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Artificial Intelligence Integration and the Transformation of Teaching and Learning in Tertiary Institutions: Implications for Educational Quality and Academic Practice

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Abstract
Artificial Intelligence (AI) is slowly seeping its way into the fabric of tertiary education, from experts' research labs into the mainstream. Intelligent tutoring systems, adaptive learning platforms, learning analytics, automated feedback, and intelligent tools for administration and management of the learning process, all powered by generative AI, are changing how we create, instruct, measure and manage knowledge. This systematic review examines the effect of using AI for tertiary education, and evaluates the implications for the quality of education and practices in education. The review is reported using the reporting principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) and it reports the outcome of a search of the scholarly literature (the database), which was limited to DOI-indexed literature published between January 2019 and August 2026, and results of a documented eligibility screening process. The review included 12 studies: one systematic review, two meta-systematic reviews, two studies that focused on AI-supported teacher practice, one study on AI-supported personalized learning, and five studies on AI-supported academic integrity. A statistical analysis of findings across studies was deemed inappropriate because of the variability of technology, educational levels, definitions and methods of outcomes across the studies reviewed. This review concludes that, if it is introduced using a suitable pedagogical design and transparency, and is accompanied by the competence of educators, AI can positively impact personalisation, feedback, student engagement, accessibility, and the ability of educators to analyse. These advantages are offset by risks in relation to privacy, bias, inequitable access, hallucination, deskilling, surveillance, academic misconduct and validity of assessment. The education industry is just two of the many sectors where AI can complement, but not supplant, human decision-making to improve the learning environment. Academics is moving towards a content delivery model to a design, orchestration, verification, coaching and ethical stewardship model. The investments that this review calls for are: investments

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in AI literacy, assessment redesign, human-in-the-loop governance, data protection, staff development, inclusive infrastructure and learning outcome evaluation. The overall finding of the review is that the implementation of AI into tertiary education is not simply a procurement activity, but a process of quality assurance and reform of professional practice which should be carefully planned with regard to technology, pedagogy, purpose and educational value.

Keywords: artificial intelligence; generative AI; tertiary education; teaching and learning; educational quality; academic integrity

1. Introduction

In higher education, Artificial Intelligence (AI) has become a notable technological advancement, manifested in various ways such as intelligent tutoring systems, adaptive learning environments, predictive analytics, automated assessment, and more (Bond et al., 2024; Wang et al., 2024). The recent adoption of generative AI will bring new features like the generation of text, code, and instant explanations, with the potential to impact traditional models of teaching, learning and academic knowledge (Bond et al., 2024; Wang et al., 2024).

Though there is some existing research that suggests a strategic use of AI in instructional design can enhance students' engagement, personalization, and access to learning (Ali et al., 2024; Merino-Campos, 2025), this does not mean that their use is automatically connected to better learning outcomes, especially in all contexts. The effect of AI on educational quality is multifaceted and sometimes contradictory (Bittle & El-Gayar, 2025; Bond et al., 2024). For example, automated feedback can speed up revision but could lead to misdirected revisions if based on inaccurate information, and predictive analytics can help boost retention but could exacerbate institutional biases if relying on ambiguous algorithms (Bittle & El-Gayar, 2025; Bond et al., 2024). Moreover, the generative tools raise a new set of challenges to the traditional model of unproctored assessments, calling for a new way of thinking within educational practice, including the creation of more authentic assessment tasks, the verification of reasoning, and the explicit teaching of AI literacy (Lee et al., 2024; Taheri et al., 2025).

Despite the swift advances in the technologies, the existing literature largely focuses on the use of AI in education rather than on the specific ways in which this is impacting the quality of education more broadly and the day-to-day roles of teachers. The introduction of AI tools must be guided by evidence-based policies and models that take into account the particular characteristics of large classes, high teaching loads and the diversity of digital infrastructure in tertiary institutions, which often heighten learning inequities (Bond et al., 2024; Merino-Campos, 2025).

This systematic review thus attempts to elucidate the pressing question of the practical implications of AI for tertiary teaching quality and academic practice in the light of recent evidence. This review doesn't assume that there is a right or wrong side of AI, but rather aims to assess the extent to which various technological implementations support or impede learning. The purpose of the review is to: summarize the evidence from the last three years; outline the potential impact of AI on learning and teaching; examine the implications for the quality of learning and academic practice; and provide evidence-based recommendations to tertiary institutions (Bond et al., 2024; Wang et al., 2024).

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Research Questions

This systematic review was guided by four questions (Bond et al., 2024; Page et al., 2021):

- What forms of AI integration are being reported in tertiary teaching and learning?
- What benefits and risks are associated with AI integration for educational quality?
- How is AI transforming the roles, responsibilities, and practices of students, lecturers, assessors, and academic leaders?
- What governance, professional-development, assessment, and infrastructure conditions support responsible and educationally meaningful AI integration?

2. Conceptual Framework

2.1 AI integration as sociotechnical change

The integration of AI isn't seen as a technology alternative but a technology change in and with technology.The use of AI is viewed as a technology shift, rather than a technology replacement. The term 'tool' is used to denote a tool that is part of a curriculum, pedagogy, assessment, professional judgement, data structure, institutional policy and student expectation. A given generative system can promote learning in one situation, and inhibit learning in another – when students are required to critique the work that it has generated, when its output is monitored (with or without its sources), when learning is evidenced by the process as well as the product, and when the limitations of the generative system are understood by the educators (Ali et al., 2024; Bond et al., 2024).

This is also a framework that embraces four levels of integration. At the Task level, AI can assist in tackling a specific task, such as brainstorming, translation, feedback, developing code, creating questions, and more. The use of AI at Course level is integrated into the learning outcomes, teaching sequences, assessment and feedback. At an institutional level, AI can be utilized for advice, retention, timetabling, quality assurance or academic administration. AI has a systemic impact on evidence, expertise, access and accountability in higher education. Task and course level possibilities are most well-established and system and level consequences are less well studied (Bond et al., 2024; Wang et al., 2024).

2.2 Educational quality

Taking the view of quality of education as a multi-dimensional concept. The first one is learning effectiveness which is knowledge, conceptual knowledge, problem solving ability, transfer ability, and lasting ability. The second is the quality of instruction in terms of the relevance/clarity, responsiveness, feedback, interaction and coherence of outcomes/instruction/assessment. The third relates to the quality of the assessment itself, that is, the validity, reliability, fairness, authenticity and trustworthiness of the assessment in representing learning. Fourth, inclusion and access – can pupils who have different needs and resources be included as a player of value? Academic and institutional integrity (Academic honesty, privacy, transparency, accountability and trust (Merino-Campos (2025); Bittle & El-Gayar (2025)) is the topic of the 5th.

