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Enhancing feedback personalisation with AI-generated analytics: A narrative review

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Artificial intelligence (AI) systems are increasingly integrated into higher education to deliver personalised, timely, and context-specific feedback. This narrative review with systematic search components synthesises evidence from 29 empirical and exploratory studies published between 2020 and 2025, identified through structured searches in several databases. The studies used diverse approaches, including generative AI (e.g., ChatGPT), learning analytics dashboards, chatbots, natural language generation, rule-based detection, and sentiment analysis. Sample sizes ranged from small pilot cohorts to large-scale experiments with more than 1,600 students.

Findings indicate that AI-mediated feedback enhances engagement, writing quality, and performance, with several studies reporting measurable improvements. Students frequently valued AI-generated feedback for its immediacy, specificity, and clarity, often rating it as comparable to human input. However, trust varied across cultural and disciplinary contexts, with some students expressing concerns about over-reliance, reduced independence, and fairness of outputs. Hybrid models that combine AI personalisation with human oversight emerged as the most effective practice for balancing scalability with pedagogical depth.

This review demonstrates that AI-driven feedback has strong potential to improve learning outcomes and student experiences, but its integration requires careful attention to ethics, transparency, inclusivity, and workload. Limitations include heterogeneity of study designs and the short-term scope of most interventions. Future research should prioritise longitudinal and comparative trials to assess sustained impacts across diverse higher education contexts.

Keywords: AI feedback, higher education, learning analytics, online learning, personalised feedback, student engagement

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Introduction

Feedback is central to learning, but delivering timely, personalised guidance at scale is difficult in higher education, particularly online. Large cohorts, workload and asynchronous teaching often limit responsiveness. Advances in AI, including large language models and learning analytics, now offer ways to provide task-aligned, personalised feedback quickly and within existing platforms (Ouyang et al., 2023; Fidan & Gencel, 2022; Leppänen et al., 2022; Lim et al., 2020a). Early studies suggest AI feedback can boost engagement and short-term performance when it is actionable and iterative, though results for complex writing and higher-order learning remain mixed (Escalante et al., 2023; Lee, 2023; Suraworachet et al., 2023).

Two perspectives shape this review. Self-regulated learning highlights how feedback supports goal setting and strategy adjustment, while feedback literacy stresses students' ability to interpret and use comments (Lim et al., 2020a; Lim et al., 2020b). AI can advance both by signalling progress, aligning comments to criteria and prompting next steps. Yet overly prescriptive guidance may reduce reflection and agency if not paired with dialogue (Darvishi et al., 2023). Issues of trust, equity and privacy are also central; students often find AI technically credible but prefer educator oversight for nuanced judgement, with benefits sometimes concentrated among stronger learners (Jin et al., 2025; Ruwe & Mayweg Paus, 2023; Yu & Canton, 2023). Hybrid human–AI models show promise for acceptance and sense-making but raise questions of transparency and governance (Escalante et al., 2023; Suraworachet et al., 2023).

This article extends our synthesis using a broader corpus identified through AI-assisted and manual search. We frame the study as a narrative review with systematic elements to balance scope and methodological diversity in this fast-moving field. Three questions guide the analysis:

1. How is AI feedback, including generative, analytics-based and chatbot systems, implemented in higher education?
2. How effective is AI-personalised feedback for learning and self-regulated learning, and how do design features and study quality influence effects?
3. How do students perceive AI feedback in terms of trust, usefulness, workload and equity?

By addressing these questions, we aim to inform responsible design and policy for AI-mediated feedback that complements, rather than replaces, educator judgement.

Methods

Review type and rationale

We conducted a narrative review with systematic search components to balance breadth and methodological diversity in this fast-moving field. While this review does not fully comply with Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), it incorporates several PRISMA-inspired practices (Moher et al., 2009). Full PRISMA compliance is not claimed because a protocol was not pre-registered, grey literature was not included, data extraction and quality appraisal were not duplicated by independent reviewers across all studies, and no quantitative meta-analysis was undertaken. Despite these constraints, we provide an evidence-based account of peer-reviewed studies published between 2020 and 2025 on AI-personalised feedback in higher education, with explicit search strings, eligibility criteria, and a study-selection flow. Table 1 summarises the PRISMA-style flow.

Table 1: PRISMA-style flow for study selection (2020-2025).

