence of procedural and relational skills. While these approaches offer promising prospects for improving validity and learner engagement, they also raise major methodological and ethical challenges related to reliability, fairness, transparency, and data protection. This contribution analyzes these challenges and proposes design principles for robust, ethical, and inclusive AI-based online assessment systems aligned with the skills required at the institutional, academic, and professional levels in the 21st century.

1 Introduction

The assessment of learning outcomes is one of the foundations of any educational system. It plays a critical role in regulating and optimizing learning by providing accurate information on the level of mastery of the knowledge, skills, and attitudes targeted by a program. Far from being limited to a simple act of measurement, it is part of a comprehensive educational support approach, where each result obtained is an indicator to guide educational decisions. From this perspective, assessment fulfills several functions: diagnostic, to identify prerequisites and gaps before learning; formative, to regulate the course of study; and summative, to attest to and certify learning outcomes at the end of the program.

From a pedagogical point of view, assessment aims to provide reliable indicators of learners' achievements and difficulties. This information can be used to regulate teaching, adapt activities, differentiate learning paths, and support the individualization of learning[1]. It therefore contributes to educational success by providing a feedback loop that guides the actions of both teachers and learners. For example, when a teacher identifies a widespread difficulty in a class (such as understanding a scientific concept), they can readjust their teaching approach.

From another technological perspective, digital environments and adaptive algorithms now make it possible to implement scalable educational scenarios capable of simulating real exam conditions and offering differentiated learning paths. However, the effectiveness of these systems depends on the quality of the content, the transparency of the algorithms, and coordination with human support, which remains essential [2].

This article provide an analysis of the contributions of artificial intelligence to online assessment learning, focusing on the opportunities it offers for enhancing exam preparation. After reviewing the evolution of assessment practices and the areas where AI is applied, we examine the technologies used and their pedagogical implications for measuring students' actual learning outcomes. Finally, special attention is given to the challenges and limitations associated with integrating AI.

2 The reconfiguration of online learning assessment through AI

2.1 From traditional assessment to online assessment

Advances in educational technology have led to a gradual transformation in assessment methods: from paper-and-pencil exams to digital tools (multiple-choice questions, online quizzes, platform-based exams). Online assessment has brought undeniable advantages: accessibility, speed of correction, traceability of interactions, and reduced logistical constraints.

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However, this transition remains largely a digitization of traditional practices, without any radical change in substance. Tasks often remain fixed, feedback standardized, and the role of the teacher remains central in the design and interpretation of results.

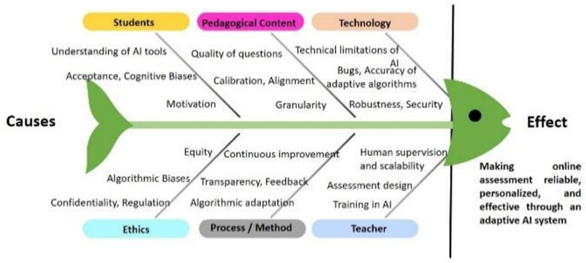

Fig. 1. Ishikawa cause-and-effect diagram : Systemic analysis of success factors for adaptive assessment based on AI

To move from simple digitization to a truly adaptive AI-based system, a systemic analysis of the success factors is required. Figure 1 (Ishikawa diagram) maps this transition by identifying the "Effect" (a reliable and personalized assessment) and its six categories of "Causes":

- **Human Factors:** The necessity of AI literacy for both students and teachers.
- **Pedagogical & Process:** The quality of question granularity and feedback loops.
- **Technical & Ethical:** The balance between algorithmic robustness and data transparency.

This model demonstrates that the effectiveness of AI assessment depends on the synergy between pedagogical quality, ethical regulation, and technical performance, rather than just the algorithm itself.

2.2 AI technologies supporting assessment

The integration of artificial intelligence into learning assessment relies on a set of complementary technologies, each of which contributes in its own way to making systems smarter, more adaptive, and more contextualized. Among these technologies, four major approaches stand out: machine learning, deep learning, natural language processing (NLP) with large language models (LLMs), and finally Retrieval-Augmented Generation (RAG) systems.

2.2.1 Machine learning et prédiction des performances

Machine learning (ML) is a key technology in educational AI. By analyzing historical student data (results, response times, revision paths), algorithms learn to predict future performance or identify at-risk students. These predictions enable personalized educational interventions and adaptive assessments tailored to individual levels.