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AI can have a positive impact on one aspect and a negative on another. The disadvantage of automated feedback is that it could be vague or inaccurate, therefore decreasing the effectiveness of the feedback if it is.The problem with automated feedback is that if it is generic or incorrect, it's not going to improve the quality. Personalisation can be a key driver of engagement, but can be an issue of privacy if pupils are not informed about the data collection and its usage. Generative tools (both dependency and helpfulness) are potentially useful to language learners and students with disabilities, and can also create dependency or be useful to students who can access them for a fee. Use, satisfaction, speed, and other metrics are not the only ones that can be used to evaluate its quality; the educational configuration as a whole should be used as the standard (Ali et al., 2024; Merino-Campos, 2025).

2.3 Academic practice and professional judgement

The understanding and competency developed and utilised in learning and practice (academic judgement/professional judgement).

Covers some of the academic activities are design of syllabus, teaching, discussion, providing feedback, assessment of learning, supervision of inquiry, advising students and research and governorship. These functions are transformed with AI. Some of the basic tasks involved in day-to-day work can be automated or speeded up, and duties involving context, ethics and interpretation, mentoring, disciplinary identity and interpersonal trust become more prominent. The analysis of the educators' perspectives shows that AI is starting to impact how assessment and teaching methods are designed, but there are factors that affect the adoption of AI such as confidence, training, perceived usefulness, institutional support, reliability and integrity concerns (Lee et al., 2024; Taheri et al., 2025).

Now the issue is not if, but how, lecturers will teach. When an explanation can be partially automated, a drawing of a draft and a translation and feedback can be partially automated, it is the meaning of teaching. As the new role, I am represented as a learning architect and a critical steward, meaning I pose intellectually challenging challenges for students, coordinate human and machine resources, coach students to question the products and am held accountable for the educational decisions I make when I use technology as a tool that cannot replace me (Bond et al., 2024; Tan et al., 2025).

3. Methods

3.1 Review Design and Reporting Framework

A systematic literature review (SLR) was used as a research methodology for this study to synthesize a body of knowledge concerning the integration of AI into tertiary education in the fields of teaching and learning, educational quality, assessment, academic integrity, literacy on AI, academic practice and institutional readiness. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement and reporting checklist (Page et al., 2021) were used to report the review. The identification, screening, eligibility assessment, inclusion, data extraction, synthesis and reporting processes were guided by PRISMA 2020.

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Given the variability among the literature included in the review regarding study design, AI application, educational context, population, and outcome measures, the review was not conducted as a meta-analysis. Empirical studies and evidence syntheses about governance and selected conceptual contributions about academic practice were included as evidence. Because of this, a pooled effect estimate was not calculated and the synthesis was based on patterns, mechanisms, benefits, risks, implementation conditions and implications for tertiary education.

The questions for the review were pre-determined and matched to the conceptual content of the manuscript:

1. What types of tertiary teaching and learning are reported are instances of AI integration?
2. What advantages and drawbacks of AI in relation to educational quality are there?
3. How is the role and responsibilities of students, lecturers, assessors and academic leaders being affected by the integration of AI?
4. What are the conditions for governance, professional development, assessment and infrastructure that enable responsible and educationally appropriate integration of AI?

3.2 Review Protocol and Registration.

Prior to the final evidence synthesis, the review protocol outlined the questions to be addressed in the review, the eligibility criteria, the concepts used to search the literature, the screening process, the data-extraction fields, the quality-appraisal approach, and the synthesis strategy. The original manuscript contained no prospective protocol registration number. The review should therefore not be presented as a prospective registration without the ability to provide a registration record by the authors.

Any protocol, search log, screening spreadsheet, data-extraction form, and risk-of-bias assessment utilized during the review should be kept as supplementary material, if allowed by the journal, for transparency. This will facilitate an independent assessment of the review procedure and increase the reproducibility.

3.3 Eligibility Criteria

Before the screening and/or full-text assessment, eligibility criteria were predetermined, and applied uniformly during screening and/or full-text assessment. The literature was reviewed from January 2019 to August 2026. It was chosen to reflect the current progress on the development of AI-enhanced educational applications such as learning analytics, adaptive systems, intelligent tutoring, and, later, generative AI.

The studies were eligible if they fulfilled all of the following criteria:
Publication dates for these were between January 2019 and August 2026; and

- had an established Digital Object Identifier (DOI) and scholarly publication history;
- existed in an electronic format (via a publisher or scholarly source);
- college university/PS education (tertiary);

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- Read, analyzed and discussed AI applications with respect to teaching, learning, assessment, academic integrity, educational quality, AI literacy, academic practice or institutional implementation;
- identified relevant educational application(s) or the mechanism of AI in education; and

Empirical studies and evidence syntheses: For these, sufficient methodological and/or analytical information to assess the relevance and credibility of the evidence was provided.
The following four types of evidence were included: (a) studies based on empirical primary research; (b) systematic or structured literature reviews; (c) meta-systematic or evidence-synthesis reviews; and (d) rigorous conceptual studies. The addition of these categories was intentional due to the educational outcomes and institutional conditions of responsible AI integration being reviewed. The primary empirical studies yielded evidence on reported practices, perceptions, implementation, assessment, and education outcomes. Systematic and meta-systematic reviews offered higher level evidence on patterns in the vast volume of literature on the use of AI in the field of education. Conceptual studies were only included if there was a rigorous conceptual study, and if it complemented the outcome-based empirical research such that its conceptual elements were relevant to the governance, practice, assessment, ethical or institutional implementation issues not sufficiently covered by the empirical research.

Studies were not included if they:
- limited to primary or secondary school;
- provided the general education on digital learning, but without a significant focus on AI;
- Technical performance/engineering of AI system, but not an educational purpose or outcome;
- were editorials, news articles, opinion pieces, informal commentaries, or other non-scholarly publications;
- had limited understanding of AI's role in tertiary education teaching and learning, assessment and evaluation, quality and academic practice;
- Was not found in a scholarly publication record that could be verified through a DOI (where inclusion was a requirement); or
- Was not retrieved adequately to allow for assessment of eligibility.

3.4 Information Sources and Search Strategy

A detailed literature search was done following the PRISMA 2020 guidelines to identify relevant scholarly literature on the integration of artificial intelligence (AI) and its implications for teaching and learning in tertiary institutions. The following scholarly databases and academic research platforms were searched, along with any relevant publisher platforms and other scholarly resources that were identified during the search: Google Scholar, ResearchGate, Semantic Scholar, and Academia.edu. These sources were chosen to reflect a wide range of empirical studies, systematic reviews, conceptual papers, and other scholarly literature relevant to higher and tertiary education and AI.

