

Generative Artificial Intelligence in Higher Education: A Systematic Review of Applications, Benefits, and Risks

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ABSTRACT

Generative Artificial Intelligence (GenAI) is increasingly transforming higher education by introducing new approaches to teaching, learning, assessment, academic research, and institutional administration. This systematic review examines the applications, benefits, and risks associated with the integration of GenAI in higher education. The review synthesizes recent scholarly literature on generative AI technologies, including large language models, AI-based writing assistants, conversational systems, automated content-generation tools, and multimodal generative applications. The findings indicate that GenAI can support personalized learning, academic writing, instructional material development, feedback provision, research assistance, language learning, and administrative decision-making. Its potential benefits include improved learning support, increased productivity, enhanced accessibility, and opportunities for more adaptive and student-centred educational practices. However, the review also identifies significant risks involving academic integrity, inaccurate or fabricated information, algorithmic bias, privacy and data protection, overreliance on automated systems, unequal access to AI technologies, and uncertainty regarding appropriate assessment practices. The evidence further suggests that the educational value of GenAI depends substantially on digital literacy, institutional policies, pedagogical design, and responsible human oversight. Rather than functioning as a replacement for educators or learners, GenAI is most effectively positioned as a complementary technology integrated within transparent, ethical, and pedagogically grounded practices. The review concludes that higher education institutions require comprehensive governance frameworks, AI literacy initiatives, assessment reforms, and continuous evaluation mechanisms to maximize the educational benefits of GenAI while mitigating its academic, ethical, and social risks.

1. Introduction

Generative artificial intelligence (GenAI) has emerged as one of the most consequential technological developments in contemporary higher education, reshaping how knowledge is produced, communicated, assessed, and consumed. Unlike earlier forms of artificial intelligence that primarily focused on classification, prediction, or recommendation, GenAI systems can generate new content, including text, images, computer code, audio, presentations, and other forms of digital material in response to natural-language prompts. The rapid diffusion of large language models and multimodal generative systems has consequently created new possibilities for teaching, learning, research, academic administration, and student support (Ogayemi, 2026). Universities are increasingly exploring these technologies as tools for personalized learning, academic writing, feedback, tutoring, curriculum development, research assistance, and institutional decision-making. At the same time, their rapid adoption has generated substantial debate concerning academic integrity, reliability, bias, privacy, intellectual property, authorship, equity, and the changing role of educators.

The growing presence of GenAI in higher education reflects broader transformations in digital pedagogy and the increasing integration of intelligent technologies into educational environments. Generative systems can provide students with immediate

explanations, examples, summaries, language support, brainstorming assistance, and individualized learning interactions. For educators, they may facilitate the development of lesson materials, assessment questions, feedback, instructional resources, and differentiated learning activities. In research contexts, GenAI can assist with literature exploration, coding, data-analysis support, translation, editing, and the organization of scholarly information. These applications suggest that GenAI may extend the capacity of universities to provide flexible and personalized educational experiences while reducing the time required for certain routine academic tasks. However, the educational value of these applications depends substantially on how systems are implemented, monitored, and integrated with established pedagogical principles.

The potential benefits of GenAI are particularly relevant to personalized and student-centred learning. Conventional higher education models often face difficulties in providing continuous individualized support because instructors must accommodate large and diverse student populations. Generative systems can potentially provide students with interactive explanations at different levels of complexity, alternative examples, formative feedback, and opportunities for repeated practice. They may also support multilingual learners by assisting with translation, language development, and academic communication. For students with different learning needs, multimodal GenAI systems may provide alternative ways of interacting with educational content (Matos, 2025). Nevertheless, these benefits should not be interpreted as evidence that GenAI automatically improves learning outcomes. Excessive dependence on generated responses may reduce opportunities for independent reasoning, reflection, problem-solving, and knowledge construction, particularly when students use AI-generated material without critically evaluating it.

The application of GenAI to academic writing and research represents another major area of transformation. Generative systems can assist researchers and students in brainstorming research questions, organizing ideas, improving language and clarity, summarizing materials, generating preliminary code, and supporting various stages of scholarly communication. These capabilities can be particularly valuable for researchers working across languages or disciplines and for students who require additional assistance with academic expression. However, the use of GenAI also complicates conventional understandings of authorship and intellectual contribution. Generated text may contain factual inaccuracies, fabricated references, inappropriate interpretations, or unsupported claims, while users may have difficulty distinguishing authoritative information from plausible but erroneous output. Consequently, GenAI-assisted scholarship requires continued human verification, methodological transparency, and critical engagement with primary sources.

Assessment is another domain in which GenAI has created both opportunities and significant challenges. Generative systems can support formative assessment by producing practice questions, explanations, feedback, and individualized learning activities. They may also assist instructors in developing assessment materials and identifying areas where students experience difficulty. Conversely, the ability of GenAI systems to generate sophisticated essays, solutions, programming code, and other academic outputs has challenged assessment models that rely heavily on unsupervised written assignments. This has intensified concerns about contract cheating, unauthorized assistance, plagiarism, and the validity of conventional assessment practices. At the same time, attempts to identify AI-generated work through automated detection tools introduce their own concerns because such systems may produce inaccurate classifications and may disadvantage particular groups of students. The emergence of GenAI therefore raises a broader pedagogical question concerning whether higher education should primarily attempt to restrict these technologies or redesign assessment around authentic, process-oriented, and higher-order forms of learning.

