



## **METHODOLOGIES OF ARTIFICIAL INTELLIGENCE IN ASSESSMENT FOR LEARNING IN HIGHER EDUCATION: A SYNTHESIS OF RECENT REVIEWS**

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### **Abstract**

This article examines methodological approaches to the application of Artificial Intelligence (AI) in assessment within higher education. The study is based exclusively on the analysis of two recent reviews: C. Zhao (2024), which synthesizes 81 empirical studies on AI-assisted assessment in universities and B. Memarian and T. Doleck (2024), which reviews 35 studies on Assessment for Learning (AFL) supported by AI. The article identifies key AI methodologies, including intelligent tutoring and personalized learning, automated assessment and feedback, learning analytics and prediction, virtual classroom support, knowledge management systems and educational chat assistants. It further analyzes the pedagogical foundations of AI-supported AFL, emphasizing formative design, continuous feedback and student learning growth. The findings indicate that AI methodologies enhance cognitive and metacognitive skills, provide real-time personalized feedback and foster positive academic emotions. However, significant challenges remain, including privacy concerns, algorithmic bias, unreliable feedback, academic integrity risks and insufficient guidance for responsible use. The study highlights the importance of user acceptance, teacher TPACK competence and discipline-specific calibration. The article concludes that AI methodologies in assessment require structured guidelines and responsible implementation to ensure pedagogical coherence and ethical use in higher education.

**Keywords:** Artificial Intelligence, Assessment for Learning, Higher Education, Automated Feedback, Learning Analytics, Responsible AI.



## Introduction

Artificial Intelligence (AI) is increasingly integrated into assessment practices in higher education. Universities use AI to support grading, feedback, learning analytics and personalized instruction. However, the methodological foundations of AI in assessment remain fragmented. There is a need to clarify how AI is applied, what pedagogical principles guide its use and what challenges influence its implementation. Two recent reviews provide important evidence. C. Zhao (2024) analyzed 81 empirical studies to examine AI-assisted assessment in higher education. The review explored tool diversity, user acceptance, cognitive and metacognitive outcomes and implementation challenges<sup>1</sup>. B. Memarian and T. Doleck (2024) reviewed 35 studies on Assessment for Learning (AFL) supported by AI. Their focus was on reformed assessment practices designed to improve student learning growth rather than only final grading<sup>2</sup>. Despite growing research, there is limited synthesis of AI methodologies in assessment. This article aims to identify and systematize key methodological approaches to AI-supported assessment and AFL in higher education. It also examines benefits, challenges and factors influencing user perceptions.

## Methods

This study adopts a qualitative secondary synthesis design. It is based exclusively on two peer-reviewed review articles: C. Zhao (2024), which systematically analyzed 81 empirical studies on AI-assisted assessment in higher education and B. Memarian and T. Doleck (2024), which reviewed 35 studies on AI-supported Assessment for Learning (AFL). No additional sources were included. The purpose of this design is to integrate and compare findings from these two comprehensive reviews in order to identify methodological patterns in AI-based assessment. The study does not re-analyze primary empirical data. Instead, it synthesizes already reported findings, methodological classifications, benefits and challenges described in the two reviews. All AI applications explicitly identified in the two reviews were extracted. These included: intelligent tutoring and personalized learning systems; automated assessment and feedback; virtual classroom and online collaboration tool; learning

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<sup>1</sup> Zhao, C. (2024). AI-assisted assessment in higher education: A systematic review. *Journal of Educational Technology and Innovation*, 6(4), 39–58. <https://doi.org/10.61414/jeti.v6i4.209>

<sup>2</sup> Memarian, B., & Doleck, T. (2024). A review of assessment for learning with artificial intelligence. *Computers in Human Behavior: Artificial Humans*, 2(1), Article 100040. <https://doi.org/10.1016/j.chbah.2023.100040>. (<https://www.sciencedirect.com/science/article/pii/S2949882123000403>)



analytics and predictive systems; knowledge management and recommendation systems; educational chat assistants; Attention Aware Systems. From the AFL review, methodological elements related to formative design, feedback orientation and continuous assessment practices were identified and categorized.

The extracted data were organized into four analytical categories:

1. Methodological Applications (types of AI tools and their pedagogical functions)
2. Pedagogical Benefits (cognitive, metacognitive, emotional outcomes)
3. User Perceptions and Acceptance Factors (TPACK, learning strategies, attitudes)
4. Challenges and Risks (privacy, bias, unreliable feedback, academic integrity, lack of guidance). This thematic categorization allowed a structured comparison between technological applications (C. Zhao, 2024) and pedagogical orientation toward AFL (B. Memarian & T. Doleck, 2024).

A comparative synthesis was conducted to identify:

- Converging findings between the two reviews
- Complementary perspectives (technological vs. pedagogical emphasis)
- Gaps and underexplored areas mentioned in both studies. Special attention was given to how AI methodologies align with formative assessment principles and how user-related factors influence implementation.

This study is limited to the evidence presented in the two selected review articles. It does not introduce external empirical data or theoretical frameworks beyond those explicitly reported in C. Zhao (2024) and B. Memarian and T. Doleck (2024). Therefore, conclusions reflect the scope, findings and limitations acknowledged within these two reviews. This methodological approach ensures transparency, conceptual clarity and strict adherence to the selected sources while enabling a structured synthesis of AI methodologies in higher education assessment.

