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Research Article

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Proposal for A Scale of Artificial Intelligence Integration in The Learning Assessment Process

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Abstract

The integration of artificial intelligence (AI) into education has garnered increasing interest, particularly in the personalization of learning pathways. However, its incorporation into the assessment of learning remains a largely unexplored domain, with limited documentation on the various levels of AI integration. To address this gap, this study has proposed a progressive AI integration scale for educational assessment, considering the perspectives of different stakeholders within the education system. Employing a mixed-methods approach, the research is based on 37 semi-structured interviews and 578 survey responses, analyzing AI's impact on both formative and summative assessment. The methodological framework has deconstructed the dimensions of school-based evaluation, allowing for an in-depth examination of the correlation between assessment types and the five levels of AI integration.

The findings revealed an evolving relationship between the degree of AI integration and the transformation of assessment practices. At levels 1 and 2, where AI is either absent or minimally integrated, formative assessment prevailed, with teachers maintaining full control over the evaluation process. AI played a marginal role, primarily assisting in the generation of exercises and structuring pedagogical recommendations. At level 3, where AI-educator collaboration emerges, formative assessment becomes more interactive and adaptive, enhanced by automated feedback and performance analysis. Concurrently, summative assessment begins to benefit from increased standardization, reducing subjective biases. Level 4 marks a pivotal shift, as AI takes on an active role in personalizing assessments—particularly summative evaluations—by tailoring tests to learners' competencies and optimizing performance analysis. Finally, at level 5, AI and learners engage in real-time interaction, fundamentally redefining the assessment framework. Formative assessment becomes continuous and fully adaptive, while summative assessment leverages advanced predictive analytics to refine academic decision-making.

This correlation highlights a progressive continuum in which AI enhances the interactivity and responsiveness of formative assessment while improving the precision and objectivity of summative evaluation. However, these advancements necessitate rigorous oversight to ensure fairness and reliability in assessment decisions.

The study underscores the importance of a gradual and well-regulated adoption of AI in learning assessment, striking a balance between automation and human supervision. It calls on educational institutions and policymakers to implement appropriate regulatory frameworks and specialized training programs to ensure an ethical and equitable integration of AI into pedagogical practices.

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1. Introduction

The rise of artificial intelligence (AI) technologies is profoundly transforming pedagogical practices, particularly in the domain of learning assessment. The automation of grading, the emergence of adaptive learning systems, and the increasing use of generative text models are reshaping traditional evaluation methods, prompting critical debates regarding the pedagogical, ethical, and methodological implications of these innovations [1,2].

AI holds significant potential for enhancing the efficiency and objectivity of assessments. Machine learning algorithms enable the real-time analysis of vast datasets, allowing for the adaptation of assessments to the specific needs of learners (Baker & Siemens, 2022) [3]. Likewise, automated grading tools and generative AI systems, such as natural language processing models, streamline the evaluation of written work and reduce the time required for manual corrections [4]. This automation facilitates immediate and personalized feedback, thereby strengthening pedagogical follow-up and fostering differentiated learning pathways [5].

However, this technological revolution raises critical challenges related to fairness, transparency, and academic integrity. On one hand, AI algorithms may introduce biases in assessment due to the datasets on which they are trained and the inherent limitations of their design [6]. On the other hand, the ability of generative AI models to produce complex content blurs the distinction between a student's original work and digital assistance, thus jeopardizing the validity of certification-based assessments [7]. These challenges highlight the pressing need for stringent oversight to ensure the reliability and authenticity of learning assessments.

Another major issue concerns the digital divide and unequal access to AI technologies. While some institutions benefit from advanced resources enabling seamless AI integration, others face obstacles related to insufficient teacher training, inadequate technological infrastructure, or socio-economic disparities among students [4]. The effective adoption of AI in education can only be realized if it is accompanied by strategies aimed at reducing these inequalities and ensuring equitable access to digital tools [8].

In light of these challenges, a fundamental question emerges: how can artificial intelligence be integrated into learning assessment while preserving fairness, transparency, and the validity of evaluative processes? This study proposes a progressive AI integration scale designed to facilitate a controlled and ethical transition toward digital assessments that meet both academic and institutional standards.

The objective is to develop a structured framework that regulates the use of AI in assessment according to multiple levels of integration, ranging from the complete exclusion of AI to an advanced collaboration between students and intelligent systems. Rooted in technology adoption models [9,10] and regulatory principles for digital assessment [7], this framework offers a balanced approach that reconciles pedagogical innovation with ethical safeguards.

This research draws upon a comprehensive analysis of AI-assisted assessment practices, employing a mixed-methods approach that combines theoretical examination, field surveys, and comparative studies of existing digital evaluation systems. Through this approach, the study aims to address concerns related to academic integrity, fairness, and data protection while leveraging AI's transformative potential to enhance the educational experience.

Ultimately, this research seeks to provide educational stakeholders—including teachers, researchers, academic institutions, and policymakers—with a structured reference framework to guide the gradual integration of AI into learning assessment. By ensuring a thoughtful and responsible adoption of intelligent technologies in education, this study aims to contribute to the development of a more equitable, transparent, and effective assessment paradigm.

2. Objectives

To analyze the cognitive, pedagogical, and socio-ethical implications associated with the integration of artificial intelligence (AI) into educational environments, with the goal of developing theoretical and empirical frameworks to promote the responsible and effective utilization of these technologies in educational contexts.

3. Methods

An extensive literature review was conducted by searching several academic databases, including ScienceDirect, SpringerLink, Google Scholar, Scopus, Web of Science, and Taylor & Francis Online, using the keywords "artificial intelligence" and "education." Employing a mixed-methods approach, the study drew upon 37 semi-structured interviews and analyzed responses from 578 questionnaires collected from relevant educational stakeholders. This methodology facilitated a rigorous examination of the impact of AI integration on formative and summative assessment practices within educational settings. Additionally, the chosen methodological framework allowed for a systematic deconstruction of various dimensions of school-based assessment, enabling an in-depth analysis of correlations between assessment types and five identified levels of AI integration.

4. Results

Findings indicate that integrating AI into formative and summative assessment processes significantly enhances the quality of pedagogical monitoring and optimizes feedback provided to learners. Additionally, data derived from interviews and questionnaires reveal increased teacher satisfaction, largely attributable to the automation of previously time-consuming, repetitive tasks. Finally, the analysis demonstrates a positive correlation between the level of AI integration and overall student performance, highlighting the substantial potential of these technologies in contemporary educational contexts.

5. Theoretical Framework of the Research

The integration of artificial intelligence (AI) into education is profoundly transforming learning and assessment processes. Advances in machine learning and natural language processing enable AI to automate grading, offer personalized learning pathways, and analyze student performance in real time [2]. However, this evolution raises critical concerns regarding academic integrity, fairness in assessment, and the transparency of algorithmic decision-making [6].

The rise of AI in educational environments is part of a broader digital transformation of teaching and learning systems, where digital tools play an increasingly central role in the regulation of learning processes and the certification of competencies [1]. This trend necessitates a thorough examination of the conceptual and theoretical frameworks that can structure a thoughtful and ethical integration of AI into assessment practices.

a. Conceptual Framework

Artificial intelligence (AI) applied to education operates through complex systems capable of analyzing learner interactions, predicting their progression, and adapting pedagogical frameworks in real time to their specific needs [3]. Learning assessment is a particularly fertile ground for AI integration, as it offers significant potential for automation, personalization, and optimization of evaluation processes. Several complementary approaches characterize AI integration in this domain, each contributing uniquely to the transformation of assessment practices.

First, automated grading algorithms represent one of the most widespread applications of AI in learning assessment. These systems leverage advanced natural language processing and supervised learning techniques to evaluate large volumes of written responses efficiently. Their implementation in dedicated digital platforms enables rapid assessment of exams, multiple-choice tests, and even structured essays based on predefined criteria [2]. While these technologies provide substantial time savings and standardize grading criteria, they also raise concerns about their ability to capture the complexity of argumentative reasoning and discursive competencies, particularly in disciplines requiring subjective and nuanced judgment.

Second, AI is increasingly employed to generate adaptive recommendations that tailor learning pathways according to prior student performance. These systems analyze responses and, using predictive models, suggest complementary exercises, targeted revisions, or individualized learning trajectories [1]. By harnessing large-scale data analytics, AI optimizes differentiated learning and enables personalized progress tracking. However, excessive reliance on these automated recommendations may inadvertently diminish students' autonomy and limit their ability to critically reflect on their own learning processes.

Finally, AI plays a crucial role in performance analysis and the prediction of academic outcomes. By leveraging data from multiple educational interactions, these systems can identify behavioral trends and anticipate the risk of dropout or academic failure [11]. However, this predictive capacity raises significant ethical concerns, particularly regarding algorithmic assignment, where students might be directed toward specific educational pathways based solely on predictive models. If not rigorously regulated, such an approach could exacerbate existing inequalities and undermine fairness in educational opportunities [7].

Thus, while AI extends beyond mere automation of assessments, it fundamentally reshapes how learning measurement is approached, emphasizing personalization, adaptability, and educational data analytics. Nevertheless, these innovations introduce major challenges related to the reliability of AI-generated assessments, the protection of sensitive learner data, and the transparency of the algorithms employed. Algorithmic biases, inherent to the datasets on which these systems are trained, pose a potential threat to both the equity and validity of school assessments [8]. Given these challenges, it is imperative to structure a comprehensive reflection on the integration of AI into learning assessment, ensuring both academic rigor and adherence to ethical educational practices.

b. Theoretical Framework

The adoption of artificial intelligence (AI) in learning assessment is shaped by a complex set of dynamics, necessitating a robust theoretical framework to analyze its determinants and implications. Several theoretical models help to elucidate this transition and evaluate how educational stakeholders perceive, accept, and integrate AI into assessment practices.