For example, systems such as ALEKS and Squirrel AI use machine learning to offer scalable assessment pathways. Derakhshan shows that learning analytics-based tools can reduce anxiety among language learners while increasing their performance through feedback based on learning models [3].

For example, in a study by Du Plooy, personalized adaptive learning was shown to be effective in improving academic performance and student engagement in higher education [4].

Similarly, Luo et al. (2025) pointed out that many AI tools in higher education rely on prediction models to recommend resources and adjust assessments [91]. These statistical approaches (regression, decision trees, SVM, random forests, Bayesian networks) make it possible to model the probability of success, propose “risk scores,” and guide students toward targeted remediation.

2.2.2 NLP and language models (LLM, GPT)

Natural language processing (NLP), and more specifically large language models (LLM, e.g. GPT-3, GPT-4, etc.), play a major role in automated text assessment. Thanks to these technologies, it is possible to analyze long responses, automatically detect conceptual errors and gaps in argumentation, and measure the syntactic and lexical complexity of a text. Correction systems such as Write & Improve, developed in collaboration with Cambridge University Press, use NLP to provide real-time feedback to learners. Finally, Zhao proposes a hybrid approach combining deep learning and fuzzy logic to evaluate linguistic production in English language learning, demonstrating increased effectiveness in detecting semantic and grammatical progress [5].

2.3 Current limitations of digital assessment tools without AI

Although digital devices have improved certain aspects of assessment, they still have critical weaknesses, particularly in three areas: excessive standardization, difficulty in capturing complex skills, and lack of real personalization.

- Excessive standardization: Closed formats (multiple choice, true/false, multiple choice) often dominate digital assessment. This choice leads to a homogenization of possible answers and limits the ability to assess critical thinking, creativity, or metacognitive skills. Furthermore, the continued use of these types of formats encourages “teaching to the test” rather than deep learning.
- Difficulty in capturing complex skills :Higher-order cognitive skills—such as analysis, synthesis, argumentation, or critical reasoning—are difficult to assess using simple automated formats. Open-ended responses, essays, and interdisciplinary projects require a detailed understanding of the content and contextual interpretation. In traditional digital practices, human correction is often unavoidable, which imposes constraints in terms of time, consistency, and subjectivity.
- Lack of real personalization: Even standard adaptive platforms generally rely on heuristic logic

or rigid thresholds. They do not always take into account the cognitive or strategic variability specific to each learner. The feedback provided remains generic (correct/incorrect), without offering personalized paths for progress.

These practices directly question the quality of assessments in online environments and limits the learner's ability to regulate their own learning effectively.

3 Cognitive Dimension of AI-Based Assessment

3.1 Trace analysis to identify gaps

One of the major contributions of AI is its ability to use digital traces (clicks, response times, browsing sequences, successive errors) to detect gaps in learning. By studying this data, machine learning models can identify recurring patterns of errors or areas of weakness in students. For example, in recent adaptive platforms, AI is able to pinpoint which sub-skills of a given subject the student has not mastered and suggest priority areas for review. According to arecent review of adaptive learning platforms, the use of these analyses can increase student results by approximately 62% compared to non-adaptive approaches.[6]

3.2 Clustering student profiles

Another technique involves applying automatic clustering/segmentation methods to group learners who exhibit similar behaviors or performance levels. These clusters can be used to define cognitive-strategic profiles, each of which can be associated with specific review paths or recommendations. For example, some students may be identified as "exploratory learners," while others may be identified as "repetitive learners," which guides the review methods (e.g., offering challenges, consolidation, or reactivation). Clustering combined with machine learning is widely used in intelligent tutoring systems to anticipate and personalize interventions.

3.3 Generating personalized recommendations

AI makes it possible to create tailored revision recommendations that take into account not only previous errors but also learning style, optimal difficulty level, and temporal context (e.g., spaced repetition, reactivation of forgotten concepts). Rather than giving generic feedback such as "this answer is wrong," AI could suggest: "Revisit the concept of..., review section 3.2 of the training, then complete exercise B or C to deepen your understanding." This capability is leveraged by many intelligent adaptive platforms to proactively guide learning[7].

3.4 Real-time progress tracking

With the help of AI, adaptive revision can become a dynamic process, capable of constantly adapting the student's learning path based on their current performance. The system has the ability to readjust the level of difficulty, reintroduce neglected or poorly mastered concepts (through spaced repetition), or focus attention on areas that still need improvement. This continuous monitoring provides constant formative feedback, transforming revision into a continuous adaptive process rather than a series of fixed sessions. The concept of feedback loops is at the core of this method.