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A search strategy was used which involved a combination of the keywords and associated terms that represented the key concepts of the review. These were: Artificial Intelligence, Generative AI, ChatGPT, Higher education, Tertiary education, University, Teaching, Learning, Pedagogy, Curriculum, Assessment, Educational Quality, Academic Integrity, AI literacy, Teacher practice, Personalised learning, Adaptive learning, Learning analytics. The terms were combined with boolean operators (AND and OR) to expand or restrict the search as needed. Some of these search combinations were “artificial intelligence AND higher education”, “generative AI AND teaching AND learning”, “ChatGPT AND tertiary education”, “artificial intelligence AND educational quality”, and “AI literacy AND academic practice”.

The timeframe for the search was limited to scholarly literature published from January 2019 to August 2026, aligning with a timeframe during which the evolving use of current AI technologies in education became more apparent and pervasive. If there were records found via one platform, citation chaining was performed by reviewing the reference lists and cited by records to find more eligible studies. Where appropriate, publisher Web sites were also checked for publication information, DOI information, and availability of the scholarly record.

The searches were carried out at Google Scholar, ResearchGate, Semantic Scholar, Academia.edu, relevant publishers' platforms, and other secondary scholarly sources on 20 August 2026. The retrieved records were checked for pre-defined eligibility criteria. Records were kept for publications for which the date of publication and/or the DOI could be substantiated and when an accessible scholarly or publisher record exists.

There were 118 records generated from the search and screening process. The 94 records located by structured DOI-indexed search were retrieved from publisher websites, with 24 more retrieved by citation chaining and website verification. After 27 duplicate records, there were 91 records left for title and abstract screening. In total, 61 records were excluded due to their shortcoming in addressing the focus of the review. The remaining 30 records were retrieved by full text or extended abstract. This left 22 studies for detailed evaluation, after eight had not been found with a verifiable DOI or a scholarly record was not available. Among them, 10 have been excluded as they cannot be clearly linked to teaching, learning, educational quality and academic-practice mechanisms. Thus, 12 studies were eligible for review and were included in the final review.

To ensure transparency and reproducibility of the information sources, search terms, eligibility criteria, screening procedures and the final number of studies included, these were documented in line with the PRISMA 2020 reporting guidelines.

3.5 Study Identification, Deduplication and Screening

Database searching, citation chaining, and verification via publishers were conducted on all records, and the results were combined into a single screening dataset. The main methods used to duplicate the records were the DOI and through bibliographic comparison. If multiple records were for the same publication, one record was kept for screening.

A preliminary search audit was conducted and found 118 records, of which 94 records were obtained through structured, DOI-indexed searching and 24 records were found through the citation chaining method and/or publisher verification. There were 27 duplicate records that were removed, resulting in 91 unique records for initial screening.

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Screening took place in two phases. Firstly, titles and abstracts (extended abstracts, if required) were evaluated against the defined eligibility criteria. At this stage, records were dropped that were clearly related to a non-tertiary education environment, to digital learning in general, to the development of the technical aspects of AI without education analysis, or to a non-scholarly document.

Second, those reports that might have been eligible for inclusion were considered in full text. If an entire article was not available, but a publisher record or extended abstract provided enough information for eligibility determination, the record was counted only if it provided enough information to establish eligibility and extract the necessary evidence. After full-text assessment, the reports which did not clearly and meaningfully relate AI and teaching/learning, educational quality, assessment, academic integrity, academic practice, or AI literacy were excluded.

In the initial screening, 30 reports have been requested for eligibility. Eight were excluded prior to full eligibility assessment due to the inability to verify the DOI or to obtain the scholarly record in a manner satisfactory to the DOI. Of the remaining 22 reports, 10 were excluded as they did not offer a mechanism in sufficient clarity for teaching, learning, the quality of education or academic practice. Twelve studies were thus left for final synthesis. These screening rates should be displayed in the PRISMA 2020 flow diagram.

3.6 Reviewer Independence and Disagreement Resolution

To reduce selection bias, enhance the reliability of the study-selection process, two reviewers completed the screening of the identified records independently using the predefined inclusion and exclusion criteria. The screening consisted of two phases: First, titles and abstracts were screened, followed by assessment of the potentially eligible full-text reports. Decision making was left to each individual reviewer prior to comparing decisions. The eligibility of each record was judged by each reviewer independently before comparisons were made.

If the reviewers disagreed on whether or not a record was eligible, the disagreement was discussed and consensus reached. When consensus was not reached in the first two evaluations, the case was sent to a third evaluator for third decision. This process helped to avoid bias in selection of articles based on a single reviewer and ensured that decisions on inclusion/exclusion were not made by one reviewer alone. This was done also when conducting a full-text assessment of potentially eligible studies.

3.7 Data Extraction

The information was systematically collected using a structured data-extraction form encompassing the information wanted in relation to the research questions. The collected data comprised details of author(s) and year of publication, geographical or institutional context, study design, study population or data source, type of artificial intelligence, educational level, teaching or learning context, outcome or issue(s) studied, main findings, academic-practice implications, recommendations, and study limitations, among others.

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If these empirical studies, other data were also obtained about the studied population, the sampling method, the measuring tools or data sources, the analysis method and the type of result. In systematic and meta-systematic reviews, data extracted included search strategy, eligibility criteria, study characteristics of included studies, approach to synthesis and main conclusions. Extraction for conceptual studies was conducted on the main conceptual statement, theoretical / analytical underpinning, implications for AI integration, implications for governance, implications for pedagogy and implications for assessment.

Data gathered were sorted by the four review questions and then by the large analytical clusters. These included applications and integration of AI; personalisation, feedback and engagement; efficiency of teaching; redistribution of academic work; validity of assessment; academic integrity; AI literacy and critical thinking; equity and access; privacy and algorithmic bias; educator adoption, and institutional readiness; governance and conditions for implementation. This organisation allowed for streamlined evidence comparison between all study designs, educational contexts, AI applications, and reported outcomes.

3.8 Quality Appraisal and Risk of Bias
To increase methodological credibility of the evidence synthesis, a formal quality appraisal and risk-of-bias assessment was conducted. Methods of appraisal were matched to the design of the study included in the review based on the various types of evidence, rather than applying one appraisal tool across all the evidence.
Quantitative empirical studies were evaluated for selection of participants, validation of measures, control of potential confounders, completeness of data, statistical analysis, and for selective reporting. Qualitative studies were evaluated with respect to the clarity of the research question, the suitability of the qualitative method, sampling, data collection methods, reflexivity, analysis of data, and the sufficiency of the data to support the interpretation.