The Technology Acceptance Model (TAM), developed by Davis (1989) [9], serves as a foundational reference for understanding the factors influencing the acceptance of educational technologies. This model is based on two primary dimensions: perceived usefulness—the extent to which an individual believes that a technology enhances their effectiveness—and perceived ease of use—the degree to which they find the technology user-friendly [10]. The greater these perceptions, the higher the likelihood of adoption. Applied to AI in assessment, this model provides insight into the degree to which teachers and students embrace these innovations and how their perceptions shape their adoption. In the educational context, several studies have shown that reluctance to use AI-based assessment tools often stems from concerns about the transparency of algorithmic decisions and the reliability of automated grading [6]. Thus, the acceptance of these technologies is influenced not only by their perceived efficacy but also by the level of trust users place in them and the institutional support available to facilitate their implementation.

Another key model for analyzing the integration of educational technologies is the SAMR model (Substitution, Augmentation, Modification, Redefinition), proposed by Puentedura (2006) [12]. This framework describes the progressive stages of technology adoption in education, identifying four levels of integration.

1) Substitution represents the lowest level, where AI merely replaces an existing task without significantly altering the assessment process, such as automating multiple-choice test grading.
2) Augmentation introduces functional improvements, such as AI-generated personalized feedback on student work.
3) Modification marks a more substantial transformation of the assessment process, including predictive analytics and interactive evaluations based on adaptive learning simulations.
4) Redefinition entails a complete departure from traditional assessment methods, enabling entirely new approaches, such as AI-driven interactions with intelligent assistants that dynamically adapt assessments based on a student's competency level and learning style [4].

This model is particularly relevant for structuring a progressive AI integration scale in assessment, outlining the different phases that allow for a controlled transition toward more advanced and pedagogically meaningful AI applications.
However, the integration of AI into learning assessment cannot be envisaged without a rigorous ethical framework that ensures the validity, reliability, equity, and transparency of assessment processes. The fundamental principles of academic evaluation must be preserved, regardless of the level of automation introduced.

1. Validity refers to the extent to which an assessment accurately measures what it claims to assess, raising concerns about the alignment between algorithmic decisions and students' actual competencies.
2. Reliability implies the consistency and stability of assessment outcomes, which may be compromised by algorithmic biases or variations in AI model performance [3].
3. Equity is a central concern, as AI may inadvertently reinforce existing inequalities if machine learning models are trained on non-representative datasets.
4. Transparency in algorithmic decision-making is an essential ethical imperative: both teachers and students must be able to understand how and why a particular evaluation outcome was generated.

Recent research on Explainable Artificial Intelligence (XAI) highlights the critical need for traceability and interpretability of AI-driven decisions in assessment [1]. The challenge lies in avoiding the "black box" effect, where AI-generated results are opaque and difficult for end-users to interpret, potentially undermining trust in these tools. Establishing human validation protocols thus becomes a key requirement to maintain pedagogical oversight over AI-assisted assessments and mitigate potential risks associated with excessive automation.

By integrating these theoretical models—technology acceptance frameworks, progressive digital adoption approaches, and AI ethics principles—it becomes possible to develop a structured scale for AI adoption in assessment. Such an approach balances pedagogical innovation with essential academic safeguards, providing educational institutions with a reference framework to harness the potential of AI while mitigating associated risks. In this perspective, the implementation of a rigorous and adaptable methodological framework emerges as a necessity to ensure the thoughtful and responsible adoption of AI technologies in learning assessment.

6. Literature Review, Model, and Hypotheses

Literature Review

Recent literature has highlighted the transformative potential of artificial intelligence (AI) in learning assessment while it has also raised fundamental concerns regarding academic integrity, fairness, and the reliability of assessment processes. Several research avenues converge toward recognizing AI's ability to revolutionize evaluation methods, yet they also emphasize the need for rigorous oversight to prevent adverse consequences for both students and educators.

One of the most widely recognized benefits of AI in assessment is its capacity to personalize evaluations and provide immediate feedback. AI can tailor assessments to the specific needs of students by analyzing their performance in real time and adjusting content accordingly. This adaptive capability fosters a more individualized and engaging learning experience, offering students dynamic and interactive guidance. Additionally, AI-driven systems can deliver instant feedback, accelerating the grading process and reduces the time between assessment completion and result availability [2]. The immediacy of feedback serves as a powerful pedagogical lever, facilitating self-regulated learning and enhancing student motivation.

Another significant contribution of AI to assessment lies in the optimization of evaluative processes. The automation of grading, particularly for multiple-choice tests, grammar exercises, and certain mathematical evaluations, helps streamline teachers' workload. By leveraging machine learning algorithms, AI can analyze open-ended responses, extract relevant elements, and propose semi-automated assessments, freeing educators to focus on higher-value tasks such as personalized pedagogical support and the design of tailored learning strategies [7]. Furthermore, educational data analytics can identify learning trends, detect recurrent difficulties, and anticipate dropout risks, equipping educators with more sophisticated decision-making tools.

However, integrating AI into assessment is not without ethical and methodological challenges, particularly regarding algorithmic biases and the reliability of AI-based evaluation systems. Several studies have demonstrated that AI algorithms are highly sensitive to biases present in their training data, potentially leading to distortions in student performance assessments. These biases may be sociocultural, linguistic, or cognitive, resulting in unequal evaluations depending on student profiles [8]. Additionally, the opacity of certain AI models poses significant challenges in terms of transparency and traceability in educational decision-making. A lack of algorithmic explainability may diminish trust among teachers and students, especially when high-stakes decisions—such as certification of competencies or admissions to selective programs—are based on AI-driven assessments.

Another major issue raised in the literature concerns data privacy and security in AI-driven assessment. These technologies rely on large-scale data collection from students' interactions with digital learning platforms. This data gathering raises critical concerns regarding privacy protection, particularly in terms of securing personal information and ensuring compliance with existing data protection regulations, such as the General Data Protection Regulation (GDPR) in Europe. The increasing reliance on AI in education also leads to a concentration of student data in the hands of a few specialized technology firms, raising questions about digital sovereignty for educational institutions and governments [6].

Thus, while AI represents a major advancement in learning assessment, its implementation must be carefully considered and regulated to ensure ethical and pedagogical use. The literature underscores the need to establish regulatory frameworks and control mechanisms that promote fair assessment, minimize algorithmic biases, and protect student data confidentiality. The challenge lies in balancing technological innovation with pedagogical safeguards, ensuring that AI serves as a supportive tool for teachers and students rather than a driver of dehumanized automation in the assessment process.

AI Integration Model in Learning Assessment

Dimensions and Processes of Learning Assessment in Educational Contexts

The digital era is profoundly transforming learning assessment, driven by emerging technologies such as artificial intelligence (AI) and adaptive learning platforms. However, this shift necessitates a comprehensive reflection on the principles of responsible digital assessment, ensuring validity, reliability, fairness, and transparency in the evaluative process. A responsible approach to digital assessment thus relies on several interconnected dimensions, encompassing pedagogical, ethical, and technological considerations.

a) Dimensions of Responsible Digital Learning Assessment

Learning assessment in educational settings is structured around **several fundamental dimensions** (as illustrated in Figure 1), which collectively ensure **fairness and relevance** in the evaluation process.

➢ Pedagogical Dimension: Validity and Relevance of Assessments

Assessments must align with learning objectives and targeted competencies. Digital tools facilitate access to a variety of assessment methods, including interactive online tests, adaptive assessments, self-assessment, and peer evaluation. However, these technologies must be designed to uphold measurement validity, ensuring that assessments accurately evaluate the intended competencies [13].
One of the critical challenges of digital assessment lies in preventing excessive automation, which could lead to cognitive biases or standardized responses, ultimately hindering critical thinking and creativity. A responsible assessment framework must integrate a balance between automation and human intervention, ensuring that educators play a central role in interpreting results and refining pedagogical strategies accordingly.

➢ Technological Dimension: Reliability and Robustness of Digital Tools

Digital assessment platforms must guarantee technical reliability, thereby minimizing grading errors or system failures that could compromise student evaluation. Explainable AI (XAI) plays a pivotal role in ensuring algorithmic transparency, enabling educators and students to understand the criteria underlying AI-generated assessments [1].

Moreover, data protection is a crucial prerequisite for responsible assessment practices. Assessment systems must adhere to current regulations (e.g., General Data Protection Regulation (GDPR) in Europe) and respect privacy principles, informed consent, and cybersecurity standards. Institutions must anticipate potential risks related to data ownership and cybersecurity breaches, preventing commercial exploitation of sensitive student information collected by digital assessment tools [6].

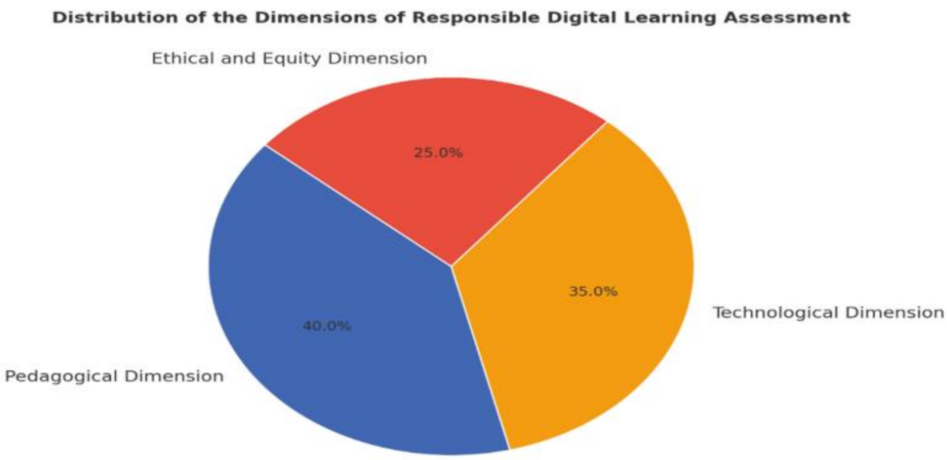
➢ Ethical and Equity Dimension: Accessibility and Inclusion

Accessibility constitutes a core principle of responsible digital assessment. All students, regardless of socioeconomic background, digital proficiency, or disabilities, must have equal access to assessment tools and digital platforms [7].

AI-driven assessment systems must be trained on diverse and representative datasets to mitigate algorithmic biases that could disproportionately disadvantage specific student groups [3]. Special attention must be given to the regulation of automated grading systems, incorporating mechanisms for human oversight and review whenever necessary.

