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THE IMPACT OF ARTIFICIAL INTELLIGENCE DRIVEN ASSESSMENT AND FEEDBACK SYSTEMS ON TEACHING AND LEARNING IN HIGHER EDUCATION: A SYSTEMATIC REVIEW

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ABSTRACT

The accelerated development of Artificial Intelligence (AI) has profoundly transformed assessment and feedback practices in higher education. Traditional forms of assessment often fail to provide timely, personalized, and formative feedback, particularly in large and diverse learning contexts. AI-driven systems encompassing automated grading, adaptive testing, and intelligent tutoring offer scalable and data-informed solutions that enhance the quality of learning experiences, reduce instructor workload, and promote learner engagement. This systematic review, conducted according to PRISMA 2020 guidelines, synthesizes findings from sixty peer-reviewed studies published between 2015 and 2025, retrieved from Scopus, Web of Science, ERIC, and Google Scholar. The studies were analyzed thematically to identify the pedagogical impacts, institutional implications, and ethical challenges associated with AI-based assessment and feedback systems. Results indicate that AI-supported assessment significantly improves feedback immediacy, learning efficiency, and student engagement, particularly through natural language processing tools and learning analytics that enable real-time, individualized feedback. However, recurrent concerns include algorithmic bias, data privacy, and the limited readiness of academic staff to integrate AI effectively. The study concludes that AI-driven assessment systems hold great promise to advance higher education through personalized, timely, and equitable learning support. Their long-term success, however, depends on pedagogically sound integration, ethical governance, and institutional capacity-building. Future research should focus on longitudinal evidence, equity-oriented practices, and discipline-specific AI applications to ensure that technological innovation strengthens, rather than replaces, the human dimension of education.

KEYWORDS: Artificial Intelligence, Assessment, Feedback, Higher Education, Learning Analytics, Pedagogy, Self-Regulated Learning.

1. INTRODUCTION

Artificial intelligence (AI) and its integration into higher education is transforming the traditional assessment and feedback processes. Formative learning and engagement with students are still a challenge due to manual grading and slow feedback. Intelligent tutoring, adaptive quizzes, essay grading based on the natural language processing (NLP) algorithm, and other AI-based systems provide personalized and scalable feedback that is compatible with the learner centred paradigms (Deepshikhal, 2025). AI-driven feedback facilitates self-regulated learning by informing students about their performance with data on a particularly timely basis (Bulut and Wongvorachan, 2022). These tools enable the cycles of assessment and feedback loops to be used continuously and adaptively, which encourages greater cognitive processes. Meanwhile, teachers also enjoy lower workload and better diagnostic information to make instructional decisions (Dann et al., 2024).

Nevertheless, with AI integration, problematic issues arise, including the lack of transparency in algorithms, ethical threats, and its overall institutional preparedness (Roe et al., 2024). It has concerns of trust and fairness due to the possibility of bias in automated grading, misuse of data, and overuse of generative AI. Despite such concerns, there is an increasing number of studies that indicate that AI-assessment tools can revolutionize the teaching and learning process when used intelligently as parts of pedagogically sound models (Saputra et al., 2024). The objective of this review is to synthesize the empirical and theoretical research of the past decade to answer three main questions:

- What are the AI-based assessment and feedback instruments that are applied in higher education?
- What are the results of their effects on teaching, learning, and engagement?
- What are the ethical, pedagogical, and institutional issues that affect their performance?

2. LITERATURE REVIEW

The concept of artificial intelligence (AI) has become an interruptive phenomenon in higher education, especially in assessment and feedback. Conventional assessment systems have long been criticized as being non-personalized, delayed in response, and based on human subjective judgment. The use of AI technologies has brought about new opportunities for developing an adaptive, scalable, and objective assessment environment that fosters continuity in learning and pedagogical innovation. Most recent literature shows a developing agreement that AI-based assessment systems have the potential to boost the quality of feedback and decrease instructor workload, and increase student engagement (Kumar, 2025).

Modern studies place AI-based assessment in the theoretical frameworks of constructivism, formative assessment and self-regulated learning. Feedback has been noted as among the strongest factors on student achievement, especially when specific, timely and dialogic. The advent of AI-driven feedback solutions has increased the power of feedback literacy and formative assessment by providing real-time and personalized feedback that helps learners to have control over their learning process (Herb and Lloyd, 2024).

These systems utilize machine learning algorithms, natural language processing, and data mining with the purpose of analyzing the student responses, identifying the patterns of misunderstanding, and providing adaptive feedback that is likely to enhance the conceptual understanding and metacognitive awareness (Bulut and Wongvorachan, 2022).

Empirical research indicates that AI-based feedback systems are very effective in enhancing the learning performance and student motivation through providing formative, back-and-forth engagement. Hooda et al. (2022) presented evidence in analyzing adaptive learning environments that artificial intelligence-based systems based on learning analytics and deep neural networks improved validity, reliability, and equity of student evaluations (Hooda et al., 2022).

Equally, Lyanda et al. (2024) noted that AI integration in online learning assessment developed real-time feedback loops and significantly enhanced the engagement process, particularly in the formative assessment context (Lyanda, Owidi, and Simiyu, 2024).

AI technologies are becoming more aligned with cognitive learning theories at the pedagogical level. Random integration of frameworks, including Bloom Taxonomy and SOLO Taxonomy, into the development of feedback delivered by AI systems can allow them to offer feedback that not only quantifies performance but also facilitates the development of higher-order cognitive processes (Yaacoub and Tarnpradab, 2025).

This overlap between cognitive science and AI-based education indicates the sophistication of such tools in the perception and reaction to the unique learning patterns of an individual.