4 Authentic Assessment Supported by AI

4.1 Operational definitions and terminology

Authentic assessment is characterized as a process aimed at measuring students' skills and knowledge in contexts that mimic real-world scenarios. In the context of remote assessment of technical skills, its principles play a central role, as they support pedagogical approaches that accurately reflect the challenges and conditions of the professional world. They are based on the design of engaging learning experiences, involving complex and meaningful tasks, often supported by advanced technologies that simulate credible professional environments.

In this context, authentic assessment appears to be an innovative alternative capable of bringing assessment tasks closer to professional practices, thereby promoting more meaningful and sustainable skills learning.

However, transposing this approach to a remote environment requires careful consideration of the methods, tools, and metrics to be used in order to ensure both the credibility of the results and fairness for learners. In this regard, educational and techno-educational engineering provides a relevant framework for designing an appropriate conceptual model that integrates the principles of authenticity, adaptability, and personalization. Artificial intelligence enriches this dynamic by enabling detailed analysis of learning traces, real-time adaptation of learning paths, and more effective regulation of the assessment process.

4.2 Validity and Reliability in Authentic AI-Based Assessment

Authentic assessment aims to evaluate students not on isolated exercises, but on tasks that are close to real-life professional or social situations: projects, case studies, simulations, portfolios, debates. AI, particularly through language models and RAG systems, can design or adapt this type of task, taking into account the learner's context, available resources, and time constraints. In other words, AI makes it possible to generate assessments that are not constrained by a fixed format, are more open and more complex, while ensuring that they are corrected or reviewed. Several recent studies have linked AI and authenticity in assessment, emphasizing that AI can go beyond simple grading to offer reflective guidance.

5 Ethical and Methodological Challenges

The integration of artificial intelligence into online assessment systems raises profound ethical, methodological, and societal questions that extend beyond technical performance. These challenges must be addressed explicitly to ensure that AI-enhanced assessment remains pedagogically legitimate, socially acceptable, and legally compliant.

5.1 Algorithmic Bias and Fairness

AI algorithms depend on historical data to “learn” patterns, which makes them susceptible to perpetuating and amplifying biases present in that data. In an educational context, this can result in assessments that disadvantage certain groups of students (based on gender, socioeconomic background, native language, disability, etc.). For example, Automated Essay Scoring (AES) systems have shown discriminatory biases based on a student's socioeconomic status or native language when the model is calibrated on predominantly homogeneous corpora [8].

These algorithmic biases can threaten the fairness of assessment and reinforce existing inequalities. Recent work highlights that “algorithmic justice” in education systems remains an unresolved challenge, particularly due to the difficulty of defining a concept of ‘fairness’ that is applicable to all educational contexts . The danger is that decisions that appear “neutral” but reproduce structural discrimination are given technological legitimacy.

5.2 Ethical values and data protection

The use of AI in assessment involves collecting, storing, and analyzing large amounts of sensitive data about students (background, results, learning records, biometric indicators). This raises several ethical issues:

- Confidentiality and privacy: It is necessary to ensure that data is properly anonymized or pseudonymized, to comply with protection standards (e.g., GDPR in Europe), and to limit collection to what is strictly necessary.
- Informed consent: Students must be informed about the uses of AI, the data collected, and the implications; they must be able to accept or refuse (opt-out).
- Responsible use: AI should not be used for intrusive or punitive surveillance, but to support learning. Georgieva & Stuart emphasize that any deployment of AI in higher education should be based on a clear ethical framework, with principles of transparency, accountability, and respect for learner autonomy [9].
- Data security: Systems must include security mechanisms to prevent leaks, intrusions, or misuse of sensitive data.

One challenge that is often mentioned is the conflict between transparency and privacy: providing explanations that are accessible to users while preserving the confidentiality of training data or algorithms.

5.3 Transparency, Explainability and Trust

One of the most critical obstacles to the acceptance of AI in education is its opacity. Complex models (particularly in deep learning and LLM) are often black boxes, making it difficult to explain their decisions. However, in an assessment context, stakeholders (students, teachers, academic leaders) demand understandable justification.

The field of Explainable AI (XAI) attempts to address this opacity by developing methods to expose the model's logic, weightings, or decision variables. A recent systematic review in 2025 on XAI in education identifies more than 60 challenges, including the lack of standardized definitions, the difficulty of explaining complex models without excessive simplification, and the tension between performance and explainability[10].