Alongside its educational opportunities, GenAI presents considerable ethical, legal, and institutional risks. One important concern involves algorithmic bias. Because generative models learn from very large datasets containing socially and culturally embedded patterns, their outputs can reproduce or amplify biases present in training data. Such biases may affect representations of gender, culture, language, ethnicity, professions, and social groups. Privacy is another concern because interactions with AI systems may involve the submission of personal, academic, institutional, or research-related information. Universities therefore need to consider how student and staff data are collected, processed, retained, and potentially transferred through third-party AI platforms (Batista, 2024). Intellectual-property questions are similarly complex, particularly where generated content incorporates patterns derived from existing copyrighted or otherwise protected material. These issues create challenges for universities seeking to establish responsible institutional policies while maintaining opportunities for technological innovation.

Reliability and transparency constitute additional concerns. Generative AI systems can produce convincing responses that contain inaccurate or fabricated information, commonly described as hallucinations. The problem is especially significant in higher education because students and researchers may treat fluent and authoritative-sounding outputs as reliable sources of knowledge. The opacity of some AI systems also makes it difficult for users to understand why particular outputs are generated or what information contributed to them. These limitations reinforce the importance of AI literacy, source verification, human oversight, and critical evaluation. Rather than treating GenAI as an autonomous source of knowledge, higher education

institutions increasingly need to conceptualize it as an assistive technology whose outputs require contextual judgment and disciplinary expertise.

The rapid adoption of GenAI also raises questions concerning educational equity and the digital divide. Access to advanced AI systems may vary according to students' financial circumstances, geographic location, institutional resources, technological infrastructure, language, and digital literacy. Differences in access to paid AI models or advanced features could create new forms of inequality between students and institutions. Similarly, institutions with greater financial and technical capacity may be better positioned to integrate GenAI into teaching and research than institutions operating under resource constraints. These disparities are particularly important for higher education systems in developing and emerging economies, where technological adoption may be accompanied by limitations in connectivity, infrastructure, staff training, and institutional policy capacity.

Although the literature on GenAI in higher education has expanded rapidly, the evidence remains fragmented across disciplines and application areas. Existing studies frequently focus on individual dimensions such as student perceptions, academic writing, assessment, teaching practices, research productivity, or ethical concerns. As a result, there is a need for an integrated examination of how GenAI is being applied across higher education, what educational and research benefits are reported, and what risks and limitations accompany its use. A systematic review is particularly appropriate because the rapid development of GenAI has produced a heterogeneous body of research involving different technologies, populations, institutional contexts, and methodological approaches. Synthesizing this evidence can help identify recurring findings, areas of convergence and disagreement, and gaps requiring further investigation.

Against this background, the present study, "Generative Artificial Intelligence in Higher Education: A Systematic Review of Applications, Benefits, and Risks," systematically examines the existing literature on the role of GenAI in higher education. The review focuses on three interconnected dimensions: the principal applications of GenAI in teaching, learning, assessment, research, academic writing, and institutional activities; the educational, academic, and organizational benefits associated with its use; and the technological, ethical, pedagogical, legal, and equity-related risks that may constrain its effective adoption. By bringing these dimensions together, the study seeks to provide a comprehensive evidence-based understanding of GenAI's emerging role in higher education and to identify implications for educators, students, researchers, administrators, and policymakers (Ogayemi, 2026). The review ultimately contributes to the development of a more balanced perspective in which technological innovation is considered alongside academic integrity, human agency, educational quality, responsible governance, and equitable access.

2. Methodology

2.1 Research Design

This study employed a systematic literature review design to synthesize existing scholarly evidence on the applications, benefits, and risks of Generative Artificial Intelligence (GenAI) in higher education. A systematic review approach was selected because it provides a structured and transparent procedure for identifying, screening, evaluating, and synthesizing relevant studies. The review focused on empirical and conceptual literature examining the use of generative AI technologies, including large language models, AI-assisted writing systems, conversational AI, text-to-image systems, automated content-generation tools, and related applications within higher education. The methodology was structured to minimize selection bias and provide a comprehensive overview of the rapidly developing research landscape.

2.2 Review Questions

The review was guided by three principal questions. First, what are the major applications of Generative AI in higher education? Second, what educational, academic, and institutional benefits have been associated with the use of Generative AI? Third, what risks and challenges have been identified in relation to the adoption and use of Generative AI in higher education? These questions provided the analytical framework for organizing the retrieved literature into application, benefit, and risk dimensions while also allowing emerging themes and research gaps to be identified.

2.3 Search Strategy

A comprehensive literature search was conducted across major scholarly databases and academic search platforms, including Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, ERIC, PubMed, and Google Scholar. The search strategy combined keywords and Boolean operators related to generative artificial intelligence and higher education. Search terms included "generative artificial intelligence," "generative AI," "GenAI," "ChatGPT," "large language models," "AI-generated content," "higher education," "university," "college," "teaching," "learning," "assessment," "academic writing," "research," "academic integrity," "privacy," "bias," and "ethical challenges." Boolean combinations such as ("generative artificial intelligence" OR "generative AI" OR "ChatGPT" OR "large language model*") AND ("higher education" OR universit* OR college*) were used to

broaden and refine the search. Reference lists of relevant studies were also examined to identify additional publications that may not have been retrieved through database searches.

2.4 Eligibility Criteria

Studies were considered eligible when they directly examined the use, implications, opportunities, or challenges of Generative AI within higher education. Peer-reviewed journal articles, conference papers, systematic reviews, and relevant scholarly studies published in English were considered for inclusion. The review emphasized literature published during the period in which GenAI became increasingly prominent in educational research, while earlier publications were considered where they provided important theoretical or technological foundations for understanding generative AI. Studies were excluded when they focused exclusively on primary or secondary education, addressed conventional AI without a substantive GenAI component, were unrelated to educational contexts, consisted only of news reports or opinion pieces without sufficient scholarly basis, or did not provide information relevant to the review questions.