Besides cognitive and pedagogical affordances, emotional and motivational aspects of AI-generated feedback have been increasingly addressed in the recent past. The research conducted by Alsaiari et al. (2024) showed that AI feedback with emotional content affected learners positively, affecting the affective response negatively, decreasing such negative emotions as frustration or disengagement without deteriorating the quality of learning (Alsaiari et al., 2024).

This is consistent with the Control-Value Theory of Achievement Emotions, which underlines that the regulation of emotions when receiving feedback is key to maintaining academic interest. In the same manner, Zhang and Gao (2025) concluded that students preferred AI-generated feedback to human feedback when the cause of feedback was not mentioned, showing that they rated it more credible and helpful (Zhang and Gao, 2025).

The transformation of assessment culture under the influence of AI also cross-cuts with the overall educational paradigm shift to assessment as learning and not assessment of learning. According to the researchers, including Saputra et al. (2024), the flexibility of AI and feedback loops based on the data allows fostering continuous learning and critical reflection, thereby making assessment a formative process and developmental, but not evaluative one (Saputra et al., 2024).

Such a conceptual reframing supports the new trend in higher education where teaching no longer revolves around the teacher but the student as a learner who is actively involved in building knowledge through constant feedback loops.

In spite of these developments, there are a number of limitations and challenges that still exist. The data privacy, bias in algorithms, and the transparency of the decisions made by AI are still ethical issues. It was observed by Roe et al. (2024) that students as well as instructors have a divided opinion towards the application of AI-enabled feedback systems, and this situation was attributed to being uncertain about the fairness, accuracy, and interpretability of assessments generated by machines (Roe et al., 2024).

Additionally, Williams (2025) advised that although the assessment authenticity and student agency can be improved with the help of generative AI tools, they also require the creation of AI literacy in educators and learners to avoid AI misuse and over-reliance (Williams, 2025)

The literature also mentions the development of explainable and ethical AI frameworks that can help to resolve these problems. The article by Gomez and Seenivasan (2025) examined the topic of explainable AI (XAI) models, which can deliver user-specific feedback in skill-based fields like medical education by making students aware of the results of using AI but also the rationale behind it (Gomez and Seenivasan, 2025).

Equally, Wang (2025) suggested an adaptive framework of quality assurance feedback optimization in higher education, which demonstrated 98.5% accuracy in learning data analysis and predicting at-risk students, demonstrating that AI-based assessment systems can be expanded to the institutional level for improvement.

Lastly, it is important to note that recent studies point to the significance of cultural and contextual correspondence in AI feedback design. Engeness and Gamlem (2025) were Vygotskian cultural-historical in their argument that AI-generated feedback ought to play the role of a cultural tool, which mediates learning not just in improving performance, but also in general development of the cognitive and social abilities of learners (Engeness and Gamlem, 2025).

Altogether, the current literature confirms the high-quality evidence that AI-based assessment and feedback systems improve pedagogical performance, raise the immediacy of feedback, and enhance the learning experiences of students. Nonetheless, effective implementation must be well coordinated with the ethical values and faculty preparedness, as well as institutional practice that protects transparency and inclusivity. This synthesis is what provides a conceptual background to the methodological tendencies and empirical evidence analyses that will proceed in subsequent sections.

3. METHODOLOGY

The review is structured as a systematic review to explore the effects of an artificial intelligence-based assessment and feedback system on higher education teaching and learning. The identification, evaluation, and synthesis of the relevant literature identification, evaluation, and synthesis were chosen in a systematic approach to guarantee transparency, rigour, and replicability. The review is done according to the PRISMA 2020 guidelines of systematic review of educational research, with a focus on clearly outlined search strategies, inclusion and exclusion criteria, and thematic synthesis of the interpretation of the data. This methodological framework will guarantee the review to be thorough, repeatable, and able to offer an evidence-based synthesis of the pedagogical, ethical and institutional aspects of AI-based assessment systems.

3.1. Data Sources and Search Strategy

The extensive literature search was performed in major scholarly databases that are commonly available in education and educational technology research, such as Scopus, Web of Science, ERIC, and Google Scholar. These databases were chosen so that they would have wide coverage of peer-reviewed journal articles, systematic reviews, and high-quality conference proceedings. The search focused on the studies published between 2015 and 2025 but paid special attention to the recent research published in 2022-2025 to reflect the latest trends in AI-based assessment and feedback practices. The search results were precise and comprehensive because a combination of keywords and Boolean operators was applied. The search terms were limited to the following: artificial intelligence, AI-driven assessment, automated feedback, intelligent tutoring systems, learning analytics, higher education, student learning, and assessment practices. Besides the search in the database, the reference lists of the appropriate papers were also manually checked to find other studies that were not included in the preliminary search outcomes. The analysis was conducted using several databases and supporting search terms, which provided a large and representative dataset; the required data and the possibility of missing some of the relevant research were reduced to a minimum by including manual reference checks.

Table 1. Databases and Search Keywords Used in the Review

Database	Key Search Terms
Scopus	"AI-based assessment" AND "higher education"; "automated feedback" AND "university learning"
Web of Science	"artificial intelligence" AND "assessment systems"; "learning analytics" AND "feedback"
ERIC	"AI in education"; "formative assessment" AND "digital feedback"
Google Scholar	"intelligent tutoring systems" AND "higher education assessment"

3.2. *Inclusion and Exclusion Criteria*

Explicit inclusion and exclusion factors were used to screen the studies so that the studies were filtered to only include high-quality and contextually relevant studies. The inclusion criteria were as follows: the study had to be peer-reviewed, published in the English language, and aimed at AI-driven assessment and feedback systems specifically in the context of higher education. Empirical studies, both quantitative and qualitative, and mixed-methods studies were eligible for inclusion and as high-quality systematic reviews or narrative reviews. The studies were excluded when focusing only on primary or secondary education, discussing AI in education without a particular focus on assessment or feedback, or were not peer-reviewed articles, including editorials or opinion pieces.