In the academic context, a survey showed that 36.9% of professors consider that the AI systems used lack transparency, which generates mistrust [11]. To build trust, it is therefore essential to incorporate mechanisms for auditability, traceability, and explanatory feedback, where users can understand why a grade or feedback has been assigned to them.

5.4 The new role of teaching staff in the face of AI: ethical issues

The introduction of AI into assessment should not lead to the marginalization of the role of teaching staff, but rather to a redefinition of that role. In this regard, several challenges arise:

- Human supervision (human-in-the-loop): even the most advanced systems must provide for human control over critical decisions. Teachers can verify, correct, or moderate the results generated by AI. Certain socio-emotional skills (creativity, critical thinking, engagement) remain difficult to assess in a fully automated manner, which justifies the need for hybrid co-assessment, incorporating human judgment.
- New skills: teachers will need to acquire AI literacy skills, understand algorithmic principles, interpret model results, and address biases or anomalies.
- Acceptability and trust: Teachers can serve as mediators, explaining how AI works to students, detecting potential errors or deviations, and reassuring them about the legitimacy of the system.
- Dependence on AI tools: It will be necessary to clearly define who is responsible when the system makes a mistake—the teacher, the model designer, or the institution. Excessive delegation that can

compromise the autonomy of teachers and institutions. The study by Li et al. shows that in some academic contexts, teachers end up adapting their teaching methods and assessment grids to the capabilities of the AI platform used, rather than according to their own professional criteria[12]. This raises concerns about the loss of pedagogical control in favor of a techno-centric model.

5.5 Institutional and regulative positioning of artificial intelligence in learning assessment in Morocco

The effectiveness of Morocco's governance framework for artificial intelligence applied to learning assessment is based on the consistency between three complementary dimensions:

- Moroccan legal framework: represented by Law No. 09-08 on the protection of personal data and the National Commission for the Control of Personal Data Protection (CNDP), which guarantees the transparency, legality, and security of digital processing[13].
- Institutional framework: embodied by bodies such as the ANEAQ (National Agency for Evaluation and Quality Assurance) and the National Evaluation Authority of the Higher Council for Education, Training, and Scientific Research, which play a role in supporting Moroccan higher education institutions, backed by the strategic guidelines of the 2030 Strategic Vision, the 2026 Roadmap, and the ESRI Pact, which aim to establish a culture of regulated innovation, quality assurance, and digital sovereignty [12].
- International framework: promoted by UNESCO through its reference framework on AI in education, the OECD and the European Union, through its AI Act currently being rolled out, provides for specific obligations on the use of AI in high-risk services, including education[14].

These international standards are gradually influencing regulatory thinking in Morocco and promoting the harmonization of AI-assisted assessment practices.

This three-pronged approach places Moroccan ethical thinking in a global context, where data protection and the governance of educational AI appear to be essential conditions for the legitimacy and sustainability of online assessment practices.

6 Conclusion and Perspectives

Exploring learning assessment in the age of artificial intelligence has highlighted the transformative potential of these technologies in higher education. AI goes far beyond simply digitizing assessment practices: it introduces a dimension of adaptive intelligence, capable of detecting learners' needs, individualizing learning paths, generating relevant and instant feedback, and ensuring greater equity through automation and the reduction of grading biases. The technologies used, whether machine learning, deep learning, language models (LLMs), or hybrid approaches such as Retrieval-Augmented Generation, offer a rich arsenal for rethinking assessment from a more authentic, formative, and contextualized perspective.

Ultimately, the contributions of artificial intelligence are not limited to the cognitive assessment of intellectual knowledge and skills, but also extend to the practical and procedural assessment of know-how. AI thus makes it possible to cover the entire assessment spectrum: from written work to experimental manipulations, from online exams to integrated practical work. This dual capability confirms the relevance of AI as a lever for the overall transformation of assessment, enabling a more comprehensive, integrated, and authentic approach to measuring learning.

However, these advances come with significant challenges, particularly related to algorithmic bias, the ethical issues of data protection, the lack of transparency of complex models, and the renewed role of the teacher. These limitations call for a cautious and responsible approach, where AI is designed as a support tool, not a substitute, in order to ensure the confidence of stakeholders and the validity of the assessment process. In short, AI opens up new possibilities for adaptive revision, transforming it into a powerful tool for augmented formative assessment, capable of supporting students in their learning and teachers in their practices, As we have presented in our previous work, which focused on the presentation of a plug-in architecture for adaptive revision for Moodle called “PER,” currently undergoing large-scale experimentation at the university level[15].

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