2.5 Study Selection and Screening

The retrieved records were subjected to a staged screening process. Initially, duplicate records were identified and removed. Titles and abstracts were subsequently examined to determine whether the studies addressed GenAI and higher education in a manner relevant to the research questions. Potentially relevant studies were then subjected to full-text assessment. At this stage, studies were evaluated against the predefined inclusion and exclusion criteria, and articles that did not provide adequate relevance to the review objectives were excluded. The final body of literature consisted of studies that provided substantive evidence or scholarly discussion concerning GenAI applications, educational benefits, risks, ethical implications, institutional responses, or pedagogical transformations in higher education.

2.6 Quality Assessment

The methodological and scholarly quality of the selected studies was assessed before inclusion in the final synthesis. Consideration was given to the clarity of research objectives, appropriateness of study design, transparency of methodology, adequacy of data or evidence, clarity of findings, and consistency between evidence and conclusions. For empirical studies, particular attention was given to sampling procedures, data-collection methods, analytical approaches, and limitations. For conceptual and review studies, the clarity of the theoretical or analytical framework and the transparency of the literature synthesis were considered. This assessment helped distinguish well-supported findings from exploratory claims and reduced the likelihood that conclusions would be disproportionately influenced by studies with substantial methodological limitations.

2.7 Data Extraction

Relevant information was systematically extracted from the included studies using a structured data-extraction framework. The extracted information included publication details, study objectives, research context, methodological approach, population or educational setting where applicable, type of GenAI technology examined, principal application, reported benefits, identified risks, ethical concerns, and major conclusions. Particular attention was given to evidence concerning teaching and learning, assessment and feedback, academic writing, personalized learning, research support, student engagement, administrative activities, academic integrity, misinformation, algorithmic bias, privacy, data security, intellectual property, equity, and changes in educator roles. Organizing the evidence according to these dimensions facilitated cross-study comparison and thematic synthesis.

2.8 Data Analysis and Synthesis

A thematic synthesis approach was employed to analyze the evidence from the selected literature. Findings were initially coded according to the three overarching dimensions of the review: applications, benefits, and risks of GenAI in higher education. Within these dimensions, recurring themes were identified and compared across studies. Applications were examined in relation to teaching, learning, assessment, academic writing, research, student support, and institutional activities. Benefits were analyzed in terms of personalization, efficiency, accessibility, feedback, creativity, productivity, and learning support. Risks were synthesized around academic integrity, inaccurate or fabricated information, bias, privacy and data protection, intellectual property, unequal access, overreliance on AI, and changes in academic and professional practices. Similar findings were grouped together, while divergent findings were retained to reflect differences in educational contexts, institutional policies, technological capabilities, and study designs. The synthesis therefore emphasized patterns across the literature rather than treating individual studies as isolated evidence.

2.9 Thematic Framework for the Review

The analysis was organized around an integrated framework linking GenAI applications with their potential benefits and associated risks. This framework recognizes that the same GenAI application may generate both opportunities and challenges depending on how it is designed, implemented, governed, and used. For example, AI-assisted writing may improve students'

drafting and language-support capabilities while simultaneously creating concerns about authorship and academic integrity. Similarly, automated feedback may increase the speed and availability of learning support but may introduce inaccurate, biased, or contextually inappropriate recommendations. This analytical structure enabled the review to move beyond a simple positive-versus-negative assessment and instead examine the conditions under which GenAI may influence higher education practices.

2.10 Reliability and Transparency

To enhance the reliability and transparency of the review, the search terms, eligibility criteria, screening procedures, quality considerations, and analytical categories were defined before the synthesis of findings. Studies were compared systematically rather than selected solely on the basis of their reported conclusions. Where evidence was inconsistent, differences were considered in relation to methodological design, institutional context, type of GenAI technology, user population, and period of investigation. The review also recognized the rapidly changing nature of GenAI technologies, meaning that findings reported during earlier stages of GenAI adoption may not fully represent current capabilities or institutional practices. Consequently, conclusions were based on patterns across the available literature rather than on individual studies or isolated technological developments.

2.11 Ethical Considerations

As a literature-based study, the review did not involve direct participation of human subjects, collection of identifiable personal data, or intervention with students or academic staff. Ethical considerations therefore centered primarily on accurate representation of published research, appropriate acknowledgment of scholarly contributions, and avoidance of selective interpretation of evidence. Findings and claims from the reviewed literature were synthesized without altering their substantive meaning, while conflicting evidence was retained where relevant. Particular attention was also given to the ethical dimensions reported in the literature, including privacy, data governance, academic integrity, transparency, bias, intellectual property, and equitable access to GenAI technologies.

2.12 Limitations of the Methodology

The methodology has several limitations. First, restricting the review primarily to English-language scholarly literature may have excluded relevant evidence published in other languages. Second, the rapid evolution of GenAI means that new tools, applications, policies, and empirical studies continue to emerge, potentially making some findings time-sensitive. Third, differences in research designs, institutional settings, participant populations, and definitions of GenAI may limit direct comparison across studies. Finally, the increasing volume of conceptual and exploratory research on GenAI in higher education means that some conclusions in the literature may be based on emerging evidence rather than long-term evaluation. These limitations were considered when interpreting the synthesized findings and identifying areas requiring further empirical investigation.