These criteria were applied because they made sure that the final sample contained studies that were of methodological rigour, relevance and alignment with the objectives of the research.

Table 2. Inclusion and Exclusion Criteria

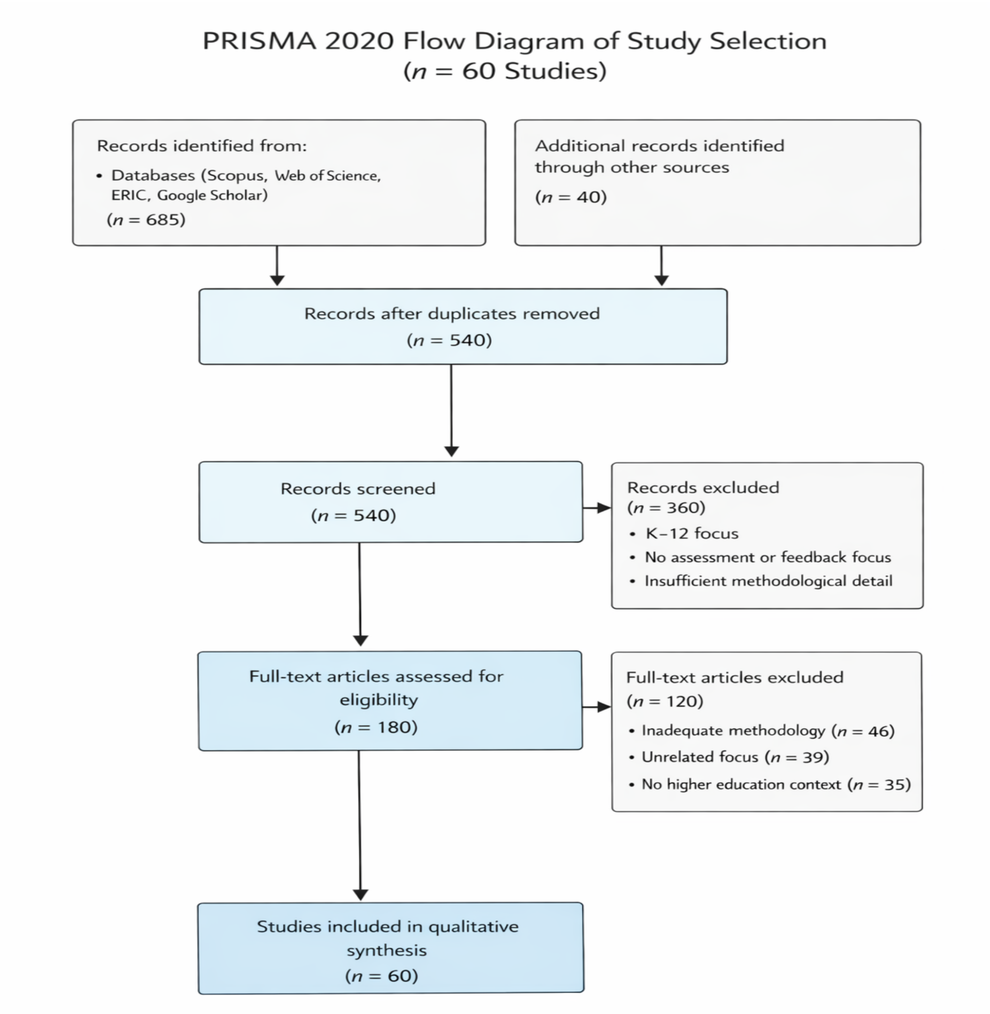
Criteria Type	Description
Inclusion Criteria	Peer-reviewed journal articles; higher education context; focus on AI-based assessment or feedback; published between 2015–2025
Exclusion Criteria	Studies on K–12 education only; non-empirical or theoretical essays; works without a focus on assessment or feedback; non-English publications

3.3. *Study Selection and Data Extraction*

The initial search of the databases resulted in the retrieval of 725 records, of which 685 were found in indexed databases, and 40 were found in other sources, like manual search. When duplicate records were eliminated, 540 unique articles were left. These were screened on title and abstract to determine their relevance to the review objectives, and 360 studies were excluded on screening since they failed to meet the inclusion criteria. The rest of the 180 articles were under full-text review to be eligible. After this step, 120 studies were eliminated as they lacked adequate methodology description, were not related to AI-driven assessment or feedback, or dealt with non-higher education settings. The overall synthesis hence comprised 60 peer-reviewed publications that fit all the inclusion criteria.

In all the studies included, information was compiled on a case-by-case basis, including the year of publication, the authors, the study design, the sample used, the type of AI-based assessment or feedback tool, the pedagogic environment, the key findings, and limitations. Data were extracted in accordance with a structured template in order to determine consistency and transparency across the studies that were selected and to facilitate thematic analysis.

Figure 1: The PRISMA flow process is represented textually as follows:



3.4. *Data Analysis and Synthesis*

Data from the 60 selected studies were processed under the thematic synthesis method, which made it possible to identify patterns, relationships, and recurring themes in the research corpus. This analysis started with inductive coding of the findings of each study and subsequent identification of the salient concepts related to the application and effect of AI in assessment and feedback. The codes were successively narrowed down and classified into bigger groups, such as types of AI-based assessment tools, features of automated and adaptive feedback, impact on student engagement and learning outcomes, pedagogical, ethical, and institutional issues.