Stage	Description	Count
Records identified from databases	Initial retrieval	4546
Records removed before screening	Duplicates	196
Records screened	Title/abstract screening	4350
Records excluded	Did not meet criteria	4200
Full texts assessed	Eligibility check	150
Studies included	Final synthesis	29

Search strategy

Searches were run across multiple databases between March and May 2025, using combinations of terms such as:

- “AI feedback” OR “artificial intelligence feedback” AND “higher education”
- “generative AI” OR “ChatGPT” AND “student learning”
- “personalised feedback” AND (“university” OR “college”)
- “learning analytics” AND “feedback”

Filters limited results to 2020–2025, peer-reviewed empirical studies in English. Reference lists of included papers were also scanned.

Screening and selection

The search returned 4,546 records (2020–2025). After removing duplicates, 4,350 records remained. Abstract and full-text screening yielded 29 studies. Inclusion criteria were: (1) higher education context, (2) AI-generated or AI-delivered feedback, (3) student-centred outcomes (e.g., engagement, learning, satisfaction), and (4) empirical studies from experimental, observational, or mixed-method designs. Exclusions were technical AI papers without educational implementation, opinion pieces, and studies outside higher education. As a result, papers which included learning analytics but did not include AI were excluded as well. Two reviewers screened independently, resolving conflicts through discussion.

Data extraction

For each study we recorded authors, year, AI technology, sample size, design, outcomes, and key findings. Reported effect sizes and qualitative themes (e.g., trust, autonomy) were also coded.

Quality appraisal

The Mixed Methods Appraisal Tool (MMAT) was used to assess methodological quality across diverse designs. Ratings contextualised findings but did not determine inclusion. Strong studies typically demonstrated clear methods, robust reporting, and alignment of AI feedback with educational aims. As not many methodological designs were found in the extracted studies, only experimental, observational, or mixed-method designs were considered.

Synthesis approach

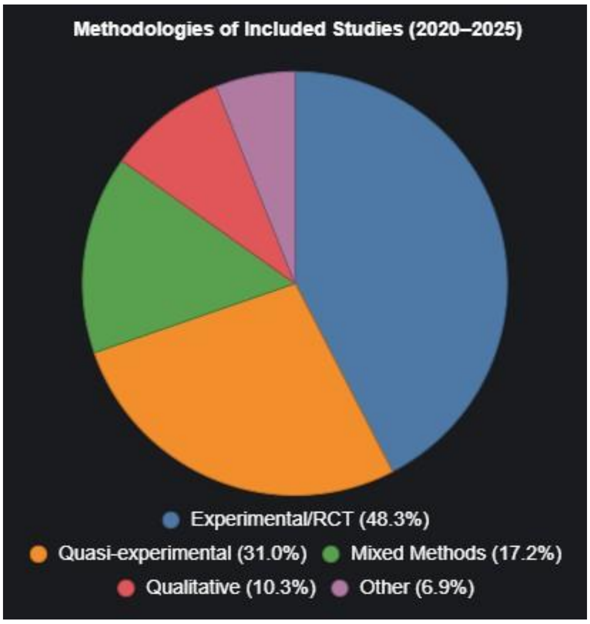
Findings were synthesised thematically around the three research questions: (1) implementation approaches, (2) personalisation effectiveness, and (3) student perceptions. Overlaps (e.g., studies trialling both generative AI and dashboards) and contradictory results were retained to reflect heterogeneity.

Results

Quality and bias profile

Figure 1 shows the proportional distribution of methodologies across the 29 studies. Experimental/randomised controlled trial (RCT) designs dominate (14 studies, 48.3%), followed by quasi-experimental (9, 31.0%), mixed methods (5, 17.2%), qualitative (3, 10.3%), and other (2, 6.9%). Positive effects should be viewed as promising but provisional, with the strongest inferences drawn from studies triangulating behavioural and learning data within dialogic cycles (Escalante et al., 2023).

Figure 1: Distribution of study methodologies.



A detailed breakdown of included technologies is presented in Table 4 (see Appendix), showing the diversity of AI tools trialled. These range from rule-based detection and NLP/ML hints to ChatGPT variants, empathic chatbots, and explainable dashboards. Sample sizes varied widely, from small pilots to cohorts of over 1,600 students.