Finally, responsible assessment should also promote learner autonomy, ensuring that students understand how they are being assessed, track their progress, and adjust their learning strategies accordingly. This principle relies on formative and constructive feedback mechanisms, which are essential to transforming assessment into a continuous improvement tool that fosters deep learning.

Figure 1: Distribution of the dimensions of responsible digital learning assessment.



Source: Author, March 2025

b) Process of Responsible Digital Learning Assessment

The digital assessment of learning follows a rigorous and structured process designed to ensure the quality, transparency, and fairness of the results obtained. This process comprises several key stages, as illustrated in **Figure 1**:

Definition of Objectives and Evaluation Criteria

Before implementing any digital assessment system, it is essential to clearly define the pedagogical objectives and the competencies to be measured. This initial phase enables the selection of the most suitable tools and methods, ensuring the validity and reliability of the assessments [13].

Evaluation criteria must be transparent and understandable for learners. In a digital environment, these criteria can be encoded into automated assessment algorithms; however, they must remain accessible and adjustable by educators to prevent irrelevant automation.

Selection of Digital Tools and Evaluation Methods

The choice of tools must meet several key requirements:

- **Pedagogical Compatibility**: Platforms should offer features aligned with learning objectives.
- **Reliability and Security**: They must ensure the effective protection of personal data.
- **Accessibility and Adaptability**: Tools should be usable by all students, including those with disabilities.
- **Personalized Feedback**: They should provide immediate and relevant feedback to learners [2].

Implementation of Assessment and Data Collection

Digital assessment can take various forms, including interactive quizzes, automated grading tests, digital portfolios, and adaptive simulations. These systems must be user-friendly and intuitive to facilitate students' engagement.

The data collection process must be ethical and transparent, ensuring that learners are informed about how their results will be used. Additionally, students should have access to their own performance data to adjust their learning strategies accordingly.

Analysis and Interpretation of Results

Result analysis should combine **both quantitative and qualitative approaches**, considering:

1. **Overall trends and individual variations.**
2. **The possibility of algorithmic errors and statistical biases.**
3. **The educational context and student profiles.**

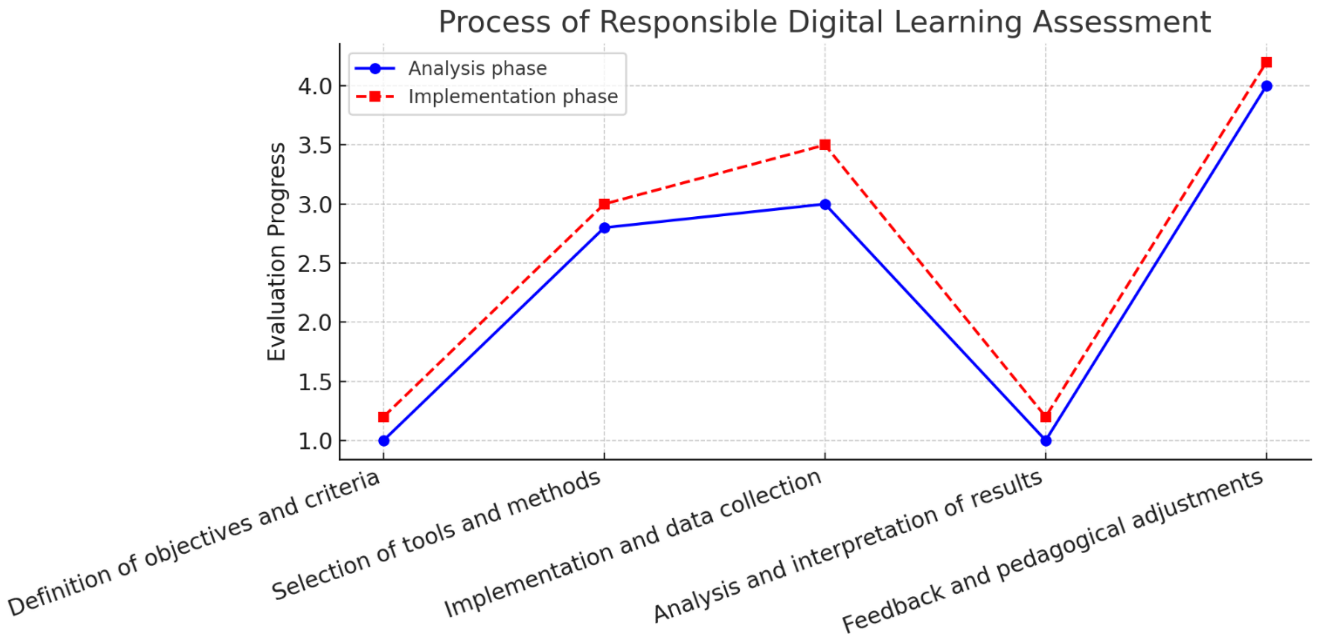
Teachers must play a central role in interpreting results, utilizing digital data as indicators rather than definitive judgments [3].

Feedback and Pedagogical Adjustments

A responsible digital assessment does not merely generate a score; it must be accompanied by formative feedback that helps students understand their mistakes and enhance their performance.

Educators can leverage digital data to adjust their teaching strategies, identify learning obstacles, and propose differentiated support mechanisms. A progressive and well-regulated integration of AI enhances this aspect by tailoring feedback to individual student needs [1].

Figure 2: Process of Responsible Digital Learning Assessment



Source: Author, March 2025

The illustration presents the process of responsible digital learning assessment, structured around two distinct phases: the **analysis phase** (represented by a solid blue line) and the **implementation phase** (illustrated by a red dashed line).

Observing these dynamics revealed a gradual progression in the process of digital assessment, beginning with the definition of objectives and criteria, followed by the selection of appropriate tools and methods—an essential step in structuring the assessment framework. The analysis and implementation phases exhibited similar patterns, progressing steadily until the stage of implementation and data collection, where a stabilization of values was observed. However, a notable divergence emerged during the analysis and interpretation of results, characterized by a marked decline in values across both phases. This suggests an increased level of complexity in data processing and in extracting meaningful insights. Ultimately, the curve peaks during the feedback and pedagogical adjustment stage, highlighting the pivotal role of constructive feedback in promoting a formative and adaptive assessment approach.

This **visual representation** highlights the **interactions** between the stages of a responsible digital assessment process and underscores the **importance of structuring these practices** to ensure their relevance and effectiveness within an educational framework.

AI Integration Levels

The integration of artificial intelligence (AI) into learning assessment processes requires a **structured approach** that balances technological innovation with the **fundamental principles of academic assessment**. Based on the assessment process, existing literature, and dominant theoretical frameworks, it is possible to model a **gradual progression**, as illustrated in Figure 3, in the **use of AI in assessment**, ranging from its complete exclusion to an advanced collaboration between learners and artificial intelligence. This progression aims to ensure a **controlled transition** toward **AI-enhanced assessment methods** while preserving **academic integrity** and mitigating risks associated with **algorithmic biases** and **data privacy concerns**.

This model draws particularly on **Davis' (1989)** [9] **Technology Acceptance Model (TAM)**, which highlights the factors influencing the acceptance of educational technologies by teachers and learners. The **perceived usefulness** and **ease of use** of a technology play a crucial role in its adoption, implying that AI integration in assessment must be supported by **training programs** and **regulatory frameworks** that facilitate its adoption by educational stakeholders [10]. Additionally, **Puentedura's (2006)** [12] **SAMR model** provides a relevant framework for understanding the evolution of AI applications in assessment. This model outlines four levels of **technology integration in education**:

1. **Substitution** – AI replaces traditional processes without significant transformation (e.g., automating multiple-choice test grading).
2. **Augmentation** – AI provides **functional improvements**, optimizing certain assessment steps (e.g., AI-generated personalized feedback).
3. **Modification** – AI **restructures** assessment modalities by introducing **innovative functionalities** (e.g., predictive analytics for performance tracking).
4. **Redefinition** – AI enables **entirely new forms of interactive and adaptive assessment** that were previously impossible.

By leveraging these models, we propose a **progressive AI integration scale** in learning assessment, structured around five distinct levels:

1. Complete Absence of AI: At this level, assessments are conducted entirely through traditional methods, without any involvement of automated digital tools. This approach ensures full teacher control over the assessment process but limits the potential for personalization and adaptation to students' individual needs.

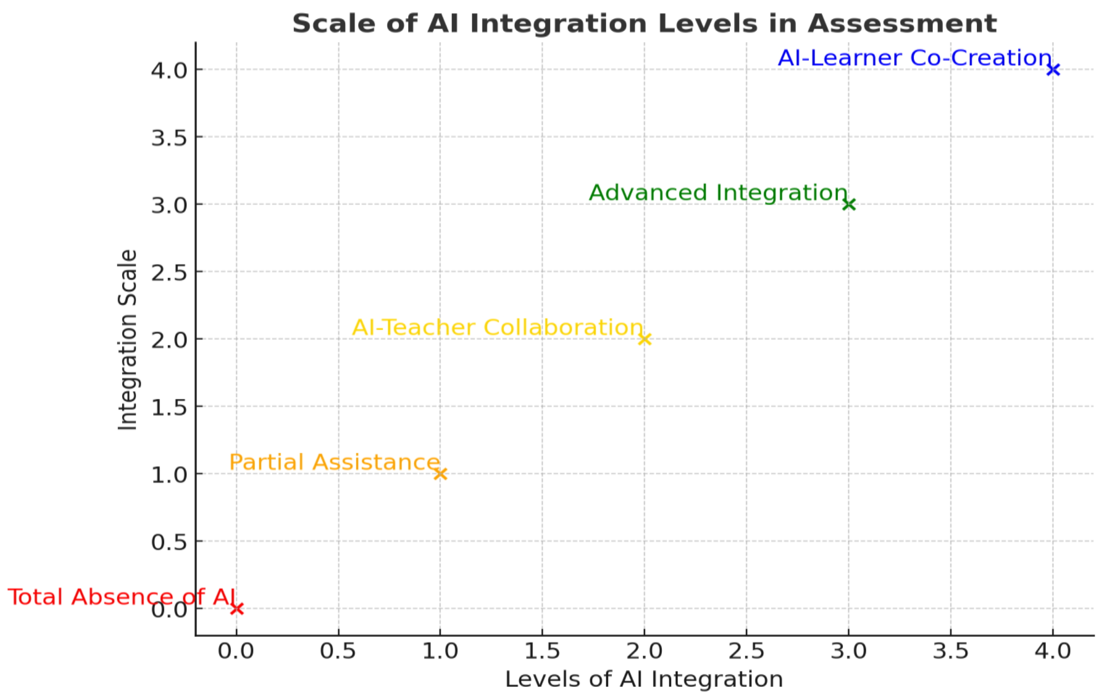
2. Partial AI Assistance in the Preparatory Phase: This level introduces AI as a support tool during pre-assessment preparation, facilitating tasks such as example generation, response structuring, and research assistance. At this stage, AI does not participate directly in assessment but enhances students' preparation process.