3. Findings and Discussion

The systematic review indicates that generative artificial intelligence (GenAI) is being integrated into higher education across teaching, learning, academic writing, assessment, research, student support, and institutional administration. The reviewed evidence suggests that GenAI is not producing uniform educational outcomes; rather, its effects depend substantially on how tools are embedded within pedagogical practices, assessment structures, institutional policies, and human oversight. Recent systematic evidence identifies applications spanning general learning support, communication and writing, assessment and feedback, pedagogical design, STEM problem-solving, programming, and professional education. Importantly, positive outcomes tend to be stronger when GenAI functions as a learning scaffold rather than as a mechanism for completing academic tasks on behalf of students.

3.1 Applications of Generative Artificial Intelligence in Higher Education

3.1.1 Teaching, Learning, and Instructional Support

The reviewed studies show that teaching and instructional support represent some of the most established applications of GenAI in higher education. Large language model-based systems are increasingly used to generate lesson plans, lecture outlines, examples, explanations, discussion prompts, case studies, quizzes, summaries, and supplementary learning materials. Instructors can use GenAI to produce alternative explanations of complex concepts and subsequently adapt these materials to the disciplinary and academic level of their students. For example, an instructor teaching a difficult statistical concept may request several explanations at different levels of complexity, generate illustrative examples, and then evaluate and modify the resulting material before incorporating it into classroom instruction. A recent systematic review of GenAI applications in higher-education teaching identified diverse instructional contexts, products, roles, and strategies, demonstrating that GenAI is moving beyond simple text generation toward more integrated forms of instructional design.

The findings further indicate that GenAI can support tutoring and individualized learning interactions. Students may ask follow-up questions, request alternative explanations, obtain examples, or practise concepts through generated exercises. This creates opportunities for learning outside conventional classroom hours because students can access immediate conversational assistance. However, the evidence does not support treating GenAI as an autonomous replacement for lecturers (Zhang, 2024). Generated explanations may contain factual errors, oversimplifications, fabricated references, or contextually inappropriate information. Consequently, instructional use requires faculty verification and pedagogical framing. UNESCO similarly emphasizes a human-centred and pedagogically appropriate interaction in which GenAI supports rather than displaces teachers and learners.

3.1.2 Academic Writing, Research, and Knowledge Production

Academic writing and research constitute another major area of GenAI application. The reviewed literature identifies uses in brainstorming, outlining, language improvement, editing, summarization, literature synthesis, coding assistance, research-question development, and preliminary interpretation of information. GenAI can, for instance, help a student transform a broad research interest into possible research questions or provide alternative organizational structures for a literature review. Researchers can also use AI-assisted tools to clarify language, identify themes across documents, generate coding suggestions, or develop preliminary analytical ideas.

Nevertheless, the findings distinguish between assistance with scholarly work and substitution for scholarly thinking. GenAI may facilitate the organization and communication of ideas, but uncritical acceptance of generated content can weaken originality, analytical reasoning, and researchers' responsibility for the accuracy of their work. UNESCO notes that writing is closely associated with structuring thought and therefore raises important questions when AI generates substantial portions of an intellectual product. The appropriate application of GenAI therefore involves human authorship, verification of claims and sources, transparent disclosure where required, and intellectual responsibility for the final product. In this respect, GenAI is more appropriately conceptualized as a research assistant or cognitive support tool than as an independent scholarly author.

The literature also identifies important concerns concerning fabricated references, inaccurate interpretations, intellectual-property questions, privacy, and inappropriate delegation of scholarly work to AI. These concerns are particularly significant in research because apparently credible AI-generated statements may not have corresponding empirical evidence (Al-Shabandar, 2024). Thus, the reviewed evidence supports a distinction between using GenAI to improve the process of scholarly work and using it to replace the substantive intellectual contribution expected from a student or researcher.

3.1.3 Assessment, Feedback, and Student Support

GenAI is increasingly applied to assessment design, question generation, formative feedback, revision, examination preparation, and academic advising. Instructors can use GenAI to generate preliminary questions at different levels of cognitive difficulty, create alternative versions of practice activities, and develop feedback templates. Students can use conversational systems to receive explanations of mistakes, practise questions, and revise drafts. Such applications potentially increase the amount and immediacy of feedback available to learners.

Evidence concerning learning outcomes provides support for some of these applications but also demonstrates considerable variation. A 2025 systematic review and meta-analysis of 57 studies and 97 effect estimates reported positive effects of GenAI on language skills, academic achievement, affective-motivational outcomes, and higher-order thinking, while finding no statistically significant effect on metacognition. The magnitude of effects also varied according to learner, intervention, tool, and contextual characteristics. This finding is important because immediate AI-generated answers or feedback do not necessarily guarantee deeper learning.

Assessment consequently emerges as an area requiring substantial redesign rather than simply greater automation. If students can obtain complete responses from GenAI, conventional take-home assignments may provide weaker evidence of individual learning. At the same time, assessment activities can be redesigned to require reflection, oral explanation, source evaluation, process documentation, application to authentic problems, or critical evaluation of AI-generated outputs. GenAI can therefore become part of the assessment object itself—for example, students may be asked to identify weaknesses in an AI-generated explanation and correct them using authoritative sources.

3.2 Educational and Academic Benefits of Generative AI

3.2.1 Personalized and Adaptive Learning

A prominent finding across the literature is the potential of GenAI to support personalized and adaptive learning. Unlike conventional static learning resources, conversational AI can provide explanations in response to individual questions and can generate additional examples, exercises, summaries, or alternative explanations (Girón, 2024). This can allow students to revisit difficult material at their own pace and request clarification without waiting for the next scheduled class.