AI feedback implementation approaches

Across the corpus, implementations fell into four overlapping categories: generative systems, rule-based or machine-learning analytics, chatbots, and Learning Management System-integrated dashboards. Generative approaches, often coupled with visualisations, improved alignment with criteria and perceived clarity (Jin et al., 2025; Escalante et al., 2023). Analytics-based tools scaffolded peer review and study behaviours, such as refining peer comments or supporting weekly planning (Darvishi et al., 2023; Ouyang et al., 2023). Chatbots offered on-demand guidance, while dashboards enabled regular course-level personalisation (Fidan & Gencel, 2022).

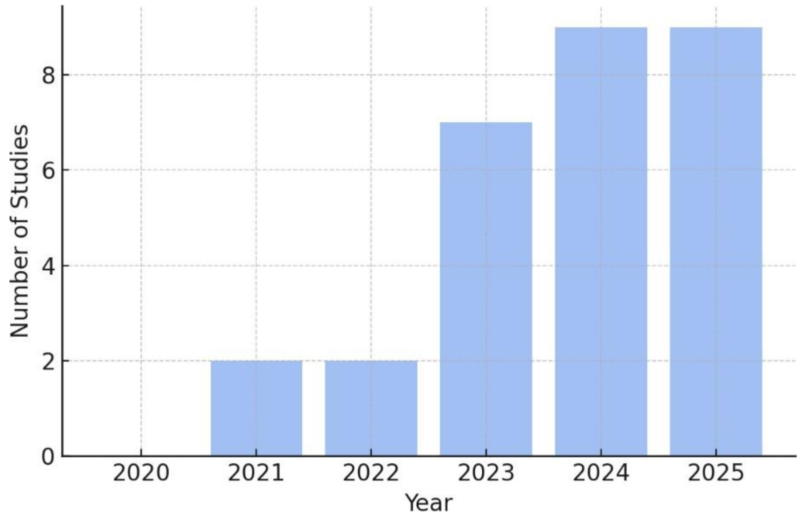
As shown in Table 2, generative AI was by far the most common approach (18 studies), followed by a diverse set of “other” AI tools (10), with fewer focusing on dashboards, chatbots, or natural language processing (NLP) or machine learning (ML) systems. Many implementations overlapped, for instance when generative AI was embedded into dashboards.

Table 2: AI feedback approaches.

AI Feedback Approach	Count
Generative AI/Large Language Models	14
Other AI Tools	10
Analytics/Dashboard	1
Chatbot	2
NLP/ML	2

Figure 2 shows the distribution of the 29 included studies by publication year, illustrating the growth of AI feedback research in higher education. It highlights a surge from 0 studies in 2020 to 9 in 2025, with notable increases in 2023 (7 studies) and 2024 (9 studies), driven by advancements like ChatGPT.

Figure 2: Publication years of included studies (2020–2025).



Personalisation effectiveness

Personalised AI feedback most consistently improved engagement, goal setting, and short-term performance. For example, personalised hints in an intelligent tutoring system produced a 23% performance gain, while predictive nudges boosted satisfaction in online courses (Kochmar et al., 2021; Ouyang et al., 2023). For writing tasks, students often rated AI comments clearer and more specific than human ones, though outcome gains were limited (Escalante et al., 2023; Lee, 2023). Some studies cautioned that highly prescriptive feedback risked reducing independent strategy use (Darvishi et al., 2023; Prakash et al., 2024).

As summarised in Table 3, reported outcomes clustered around engagement, performance, writing skills, and self-regulation, with each outcome appearing in four studies. Other frequently reported outcomes included motivation, satisfaction, trust, equity, and over-reliance.

Table 3: Reported outcomes across studies.

Reported Outcome	Frequency
Engagement	4
Performance	4
Writing skills	3
Self-regulation	4
Motivation	4
Satisfaction	4
Trust	4
Equity	4
Over-reliance	4

Student perceptions and experiences

Students valued immediacy, specificity, and visibility of progress. Large cohorts reported strong willingness to reuse generative tools when outputs were actionable, though credibility was mixed for nuanced judgement tasks (Huesca et al., 2025; Escalante et al., 2023; Jin et al., 2025). Personalised language and clear next steps enhanced usefulness, Students valued immediacy, specificity, and visibility of progress. Large cohorts reported strong willingness to reuse generative tools when outputs were actionable, though credibility was mixed for nuanced judgement tasks (Huesca et al., 2025; Escalante et al., 2023; Jin et al., 2025). Personalised language and clear next steps enhanced usefulness, but disclosure and labelling (making it explicit whether feedback was generated by AI or by a human, and, where relevant, identifying the AI tool used) shaped trust.