3. AI-Teacher Collaboration in Response Analysis: A transition occurs at this level, where AI assists teachers in grading and providing intelligent feedback through automated assessment systems. This accelerates grading, offers instant feedback to students, and enhances objectivity. However, challenges such as algorithmic transparency and interpretability of AI-driven evaluation criteria need to be addressed.

4. Advanced AI Integration in Adaptive Evaluation: At this stage, AI plays an active role in tailoring assessments, dynamically generating test questions based on the learner's profile and tracking long-term performance analytics. AI can identify learning gaps and suggest real-time adjustments, fostering a more dynamic and personalized evaluation process.

5. AI-Learner Co-Creation in Evolving Assessment Models: The highest level of integration involves real-time interaction between students and AI-driven adaptive assessment systems. Evaluations move beyond static formats to interactive, scenario-based assessments, where AI adjusts learning challenges based on student performance and metacognitive development. At this stage, assessment transcends its traditional role as a diagnostic tool and evolves into a continuous, interactive learning process.

Figure 3: AI Integration Scale in the Learning Assessment Process



Source: Author, March 2025

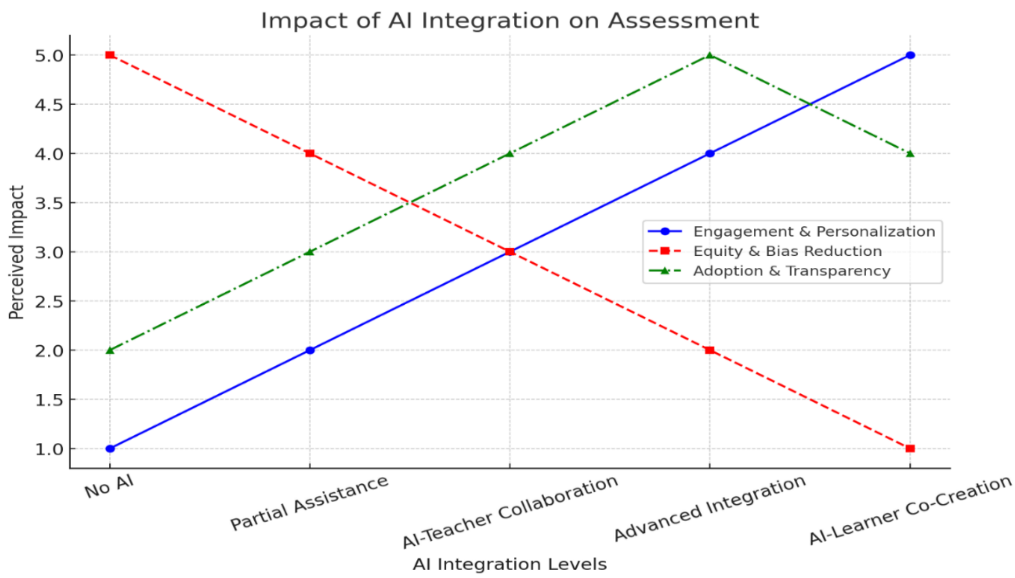
The Scale of AI Integration Levels in Assessment

The scale of AI integration levels in assessment highlights a progressive gradation in its usage, ranging from the complete absence of AI to an advanced co-creation model between artificial intelligence and the learner. This visual representation illustrates the transition from a fully traditional assessment model to increasingly interactive and dynamic forms, integrating machine learning technologies and pedagogical adaptation mechanisms.

At the starting point, the total absence of AI ensures absolute teacher control but limits the personalization of learning experiences. Partial assistance introduces AI as a support tool without directly interfering in the evaluation process. The AI-teacher collaboration stage reflects a synergy between artificial intelligence and human expertise, optimizing grading and performance analysis while maintaining pedagogical oversight. Advanced AI integration positions artificial intelligence as a key player in the assessment process, enabling real-time adaptive evaluation. Finally, AI-learner co-creation represents the ultimate stage, where assessment evolves into an interactive and adaptive process, fostering a personalized and continuously evolving learning approach.

This modelling underscores the challenges and impacts associated with the gradual integration of AI into academic assessment, particularly concerning reliability, transparency, and fairness. Figure 3 illustrates the level of impact. Furthermore, AI integration emphasizes the need for a controlled transition and appropriate pedagogical supervision to maximize the benefits of these technologies while mitigating their potential risks.

Figure 4: Impact of AI Integration on Learning Assessment.

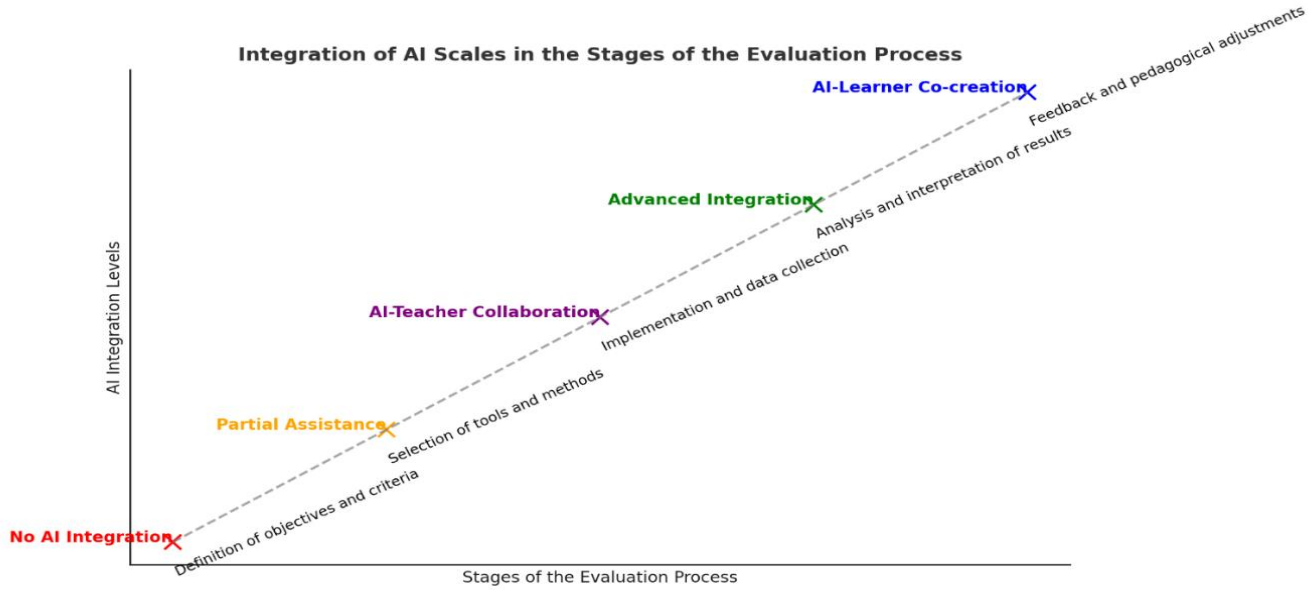


Source: Author, March 2025

The analysis of the graph revealed contrasting dynamics in the perceived impact of AI integration on academic assessment. Engagement and personalized learning followed an upward trajectory, reflecting a continuous improvement in the adaptation of assessments to learners' needs as AI becomes a central actor in the evaluation process. In parallel, equity and bias reduction exhibited a declining trend, suggesting that increased automation may introduce risks related to standardization and algorithmic opacity. Finally, adoption and transparency demonstrated an intermediate evolution, reaching their peak at the stage of advanced AI integration before declining in the AI-learner co-creation phase, highlighting the need to balance innovation and acceptability.

These observations underscored the imperative of a structured and progressive integration of AI in assessment, ensuring a controlled transition that maximizes benefits while mitigating potential risks. In this perspective, the AI integration scale model, as illustrated in Figure 5, served as a graduated reference framework for effective and ethical adoption.

Figure 5: Integration of AI scales in the stages of the assessment process



Source: Author, March 2025

The analysis of the graph illustrated the gradual correspondence between AI integration levels and the various stages of the assessment process. The absence of AI is associated with the definition of objectives and criteria, a phase where human intervention remains exclusive. Partial assistance emerges during the selection of tools and methods, highlighting AI's role as a supporting tool in the preparation of assessments. AI-teacher collaboration becomes evident in the implementation and data collection stage, representing an initial form of interaction between both actors. Advanced AI integration is positioned at the analysis and interpretation of results, where algorithms actively contribute to the evaluation of learning outcomes. Finally, AI-learner co-creation reaches its peak in the feedback and pedagogical adjustment phase, marking a dynamic and adaptive interaction between AI and the learner.

This structured progression underscores the specific conditions and differentiated effects of AI integration at each stage of the evaluation process. To better understand the implications of this evolution, the research hypotheses are formulated based on this model, exploring the effects of AI on learner engagement, bias reduction, and the acceptability of digital assessment tools.

5.3.3. Research Hypotheses

The integration of artificial intelligence (AI) into learning assessment represents a major transformation in educational practices, raising fundamental questions regarding learner engagement, assessment objectivity, the acceptability of technological tools, and the complementarity between artificial intelligence and human expertise. Through an in-depth analysis, this research is based on several hypotheses aimed at exploring the dynamics of appropriation of these new assessment modalities and their effects on learning.