Search strategies, eligibility criteria, transparency of study selection, methodological assessment of included studies, synthesis approach and potential for reporting bias were evaluated during the process of assessing systematic reviews and meta-systematic reviews. Conceptual studies were evaluated not only for the empirical evidence presented, but also for the clarity and coherence of their conceptual reasoning, relevant literature basis, transparency and relevance of their assumptions, and the relevance of their concepts to the questions of the reviews.

Design-appropriate critical appraisal criteria were borrowed from existing critical appraisal instruments, such as the Joanna Briggs Institute (JBI) critical appraisal tools, Critical Appraisal Skills Programme (CASP) checklists, Mixed Methods Appraisal Tool (MMAT), and A MeaSurement Tool to Assess systematic Reviews 2 (AMSTAR 2), depending on the methodological design of the individual study. Judgements of the quality of the evidence were then made as part of the interpretation of the evidence, rather than being reduced to a single numerical quality score for the fundamentally different types of study design.

Research with significant methodological weaknesses was treated with great caution and was not regarded as being as valid as the better methodologically conducted research. Thus the strength of the evidence in support of each of the major conclusions was evaluated considering the design, methodological quality and limitations of the contributing studies.

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3.9 Management of Overlap Among Systematic Reviews

Potential overlap in evidence syntheses was clearly studied, due to the use of systematic and meta-systematic reviews in the evidence base. There may be some overlap in the primary studies that are reviewed if the same studies are included in multiple reviews, and this can lead to unintended double-counting in multiple reviews when considered as separate observations.

This risk was minimised by reviewing the included systematic and meta-systematic reviews in the context of their search time, inclusion criteria, number of included studies and, where possible, the list of included primary studies for each review that formed the basis for their respective syntheses. Evidence-based reviews that cover similar evidence bases were not considered as separate empirical observations. Rather, their findings were compared at the level of the evidence synthesis. Pieces of evidence that were more substantive, methodologically transparent, comprehensive, and recent received more weight in the event that multiple reviews covered the same substantive domain. Interpretations of findings from overlapping reviews were thus viewed as corroborating, complementary or conflicting syntheses rather than as independent studies. This minimised the risk of giving disproportionate weight to evidence simply because it was cited in several reviews. The main purpose for using the evidence from the meta-systematic reviews was to characterise the overarching picture of the evidence, identify common themes and to put in context the process of the development of the AI integration in tertiary education. Where possible, specific evidence relating to educational practices, perceptions, implementation experiences, and assessment-related issues at the study level was provided by primary empirical studies. To further reduce the double counting, evidence synthesis and primary research were preserved throughout the analytical process.

3.10 Data Synthesis

Given the significant heterogeneity of the included studies across the studies in terms of the type of AI technology, educational context, study populations, research designs, outcome measures, and methodological approaches, a narrative synthesis was conducted. There was not enough uniformity of the evidence base to allow meaningful statistical pooling of evidence, and hence a meta-analysis was not carried out.

The evidence was initially classified on the basis of study design, (AI) application, educational context, principal finding, academic-practice implication, and methodological strength. The results were then classified in thematic areas related with the four review questions. This was a process that allowed for a comparison of patterns across empirical studies, systematic reviews, meta-systematic reviews and conceptual contributions.

Special effort was made to identify the difference between reported perceptions, observed practices, theoretical possibilities, causal effects and association. Data that were obtained mainly from cross-sectional surveys, self-perceptions, qualitative narratives, or conceptual reasoning did not necessarily reflect causal relationships. Likewise, recommendations on the educational policy or governance or institutional practice were separated from the empirically demonstrated findings.

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Evidence was analysed for convergent and divergent findings. If the studies were consistent, the consistency of the evidence was taken into account in terms of study design, population, educational context, and methodological quality. Differences in findings were explored with regard to differences in AI technologies, conditions of implementation, institutional context, outcome measures, and methodological approaches.

Additionally, the synthesis took into account the strength and limitations of the evidence for each of the larger conclusions. The interpretation of claims of improvements in learning outcomes, educational quality, student engagement, teaching efficiency, or institutional transformation was then guided by the methodological aspects of the evidence provided to support the claim. Special care was taken in cases where self-reported perceptions, short-term outcomes, cross-sectional designs, small samples or context-specific samples, and different implementation contexts were used to draw conclusions.

3.11 PRISMA 2020 Flow of Studies

The process of selecting studies was reported following the PRISMA 2020 guidelines and illustrated in the PRISMA 2020 flow diagram. Records flow documented by the review process of identification, duplicate removal, screening, retrieval, eligibility assessment, exclusion and final inclusion.

An initial literature search found 118 records. Of these, 94 were located using structured DOI-indexed searching and 24 were located via citation chaining and verification via the publishers' websites. After discarding 27 duplicate records, 91 records were left to screen.

Titles and abstracts/extended abstracts of the 91 records were scanned for inclusion in the review according to the predetermined inclusion criteria, and 61 records were excluded as they did not adequately address the focus of the review. A total of 30 reports were then requested, for the purpose of determining their eligibility. Of these, eight were discarded for failure to establish the validity of the DOI and/or for insufficient retrieval of scholarly information.

Twenty-two other reports were considered for eligibility. There were an additional 10 reports which did not provide evidence of a clear link to teaching and learning; educational quality; and/or academic-practice mechanisms that were applicable to the review questions. Thus, twelve studies were selected for the final synthesis.