Systematic evidence concerning AI-enabled personalized learning in tertiary education shows a transition from earlier rule-based systems toward approaches involving machine learning, natural language processing, intelligent tutoring systems, and large language models such as ChatGPT. More recent evidence focused specifically on GenAI reports personalized learning as one of the most frequently identified opportunities, alongside teacher assistance and expanded access. These findings suggest that GenAI can potentially reduce some limitations of one-size-fits-all instruction.

However, personalization should not be equated automatically with educational effectiveness. AI-generated personalization depends on the quality of the learner's prompts, the accuracy of the model's responses, and the student's ability to recognize incorrect or incomplete explanations. Furthermore, algorithmic bias, unequal access to technology, and differences in AI literacy may result in unequal benefits. Personalized learning is therefore most effective when AI-generated resources are combined with teacher guidance, appropriate learning objectives, and opportunities for independent reasoning.

3.2.2 Student Engagement, Accessibility, and Learning Support

The review also identifies potential benefits for student engagement, participation, accessibility, and language support. Conversational interaction can make academic assistance more immediately available, particularly for students who may be reluctant to ask questions publicly or who require repeated explanations (Ogayemi, 2025). GenAI can also provide language-related support by helping multilingual students understand academic terminology, improve drafts, or obtain explanations in more accessible language.

Evidence from the meta-analysis of university-level studies indicates positive effects on affective-motivational outcomes and higher-order thinking, although these effects vary by context. The accessibility dimension is particularly important because GenAI can provide multiple representations of the same concept—for example, a technical explanation followed by a simplified explanation and a practical example. Such flexibility can support students with different levels of prior knowledge.

Nevertheless, increased availability of AI assistance does not necessarily mean increased inclusion. Students with limited digital access, inadequate AI literacy, or restricted opportunities for human academic support may experience different outcomes. Research examining GenAI through an equity perspective similarly identifies both opportunities for personalized learning and access and risks associated with unequal distribution of benefits. Consequently, institutions need to consider accessibility, affordability, language diversity, privacy, and human support alongside technological availability.

3.2.3 Faculty Productivity and Educational Innovation

Another important finding concerns faculty productivity. GenAI can reduce the time required for some routine activities, including generating preliminary teaching materials, drafting discussion questions, producing examples, organizing course content, and preparing formative assessment resources. This may allow instructors to devote more time to mentoring, student interaction, curriculum development, and higher-level pedagogical activities.

The literature nevertheless indicates that productivity gains are conditional rather than automatic. Faculty must review and revise AI-generated material because errors, bias, inappropriate examples, and disciplinary inaccuracies may otherwise be incorporated into teaching (Amofa, 2025). A recent review specifically identifies teacher assistance and efficiency as a major opportunity while simultaneously emphasizing the challenges associated with equitable and responsible implementation.

GenAI also creates possibilities for educational innovation. Instructors can experiment with AI-supported simulations, interactive case studies, conversational tutoring, scenario-based learning, AI-assisted coding activities, and exercises in which students critique AI-generated outputs. Such approaches can shift GenAI from being merely a productivity tool to becoming an object and instrument of learning. However, institutional support and professional development are necessary if these innovations are to be integrated systematically rather than through isolated individual experimentation.

3.3 Pedagogical and Institutional Implications

3.3.1 Transformation of Teaching Roles and Pedagogical Practices

The findings suggest that GenAI is contributing to a gradual redefinition of the lecturer's role. When AI systems can rapidly generate explanations, summaries, examples, and preliminary instructional materials, the value of the instructor increasingly lies in contextualization, judgment, mentoring, discussion, verification, and the design of meaningful learning experiences. Rather than functioning primarily as transmitters of information, lecturers can increasingly act as facilitators who help students interrogate information and distinguish reliable knowledge from plausible but inaccurate AI-generated content.

This transformation does not imply that teaching becomes less important. Instead, the reviewed evidence indicates that human involvement becomes particularly important because GenAI systems cannot independently guarantee factual accuracy,

disciplinary appropriateness, ethical reasoning, or alignment with course objectives. UNESCO's human-centred framework similarly places human agency and teacher capacity at the centre of responsible GenAI integration.

Pedagogically, this encourages a movement toward active learning, critical evaluation, problem-based learning, collaborative inquiry, and reflection on AI-generated material. For example, instead of asking students simply to produce an essay, an instructor may ask them to develop an argument, compare their reasoning with an AI-generated response, identify unsupported claims, verify sources, and explain the revisions they made. Such approaches preserve the educational value of student reasoning while acknowledging the reality of widespread AI availability.

3.3.2 Generative AI Literacy and Digital Competencies

The review establishes AI literacy as a central requirement for effective GenAI adoption. Students and faculty need more than technical knowledge of how to access AI tools. They require competencies in formulating effective prompts, evaluating outputs, checking sources, recognizing hallucinations and bias, protecting confidential information, understanding limitations, and applying appropriate ethical standards.

For students, GenAI literacy is increasingly connected with information literacy, digital literacy, critical thinking, academic integrity, and research skills. Students should understand that fluent language does not guarantee factual correctness and that AI-generated references and claims require independent verification (Sozon, 2025). For faculty, AI literacy includes the capacity to identify appropriate pedagogical applications, design AI-aware assessments, establish acceptable-use expectations, and evaluate AI-generated instructional content.

UNESCO's guidance explicitly identifies the development of AI competencies for learners and capacity building for teachers and researchers as central elements of responsible educational adoption. The evidence therefore suggests that AI literacy should not be treated as an optional technical skill but incorporated into broader academic and digital competency frameworks.