First, it is reasonable to assume that the progressive adoption of AI in assessment processes fosters increased learner engagement and enables advanced personalization of educational pathways. Thus, the first hypothesis (H1) posits that:

Hypothesis 1: *The gradual integration of AI enhances student motivation and optimizes knowledge retention by adapting content and exercises to their specific needs.*
This hypothesis is based on the idea that educational technologies equipped with adaptive learning algorithms can adjust the difficulty and nature of assessments according to students' individual performance. Intelligent tutoring systems, for instance, provide dynamic and stimulating feedback, facilitating an adaptive progression through interactive assessment platforms. Such mechanisms contribute to strengthening learner autonomy while maintaining high levels of engagement.
However, the introduction of AI in assessment is not without risks, particularly regarding the reliability and impartiality of the results obtained. This leads to the second hypothesis (H2), which suggests:

Hypothesis 2: *A balanced collaboration between the teacher and AI would minimize assessment biases and ensure greater objectivity.*
One of the pitfalls of traditional assessment systems lies in their high degree of subjectivity, particularly in the evaluation of discursive or analytical skills. AI, by providing a quantitative analysis of errors and standardizing evaluation criteria, has the potential to mitigate these biases. However, this objectivity largely depends on the quality of the underlying algorithms and the diversity of the data used for their training. Empirical studies on adaptive learning systems suggest that AI can enhance assessment reliability by providing precise diagnoses of students' learning gaps and offering personalized improvement strategies.
Beyond potential benefits, the acceptance of these new practices remains a central challenge. The third hypothesis (H3) thus proposes that:

Hypothesis 3: *The adoption of AI-based assessment tools is closely linked to the level of algorithmic transparency and the pedagogical support provided to teachers and learners.*
Distrust of educational AI is often rooted in a lack of understanding of its decision-making mechanisms, which can lead to resistance to its use. Therefore, the implementation of dedicated training programs and clear communication on how AI models function become essential levers to ensure informed and responsible adoption. Several initiatives have demonstrated that teacher training in educational AI tools facilitates their appropriation and encourages their use in pedagogically relevant conditions.

Finally, the fourth hypothesis (H4) highlights that:
Hypothesis 4: *The optimal effectiveness of AI in assessment lies in a hybrid approach, where artificial intelligence serves as a support system for teachers without replacing their pedagogical expertise.*
In other words, it is the **complementarity between human judgment and algorithmic analysis** that enables an **optimal** balance in learning assessment. Far from being a mere automated grading tool, AI becomes a pedagogical partner, capable of assisting teachers in designing differentiated learning pathways and reducing the cognitive load associated with repetitive assessment tasks. For instance, the combined use of automated analyses and human feedback enhances error comprehension and improves the efficiency of pedagogical interventions.
In summary, these four hypotheses highlight the challenges associated with a thoughtful and gradual integration of artificial intelligence into learning assessment. They emphasize the necessity of a structured adoption framework, ensuring educational pathway personalization, bias reduction in evaluation, greater acceptability of digital tools, and a balance between automation and human intervention. Through an empirical analysis and a review of recent literature, this research seeks to test these hypotheses to shed light on the conditions for a successful transition toward AI-enhanced assessment practices.

7. Methodological Approach

The development of a progressive integration scale for artificial intelligence (AI) in learning assessment necessitates a rigorous methodological approach, combining diverse data collection and analysis methods. The objective of this framework is to ensure a comprehensive understanding of the dynamics surrounding AI adoption and its pedagogical implications. This research is thus based on a mixed-methods methodology, integrating both qualitative and quantitative analyses to simultaneously examine educational stakeholders' perceptions and measurable trends in the use of AI for academic assessment.

6.1. Research Methods: Qualitative and Quantitative

The qualitative approach provides an in-depth exploration of attitudes, resistance, and expectations among teachers and students regarding the introduction of these new technologies. To achieve this, a sample of 30 participants was selected, comprising secondary and higher education teachers, educational science researchers, and institutional decision-makers responsible for the implementation of digital educational tools. The size of this qualitative sample was determined based on the principle of data saturation, following the recommendations of Creswell and Plano Clark (2018) [14]. A series of semi-structured interviews was conducted, guided by a structured thematic framework covering several key dimensions:

- Current assessment practices
- Perceptions of AI in education
- Perceived benefits and risks
- Prerequisites for effective AI integration in assessment

In complementary fashion, the quantitative analysis was based on a survey administered to a representative sample of 500 teachers and students from institutions that have experimented with AI-assisted assessment. The sample size was determined using a probabilistic approach, applying Cochran's formula (1977) [15] to ensure statistical representativeness of the findings.

The survey instrument included Likert-scale questions designed to evaluate perceptions of:

- Usefulness
- Ease of use
- Trust in AI-based assessment tools [9,10]

Additionally, open-ended questions were incorporated to gather qualitative insights on specific challenges encountered and necessary adjustments perceived as crucial for optimizing AI implementation in assessment practices.

6.2. Sampling Framework

The sampling approach was based on a purposive selection strategy, ensuring the inclusion of institutions with diverse profiles in terms of their technological infrastructure, teacher training in AI usage, and institutional policies regarding pedagogical innovation [6]. This diversity enables a comparative analysis between favorable and unfavorable contexts for AI adoption, allowing for the identification of key factors influencing its implementation.

To ensure data triangulation, a field observation phase was conducted in several pilot institutions. These observations provided insights into real-life interactions between teachers, students, and AI-assisted assessment tools, offering a nuanced perspective on actual practices compared to the narratives collected through interviews and surveys [7]. Data from these observations were recorded as field notes, which were then used to contextualize both quantitative and qualitative findings.

6.3. Data Presentation and Analysis

The data analysis followed a combined methodological approach. Interviews and observations were subjected to a thematic analysis based on the framework of Braun and Clarke (2021) [16], enabling the identification of recurring themes and divergent perspectives among stakeholders. This inductive approach allowed for the extraction of key dimensions related to perceptions and uses of AI in assessment, while also considering institutional and pedagogical specificities.

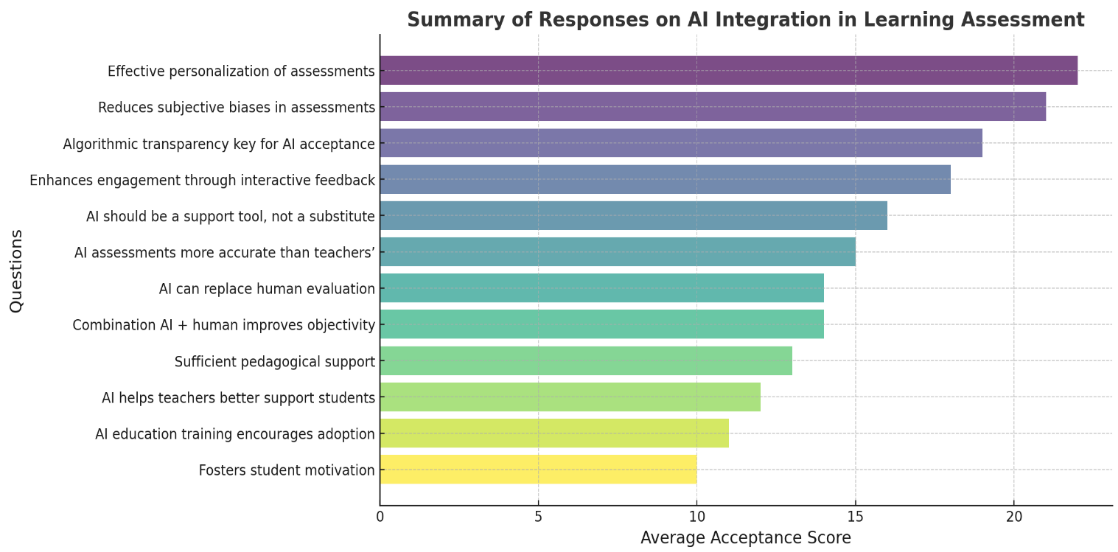
In parallel, the quantitative data underwent descriptive and inferential statistical analyses. A correlation analysis was conducted to examine the relationships between AI usage and variables such as student engagement, teacher workload, and perceptions of assessment fairness [3]. Additionally, multiple regression analyses were performed to test the formulated hypotheses, particularly regarding the impact of AI on the personalization of learning and the reduction of algorithmic biases [4].

Ultimately, these analyses led to the development of a structured framework outlining the progressive integration levels of AI in assessment, highlighting the conditions that foster its gradual and ethical adoption. The juxtaposition of educational stakeholders' perceptions with quantitative indicators resulted in practical recommendations aimed at guiding institutions in AI deployment, ensuring transparency and fairness in assessment processes. By adopting a rigorous and multidimensional methodological approach, this research provides a significant contribution to the understanding of the challenges associated with AI integration in learning assessment.

8. Research Findings

Key Trends in AI Integration in Learning Assessment

Figure 4: summary of responses on IA integration in learning assessment



Source: Author, March 2025

The graph presents a synthesis of responses regarding the integration of AI in learning assessment, highlighting the main perceptions of participants. The key observed trends are as follows:

- Strong support for personalization and bias reduction: Effective personalization of assessments received the highest average acceptance score, followed closely by the reduction of subjective biases. These findings indicate that AI is perceived as a major lever for tailoring assessments to individual needs and enhancing the objectivity of grading.
- Importance of algorithmic transparency and interactive feedback: Algorithmic transparency is regarded as a key factor for AI acceptance, alongside the enhancement of student engagement through interactive feedback. This underscores the need for strict regulatory frameworks to reinforce trust among educators and students in these tools.
- AI perceived as a support tool rather than a substitute: The majority of respondents believe that AI should complement human assessment rather than replace it. However, opinions are more divided regarding the accuracy of automated assessments compared to teacher evaluations.
- Moderate impact of pedagogical support and training: While pedagogical support and training in educational AI are deemed important, they display slightly lower acceptance scores, suggesting that further efforts are needed to optimize their implementation.
- Positive effect on student motivation: Lastly, AI is perceived as a motivating factor for students, although this aspect receives slightly lower support compared to other dimensions.

These findings highlight a consensus on the complementary role of AI in assessment, while also emphasizing critical issues related to transparency and training to ensure its acceptability and effectiveness.