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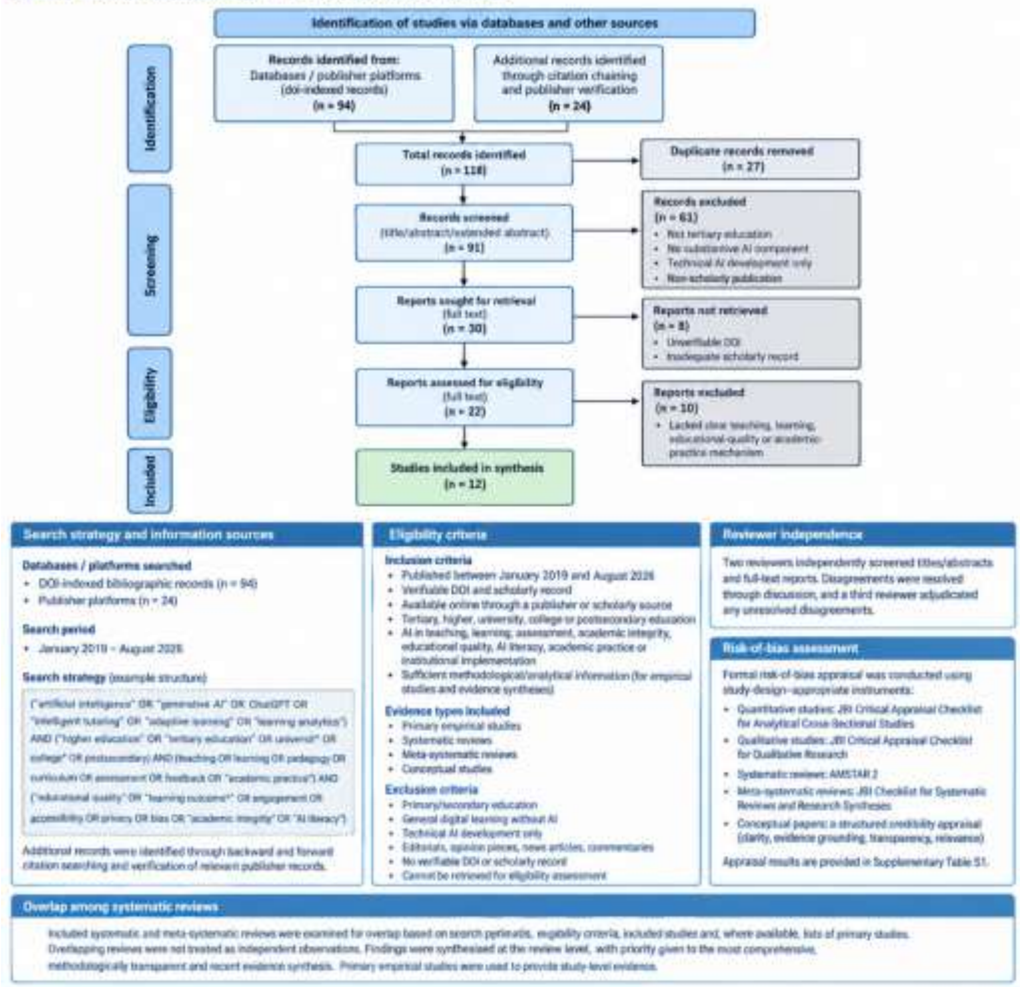

Figure 1. PRISMA 2020 flow diagram of the study selection process

The study-selection process is presented in Figure 1, which summarises the identification, screening, eligibility assessment, and inclusion of studies in accordance with PRISMA 2020.

3.12 Transparency and Reproducibility

Documentation of the review procedures to ensure transparency and reproducibly. The review methodology included details of the information sources, the database search strategies, the search dates, the search concepts, the eligibility criteria, the screening processes, reasons for exclusion at the eligibility stage, the data-extraction processes, and the quality-appraisal processes.

The search was made in Google Scholar, ResearchGate, Semantic Scholar, Academia.edu, in the specific publishers' websites, and further scholarly sources, on 20 August 2026. The search strategy used combinations of the following terms related to the AI search: artificial intelligence, generative AI, ChatGPT, higher education, tertiary education, teaching, learning, assessment, educational quality, academic integrity, AI literacy, teacher practice, personalised learning, adaptive learning, and learning analytics.

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The review also kept track of how many records were retrieved from the various information sources before they have been deduplicated. The process of screening and reasons for excluding were recorded during screening. Information and characteristics of the individual studies included in the scoping review were extracted in a structured way; the methodology of the studies was assessed using the design-appropriate quality-appraisal tools to inform the methodological strength of the evidence.

Methodological eligibility criteria for this review were (1) requirement for a verifiable DOI and (2) publicly retrievable scholarly record. This may have restricted the evidence base as a number of publications that were potentially relevant, but that did not have a DOI, were locally published, or were practitioner reports, were not retrieved. The evidence base thus emerged was, therefore, a bounded representation of the available evidence and literature and not an exhaustive representation of all evidence and literature on AI and tertiary education.

3.13 Ethical Considerations

This study was conducted by systematically identifying, appraising and synthesising information from the previously published scholarly literature, and not by recruiting human participants and collecting identifiable primary human subject data. Thus, ethical approval by institutions was not required.

In spite of this, the review was carried out following responsible scholarly practice principles such as reporting of search and selection process, representation of the evidence presented in the source texts, proper citation of all relevant sources, and distinguishing between the conclusions drawn from the evidence presented and the interpretation of the reviewers. All methodological procedures were implemented uniformly while undertaking the identification, screening, appraisal, extraction and synthesis stages, to ensure the integrity, transparency and reproducibility of the review.

4. Findings and Discussion

4.1 Characteristics and Overall Pattern of the Evidence

The reviewed studies included 12 studies covering various aspects of the use of AI in tertiary education. The evidence was systematic reviews, a meta-systematic review, empirical research on students and educators, and evidence on AI competence, assessment, academic integrity, and institutional adoption. The evidence that was included in the analysis was therefore methodologically diverse and varied in terms of the AI technologies that were explored, the education contexts, populations, outcomes and the ways in which evidence was produced. The heterogeneity made pooling of findings at a statistical level inappropriate and warranted the use of narrative synthesis.

The majority of the studies included in the evidence-confidence assessment had moderate evidence-confidence grades. Bond et al. (2024) offered a meta-systematic overview of the use of AI in higher education, and indicated significant activity in areas of intelligent systems, learning analytics, assessment and personalised learning, but also pointed to gaps in the incorporation of education and ethical considerations. Wang et al. (2024) also highlighted the diversity of educational applications of AI and the need to align technological features and capabilities with educational outcomes. These review level findings give a general overview of the field, but are not

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conclusive about the uniformity of improvements in learning that can be attributed to AI in tertiary institutions.

The findings relating to generative AI and academic integrity were also mostly of moderate confidence. Bittle and El-Gayar (2025) concluded that generative AI challenges existing notions of authorship, originality and academic integrity. The same assessment design and institutional policy were cited as key issues by Evangelista (2025) for the upholding of academic integrity in the era of ChatGPT. Empirical studies by Gruenhagen et al., (2024), Kofinas et al. (2025), and Lee et al. (2024) gave more specific evidence relating to the use of, assessment of and experiences with students' work. Tan et al. (2025) also reported that factors such as teachers' AI competence, technological pedagogical content knowledge, and their teaching performance were found to be associated, and Taheri et al. (2025) found that perceived usefulness, competence, trust, context, and organisational support were found to be factors associated with teachers' AI adoption.