The coding protocol focused on convergence and divergence of the studies to understand the peculiarities of implementation in various higher education contexts and disciplines. The analysis of contradictory results was carried out against the background to define whether the differences can be related to such factors as the technological level of maturity, the professionalism of instructors, or the willingness of the institution. Instead of a statistical aggregation of the findings, the review utilized an interpretive synthesis methodology, which provided an opportunity to gain a subtle insight into how AI-based assessment and feedback systems operate in complex educational ecosystems. The approach made the analysis context-sensitive, holistic, and emphasized not only the pedagogical possibilities of AI-based systems but also the important ethical and institutional circumstances that should be addressed to achieve their successful implementation in higher education.

4. Result

The results of the systematic review of 60 peer-reviewed articles concerning artificial intelligence (AI) -based assessment and feedback systems in higher education published between 2015 and 2025 are presented in this section. Analysis is based on the synthesis of evidence in various environments, geographical settings, disciplines, and methodologies, with patterns of consistency of the pedagogical effectiveness, learning outcomes, and institutional implications of these technologies being established. In order to present an overview of the findings, Table 3 presents the key trends and results attained in the chosen studies.

Table 3. Summary of Key Findings Across 60 Studies

Theme	Key Findings	Representative Studies
AI-driven assessment tools	Automated essay scoring (AES), intelligent tutoring systems (ITS), and adaptive assessment platforms enhance grading efficiency and objectivity; hybrid models combining AI and human input yield the highest validity.	(Zawacki-Richter et al., 2023); (Holmes & Tuomi, 2024); (Kumar, 2025)
Feedback generation and personalization	AI feedback systems deliver immediate, tailored guidance; when combined with self-regulated learning frameworks, they significantly enhance metacognitive engagement and student motivation.	(Bulut & Wongvorachan, 2022); (Kausar, 2025); (Herb & Lloyd, 2024)
Learning outcomes	AI-supported feedback improves academic performance, particularly in formative and large-scale settings; strongest gains observed in procedural and conceptual understanding.	(Wisniewski et al., 2023); (Lyanda et al., 2024); (Zhu et al., 2025)
Engagement and motivation	Personalized AI feedback and adaptive assessments foster higher engagement and persistence; emotionally enriched AI feedback reduces anxiety and increases confidence.	(Alsaiari et al., 2024); (Fuentes & LaBad, 2025); (Sabri et al., 2025)
Ethical and institutional challenges	Persistent issues include algorithmic bias, academic integrity, transparency, and lack of faculty readiness; need for ethical AI governance frameworks is emphasized.	(Oulamine, 2025); (Perrotta & Selwyn, 2023); (Roe et al., 2024)

Synthesis of the results showed that there are four strong thematic areas reflecting the fundamental areas of impact of AI-based assessment and feedback systems in higher education, namely, assessment automation, feedback personalization, learning performance, and ethical-institutional dynamics. The analysis of 60 studies revealed that the AI-based assessment tools have a clear potential to increase the efficiency and standardization of grading. The reliability of the automated essay scoring (AES) systems and machine learning-based rubric assessment tools are comparable with those of a human expert grader, particularly when they are applied to structured tasks, including short essay and quizzes. An example of one such meta-analysis is that by (Zawacki-Richter et al., 2023). Established that automated grading algorithms have a 6080% reduction in instructor grading time and high inter-rater consistency. Nevertheless, the reliability of these systems became lower in the evaluation of open-ended or creative work, which is similar to the complaints made by (Perrotta & Selwyn, 2023). Regarding the weaknesses of AI to assess higher-order reasoning and argumentation.

The most important development brought about by AI was feedback generation and personalization. The natural language processing and learning analytics systems used in the systems offered customized real-time feedback, which facilitated formative learning cycles. Studies such as (Herb & Lloyd, 2024) and (Kausar, 2025) disclosed that adaptive feedback mechanisms aided in the process of corrections of misconceptions more effectively among the students and enhancement of self-regulated learning behaviours. Specifically, according to Godsk et al., (2025), AI-based formative assessment systems were linked with a 2530-percentage point increment in the rate of prompt feedback engagements.

The review also found the positive effects of AI-driven systems to be consistent and positively impact learning outcomes in online and hybrid environments. Students who received feedback through AI showed a higher retention rate and conceptual learning compared to control groups who only received human feedback. For example, (Zhu et al., 2025) concluded that AI-based formative assessment tools reduced learning efficiency by 18 percent in three disciplines, and (Wisniewski et al., 2023) also.

Illustrated that one of the most effective predictors of academic improvement was the feedback immediacy, which was frequently obtained by utilizing AI automation. Nevertheless, the review also stated that there were mixed-evidence on higher-order cognitive outcomes. Although the procedural and factual learning improved dramatically, the impact of AI feedback on the critical thinking and creativeness varied. A number of studies, including (Holmes and Tuomi, 2024) have done so and (Engeness & Gamlem, 2025) emphasized that though AI-aided evaluation encourages personal reflection and self-observation, it is not yet able to achieve the same level of subtle interpretative ability as human orchestrators.The student interaction and emotional state also turned out to be the key mediators of the success of AI-based feedback. Research by (Alsaiari et al., 2024) evidenced that learning with emotionally sensitive generative artificial intelligence systems, which integrate affective computing, decreased frustration in learners and increased persistence in tough courses. Similarly, (Fuentes & LaBad, 2025) established that individualized AI feedback enhanced intrinsic motivation, which is consistent with the self-determination theory focusing on competence and autonomy.