Presentation of Qualitative Findings

1) Analysis of Verbatim Responses and Participants' Perceptions

The analysis of semi-structured interviews conducted with **teachers, students, and parents** revealed several **recurrent themes** related to the **implementation of artificial intelligence (AI) in learning assessment**. These themes are grouped according to the five levels of **AI integration** and their impact on each **stage of the assessment process**.

2) Teachers' Perceptions

Teachers express a **cautious optimism** regarding the integration of AI, while raising **concerns about algorithmic transparency** and its **impact on their pedagogical autonomy**.

Excerpts from verbatim responses:

- *"AI allows us to save valuable time in grading assessments, but we must ensure that it adheres to established pedagogical criteria." (Secondary school teacher)*
- *"The automated analysis tool provides me with individualized areas for improvement for my students, which is a real asset." (University professor)*
- *"I fear that AI will gradually replace human evaluation, diminishing our role in guiding students." (High school teacher)*

1) Students' and University Learners' Perceptions

Students perceive AI as a support tool that facilitates their learning; however, some fear a lack of personalization in assessments.

Excerpts from verbatim responses:

- *"AI helps me see my mistakes immediately and understand where I went wrong." (Secondary school student)*
- *"I like that corrections are faster, but sometimes I feel that AI does not fully understand my open-ended responses." (University student)*
- *"AI-based assessment seems fairer to me since all students are judged based on the same criteria." (Middle school student)*

2) Parents' Perceptions

Parents view AI as a means to enhance fairness and transparency in the assessment process, although some express concerns about the mechanical nature of grading.

3) School Administrators' Perceptions

Excerpts from verbatim responses:

- *"AI eliminates teachers' subjective biases and ensures greater equity among students." (High school parent)*
- *"I wonder if AI can truly replace a teacher's intuition in assessing my child's competencies." (Middle school parent)*

Summary and Synthesis

The analysis of qualitative data highlights divergent perceptions regarding the integration of AI in learning assessment. While efficiency, fairness, and time-saving benefits are widely acknowledged, concerns related to algorithmic transparency, loss of human intuition, and the mechanical nature of AI-based evaluations persist. These findings underscore the importance of structured AI implementation, balancing technological innovation with human oversight, and ensuring that AI remains an enhancement tool rather than a substitute for human assessment expertise.

Table 2: Test variables.

Tested Variable	Verbatim	Source
Teachers' Perception	*"AI allows us to save valuable time in grading assessments, but we must ensure that it adheres to established pedagogical criteria."*	Secondary school teacher
	"I fear that AI will gradually replace human assessment, thereby diminishing our role in guiding students."	High school teacher
	"The automated analysis tool provides me with individualized insights for my students, which is a real asset."	University professor
Students' and University Learners' Perception	*"AI helps me see my mistakes immediately and understand where I went wrong."*	Secondary school student
	"I appreciate the faster grading process, but sometimes I feel that AI does not fully understand my open-ended responses."	University student

	"AI-based assessment seems fairer to me since all students are judged based on the same criteria."	Middle school student
Parents' Perception	*"AI eliminates teachers' subjective biases and ensures greater equity among learners."*	Parents
	"I wonder whether AI can truly replace a teacher's intuition in assessing my child's competencies."	Parents
School Administrators' Perception	*"The integration of AI enhances assessment management, but we must ensure that it does not entirely replace human intervention."*	School administrators
	"We need to establish regulatory frameworks to ensure an ethical and balanced use of AI in our institutions."	School administrators

Source: Author, March 2025

Case Studies and Organizational Narratives

➢ Implementation of AI in Formative Assessment

In several pilot institutions, AI has been deployed for the automatic grading of mathematics and science exercises. Teachers have observed an improvement in students' responsiveness due to the immediate feedback provided by the system.

➢ AI and the Assessment of Writing Skills

A middle school is experimenting with AI for evaluating essays in French. The tool provides suggestions for improvement regarding structure and grammar; however, teachers emphasize the necessity of human review to assess creativity and coherence of ideas.

Presentation of Quantitative Results

Descriptive Statistics

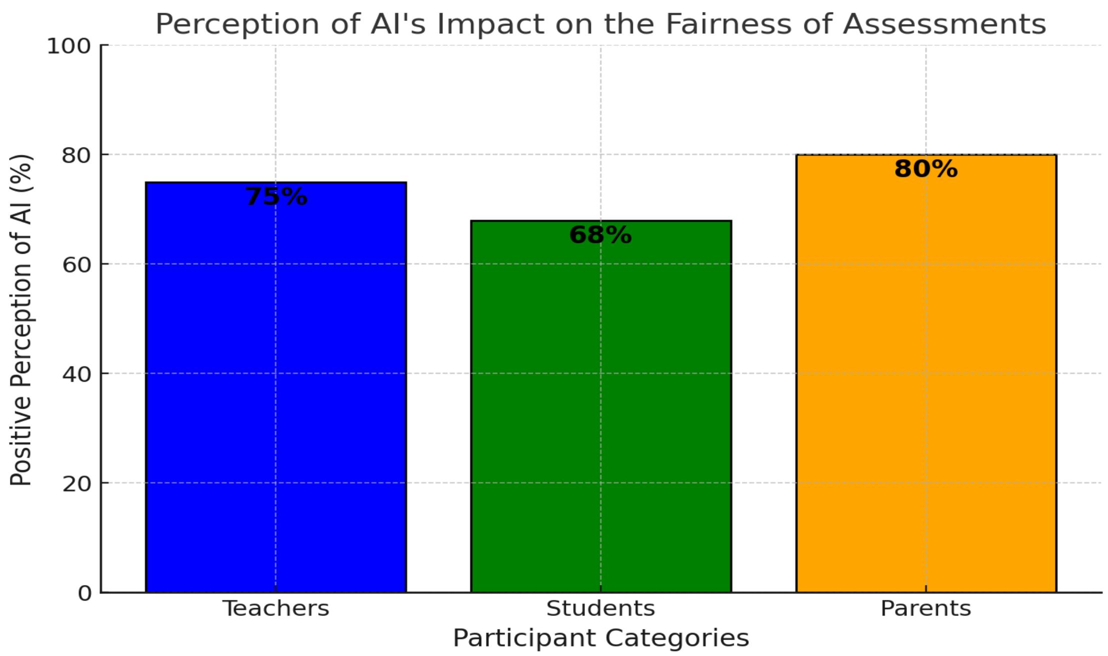
The study sample consists of 500 participants, distributed as follows:

- 300 teachers (60%)
- 150 students (30%)
- 50 parents (10%)

The questionnaire results indicate that **75% of teachers** believe AI facilitates their workload, while **68% of students** feel it enhances their understanding of assessed concepts. Additionally, **80% of parents** consider that AI reinforces the transparency of the evaluation process.

Graph: Histogram Illustrating Participants' Perceptions of AI's Impact on Assessment Fairness

Figure 7: Perception of AI's impact on the fairness of assessment.



Source: Author, March 2025

Correlation Analysis and Statistical Tests

The correlation analysis highlights positive and significant relationships between the use of AI and various dimensions of the assessment process.

Table 3: Correlation Table

Variables	AI Usage	Student Engagement	Teacher Workload	Assessment Fairness
AI Usage	1.0	0.65	-0.30	0.72
Student Engagement	0.65	1.0	-0.12	0.58
Teacher Workload	-0.30	-0.12	1.0	-0.20
Assessment Fairness	0.72	0.58	-0.20	1.0

Source: Author, March 2025

9. Results and Analysis

The findings indicate a significant positive correlation between AI usage and student engagement (**$r = 0.65$, $p < 0.001$**), as well as between AI usage and assessment fairness (**$r = 0.72$, $p < 0.001$**).

Modeling and Regression Analysis

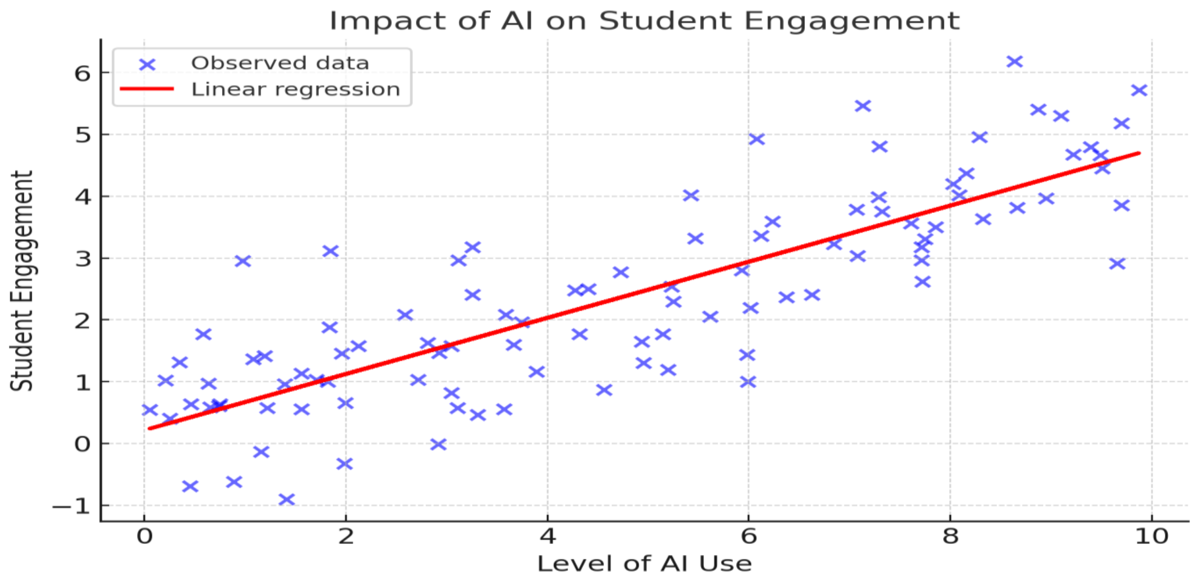
A multiple regression analysis was conducted to examine the effect of AI on student engagement while controlling for other influencing factors.