The evidence collectively provides a multi-dimensional picture of the integration of AI in tertiary education. The most compelling and consistent evidence relates to specific educational tasks and practices, particularly formative support, feedback, assessment, academic integrity, educators' adoption, and AI literacy. There is relatively little evidence of wider impacts on achievement in sustained learning, the quality of education within an institution or long-term outcomes for students. The results, therefore, lend credence to the view of AI as a contextually appropriate educational intervention where the value of its application is highly dependent on the context and purpose of its usage and not as a technology with a uniform educational impact.

4.2 Personalisation, Feedback and Student Engagement

One of the recurring themes in the potential advantages of integrating AI was the aspect of personalisation. In the literature review, Merino-Campos (2025) found the following benefits mentioned repeatedly: adaptive learning, personalised feedback, engagement and some administrative applications. The computer systems can be modified with the aid of AI technology to adapt content, speed, explanations, tips, and feedback based on learner interaction. Conversational systems can also allow students to ask questions like explanations, examples, translations, practice questions, feedback, etc. outside the classroom hours.

However, evidence does not confirm that in all cases personalisation leads to better learning outcomes. It seems that the educational value of personalised support is contingent on how well it is in line with learning goals and how much students are able to critically reflect on the information that is offered. For instance, conversational AI can offer easily digestible explanations or different presentations that are helpful for students who need extra language support or are not interested in seeking clarification in speech. However, fluency and responsiveness in an artificial intelligence system is not necessarily synonymous with conceptual correctness. The literature reviewed reveals a need for students to have the ability to validate information, compare sources, identify incorrect information in a claim, and identify plausible but incorrect information provided by AI.

The results thus indicate that the use of AI for personalisation is more a way of providing greater opportunities for practice and formative interaction than of achieving greater attainment. Evidence of sustained effects on retention, transfer, progression or long term learning is comparatively less. The difference is that a technology can help a student complete a current assignment but not

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necessarily lead to a deeper understanding or independence, as the educational activity is designed to foster.

Evidence is favorable from an educational-quality standpoint when AI is used to provide personalised support as part of a unified goal of learning and when students are expected to assess and respond to the feedback they receive. Feedback that is inaccurate or generic or too little or goes too far may diminish and not enhance educational value, especially if not tailored to the context of the discipline. The use and effectiveness of the system should not be the only measure of personalisation; it should be measured in terms of the quality of the processes and outcomes of learning.

4.3 Teaching Efficiency and the Redistribution of Academic Work

The surveyed evidence show that AI can support various common schoolwork tasks. AI systems can be used by educators for creating examples, asking formative questions, writing alternative explanations, sorting and summarizing student answers, spotting patterns in student work, or to assist in devising teaching materials. The use of these applications can decrease the time needed for certain types of routine production and might also provide some opportunities for interaction, supervision, feedback, and curriculum development.

The evidence doesn't, however, back up the more general argument that using AI will lessen academic burdens. Redistribution of tasks can include new responsibilities in terms of verifying AI-created content, developing prompts, adapting them to the context, protecting data, redesigning assessments, advising students, and managing academic integrity concerns regarding AI. Lee et al. (2024) noted that teachers were already adapting their teaching and assessment processes, and were unsure and concerned about the use of AI. The same items were found to be important by Taheri et al. (2025), which is organisational support, competence, trust and perceived usefulness.

Furthermore, Tan et al. (2025) have added more evidence that the competence in AI is correlated with technological pedagogical content knowledge and that the relationship between these is meaningful to teaching performance. It does not suggest that the ability to use AI is enough to improve the performance of individual teachers, but that using the technology is more educationally relevant if it is used in conjunction with pedagogical and disciplinary knowledge.

The results thus show a re-distribution and not a mere dismantling of academic labour. Production-related activities may increase in speed while professional activities, such as judgement and verification, design of assessment, mentoring, interpretation, and ethical decision-making may gain importance. This is relevant whenever organizational decisions are made related to adoption, as it is not easy to determine the amount of professional work that should be done when using AI responsibly based on the time saved.

4.4 Assessment Validity and Academic Integrity

The most obvious impact of generative AI became apparent in assessment. The use of generative AI systems can result in coherent essays, explanations, solutions and computer code, which would reduce the degree to which an unobserved final product can stand alone to show a student's knowledge or reasoning. Bittle and El-Gayar (2025) identified significant shortcomings in current conceptions of authorship and academic dishonesty, while Gruenhagen et al. (2024) found students

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reported using chatbots to provide them with support for academic assignments, which may pose difficulties in distinguishing acceptable academic support from substitution of student work.

Kofinas et al. (2025) also discovered that generative systems can generate plausible answers that make it more difficult to scrutinize in conventional assessments. They found evidence of the iterative process of developing an assessment product, explanations, oral defence, and other evidence of individual reasoning to advocate for increased attention to evidence of this process. It does not mean that traditional assessment is always invalid, but rather that the validity of the assessment is increasingly dependent on the credibility of the evidence provided by the assessment format to the learning outcomes it is intended to measure.

There is also evidence that suggests that an all-AI-detection approach has its limitations. Detection systems can yield unreliable results, and can vary in their performance with respect to language, writing style and context. Therefore, it should not be assumed that a detection has been a definitive sign of misconduct. A better guarded strategy is to implement an assessment strategy that is effective and coupled with clear institutional rules, human oversight, and fairness. Instead of detection-only responses, therefore, Evangelista (2025) emphasizes assessment redesign.

The findings are in favor of the approaches of learning to be made visible in the assessment process. These can include a series of assignments, drafts, reflective commentary, oral questioning, supervised components, process documentation and authentic disciplinary tasks as required by disciplines. It is not intended to prevent the use of AI, but rather to ensure that any assessment produces credible evidence of the knowledge, judgement, skills and reasoning of the learning outcomes.

4.5 AI Literacy and Critical Thinking

AI literacy is not just about effective prompting; it's a more comprehensive capability that came from the fusion.The fusion resulted in a broader capability called AI literacy. The evidence suggests that successful AI students will be literate in the following aspects: understanding how AI systems work, understanding the properties and limitations of AI-produced output, knowing about bias and hallucination, assessing evidence, safeguarding personal information, using topics in a responsible way, and using topics ethically. According to Bond et al. (2024) and Ali et al. (2024), critical evaluation and responsible use are key elements of effective integration of AI.

The results also show that there is a significant disciplinary aspect to AI literacy. The critical engagement a health student, engineer, lawyer, or business student must demonstrate may vary due to different expectations for evidence, accuracy, professional responsibility and acceptable use in different disciplines. In some cases, AI-generated code might need to undergo technical testing, legal outputs need to be checked against authoritative sources, and health-related information might need special care when accuracy and safety are concerned.