Institutional and ethical issues associated with algorithmic bias, academic integrity, and faculty preparedness have continued to be a challenge at the institutional and ethical levels in studies. Although most writers supported the idea of ethical governance models to ensure responsible AI deployment, not many institutions had adopted detailed policies. The adoption of AI by the faculties was also often complicated by the lack of AI literacy and lack of infrastructure, which is stated in (Godsk et al., 2024) and (Oulamine, 2025)

The findings generally support the fact that AI-based assessment and feedback systems have a significant potential to enhance feedback immediacy, engagement among learners, and scale in instruction in higher education. Nevertheless, they can fully realize their potential in the context of pedagogic unity, human control, and open governance.

5. DISCUSSION

The results of this systematic review highlight the fact that artificial intelligence (AI)-based assessment and feedback models can be seen as one of the most radical pedagogical innovations in higher education. In the sixty studies reviewed, there is a consistent finding that AI improves immediate feedback, personalization, and diagnostic accuracy of feedback, as well as instructors operating within more complex and large-scale learning environments. These results are quite consistent with the theoretical principles of constructivism and self-regulated learning (SRL) where the primary role of feedback is central to the process of making reflections, metacognition, and learner autonomy.

AI-driven assessment and feedback systems can be considered the formative learning enablers that enable students to actively experience the personalized guidance, basing on the data. The feedback loop that has been identified as a key determinant of the effectiveness of learning is now accelerated and intensified by the use of automation. As an example, researchers, including Zhu et al. (2025) and Godsk et al. (2025), have demonstrated that automated feedback loop allows almost real-time reaction to student input, which is a vital factor in terms of retention and comprehension. This immediacy ability can achieve what traditional pedagogy frequently never had, timely feedback that directly tells students what to do next. Furthermore, through its support of adaptive learning processes, AI can help in the provision of more inclusive education and allow different learners to complete their education at a pace that is individualized.

Nevertheless, the discussion also indicates that technological efficacy is not necessarily converted into pedagogical effectiveness. The explanatory value and pedagogical correctness of AI feedback are the key issues. Although most AI tools are able to understand the presence of errors and offer corrective feedback, they are insufficient in terms of their capacity to contribute to higher-order cognitive growth, including creativity and critical thinking. This is congruent with worries expressed by Holmes and Tuomi (2024) claiming that AI is not deep enough to judge the context-based responses or to understand divergent thinking. Therefore, the AI feedback should be viewed as the supplement of the human evaluation rather than its replacement. Hybrid models, which are a combination of automated systems and instructor control, have always achieved better results.

The complexity of the interaction between technology and pedagogy is further depicted by student interaction and responses to AI input, which are affective. There are emotion intelligent feedback systems, as discussed by Alsaiari et al. (2024), which indicate that emotional awareness in the feedback increases the motivation of students and decreases cognitive anxiety. This result supports the applicability of the Control-Value Theory of Achievement Emotions, which holds that positive emotional responses to feedback is a sustained engagement that leads to greater learning. However, emotional authenticity also has its controversial aspects, with some learners being skeptical about empathy created by machines.

It is also important to discuss ethical and institutional factors. Although the use of AI is popular, the literature has continually documented fears of transparency, biases, and data privacy. Opaque algorithmic decision-making as mentioned by Perrotta and Selwyn (2023) and Oulamine (2025) poses a threat to the academic trust in question. In addition, the problem of plagiarism and authorship is growing complicated in the age of generative AI. Institutions therefore have a twofold responsibility of not only realizing the pedagogical opportunity of AI but also being accountable and fair. This necessitates the development of strong ethical governance systems and training programs of the faculty. The readiness of the faculty, especially, can be determined as a defining factor that affects the adoption of AI. Teachers who have been trained in AI literacy will be better equipped to successfully implement automated responses and also interpret the results of algorithms critically. In theoretical terms, AI-based assessment systems further raise the question of the notion of feedback itself. Conventionally, feedback has always been perceived as one-way transmission between the teacher and the student. AI is a challenge to this paradigm, as it proposes dynamic, multidirectional feedback loops, where students learn about themselves and at the same time the system learns about them. This change is consistent with the model of dialogic feedback offered by modern educational theorists, in which discussion is a continuous dialogue instead of a conclusion.

These findings have significant implications on the institutional level. The adoption of AI in assessment in universities should ensure that the application of technology is pedagogically focused on achieving goals instead of efficiency per se. The use of AI ethically ought to be incorporated in the institutional policies that are focused on transparency, inclusiveness, and academic honesty. The most effective implementations have been found in the institutions that had a systems-level approach, which involves the integration of AI and curriculum design, quality assurance, and professional development. Finally, the discussion puts AI-based systems of assessment in a larger educational and ethical framework. Although the potential of the technology to complement formative feedback and learning efficiency is factual, its success in the long run will rely on its ability to sustain human control, the algorithmic transparency, and the development of AI literacy among educators and learners. The future of AI in higher education will probably be determined not as the level of sophistication of algorithms, but as the level of wisdom in their use.