Equity concerns emerged, as higher-attaining students reported greater satisfaction and benefit, underscoring the need to scaffold feedback literacy for peers with less prior experience (Yu & Canton, 2023; Ruwe & Mayweg-Paus, 2023). Hybrid human–AI feedback models were preferred for complex or discipline-specific work, helping students make sense of AI output without displacing educator judgement (Lee, 2023; Zhang et al., 2025).

Discussion

This review shows that AI-generated feedback offers clear benefits in higher education but also raises important challenges. Across diverse contexts, AI tools consistently delivered timely, precise, and personalised feedback that addressed gaps in traditional methods. Analytics enhanced engagement and motivation by providing context-specific guidance (Ouyang et al., 2023; Kochmar et al., 2021), while immediacy and personalisation supported writing, goal setting, and metacognitive awareness (Yu & Canton, 2023). Students valued the clarity and actionability of AI feedback, often rating it as trustworthy and useful alongside human input (Escalante et al., 2023; Jin et al., 2025).

Yet several limitations temper these benefits. Over-reliance on prescriptive guidance risked reducing independent strategy use (Darvishi et al., 2023), and effects varied by student background and context, with stronger outcomes for higher-attaining learners (Yu & Canton, 2023). Most studies drew on self-regulated learning and feedback literacy frameworks, with others referencing community of inquiry, control-value theory, or constructivism (Ahmad et al., 2025; Ba et al., 2025; Degen, 2025). These foundations highlight the need for adaptive feedback strategies that accommodate diverse learners.

Conceptual framing

The strongest outcomes occurred when AI feedback operationalised principles of self-regulated learning and feedback literacy, aligning comments to criteria, surfacing progress, and prompting next steps in iterative cycles (Lee, 2023). Generative and analytics-based systems worked best when supporting student planning and sense-making rather than replacing them, explaining why engagement and goal setting improved more consistently than complex writing quality (Escalante et al., 2023). Evidence for deeper learning and transfer was mixed, with some studies warning of “metacognitive laziness” when feedback reduced the need for reflection (Fan et al., 2024; Ahmad et al., 2025).

Ethics, equity and trust

Trust hinged on transparency and provenance. Students often found AI feedback useful but still preferred educator oversight for nuanced, discipline-specific judgement (Escalante et al., 2023; Jin et al., 2025). Disclosure and source labels influenced credibility (Ruwe & Mayweg-Paus, 2023), while equity concerns arose when higher-achieving students benefited more than peers with weaker feedback literacy (Yu & Canton, 2023). Privacy and governance expectations were particularly salient for dashboards drawing on behavioural data (Jin et al., 2025).

Design and policy implications

Responsible implementation of AI feedback requires embedding it within cycles that include reflection, revision, and dialogue, with messages calibrated to task criteria and framed as clear, appropriately challenging next steps. Transparency is central: disclosures, source labels, and explanations of how feedback is generated can strengthen trust, while opt-in data use, privacy safeguards, and auditable logs address governance concerns. To mitigate inequities, additional scaffolds should support students with lower prior achievement or feedback literacy, while hybrid models combining AI outputs with educator checkpoints are best suited for complex or high-stakes tasks. Sustaining these practices depends on adequate resourcing, staff training, manageable workload, and dedicated time for oversight and adaptation, together with regular monitoring of AI outputs for bias, factual errors, and tone. Finally, institutional policy should emphasise critique and transformation of AI-generated text rather than wholesale adoption, ensuring evaluations go beyond satisfaction to include learning outcomes and effect sizes.

Conclusion

AI-mediated feedback has shown consistent benefits in higher education, improving engagement, planning, and short-term performance while offering clarity, timeliness, and alignment to task criteria. Yet challenges remain, particularly around trust and privacy, student preference for human-mediated nuanced judgement, and the risk of over-reliance. The most defensible model is hybrid, where AI delivers scalable, criteria-aligned guidance and educators provide context, dialogue, and oversight. This balance strengthens feedback literacy and self-regulated learning while protecting integrity and equity.