This is confirmed by evidence from teachers. Tan et al. (2025) determined that the AI competence is more meaningful when it is combined with technological pedagogical content knowledge alongside with it rather than AI technical knowledge. In the same vein, Lee et al. (2024) found that teachers were using AI tools in their instruction and assessments, yet they expressed hesitation about their proper application and expectations of their institutions. The results indicate that AI

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literacy applies to students and faculty, and needs to include technical, pedagogical, ethical, and disciplinary aspects.

AI usage and critical thinking are sensitive areas to be approached with care. The reviewed evidence can be used to justify the view that critical appraisal of AI-generated artefacts is an important educational activity, without proving that the use of AI in education leads to an enhancement or hindering of critical-thinking skills. The educational impact is related to whether students are tasked with questioning, checking, comparing, modifying, explaining, or disproving AI-generated products. Therefore, AI may be used as a tool of critical enquiry, or an alternative to the intellectual work the learning activity is designed to produce.

4.6 Equity, Accessibility, Privacy and Algorithmic Bias

Some evidence notes opportunities for inclusion and equity concerns of integrating AI. Some students with diverse language, learning, and/or accessibility needs might benefit from features like AI-assisted translation, alternative explanations, flexible pacing, conversational interaction, and ongoing access to academic support. This could be one way in which AI can expand academic support provision. Yet there is no evidence to show the equal provision of these benefits to pupils.

There might be financial, institutional, connectivity, digital competence and familiarity with the technologies requirements for access to AI tools. While ChatGPT has the potential to enhance teaching and learning, Mai et al. (2024) also pointed out several risks and inequalities associated with its use.In addition to the benefits of ChatGPT-supported teaching and learning, Mai et al. (2024) highlighted several risks and inequalities in the use of ChatGPT. AI, then, does not automatically mean access to and equity in its educational benefits.

Educational quality is another aspect of privacy. Behavioural or educational data can be used in a personalised system or application to provide recommendations. If this data is incomplete or imprecise, inferences regarding students' ability or risk will also be incomplete or imprecise. The reviewed evidence thus confirms the need for human oversight of an AI-supported decision, especially in cases in which students' learning opportunities, learning progression, assessment, or support of students is influenced by automated systems.

A related issue is that of algorithmic bias. AI systems can perpetuate or exacerbate constraints in the training data, system design, or institutional datasets. The evidence suggests that we need to analyze the context in which automatic recommendations are created, and not take it for granted that algorithmic ideas are neutral. These concerns are especially important in the context of decisions with institutional consequences made by AI.

4.7 Institutional Readiness, Governance and Accountability

The synthesis suggests that institutional readiness is a multi-dimensional phenomenon and encompasses leadership, policy, infrastructure, staff development, technical assistance, procurement, data protection, and ongoing assessment and review. According to Taheri et al. (2025) there is a variation in educator adoption, depending on the perceived usefulness, competence, trust, context and organisational support. Similarly, Lee et al. (2024) found that practical advice, time and institutional support are also crucial factors in the use of generative AI by educators.

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The evidence suggests that having the technology for AI does not imply setting up institutions. An institution could have advanced AI systems but be unsure of their academic integrity policies, privacy policies, accountability policies, assessments, or the role of staff. On the other hand, institutions with less technological resources could still benefit from the educational value of specific applications, which are carefully selected and implemented with critical evaluation and competence of the staff.

The governance of where AI output has a significant impact on consequential academic decisions is especially significant. If an algorithm generates a recommendation, it can't be the responsibility of that algorithm. There is still a shared responsibility of accountability between students and lecturers, programme leaders, administrators and institutional leadership depending on their respective roles. Therefore, Bittle and El-Gayar (2025) and Bond et al. (2024) support governance arrangements that establish accountability, acceptable use, oversight and responsibility and institutional accountability.

The evidence thus supports a human-supervised mode of operation where AI can be used to facilitate and support, but where the education judgement is still in the hands of qualified academic personnel. This position is strengthened by the aggregated results of the studies of educator competence, the validity of assessment, academic honesty, privacy, and institutional governance.

4.8 Implications for Educational Quality and Academic Practice

The four review questions reveal that the value of AI in education is not necessarily about using technology but about the links with learning outcomes, pedagogy, assessment, professional judgement and institutional context. The most recent studies are those at the task and course level, and at the institutional and system level are less well documented.

AI seems to have best fit in providing formative support, personalising interactions, providing content assistance, giving feedback, and providing selected academic task supports. Simultaneously, the same technologies pose problems of false information, dependence, privacy, bias, unequal access, academic dishonesty, and the validity of assessments. Coexistence of benefits and risks also implies that it is not possible to draw educational conclusions from the shares of adoption or satisfaction or speed of processing alone.

Also evidence indicates that academic practice is being shifted instead of being mechanized. AI can help with everyday production work, but there are still key tasks like verification, interpretation, assessment design, mentoring, ethical judgement and quality assurance that can't be automated. While all three studies (Lee et al., 2024; Tan et al., 2025; Taheri et al., 2025) suggest that AI competence is not enough to ensure effective implementation and that institutional support is essential, they also highlight the importance of learning through practice.All three studies (Lee et al., 2024; Tan et al., 2025; Taheri et al., 2025) emphasize learning by doing as well as competence and institutional support for effective AI integration.

Important constraints of the evidence base are that many studies are perception, self-reported, and cross-sectional and/or have short-term outcomes. The review therefore provides better evidence on reported practices, perceived benefits and risks, implementation conditions than some aspects of long-term effects on attainment, retention, transfer, critical thinking, progression or institutional

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quality of education. Positive short term experiences do not constitute evidence of long term educational improvement as there is no strong evidence of this.

In summary, the results validate a selective, transparent, inclusive and pedagogically integrated strategy for the use of AI in tertiary education. There is only some evidence, not enough to endorse or condemn. Instead, the potential for AI integration should be assessed based on how well it enhances the desired learning experience, preserves the integrity of the assessment, fosters fair access, safeguards privacy, and ensures a proper balance of human involvement.

5. Conclusion and Recommendations

5.1 Conclusion

This systematic review explored and summarised the reported modes of AI integration in tertiary learning and teaching, the potential advantages and disadvantages to the quality of education, transformations in academic roles, and changes in academic practices, as well as institutions' conditions for a responsible implementation. The data presented in the 12 studies included in this review suggests that AI is being used increasingly across the areas of learning support, feedback, assessment, content creation, academic practice and institutional activities. But there is no strong consensus that AI has a positive or negative impact on tertiary education.