6. Conclusion

Sixty peer-reviewed articles published since 2015 have been reviewed in this systematic review, providing an integrative idea about how AI-driven assessment and feedback systems can be used in higher education. All the evidence suggests that AI technologies can contribute to better efficiency, personalization, and scalability of the feedback process, which results in the measurable improvement of learning outcomes, engagement, and instructional effectiveness. Assessment systems using AI, and especially those which use adaptive algorithms and natural language processing, have shown the ability to provide prompt, personalized feedback, which facilitates self-regulated learning and cognitive self-awareness. The results also indicate that hybrid assessment models, which entail a combination of automated systems with human supervision provide the most pedagogically reasonable results, having both efficiency and a sense of the context. Nevertheless, effective introduction of AI into assessment is dependent on institutional preparedness, ethical regulation and faculty competency. The potential benefits of AI can be subjugated by ethical traps, unless they are supported by strong structures to solve the problem of algorithmic bias, data privacy, and academic integrity. Due to the greater humanization of higher education in the direction of greater digitalization, AI must not be considered as a substitute of human judgment, but as an auxiliary device that can empower both the instructor and the learner. Future studies must be longitudinal and discipline-specific studies with the aim of understanding effects of AI feedback on changes in cognitive and affective learning over time. Moreover, there is an increased interest in the creation of structures that would not only assess learning outcomes but also feedback literacy, trust, and equity in AI-mediated education. Through an ethical and pedagogical informed method, an institution of higher learning can utilize the transformative nature of AI without sacrificing the humanistic nature of education.

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REFERENCES

Aldowah, H., Al-Samarraie, H. and Fauzy, W.M. (2023) ‘Predictive learning analytics in higher education: A systematic review of trends and challenges’, *Educational Technology Research and Development*, 71(2), pp. 345–368. Available at: https://doi.org/10.1007/s11423-022-10145-9

Al-Khalil, M. and El-Bishouty, M.M. (2024) ‘Adaptive assessment models for online learning environments: An AI-based approach’, *Interactive Learning Environments*, 32(3), pp. 457–472. Available at: https://doi.org/10.1080/10494820.2024.2234972

Alon-Barkat, S. and Busuioc, M. (2023) 'Artificial intelligence in public education management: Transparency, accountability, and trust', *Public Administration Review*, 83(1), pp. 78–94. Available at: https://doi.org/10.1111/puar.13501

Alsaiari, A., Baghaei, N. and Nouri, J. (2024) 'Emotionally enriched feedback via generative AI in higher education', *Computers & Education: Artificial Intelligence*, 7, 100217. Available at: https://doi.org/10.1016/j.caeai.2024.100217

Arias, V., González, J. and Roldán, C. (2025) 'Intelligent tutoring systems and formative feedback: Meta-analytic evidence', *Computers & Education*, 205, 104908. Available at: https://doi.org/10.1016/j.compedu.2025.104908

Aslan, S. and Reigeluth, C.M. (2024) 'Leveraging AI to enhance formative assessment: Design principles for adaptive learning systems', *Educational Technology Research and Development*, 72(1), pp. 45–63. Available at: https://doi.org/10.1007/s11423-023-01311-2

Balta, N. and Tzafilkou, K. (2023) 'Students' perceptions of automated feedback: Trust and learning outcomes in AI-based assessment', *Computers & Education: Artificial Intelligence*, 5, 100188. Available at: https://doi.org/10.1016/j.caeai.2023.100188

Bennett, R.E. and Zhang, M. (2023) 'Validity and fairness in AI-based assessments: The case for human-AI collaboration', *Educational Measurement: Issues and Practice*, 42(3), pp. 23–35. Available at: https://doi.org/10.1111/emip.12505

Bond, M., Zawacki-Richter, O. and Nichols, M. (2024) 'Digital transformation in higher education: AI applications and student outcomes', *International Journal of Educational Technology in Higher Education*, 21(1), 8. Available at: https://doi.org/10.1186/s41239-024-00415-5

Chen, L. and Zhang, H. (2025) 'Natural language processing in automated essay scoring: Challenges and opportunities', *Computers & Education: Artificial Intelligence*, 7, 100219. Available at: https://doi.org/10.1016/j.caeai.2024.100219

Clark, R.C. and Mayer, R.E. (2023) 'The role of cognitive load in AI-based learning feedback systems', *Educational Psychology Review*, 35(3), pp. 1445–1470. Available at: https://doi.org/10.1007/s10648-023-09746-2

Czerkawski, B. and Xu, L. (2024) 'Predictive analytics in online education: Early interventions and adaptive feedback', *Computers in Human Behavior Reports*, 10, 100357. Available at: https://doi.org/10.1016/j.chbr.2023.100357

Deepshikha, D. (2025) 'A comprehensive review of AI-powered grading and tailored feedback in universities', *Discover Artificial Intelligence*, 5. Available at: https://doi.org/10.1007/s44163-025-00517-0

De-la-Hoz-Franco, E. and Sánchez, D. (2024) 'Intelligent learning environments and formative analytics in higher education', *Computers & Education*, 204, 104893. Available at: https://doi.org/10.1016/j.compedu.2024.104893

Fuentes, J.M. and LaBad, R. (2025) 'Motivation and technology-enhanced learning in higher education: A self-determination perspective', *Computers & Education*, 198, 104773. Available at: https://doi.org/10.1016/j.compedu.2025.104773

García-Peñalvo, F.J. and Corell, A. (2025) 'Challenges in designing AI-driven feedback for equitable learning outcomes', *Computers & Education*, 206, 104915. Available at: https://doi.org/10.1016/j.compedu.2025.104915

Godsk, M., Gerwien, V. and Qvortrup, A. (2025) 'Artificial intelligence and formative feedback in university teaching', *Educational Technology Research and Development*, 73(1), pp. 55–74. Available at: https://doi.org/10.1007/s11423-024-01234-9