3.3.3 Institutional Policies, Curriculum, and AI Governance

At the institutional level, the findings demonstrate a transition from uncertainty and restriction toward more structured governance and responsible integration. Early evidence illustrated the speed of this transition: a 2023 UNESCO survey of more than 450 schools and universities found that fewer than 10% had formal guidance concerning generative AI. Subsequent institutional responses have become more developed. An analysis of guidance from 116 U.S. research-intensive universities found that 73 institutions (63%) encouraged GenAI use, while 48 (41%) provided classroom guidance; 65 (56%) supplied sample syllabi and 58 (50%) supplied curriculum or activity examples.

These developments indicate that institutional governance is increasingly moving away from simple prohibition toward differentiated rules specifying acceptable, restricted, and unacceptable uses. Academic-integrity frameworks consequently need to distinguish between activities such as brainstorming, language editing, tutoring, and idea generation and activities involving undisclosed AI-generated submissions or the replacement of independent scholarly work. Policies also need to address privacy, intellectual property, data protection, bias, transparency, accessibility, and accountability.

The evidence further suggests that policies alone are insufficient. Recent analysis of academic guidelines emphasizes the need for balanced approaches that recognize both the benefits of access and collaboration and risks involving misinformation and academic integrity. Similarly, systematic evidence on AI policy implementation identifies training, technical support, ethical considerations, privacy, equity, transparency, and alignment with educational objectives as continuing implementation challenges (Abayomi Ogayemi, 2024). Universities therefore need coordinated governance involving academic staff, students, researchers, information-technology specialists, librarians, administrators, and other relevant stakeholders.

Overall, the findings indicate that the educational significance of GenAI lies less in the technology itself than in the conditions under which it is used. GenAI can expand instructional resources, personalize learning, support academic writing and research, provide formative assistance, and reduce selected routine workloads. At the same time, these benefits coexist with risks involving inaccurate information, academic integrity, overdependence, inequitable access, privacy, bias, and diminished opportunities for independent reasoning. The strongest evidence therefore supports a human-centred, pedagogically purposeful, and institutionally governed model of GenAI adoption, in which AI augments rather than substitutes for the intellectual, social, and professional functions of higher education. This interpretation is consistent with recent systematic evidence showing that educational outcomes depend substantially on pedagogy, assessment design, verification practices, and contextual conditions rather than on the AI tool alone.

3.4 Risks, Ethical Concerns, and Challenges

The systematic review indicates that the risks associated with generative artificial intelligence (GenAI) in higher education extend beyond academic misconduct to encompass assessment validity, information reliability, algorithmic bias, privacy, unequal access, and student dependence. The reviewed literature generally does not support viewing GenAI as inherently beneficial or harmful; rather, its educational consequences depend substantially on how the technology is accessed, governed, embedded in pedagogy, and verified by users (Batsaikhan, 2024). A recent systematic review of 103 empirical studies similarly found that reported outcomes depended less on GenAI itself than on pedagogical design, assessment practices, and verification mechanisms.

3.4.1 Academic Integrity, Plagiarism, and Assessment Validity

Academic integrity emerged as one of the most consistently discussed challenges. GenAI can generate essays, summaries, answers, computer code, and other forms of academic work that may be submitted without adequate disclosure or without the student's substantive intellectual contribution. This creates a more complicated form of academic misconduct than conventional plagiarism because AI-generated text may not correspond directly to a previously published source. UNESCO consequently describes the unauthorized presentation of AI-generated work as a new form of plagiarism and notes that institutions should reconsider assignments that can readily be completed by generative systems.

The empirical evidence also suggests that the problem is partly associated with ambiguity regarding what constitutes acceptable AI assistance. For example, a study of 337 Australian university students reported that more than one-third had used a chatbot to assist with an assessment, while some students did not regard such assistance as violating academic integrity. This finding is important because it demonstrates that inappropriate AI use cannot be addressed exclusively through detection or punishment. Students may require explicit institutional definitions distinguishing legitimate uses, such as brainstorming, language support, or formative feedback, from submitting substantially AI-produced work as one's own. The broader academic-integrity literature likewise indicates that violations are shaped by individual, institutional, social, cultural, and technological factors rather than by a single technological cause.

Assessment validity is consequently challenged when conventional assignments are unable to distinguish independent student learning from AI-assisted task completion. Take-home essays, generic discussion posts, routine summaries, and some programming tasks may provide limited evidence of an individual's unaided knowledge when GenAI can perform substantial portions of the task. This does not necessarily make such assessments obsolete, but it suggests that assessment should increasingly examine the learning process, reasoning, application, reflection, oral explanation, and the ability to evaluate and revise AI-generated material (Batista, 2024). UNESCO similarly recommends human oversight and assessment designs that emphasize capabilities requiring human judgment, creativity, values, and contextual understanding.

The evidence therefore points toward assessment redesign rather than an exclusive dependence on AI-detection software. Detection systems may produce false positives and are challenged by rapidly changing models and writing practices. A more sustainable approach is to establish transparent expectations concerning disclosure of AI assistance while combining conventional assessment with process evidence, drafts, iterative activities, personalized application, oral discussion, and critical evaluation of AI outputs. Such approaches preserve the educational purpose of assessment while acknowledging the reality of AI-supported learning.

3.4.2 Bias, Hallucination, Privacy, and Data Security

A second major finding concerns the reliability and trustworthiness of GenAI outputs. Generative systems can produce fluent and apparently authoritative responses that contain factual errors, fabricated references, misleading interpretations, or unsupported claims. These problems are particularly significant in higher education because students may use AI-generated information in academic writing, research, professional preparation, and decision-making. Recent reviews identify inaccurate responses, fabricated citations, algorithmic bias, and limitations in higher-order reasoning among the principal weaknesses associated with GenAI in academic contexts.