Future research should adopt standardised outcome frameworks, report effect sizes transparently, and extend to longitudinal studies that capture retention and transfer. Comparative evaluations of hybrid, AI-only, and human-only models across disciplines and task types are needed, as are equity-focused trials that support students with lower prior achievement or feedback literacy. Governance research should prioritise explainability, data minimisation, access control, and staff workload. With these foundations, institutions can embed AI feedback in ways that are effective, ethical, and sustainable, enhancing learning at scale without eroding student agency or educator judgement.

Disclosure of conflicts of interest

The authors declare no conflicts of interest.

Disclosure of the use of AI-assisted technologies during writing

AI-assisted tools (i.e., ChatGPT, Elicit.org) and Covidence were used during the literature search, extraction, and for drafting purposes. All content was critically reviewed and revised by the authors to ensure academic integrity and originality.

About the authors

Behnam Khayer is a Senior Software Engineer and academic tutor at the University of South Australia. He has more than ten years of professional experience in software development and project delivery across banking, fintech, and enterprise systems. In academia, he supports student learning in capstone and systems requirements courses, focusing on software engineering practice, teamwork, and applied project work. His research interests include the use of artificial intelligence in higher education, with particular emphasis on feedback personalisation, learning analytics, and trust in AI-mediated systems. Behnam is currently pursuing research in AI, cybersecurity, and education, aiming to bridge industrial practice with academic innovation.

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Appendix: Overview of AI technologies

Table 4: Overview of AI technologies in the included studies (NA: Not Available/Reported, each line represents a separate study)

Author (Year)	AI Technology	Sample Size	Methodology
Afzaal et al. (2021)	Explainable machine learning dashboard	NA	Mixed methods (longitudinal)
Ahmad et al. (2025)	GPT-4o-based feedback tool	NA	Experimental (RCT), mixed methods
Alsofyani & Barzanji (2024)	ChatGPT	NA	Mixed methods, quasi-experimental
Ba et al. (2025)	Generative artificial intelligence (GAI)	NA	Quasi-experimental
Chan et al. (2024)	GPT-3.5-turbo large language model	918	Experimental (RCT), mixed methods
Chen (2025)	Automated writing evaluation, ChatGPT, corpus tools	NA	Qualitative
Chen et al. (2025)	ChatGLM-4; generative AI dashboard	NA	Quasi-experimental
Darvishi et al. (2023)	Rule-based detection; semantic similarity	1,625	Experimental
Er et al. (2024)	Large language models	NA	Experimental (RCT)
Escalante et al. (2023)	ChatGPT (GPT-4) writing feedback	91	Mixed methods
Fidan & Gencel (2022)	Chatbot-driven feedback	144	Quasi-experimental
Huesca et al. (2025)	Generative AI feedback	263	Experimental
Jin et al. (2025)	Generative AI (ChatGPT); dashboard analytics	18	Mixed methods
Kochmar et al. (2021)	NLP and machine-learning hints	183	Experimental pilot
Lee (2023)	AI-enabled essay evaluation	605	Mixed methods
Lee & Moore (2024)	Generative AI (ChatGPT, Claude, LLMs)	NA	Systematic review
Leppänen et al., 2022	Natural language generation feedback	NA	Pilot study
Naseer & Khawaja (2025)	AI-driven adaptive feedback	700	Quasi-experimental
Naz & Robertson (2024)	ChatGPT-3	NA	Mixed methods
Ortega-Ochoa et al. (2024)	Empathic chatbot (DSLab-Bot)	NA	Quasi-experimental
Ouyang et al. (2023)	AI performance prediction model	62	Quasi-experimental
Prakash et al. (2024)	Sentiment analysis; ML-driven feedback	NA	Exploratory study

Author (Year)	AI Technology	Sample Size	Methodology
Qushwa (2023)	AI-driven personalisation	NA	Qualitative exploratory
Ruwe & Mayweg-Paus (2023)	AI-generated feedback	98	Experimental
Solak (2024)	ChatGPT	NA	Qualitative
Yang et al. (2025)	ChatGPT	NA	Quasi-experimental, mixed methods
Yu & Canton (2023)	SafeAssign; Grammarly; Packback	68	Observational mixed methods
Zhang & Wang (2025)	XIPU AI (Azure OpenAI)	NA	Mixed methods
Zhang et al. (2025)	Claude 3.5 Sonnet; co-produced feedback	NA	Experimental (RCT)