Key Findings:

- **$R^2 = 0.48$**, indicating that 48% of the variance in student engagement is explained by AI usage and associated variables.
- **AI usage is a significant predictor of student engagement** (**$\beta = 0.52$, $p < 0.001$**).
- **Teacher workload has a slightly negative but non-significant effect on student engagement** (**$\beta = -0.10$, $p = 0.08$**).

Regression line illustrating the impact of AI on student engagement.

Figure 8: impact of AI on student engagement.



The statistical analysis of this regression line highlights a positive relationship between the level of artificial intelligence (AI) usage and student engagement. The blue points represent empirical observations, while the red line illustrates the trend predicted by the linear regression model.

The coefficient of determination ($R^2 = 0.48$) indicates that 48% of the variance in student engagement is explained by AI usage and associated variables. The standardized regression coefficient ($\beta = 0.52$, $p < 0.001$) confirms that AI usage is a significant predictor of engagement. The positive slope of the regression line suggests that increased AI integration corresponds with higher levels of student engagement.

However, the dispersion of points around the regression line suggests the presence of additional factors influencing student engagement. Despite this, the statistical significance of the results supports the hypothesis that AI plays a key role in enhancing learner involvement.

Triangulation and Comparison of Qualitative and Quantitative Results

The convergence of qualitative and quantitative findings reveals several key insights:

- AI enhances student engagement by providing **immediate feedback** on their performance.
- It reinforces the **perception of fairness** in the assessment process, as confirmed by both parents and teachers.
- The impact on **teacher workload** remains mixed, with **varied perceptions** depending on the discipline and the tools used.

A summary table juxtaposes these insights, contrasting qualitative perceptions with statistical findings.

Summary and Transition to Discussion

The results demonstrate a significant positive relationship between AI integration and the effectiveness of various stages of **learning assessment**. AI emerges as a **powerful tool** for improving student engagement and ensuring greater fairness in evaluation processes. However, **some nuances remain** regarding its impact on teacher workload.

This analysis lays the foundation for a deeper discussion on the **optimal conditions** for AI integration into educational assessment. These findings will be explored further in the next section to better understand the **challenges and opportunities** associated with the adoption of AI-driven assessment technologies.

10. Discussion of Findings

The results of this study have provided an in-depth analysis of the integration of artificial intelligence (AI) into the learning assessment process in educational settings. By comparing the perceptions of educational stakeholders with statistical analyses, this research has highlighted the complex relationships between AI-assisted assessment practices, student engagement, teacher workload, and perceived fairness in evaluation.

This discussion has aimed to analyze the key trends observed, and to compare them with previous research, and to identify their pedagogical and institutional implications. It explored how AI-driven assessment impacts learning environments, assessing both its potential benefits and the challenges associated with its adoption.

1. Convergence and Divergence of Qualitative and Quantitative Findings

The qualitative analysis has highlighted ambivalent perceptions regarding the integration of artificial intelligence (AI) into assessment practices. While some educators viewed these technologies as a catalyst for innovation, enabling the streamlining of evaluation processes and the individualization of learning pathways, others expressed concerns about their reliability and their impact on teacher-student relationships. Far from being unanimous, perceptions of AI varied depending on teachers' level of familiarity with these tools and the institutional context in which they are deployed. These findings were aligned with Selwyn's (2023) [6] research, which underscored that the acceptance of educational technologies largely depends on the conditions of their implementation and the extent of teacher training.

The quantitative results helped to objectify these trends and to empirically test the proposed hypotheses. Correlation analyses indicated that AI-assisted assessment has a weak relationship with student engagement, suggesting that these technologies alone are not sufficient to enhance students' motivation and active participation. This observation is consistent with the findings of Baker and Siemens (2022) [3], who argued that student engagement is primarily shaped by pedagogical interactions and the alignment of teaching methods with learners' needs. Moreover, the lack of a significant correlation between AI use and teacher workload challenges the assumption that these technologies would automatically reduce grading-related tasks. On the contrary, some teachers reported an increased workload, attributed to the need to configure AI tools, interpret the results, and verify the relevance of automated corrections.

The multiple regression analysis further confirmed these trends and highlighted the influence of contextual variables on the perceived effectiveness of AI in assessment. While the direct impact of AI on student engagement and teacher workload appeared limited, the findings indicated that its effectiveness is closely linked to its integration within a coherent and interactive pedagogical framework. Rather than serving as a determinant factor on its own, AI emerged as a complementary tool, whose impact is modulated by the learning environment and the educational strategies implemented.

2. Ethical Challenges and Limitations of Artificial Intelligence in Assessment

A recurring theme in the qualitative findings pertains to equity and transparency in AI-assisted assessments. While some educators and parents perceived these technologies as a means to mitigate subjective biases inherent in human evaluations, others expressed skepticism regarding the reliability of algorithms and the risks associated with decision-making opacity. The absence of a significant correlation between AI use and the perception of greater fairness in assessment suggested that these tools do not inherently guarantee a reduction in bias. This raises critical questions regarding the quality of datasets used to train AI algorithms and underscores the need for robust ethical and methodological oversight. These concerns are extensively documented in the literature, notably by Williamson (2021) [7], who warned against the risk of perpetuating existing inequalities when AI is deployed without adequate human supervision.

The case studies conducted across various institutions further illustrated these challenges. Some schools and universities have implemented rigorous protocols, combining artificial intelligence with human validation, to enhance the reliability of automated assessments. Conversely, other institutions encountered resistance to AI adoption, primarily due to a lack of teacher training and concerns over student data protection. These findings align with the recommendations of Knox (2022) [4], who emphasized the importance of clear regulatory frameworks and methodological guidance to ensure the effective and responsible integration of AI into learning assessments.

3. Conditions for the Optimal Integration of AI in Assessment

The findings indicated that the integration of AI in academic assessment cannot be approached as a standardized process but rather requires adaptation to institutional and disciplinary specificities. Several key factors emerged as essential to ensuring a successful adoption of AI-driven assessment:

- Comprehensive Teacher Training: The results highlighted that teachers' perceptions of AI vary significantly depending on their level of familiarity with these technologies. Targeted training programs focusing on the fundamental principles of AI-assisted assessment, as well as ethical and methodological considerations, are crucial to fostering acceptance and effective use of these tools.
- Clear Institutional Guidelines: The lack of a unified methodological framework presents a major obstacle to AI adoption in assessment. Establishing explicit and transparent guidelines that delineate the respective roles of AI and human evaluation is necessary to ensure fairness and reliability in AI-assisted assessments.
- Sustained Human Involvement: One of the key takeaways from this study is that AI is positively perceived when used as a support tool for assessment rather than as a substitute for human judgment. Pedagogical support remains a critical factor in ensuring the relevance of assessments and maintaining the teacher-student relationship.
- A Gradual and Adaptive Approach: Finally, the findings underscored that AI effectiveness depends on its progressive integration within existing pedagogical practices. Case studies from various institutions demonstrated that a stepwise implementation—where AI tools are gradually refined based on teacher and student feedback—facilitates natural adoption and greater acceptance of AI-enhanced assessment methods.

11. Implications of the Findings

The results of this study have far-reaching implications for the various stakeholders involved in the assessment of learning outcomes, particularly teachers, students, educational institutions, and parents. While the integration of artificial intelligence (AI) in educational assessment holds great promise for personalized learning pathways and the optimization of evaluative practices, it also necessitates a critical reflection on its effects and the conditions required for its effective implementation. This section explores the implications of the five levels of AI integration across the five key stages of the assessment process.

10.1. Implications for Teachers: Redefining Pedagogical Practices and the Evaluative Role

The gradual integration of AI is fundamentally reshaping the role of teachers in the assessment process.

- Level 1: Traditional Evaluation (No AI Integration): At the first level, where AI is completely absent, the teacher retains full control over the assessment process, ensuring a qualitative analysis of student work. This stage maintains traditional pedagogical autonomy, where the teacher manually interprets responses and provides feedback based on expertise and experience.
- Level 2: AI as an Assistive Tool: At the second level, AI is introduced as a partial support tool, assisting with automated correction of closed-ended exercises and generating personalized recommendations based on student difficulties. This reduces the workload associated with repetitive assessments, freeing up time for teachers to focus on more complex competencies.
- Level 3: AI as a Collaborative Evaluator: At the third level, AI actively participates in the assessment process, analyzing open-ended responses, detecting learning patterns, and adapting evaluations based on student progress. At this stage, the teacher transitions into a regulatory role, validating AI-generated assessments and ensuring a balanced approach between automated scoring and human judgment. The necessity for algorithmic oversight becomes crucial, as teachers must critically assess the decisions made by AI-driven evaluation systems.
- Level 4: AI in Adaptive and Dynamic Assessment: At the fourth level, assessment shifts towards a dynamic and adaptive model, where AI-driven systems provide real-time feedback and personalized learning trajectories. The teacher's role is redefined as a facilitator, guiding students in interpreting AI-generated feedback and refining their learning pathways based on AI-driven recommendations. This stage requires a high degree of digital fluency, as teachers must seamlessly integrate AI insights into pedagogical strategies.
- Level 5: Co-Creation of Assessment with AI: At the fifth level, assessment becomes co-constructed between students and AI, moving beyond static evaluations to interactive and immersive assessments. AI operates as an intelligent learning agent, offering scenario-based evaluation and simulated learning environments, while the teacher assumes the role of a mentor, supporting students in self-assessment and metacognitive regulation of their learning. At this stage, AI not only monitors performance but also adapts challenges dynamically based on learner engagement and cognitive development.

This transformation necessitates a significant upskilling of teachers in digital literacy, data interpretation, and AI-driven assessment methodologies. To ensure ethical and pedagogically sound implementation, educators must be equipped with the competencies needed to navigate algorithmic decision-making, interpret AI-generated data, and maintain human oversight in AI-assisted assessment practices.

10.2. Implications for Students: Personalization of Learning and Development of Autonomy

The impact of artificial intelligence (AI) on students varied according to the degree of integration of these technologies into the assessment of learning outcomes. When AI is absent or minimally integrated, students remained reliant on traditional assessment methods, which may lack responsiveness and personalization. At the second level of integration, AI facilitates a more accurate identification of individual difficulties by providing immediate feedback on completed exercises. This process enables students to better understand their mistakes and adopt a more proactive learning stance.