## **Results**

C. Zhao (2024) reports 69 distinct AI tools used in universities. These include:

- Intelligent tutoring and personalized learning systems
- Automated assessment and feedback tools
- Virtual classroom and online collaboration systems
- Learning analytics and prediction models
- Knowledge management and resource recommendation systems
- Educational chat assistants



- Attention Aware Systems

B. Memarian and T. Doleck (2024) emphasize AI-supported Assessment for Learning (AFL). In this approach, assessment is designed to improve student learning growth. AI is used to provide continuous feedback and support formative practices. These methodologies shift assessment from static grading to dynamic monitoring of learning processes.

AI provides real-time, high-quality, personalized feedback. This supports student learning beyond traditional exams. AI tools enhance cognitive skills such as reasoning and memory. They also strengthen metacognitive skills, including planning, monitoring and evaluating learning processes.

C. Zhao (2024) reports that AI-assisted assessment can foster positive academic emotions. Educational chat assistants can also provide emotional support, reducing stress. B. Memarian and T. Doleck (2024) highlight the role of AI in formative assessment design. AI supports continuous data collection and feedback, aligning with the principles of AFL. C. Zhao (2024) emphasizes the importance of TPACK (Technological Pedagogical Content Knowledge). Teachers with stronger TPACK are more willing to adopt AI. Student perceptions vary depending on learning strategies. Surface learners value AI for memory support. Deep learners expect analytical feedback. Both reviews indicate that perceptions influence effective implementation. Improving user confidence and providing clear guidance are necessary. C. Zhao (2024) also highlights the need for discipline-specific calibration. AI systems must function differently in STEM and Humanities contexts. Additionally, neurotypical bias may disadvantage neurodivergent students. B. Memarian and T. Doleck (2024) emphasize conceptual and practical challenges in aligning AI tools with AFL principles.

## **Discussion**

C. Zhao (2024) offers a broad empirical mapping of AI-assisted assessment. The review identifies 69 distinct AI tools and examines their impact on cognitive skills, metacognitive development, emotional responses and user acceptance. The emphasis is practical and implementation-oriented. It highlights how AI tools function in real university contexts, what benefits they produce and what barriers limit adoption. In contrast, B. Memarian and T. Doleck (2024) concentrate on the pedagogical foundations of Assessment for Learning (AFL). Their review examines how AI can



support reformed assessment practices that prioritize learning growth rather than final grading. The focus is conceptual and formative. The authors analyze how AI aligns - or fails to align - with AFL principles such as continuous feedback, activity design and improvement-oriented evaluation. When considered together, the two reviews suggest that technological sophistication alone does not guarantee pedagogical value. Automated grading systems or analytics dashboards are not inherently formative. AI methodologies become educationally meaningful only when embedded within AFL-oriented designs that promote reflection, monitoring, and iterative improvement. C. Zhao (2024) demonstrates that AI tools enhance metacognitive abilities such as planning and self-monitoring. B. Memarian and T. Doleck (2024) emphasize that such outcomes are central to AFL. This convergence indicates that AI has the potential to operationalize formative assessment principles at scale, but only when the design of activities and feedback explicitly targets learning development.

Both reviews underline the importance of user perceptions. C. Zhao (2024) shows that teacher adoption depends strongly on TPACK competence. If educators cannot align AI tools with pedagogical goals and disciplinary content, implementation remains superficial. Similarly, student perceptions vary according to learning strategies. Surface learners may use AI primarily for memory support, while deep learners expect analytical and reflective feedback. These findings suggest that AI methodologies are not neutral tools. Their impact depends on how users interpret and integrate them into learning processes. Therefore, training, clear guidance and pedagogical framing are necessary to strengthen trust and effective use. Both reviews emphasize concerns related to privacy, algorithmic bias, unreliable feedback and academic integrity. C. Zhao (2024) notes that negative attitudes and distrust may arise when systems lack transparency or produce inconsistent results. B. Memarian and T. Doleck (2024) highlight the need to consider challenges in aligning AI systems with ethical and formative principles. The discussion across both reviews implies that responsible AI implementation requires structured guidelines. Institutions must address data security, ensure fair algorithms and develop policies to prevent academic dishonesty. Without clear frameworks, AI methodologies risk undermining assessment credibility. C. Zhao (2024) also points to the need for discipline-specific calibration. AI systems may require different configurations in STEM fields compared to Humanities. Additionally, the review raises concerns about neurotypical bias in attention-based systems, which may disadvantage certain learners. This



suggests that AI methodologies must be context-sensitive. Standardized solutions may not suit diverse disciplinary and learner needs. Both reviews indicate that future research should focus on:

- Developing clearer pedagogical models for AI-supported AFL
- Improving user training and TPACK development
- Designing transparent systems that reduce bias and increase trust
- Establishing responsible AI guidelines for assessment

Overall, the combined evidence suggests that AI in higher education assessment should be understood as a socio-pedagogical system rather than a purely technical innovation. Its effectiveness depends on alignment between technology, pedagogy, user competence and ethical governance.

## **Conclusion**

AI methodologies in higher education assessment are diverse and expanding. They include intelligent tutoring, automated feedback, learning analytics, virtual collaboration systems and chat assistants. These methodologies support personalized learning, cognitive development and formative assessment. However, successful implementation depends on user acceptance, teacher competence, ethical safeguards and structured guidance. Privacy, bias and academic integrity remain central concerns. AI in assessment should not replace pedagogy. It should enhance Assessment for Learning through responsible, transparent and evidence-based application. Further research is needed to refine methodological frameworks and improve responsible AI integration in higher education.

## **References**

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