The most consistent evidence relates to the possibility of AI's interaction, formative support, feedback, accessible explanations and assistance in selected academic tasks in a personalised way. The applications can enhance the accessibility and responsiveness of educational support, especially in the context of the learning outcomes clearly defined and with proper human supervision. But the impact on attainment and retention, transfer, critical thinking, progression and educational quality of the whole institution is limited. There are numerous studies available, which are based on perceptions, self-reported use, context-specific observations, and which are not well suited for stronger causal inferences.

The review also highlights the key challenges of validity of assessment and academic integrity that arise with the use of AI. For some traditional assessment formats, the use of Generative AI may render them less effective tools for determining student understanding and thinking skills. The evidence thus confirms the need to emphasis more on assessment designs that increase students' reasoning, development, reflection and disciplinary judgement. Meanwhile, the use of AI-detection technologies should not be considered as conclusive proof of wrongdoing, as results can be ambiguous and depend on the context.

Another key precondition for responsible integration is the "AI literacy". Based on the evidence, the key competencies of meaningful AI literacy include critical evaluation, checking outputs, understanding the impact of bias and hallucination, safeguarding personal information, promoting academic integrity, and demonstrating discipline-specific judgement. Academic staff: AI competence is most useful when it is reinforced by the pedagogical and subject knowledge. AI literacy should, therefore, be viewed as a means of learning and a professional trait, and not just a technical skill.

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The review also shows that AI's incorporation affects the distribution of academic work. While there may be some efficiencies in routine tasks, there are also new tasks that arise with verification, assessment redesign, student guidance, professional learning, data protection and institutional governance. Thus, there is no correlation between technological adoption and automatic workload reduction.

Equity, privacy, bias and institutional accountability continue to be significant factors in determining educational value. While AI could help increase access to translation, alternative explanations, flexible learning support, and other modes of assistance, unequal access to technology and variations in digital competence can have the potential of reproducing existing inequalities. Likewise, the application of student data and algorithmic recommendations also requires transparency, safeguards for privacy, human oversight and accountability.

Based on the evidence presented, the concept of AI in education is characterised as a context-specific educational technology that is contingent on the interplay between technology, pedagogy, assessment, professional competence, student agency and institutional governance. The evidence is thus in favor of human-assisted AI not human-replaced academic expertise and responsibility. It is pedagogically sound and defensible integration of appropriate use of AI where there is a pedagogically defensible reason for using it, limitations are known, and the decision to use it falls within the purview of appropriately qualified humans.

5.2 Recommendations

Based on the findings of this review, the following recommendations are proposed.

1. Establishment of institution-wide AI governance system.
Tertiary institutions should develop guidelines for acceptable and unacceptable usage of AI in teaching, learning, assessment, research, and administration, among other areas. These frameworks should include disclosure obligations, privacy safeguards, human review obligations, accountability systems, and dispute resolution mechanisms to deal with disputes or suspected misuse. Governance should be commensurate with the potential impacts of the use of each AI application.

2. Easing the integration of AI literacy in the curriculum.
AI literacy should not be viewed as a standalone orientation task, but should be a part of the programme of study. Students should learn how to assess the accuracy and bias of AI-generated information, how to safeguard personal data, how to give credit to AI when needed, and be able to apply appropriate judgement to the discipline regarding the acceptability of AI-generated information. AI literacy content and intensity should be based on specific disciplines' needs.

3. Re-thinking assessment on the basis of evidence of learning.
In times and places where generative AI can be used, the methods of assessment should be considered and aligned to continue to provide evidence for the intended learning outcomes. If applicable, staged work, drafts, self-judgement, oral presentation, supervised components, process documentation and authentic disciplinary tasks should be included. Using AI detection doesn't replace human investigation, judgement or procedural fairness and may be incorporated into an institutional response to suspected misuse.

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4. Ongoing teaching staff professional development.
Institutions must deliver ongoing professional learning that integrates AI skills and competence with pedagogy, discipline content, assessment design, ethics, and governance. Training must help lecturers to review and reflect critically on AI tools, determine suitable use in education, verify AI-generated outputs, rethink assessments, and put expectations clearly.

5. The preservation of significant, human supervision.
Any decisions, recommendations, feedback, content that could impact students must be reviewed by humans appropriately as well.Recommendations, feedback, content and decisions made with AI technology should be reviewed by humans appropriately. Educational judgements should not be delegated to automations. Careful human supervision is especially needed when AI is employed in the assessment, student-risk prediction, progression decision, or other meaningful academic activities.

6. Respecting privacy and good data stewardship.
Institutions need to define procedures for the collection, processing, storage and sharing of student and staff information on the part of AI systems. AI usage should be linked with suitable privacy protection, data practices transparency, and systems to detect and mitigate algorithmic biases.

7. Support to fair access to AI-based learning.
Solutions involving AI should be applied in a manner that does not negatively impact students with limited financial, connectivity, digital literacy and access to high-quality AI tools. Institutions need to take into account the technical characteristics, access and support needed to enable students to engage in AI-supported learning in a meaningful way.

8. Assessment of educational results in the context of adoption only.
Beyond adoption, usage, processing speed or user satisfaction, institutional evaluation of AI should go beyond that. Learning outcomes, quality of feedback, participation of students, validity of assessment, equity, academic integrity, workload of teachers, and ability of students to make their own judgments should be taken into account. For short-term benefits, longitudinal assessment should be adopted to check for the long-term effects, wherever possible.

9. Awareness of the evolving nature of academic work.
Planning for institutions should take account of the fact that AI might be reallocating rather than replacing academic labour. Time and resources should be allocated for re-designing assessments, verifying AI generated assessments, professional development, student guidance, policy development and quality assurance. This will enable a cost-benefit analysis of selected AI applications based on efficiency to be performed along with the added professional burden they impose.

10. When swamped with context, implement and review.
Implementing AI needs to be tailored to the institutional capacity, the disciplinary needs, the infrastructure available, and the needs of pupils and staff. There is no evidence that an intervention that seems appropriate and useful in one institutional setting would yield similar results in other settings. Therefore, it is crucial for institutions to track and assess results, record negative impacts, and make necessary adjustments as evidence accumulates and AI technologies evolve.

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Appendix A. Search concepts and eligibility logic

Concept	**Indicative terms**
Technology	artificial intelligence, generative AI, ChatGPT, intelligent tutoring, adaptive learning, learning analytics
Educational setting	higher education, tertiary education, university, postsecondary, college
Educational process	teaching, learning, pedagogy, curriculum, assessment, feedback, academic practice
Quality and risk	educational quality, learning outcome, engagement, accessibility, privacy, bias, academic integrity
Source filter	2019 onward; DOI verified; online scholarly record accessible