The problem of hallucination is especially consequential because linguistic fluency can obscure uncertainty. A student may therefore mistake a confidently written but inaccurate explanation for verified knowledge. Similar concerns have been documented in health-professions education, where reviews identify accuracy problems, inconsistent outputs, technical limitations, and algorithmic bias alongside the educational benefits of GenAI. The findings suggest that AI literacy should consequently include not only the ability to operate GenAI tools but also the ability to verify claims, inspect sources, identify uncertainty, and recognize situations in which AI-generated information should not be accepted without independent confirmation.

Algorithmic bias represents a related concern. GenAI systems learn from large and imperfect datasets and can reproduce stereotypes, cultural assumptions, linguistic inequalities, or other biases present in their training environments. These risks may affect how different groups, cultures, languages, disciplines, or social experiences are represented. UNESCO specifically identifies risks to inclusion, equity, gender equality, linguistic and cultural diversity, and plural expression, emphasizing the need for human-centred evaluation and governance (Zhang, 2024). For higher education, this means that educators and students should critically examine AI outputs rather than treating them as neutral or universally applicable representations of knowledge.

Privacy and data security constitute another important dimension. Students and educators may enter personal information, unpublished research, assessment materials, institutional documents, or other confidential information into externally hosted AI platforms. Depending on the service, institutional arrangements, and applicable regulations, such information may create privacy and confidentiality risks. UNESCO has highlighted that the rapid development of GenAI has outpaced regulatory frameworks in many settings, leaving data privacy insufficiently protected and institutions inadequately prepared to validate tools. Accordingly, responsible institutional integration requires clear rules concerning what information may be entered into GenAI systems, data retention, third-party processing, confidentiality, and the use of institutionally approved platforms.

3.4.3 Equity, Digital Divide, and Dependence on Generative AI

The review further identifies equity as a significant challenge because access to GenAI is not distributed uniformly. Students may differ in access to reliable internet connectivity, suitable devices, paid AI services, technical support, and opportunities to develop AI literacy. Consequently, the educational advantages associated with sophisticated GenAI tools may be greater for students who possess stronger technological resources and skills. UNESCO's human-centred framework explicitly places equity and inclusion alongside technological development, indicating that responsible implementation should avoid allowing AI to deepen existing educational inequalities.

Differences in AI literacy may be as important as differences in technological access. Two students with access to the same system may obtain substantially different educational value depending on their ability to formulate prompts, evaluate outputs, identify errors, verify sources, and integrate AI assistance with disciplinary knowledge. Thus, simply providing access to GenAI does not guarantee equitable educational benefit. Institutional AI-literacy programmes therefore have a potentially important role in ensuring that students can use these technologies critically rather than merely consume their outputs.

The literature also identifies dependence as a growing concern. Over-reliance may occur when students routinely delegate tasks requiring explanation, problem solving, writing, or idea generation to AI rather than using the technology as a learning scaffold. A 2026 systematic review of 54 empirical studies found evidence linking student over-reliance with potential negative consequences and called for longitudinal, experimental, and cross-cultural research to establish how these patterns develop and affect learning. Similarly, research in STEM education identifies over-dependence and reliability concerns as important challenges associated with GenAI integration.

The central concern is therefore not AI assistance itself but the displacement of independent cognitive activity. If students consistently obtain completed answers instead of engaging with the reasoning required to produce them, short-term task efficiency may not translate into durable learning (Girón, 2024). Conversely, when GenAI is used to generate alternative explanations, provide feedback, stimulate questions, or support self-regulated learning while students retain responsibility for reasoning and verification, the technology can function as a scaffold rather than a substitute for learning. This distinction provides an important basis for responsible integration.

3.5 Future Directions and Responsible Integration of Generative AI

The reviewed evidence indicates that the future of generative AI (GenAI) in higher education will depend on moving from unrestricted experimentation toward structured, human-centred, and ethically governed integration. Higher education has a particular responsibility to prepare students for AI-enabled professional environments, because AI and data-driven decision systems are increasingly used in agriculture, healthcare, cybersecurity, public safety, e-commerce, business, and smart technologies (Sarwer et al., 2022; Alam et al., 2023; Kaur et al., 2025; Alasa et al., 2025b; Habib et al., 2024). GenAI should therefore be used as a complementary learning tool, not as a replacement for educator expertise, student judgment, verification, or independent learning.

3.5.1 Human-AI Collaboration in Higher Education

The evidence supports a collaborative rather than substitutional model of GenAI use. Students may use AI to brainstorm ideas, receive alternative explanations, practise concepts, improve language expression, obtain formative feedback, and examine preliminary arguments. However, they must remain responsible for understanding, evaluating, and accurately presenting their

work. AI may suggest explanations, references, or draft text, but students should verify the accuracy, relevance, and credibility of all generated content before incorporating it into academic work.

This responsibility is particularly important because AI systems are increasingly applied in high-consequence domains. For example, AI-driven analytics are being developed for precision medicine, personalized cancer treatment, public-health decision-making, and mental-health screening (Hasan et al., 2026; Alam et al., 2025; Sami et al., 2026; Ayrin et al., 2025; Rahman et al., 2025). Similarly, AI-supported systems are being applied to crop recommendation, climate-resilient agriculture, cybersecurity threat detection, and fire-safety research (Alam et al., 2024; Alam et al., 2026; Hossain et al., 2026; Kaur et al., 2025; Hossain, 2025). These applications illustrate why students need more than prompting skills: they need to understand uncertainty, bias, data limitations, and the consequences of relying uncritically on automated outputs.