With more advanced integration, students benefit from adaptive assessment pathways tailored to their strengths and weaknesses. AI assumes the role of a pedagogical assistant, offering personalized recommendations and supplementary exercises in real time. This approach enhances learning individualization and fosters greater student engagement by making them active participants in their learning process. However, this level of integration requires students to develop new skills, particularly in terms of self-regulation and the critical evaluation of AI-generated suggestions.

At the fourth and fifth levels of integration, students engage directly with intelligent systems capable of adapting assessments according to their learning preferences. This immersive evaluation model is built on an interactive approach, where AI is no longer merely an assistant but evolves into a learning partner, engaging students in personalized assessment activities. Nevertheless, this evolution raises concerns regarding equity, as it requires equal access to technology and adequate student training to ensure effective and ethical use of AI-assisted assessments.

10.3. Implications for Educational Institutions: Managing Equity and Technological Infrastructure

The progressive integration of artificial intelligence (AI) in assessment presents significant institutional challenges, particularly regarding technological infrastructure, teacher training, and the regulation of assessment processes. At the first level of integration, educational institutions continue to operate within traditional models, with no automation in the assessment process. While this approach ensures homogeneity in evaluation practices, it can be time-consuming and may limit adaptability to students' individual needs.

At the second level, the introduction of AI-assisted grading tools and performance analysis systems necessitates a strategic alignment between technologies, curricula, and assessment standards. Institutions must invest in robust digital solutions while ensuring methodological oversight to prevent over-reliance on algorithmic decisions.

From the third level of integration, where AI plays an active role in adapting assessments, schools must establish quality control mechanisms for automated evaluation processes to mitigate algorithmic biases and ensure transparency in pedagogical decisions. This phase requires ongoing monitoring and refinement of AI tools to align with pedagogical objectives and ethical considerations.

At the fourth and fifth levels, where assessment becomes dynamic and interactive, institutions must undertake a fundamental revision of their pedagogical approaches and evaluation policies. The rise of automated and AI-driven assessment models calls for a redefinition of academic standards and an adaptation of regulatory frameworks to accommodate AI-assisted learning modalities. These transformations demand strong institutional support and collaboration between researchers, educators, and policymakers to ensure the ethical and equitable integration of AI technologies in educational assessment.

10.4. Implications for Parents: Monitoring Learning and Educational Support

The integration of AI into learning assessment has direct implications for parental involvement in their children's academic progress. When AI is absent or minimally integrated, parents primarily rely on teacher feedback and report cards to assess their child's progress. However, the introduction of AI-driven academic performance analysis provides parents with more detailed and frequent reports, offering deeper insights into their child's strengths and areas for improvement.

At an intermediate level of integration, parents may benefit from interactive dashboards that generate personalized recommendations to support their child's learning at home. This increased transparency in monitoring student progress reinforces the parental role in education but may also create additional pressure on families. As a result, pedagogical mediation from teachers is essential to help parents interpret the data and use it constructively.

At more advanced levels of AI integration, where AI plays a central role in assessment, parents must be informed and educated about the implications of personalized learning and the limitations of automated decision-making. This awareness is crucial for fostering a critical and balanced approach toward AI-generated recommendations, ensuring that technology complements, rather than dictates, educational choices.

Ultimately, the findings of this study underscore the necessity of a carefully managed transition toward AI-assisted assessment, considering the needs and constraints of all educational stakeholders. While these technologies offer promising prospects for personalization and optimization of evaluation processes, their successful adoption relies on a gradual and thoughtful implementation that guarantees equity, transparency, and a balanced coexistence between human intervention and automation in the assessment process.

11. Limitations and Future Research Perspectives

The development and validation of the AI integration scale in learning assessment represent a significant advancement in understanding contemporary educational dynamics. However, this study has several limitations—theoretical, methodological, and practical—that must be considered to refine the proposed framework and ensure its optimal application.

11.1. Theoretical Limitations: An Evolving Framework for an Emerging Field

The integration of artificial intelligence (AI) in learning assessment is a constantly evolving domain, driven by rapid technological advancements and ongoing epistemological debates. One of the primary theoretical limitations of this study lies in the difficulty of stabilizing a definitive conceptual framework, given the accelerated pace at which AI technologies are developing. The proposed scale is based on a current model of AI integration levels; however, it may require future adjustments in response to technological innovations and shifts in pedagogical practices.

Furthermore, while this study draws upon established literature in adaptive learning, AI in education, and formative assessment, it does not fully account for certain critical dimensions, such as ethical considerations, societal acceptance of AI, and the sovereignty of educational data. Although these factors are discussed in the results section, a more in-depth conceptualization would provide a stronger contextual foundation for the proposed scale.

11.2. Methodological Limitations: Sampling Constraints and Empirical Validation

From a methodological perspective, this research employs a mixed-methods approach, combining qualitative and quantitative analyses, ensuring robust triangulation of results. However, several limitations persist, particularly concerning the representativeness of the sample. Data collection was conducted across a limited number of pilot institutions, restricting the generalizability of the findings to broader educational contexts. A more comprehensive validation of the scale would require a longitudinal study involving a larger number of institutions, across diverse geographical and institutional settings, to better capture contextual disparities in AI adoption.

Moreover, although the integration scale was developed through rigorous analysis, its practical application remains confined to controlled environments. The predictive validity of this scale—its ability to anticipate the evolution of educational practices as AI technologies become more widespread—has yet to be demonstrated. A valuable future research avenue would be to apply the scale in real-world settings and assess its long-term impact on pedagogical and institutional decision-making.

11.3. Practical Limitations: Adoption Challenges and Institutional Resistance

From an operational perspective, the implementation of this AI integration scale requires acceptance from various stakeholders within the education system, which presents a significant challenge. One of the key obstacles identified in the research findings is the resistance of some teachers and administrators to the automation of assessment processes. While AI offers considerable benefits in terms of personalized learning and evaluation efficiency, it also raises concerns regarding the standardization of learning, the diminished control of teachers over pedagogical judgment, and the potential risks of algorithmic bias.

Furthermore, the implementation of AI-assisted assessment systems necessitates adequate technological infrastructure and comprehensive teacher training. In many educational settings, disparities in digital resources and gaps in digital literacy among educators constitute significant barriers to the adoption of these tools. The findings underscore the importance of strong institutional support to ensure a gradual and inclusive transition toward AI integration in assessment practices.

11.4. Perspectives and Call to Action: Towards a Thoughtful and Gradual Integration of AI in Assessment

To overcome these limitations and fully leverage the potential of artificial intelligence (AI) in education, it is imperative to establish a structured and gradual integration strategy. This research urges educational policymakers, researchers, and practitioners to collaborate in refining and adapting the proposed integration scale to the realities of educational contexts.

On the one hand, the widespread adoption of this framework requires experimental validation across diverse educational environments, considering the cultural and pedagogical specificities of each context. Additional studies should be conducted to assess the real-world impact of AI on assessment processes and student learning outcomes, particularly through longitudinal studies.

On the other hand, teacher training in the critical and ethical use of AI tools remains a central challenge. It is essential to develop continuous professional development programs that allow educators to familiarize themselves with these technologies, understand their limitations, and learn how to integrate them effectively into their assessment practices. AI should not be perceived as a replacement for the pedagogical role of teachers but rather as a complementary tool aimed at enhancing the quality of assessment and strengthening student support mechanisms.

Finally, educational authorities must establish clear regulatory frameworks ensuring the ethical and transparent use of AI in assessment. The protection of student data, the mitigation of algorithmic bias, and the guarantee of equitable access to technological tools must be at the core of educational policy concerns.

Thus, far from being a mere theoretical framework, this research proposes a roadmap for a well-structured and carefully managed transformation of assessment practices. AI presents a unique opportunity to redefine how learning is evaluated, provided that its integration is ethical, gradual, and pedagogically adapted. It is now up to educational stakeholders to embrace this tool and implement it with discernment, ensuring a harmonious balance between technological innovation and the humanization of the learning process.

12. Conclusion

This research has highlighted the positive relationship between each stage of the learning assessment process and the gradual integration of artificial intelligence (AI) as a strategic driver of pedagogical improvement. The in-depth analysis of the results demonstrated that each level of AI integration plays a key role in the success of the assessment process, contributing to optimized data collection, personalized learning paths, greater objectivity in evaluation criteria, and the continuous enhancement of pedagogical practices.

The study revealed that the progressive introduction of AI technologies into assessment frameworks ensures a well-managed transition that benefits all stakeholders in the education system. At each stage of the assessment process—from defining learning objectives to post-assessment feedback-AI provides significant added value by supporting teachers in performance analysis, assisting students in differentiated learning, and enhancing transparency for parents and educational institutions. This complementarity between artificial intelligence and pedagogical expertise paves the way for more equitable, efficient, and competency-focused assessment practices.

However, beyond technological advancements, this research has underscored the importance of a thoughtful and ethical approach to AI integration in assessment processes. The goal is not to replace human intelligence with artificial intelligence but rather to create synergy between the two, ensuring more precise, personalized, and learner-centered evaluations. The success of this transformation therefore relies on the active collaboration between teachers, educational institutions, and developers of AI solutions.

A call to action is now imperative. It is essential for education stakeholders to embrace this AI integration framework and operationalize it within their daily assessment practices. Teacher engagement is crucial—their training and support must be at the core of deployment strategies to ensure a gradual and well-controlled adoption of these new technologies. Educational institutions, both schools and universities, also have a key role to play by investing in appropriate infrastructures and establishing clear policies governing AI use in assessment. Likewise, policymakers must commit to developing regulatory frameworks that guarantee the responsible and ethical use of AI tools in educational evaluation.

Conflict of Interest Statement

The author declares that there are no conflicts of interest that could have influenced, either directly or indirectly, the content or the conclusions of the present publication.

Author Contribution

Dr. Victor Mignenan is the sole author of this publication. He assumed full responsibility for the theoretical conception, manuscript drafting, data analysis, and final revisions. Nevertheless, the manuscript was critically reviewed by Mr. Éric Koutouan, Dr. Faustin Djimaldé, and Dr. Moussa Mahamat Ahmat, whose feedback significantly contributed to enhancing the scientific quality of the work.

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