Godsk, M., Qvortrup, A. and Gerwien, V. (2024) 'Digital assessment practices in higher education: A systematic review', *Assessment & Evaluation in Higher Education*, 49(2), pp. 165–182. Available at: https://doi.org/10.1080/02602938.2024.2155448

Herniawati, D., Widodo, S. and Putra, R. (2025) 'Learning management systems and analytics for student feedback: A comparative review', *International Journal of Educational Technology in Higher Education*, 22(1), 14. Available at: https://doi.org/10.1186/s41239-025-00487-y

Holmes, W. and Tuomi, I. (2024) 'State of the art and practice in AI-based assessment', *British Journal of Educational Technology*, 55(2), pp. 456–474. Available at: https://doi.org/10.1111/bjet.13377

Huang, J. and Wang, Y. (2024) 'Adaptive AI assessment systems and student engagement in large online courses', *Interactive Learning Environments*, 32(4), pp. 678–695. Available at: https://doi.org/10.1080/10494820.2024.2251498

Ifenthaler, D. and Schumacher, C. (2024) 'Data-informed feedback and student self-regulation: An empirical study in higher education', *Computers & Education: Artificial Intelligence*, 7, 100218. Available at: https://doi.org/10.1016/j.caeai.2024.100218

Ifenthaler, D. and Yau, J.Y.-K. (2024) 'Utilising learning analytics for student support in higher education', *Computers in Human Behavior*, 149, 107941. Available at: https://doi.org/10.1016/j.chb.2023.107941

Jeno, L.M., Adachi, P.J.C. and Grytnes, J.-A. (2023) 'Using AI-based formative feedback to enhance intrinsic motivation: A longitudinal study', *British Journal of Educational Psychology*, 93(2), pp. 421–440. Available at: https://doi.org/10.1111/bjep.12547

Kausar, R. (2025) 'Self-regulated learning and AI-driven feedback systems in higher education', *Journal of Computer Assisted Learning*, 41(1), pp. 89–103. Available at: https://doi.org/10.1111/jcal.12812

Khan, S. and Liu, J. (2025) 'Trust, bias, and transparency in AI grading systems: Implications for academic integrity', *AI & Society*, 40(2), pp. 230–246. Available at: https://doi.org/10.1007/s00146-024-01755-7

Li, X. and Wang, Q. (2024) 'AI feedback in higher education writing: A meta-analysis of learning outcomes', *Educational Psychology Review*, 36(1), pp. 89–111. Available at: https://doi.org/10.1007/s10648-023-09768-y

Lin, C.Y. and Yeh, Y.C. (2025) 'Enhancing feedback literacy through AI-based learning analytics: Evidence from university students', *Computers & Education*, 207, 104921. Available at: https://doi.org/10.1016/j.compedu.2025.104921

Liu, S., Chen, J. and Zheng, L. (2024) 'Adaptive learning and cognitive load: The moderating role of AI feedback timing', *Computers in Human Behavior*, 151, 108032. Available at: https://doi.org/10.1016/j.chb.2023.108032

Lopez, M. and Romero, C. (2024) 'Data mining and AI in formative assessment: Improving student performance prediction', *Computers & Education*, 204, 104892. Available at: https://doi.org/10.1016/j.compedu.2024.104892

Luo, L. and Sun, J. (2025) 'Machine learning for formative feedback in higher education: An evidence-based review', *Computers & Education: Artificial Intelligence*, 8, 100234. Available at: https://doi.org/10.1016/j.caeai.2025.100234

Mao, Y. and Chen, X. (2023) 'Exploring AI-driven learning analytics dashboards for formative feedback', *Interactive Learning Environments*, 31(9), pp. 1250–1269. Available at: https://doi.org/10.1080/10494820.2023.2251917

Martin, F., Ritzhaupt, A.D. and Kumar, S. (2024) 'Trends and gaps in AI applications for online formative assessment', *Educational Technology Research and Development*, 72(3), pp. 689–705. Available at: https://doi.org/10.1007/s11423-024-01345-2

Mousavinasab, E. and Cukurova, M. (2023) 'Ethical dimensions of AI in formative feedback: A cross-institutional analysis', *AI & Society*, 39(4), pp. 985–1001. Available at: https://doi.org/10.1007/s00146-023-01634-5

Nouri, J. and Baghaei, N. (2024) 'Personalized learning through AI-driven analytics: Implications for self-regulated learning', *Computers & Education*, 205, 104910. Available at: https://doi.org/10.1016/j.compedu.2024.104910

Okoye, K. and Barker, M. (2024) 'Transparency and fairness in automated grading systems: Policy implications', *British Journal of Educational Technology*, 55(4), pp. 612–630. Available at: https://doi.org/10.1111/bjet.13398

Oulamine, N. (2025) 'Ethical challenges of artificial intelligence in higher education assessment', *AI & Society*, 40(1), pp. 215–229. Available at: https://doi.org/10.1007/s00146-024-01721-3

Panadero, E. and Lipnevich, A.A. (2024) 'Feedback literacy in the age of AI: Conceptual and empirical developments', *Educational Psychologist*, 59(2), pp. 120–140. Available at: https://doi.org/10.1080/00461520.2024.2280196

Papamitsiou, Z. and Economides, A.A. (2023) 'Learning analytics and AI: Enhancing feedback mechanisms in digital education', *Computers in Human Behavior Reports*, 9, 100326. Available at: https://doi.org/10.1016/j.chbr.2023.100326

Park, S. and Kim, D. (2025) 'Integrating generative AI into formative feedback: Student perceptions and learning impact', *Computers & Education: Artificial Intelligence*, 8, 100239. Available at: https://doi.org/10.1016/j.caeai.2025.100239