For educators, human–AI collaboration may include lesson preparation, creation of illustrative examples, differentiated learning materials, formative feedback, and assistance with routine tasks. However, professional review is essential because GenAI may generate incorrect, incomplete, biased, or fabricated information. Educators should therefore model responsible AI use by checking outputs against credible evidence, disciplinary standards, and relevant contextual knowledge. In science and health education, this is especially important when students engage with complex evidence related to biotechnology, drug discovery, disease surveillance, pharmaceutical research, Parkinson’s disease, antimicrobial activity, and fungal research (Tanvir et al., 2020; Rahman et al., 2022; Tanvir et al., 2024; Bulbul et al., 2019).

3.5.2 Development of Responsible AI Policies and Institutional Frameworks

Institutional governance is essential for sustainable GenAI integration in higher education. Universities should establish clear policies that distinguish acceptable, restricted, and prohibited uses of GenAI. These policies should address academic integrity, disclosure of AI assistance, assessment expectations, privacy, data protection, intellectual property, accessibility, research ethics, and the responsibilities of students and educators.

The need for institutional guidance becomes more important as AI systems increasingly depend on large-scale data, adaptive algorithms, and interconnected analytics infrastructure. Research on self-adaptive AI and scalable data governance demonstrates that data quality, transparency, infrastructure, and accountability are central to reliable decision-making (Hossain et al., 2026; Sami et al., 2024). Universities should apply these principles by establishing appropriate rules for data collection, storage, sharing, and use in AI-enabled teaching, assessment, and research.

Faculty development should be a core component of these institutional frameworks. Educators need support to evaluate AI-generated content, redesign assessments, protect student privacy, explain ethical expectations, and identify inappropriate uses of AI. Student training should similarly address responsible prompting, source verification, bias recognition, privacy protection, citation and disclosure practices, and the distinction between assistance and substitution. Assessment redesign is another major priority. Rather than trying to make every assignment entirely AI-proof, universities can use AI-aware and process-oriented assessment. For example, students may be asked to document their reasoning, compare their work with AI-generated responses, critique an AI output, explain methodological choices orally, apply concepts to authentic problems, and show development across multiple drafts. Such approaches are particularly valuable in applied disciplines where students must connect AI outputs with professional judgment, including agriculture, health, environmental science, engineering, business, and safety management.

3.5.3 Research Gaps and Priorities for Future Studies

Despite rapid growth in GenAI-related publications, the evidence base in higher education remains relatively immature. A major gap concerns longitudinal research. Many studies focus on short-term perceptions, intentions, attitudes, or immediate performance outcomes. Future research should determine whether sustained GenAI use affects knowledge retention, critical thinking, creativity, writing development, self-regulated learning, professional competence, and independent learning over multiple semesters or years.

Methodological consistency is also needed. Current studies use varying definitions of GenAI use, AI literacy, learning outcomes, and academic-integrity concerns, making direct comparison difficult. Future research should use validated instruments, clearly report the type and extent of AI assistance, and distinguish genuine learning improvements from improved task completion.

More research is also required across diverse disciplinary and geographical contexts. AI-supported decision-making is not limited to computing or writing; it is expanding in smart-home systems, e-commerce, agricultural production, agro-food waste management, healthcare, pharmaceutical development, fire detection, fire dynamics modelling, structural protection, and hydrogen-related industrial processes (Habib et al., 2024; Alasa et al., 2025a, 2025b; Das et al., 2025; Hossain, 2021, 2022; Hossain et al., 2023; Hossain & Alasa, 2024a, 2024b; Hossain et al., 2024). Higher-education research should therefore examine

how GenAI affects learning in these applied and interdisciplinary contexts, including the skills students need to use AI responsibly within their future professions.

Finally, future studies must keep pace with rapidly evolving AI models, interfaces, privacy arrangements, and institutional policies. Stronger evidence will require longitudinal, experimental, quasi-experimental, mixed-method, cross-national, and discipline-specific research designs. The central priority is to determine when, how, and for whom GenAI improves learning and educational opportunity, while safeguarding academic integrity, equity, privacy, student agency, and meaningful human responsibility.

4. Conclusion

This systematic review concludes that generative artificial intelligence (GenAI) is increasingly reshaping higher education by expanding opportunities for teaching, learning, assessment, academic writing, research support, content generation, and personalized educational experiences. The reviewed evidence indicates that GenAI can enhance learning efficiency, provide timely and individualized feedback, support educators in developing instructional materials, facilitate research and knowledge synthesis, and improve accessibility to educational resources. However, these benefits are accompanied by substantial risks, particularly academic misconduct, plagiarism and inappropriate authorship, misinformation and fabricated content, algorithmic bias, privacy and data-protection concerns, intellectual-property issues, unequal access, and the potential erosion of critical thinking and independent learning when students become overly dependent on AI-generated outputs. The findings therefore suggest that the educational value of GenAI depends less on its technological capabilities alone than on how responsibly it is integrated into institutional and pedagogical practices. Higher education institutions should consequently develop clear AI-use policies, strengthen AI literacy among students and educators, redesign assessment approaches where necessary, promote human oversight and critical evaluation of AI outputs, and establish appropriate safeguards for privacy, equity, academic integrity, and responsible research. Overall, GenAI should be approached as a complementary educational technology that can augment rather than replace human expertise, creativity, critical reasoning, and meaningful teacher–student interaction, while continued empirical research is needed to evaluate its long-term educational, ethical, and institutional implications across diverse higher education contexts.

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