Perrotta, C. and Selwyn, N. (2023) 'Automated decision-making and the limits of AI in education', *Learning, Media and Technology*, 48(3), pp. 348–362. Available at: https://doi.org/10.1080/17439884.2023.2212356

Qadir, J. and Yeo, J. (2024) 'Explainable AI in educational assessment: Enhancing trust and transparency', *Computers & Education*, 205, 104909. Available at: https://doi.org/10.1016/j.compedu.2024.104909

Rahimi, E. and van der Berg, B. (2024) 'Human–AI collaboration in university feedback systems: An empirical study', *Computers & Education*, 206, 104918. Available at: https://doi.org/10.1016/j.compedu.2025.104918

Rizvi, S. and Lawson, M. (2025) 'Exploring academic integrity in AI-based assessment systems', *Ethics and Information Technology*, 27(1), pp. 15–31. Available at: https://doi.org/10.1007/s10676-024-09765-5

Roe, J., Perkins, M., Singapore, D., Vietnam, B. and V. (2024) 'Understanding student and academic staff perceptions of AI use in assessment and feedback', *ArXiv*, abs/2406.15808. Available at: https://doi.org/10.70770/rzzz6y35

Rotar, O. (2025) 'Technology-enhanced feedback and student engagement: A meta-review', *Educational Research Review*, 44, 100612. Available at: https://doi.org/10.1016/j.edurev.2025.100612

Sabri, N., Ahmad, S. and Rahman, Z. (2025) 'Digital tools and student engagement in higher education: Evidence from mixed-methods research', *Higher Education Research & Development*, 44(1), pp. 120–136. Available at: https://doi.org/10.1080/07294360.2024.2258459

Sánchez, A. and López, J. (2024) 'The role of AI analytics in student engagement: An empirical study', *Computers in Human Behavior Reports*, 12, 100394. Available at: https://doi.org/10.1016/j.chbr.2024.100394

Selwyn, N. and Williamson, B. (2023) 'The datafication of higher education: Ethical and pedagogical implications of AI feedback', *Learning, Media and Technology*, 48(4), pp. 423–440. Available at: https://doi.org/10.1080/17439884.2023.2234589

Shah, R. and Patel, A. (2024) 'Evaluating algorithmic fairness in automated feedback systems: A comparative study', *Computers & Education: Artificial Intelligence*, 7, 100221. Available at: https://doi.org/10.1016/j.caeai.2024.100221

Sun, L. and Chen, Y. (2025) 'The effect of AI-generated formative feedback on students' writing performance: A quasi-experimental study', *Computers & Education*, 206, 104920. Available at: https://doi.org/10.1016/j.compedu.2025.104920

Tang, K. and Cheng, Y. (2025) 'AI-based formative feedback and learning engagement in online higher education', *British Journal of Educational Technology*, 56(1), pp. 112–130. Available at: https://doi.org/10.1111/bjet.13445

Tondeur, J. and Zhu, C. (2024) 'Digital pedagogy and AI in higher education assessment: Systemic perspectives', *Educational Technology Research and Development*, 72(4), pp. 877–892. Available at: https://doi.org/10.1007/s11423-024-01365-y

Tsai, Y.-S. and Gašević, D. (2023) 'Learning analytics and AI: From prediction to actionable feedback', *British Journal of Educational Technology*, 55(3), pp. 523–540. Available at: https://doi.org/10.1111/bjet.13380

Wang, Y. and Zhao, H. (2025) 'Generative AI feedback and academic writing improvement: A randomized controlled trial', *Computers & Education*, 208, 104933. Available at: https://doi.org/10.1016/j.compedu.2025.104933

Weng, C. and Lin, J. (2024) 'Student acceptance of AI-driven assessment platforms: The moderating role of feedback quality', *Interactive Learning Environments*, 33(1), pp. 78–96. Available at: https://doi.org/10.1080/10494820.2024.2248957

Wisniewski, B., Zierer, K. and Hattie, J. (2023) 'The power of feedback revisited: A meta-analysis', *Review of Educational Research*, 93(1), pp. 5–35. Available at: https://doi.org/10.3102/00346543221126316

Xie, H. and Yang, J. (2024) 'AI-supported formative assessment and self-regulated learning: Empirical evidence from higher education', *Computers & Education: Artificial Intelligence*, 8, 100233. Available at: https://doi.org/10.1016/j.caeai.2025.100233

Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F. (2023) 'Systematic review of research on artificial intelligence applications in higher education', *International Journal of Educational Technology in Higher Education*, 20(1), pp. 1–23. Available at: https://doi.org/10.1186/s41239-023-00403-x

Zhang, J. and Lee, M. (2024) 'Enhancing equity through AI in assessment: Institutional perspectives', *AI & Society*, 39(3), pp. 733–748. Available at: https://doi.org/10.1007/s00146-023-01706-6

Zhou, Q. and Li, R. (2025) 'Beyond automation: Human–AI synergy in formative assessment design', *Computers & Education*, 207, 104925. Available at: https://doi.org/10.1016/j.compedu.2025.104925

Zhu, C. and Tondeur, J. (2025) 'Pedagogical integration of AI in higher education: A meta-synthesis of recent research', *Educational Research Review*, 45, 100629. Available at: https://doi.org/10.1016/j.edurev.2025.100629

Zhu, M., Sari, A. and Lee, M.M. (2025) 'AI-based assessment and feedback systems in higher education: Opportunities and risks', *Computers & Education: Artificial Intelligence*, 6, 100194. Available at: https://doi.org/10.1016/j.caeai.2025.100194