



Vol.9 No.1 (2026)

Journal of Applied Learning & Teaching

ISSN: 2591-801X

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Content Available at: <https://jalt.open-publishing.org/index.php/jalt/index>

Is AI the solution to the problems that make higher education “ill” in the first place? Towards a technology-agnostic, future-proof approach

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Keywords

Access;
artificial intelligence (AI);
automation;
cost;
equity;
higher education;
personalization;
quality;
virtual learning environment.

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Article Info

Received 5 January 2026

Received in revised form 28 February 2026

Accepted 4 March 2026

Available online 24 March 2026

DOI: <https://doi.org/10.37074/jalt.2026.9.1.14>

Abstract

Artificial intelligence (AI) is being deployed in higher education at an unprecedented scale and pace as a silver bullet for the “sick” higher education system. This opinion paper examines whether and to what extent AI is the solution to the problems that make higher education purportedly outmoded and/or dysfunctional in the first place. It begins by identifying two persistent challenges confronting the sector: uneven quality and enduring inequities in access. The discussion then turns to the deeper structural causes of these challenges, before examining four potential roles that AI is commonly assumed to play in addressing them. In doing so, the paper critically explores whether AI can meaningfully remedy higher education’s underlying problems, and concludes by proposing a technology-agnostic, future-proof approach to transforming higher education in more sustainable and principled ways. The position of this paper is that the future of higher education should not hinge on any particular technology, no matter how cutting-edge it may appear. Accordingly, a fundamental principle for the selection and use of technology in higher education is proposed, whereby a technology should be adopted only when it enables educators to do what they otherwise cannot, or when it demonstrably performs better than educators at an affordable cost, or when it performs as well as educators while reducing costs. Higher education should remain open to technological advancement, but it must not allow itself to be defined by it.

Introduction

The attempt to use artificial intelligence (AI) for educational purposes dates back more than half a century (Carbonell, 1970). AI has been with educators ever since, albeit with its ups and downs. However, it was not until OpenAI released ChatGPT to the public in late 2022 that this technology came into the spotlight. The fervent enthusiasm for AI in education appeared almost overnight and has continued to gain powerful momentum. Stakeholders are no longer limited to the higher education community and EdTech businesses; they now include national governments as well as regional, international, and even global organisations such as the EU, UNESCO, and the OECD. The prevailing discourse suggests that AI is good, necessary, and inevitable for education.

Is AI always good for education? Why is it considered a necessity? What renders its use inevitable? In other words, what problems does the current higher education system face that are thought to require an AI fix? Exploring these questions is of both theoretical and pragmatic relevance to the future of higher education, which in turn has profound implications for the future of human society. While Rudolph et al. (2025a) provide illuminating insights into the impact of AI in higher education by critically interrogating eight popular myths in contemporary AI discourse, this opinion paper adopts a narrower scope and examines whether, and to what extent, AI is the solution to the problems that purportedly render higher education outmoded or dysfunctional in the first place.

The paper begins by outlining the problems facing higher education as identified in literature. It then analyzes their root causes, summarizes the potential roles of AI in addressing these problems, and evaluates whether AI can cure higher education's "illnesses". It concludes by proposing a technology-agnostic, future-proof approach to transforming higher education for the better.

What are the problems of the current higher education system in the discourse of AI?

The higher education system is not perfect. However, given that no panacea exists for all the problems of any sector of human society, we need to identify its existing problems to develop the right cures for them. This point is self-evident, though often ignored.

The arguments for using AI in higher education can be categorized into two major types according to relevant literature. One is that existing curricula and/or courses are outmoded and need updating to teach students AI-related knowledge and skills, thereby preparing an AI-capable workforce for an AI-dependent future (Gao et al., 2024; Jin et al., 2025; O Donnell et al., 2024; Zhai et al., 2021). The other is that AI can decisively expand equitable access to quality education for all and, in doing so, advance Sustainable Development Goal Four (SDG 4) (Cazzaniga et al., 2024; UNESCO, 2019; Zhai et al., 2021).

Often, problems related to these arguments are taken for granted and not spelt out (Xiao & Bozkurt, 2025). When this is the case, we infer what problems are being referred to by drawing on the theory of conversational implicatures (Grice, 1975). For example, by stating that AI "can redefine higher education, fostering an ecosystem where learning is more personalised, equitable, and efficient" (Howard & Ulferts, 2025, p. 1), the authors imply that the current system fails to sufficiently cater for individual learners' needs, ensure equitable access to education for all, and operate efficiently. Another case in point is UNESCO (2021), which outlines five master plans for using AI to address problems associated with an outdated education system. They are to:

- I leverage AI to boost and upgrade education management and delivery;
- I cultivate learner-centered use of AI to enhance learning and assessment;
- I ensure that AI is used to empower teachers;
- I plan the use of AI to support lifelong learning across ages, locations and backgrounds;
- I develop values and skills for life and work in the AI era (UNESCO, 2021, pp. 34-36).

As Mochizuki et al. (2025) aptly observe, these plans rest on the implication that current education systems suffer from inefficient administration, ineffective pedagogy and learning assessment, the disempowerment of teachers, limited flexibility, and a failure to cultivate skills deemed relevant for the future (pp. 10-11).

The first argument for AI in higher education, namely that existing curricula and/or courses need updating, is largely self-evident. The second argument, namely that AI can contribute to the delivery of SDG 4, functions more as an umbrella claim, covering a range of issues that broadly center on two concerns: the quality of higher education and access to it. It is therefore important to distinguish between AI as knowledge and skills to be taught, which underpins the first argument, and AI as a means of improving learning and teaching and widening access, which underpins the second (Xiao & Bozkurt, 2025). These two are often conflated in the literature (for example, Jin et al., 2025; Sousa et al., 2021). While university students must indeed acquire AI-related knowledge and skills (Waring, 2024), it remains, as Selwyn (2025a, p. 39) cautions, “a highly questionable presumption” that the digitization of education in itself prepares students for future forms of work. In other words, simply adopting AI as a means of educational delivery does not necessarily improve students’ job readiness.

What are the root causes of higher education problems?

Looking back, higher education institutions have regularly revised and updated curricula and courses to respond to changing societal needs. A comparison between what universities offered five or ten years ago and what they offer today readily reveals this capacity for self-initiated adaptation. Such adaptability is the norm and therefore hardly warrants special emphasis, even in the case of AI. AI-related knowledge and skills will be integrated into university curricula and courses and are likely to become increasingly “invisible”, much as earlier technological and disciplinary additions have been absorbed into higher education programs. Universities are able to adapt to this need on their own, whether or not national governments or regional, international, or global organizations explicitly call for the inclusion of AI in curricula and courses. Given this institutional adaptability, the remainder of the paper focuses on problems associated with the second argument, namely issues of quality and access.

The problems underlying the second argument are, broadly speaking, unsatisfactory quality and insufficient access, both of which stem from inadequate funding for higher education in the first place. Global higher education enrolment rates bear clear testimony to the impact of funding on the sector. As UNESCO (2024a, p. 32) reports, high-income countries reached an enrolment ratio of over 79 per cent in 2022, whereas the corresponding figure for low-income countries was only 10 per cent. Economically developed regions such as Europe, North America, and East and Southeast Asia consistently record much higher enrolment ratios than less developed regions, including Central and South Asia and Sub-Saharan Africa. This disparity helps explain why insufficient funding remains a major barrier to widening access to higher education. At the same time, economically developed countries are also home to the world’s leading universities, including those ranked in the top 200 of the Times Higher Education World University Rankings 2025 (Times Higher Education, 2025). Moreover, North America and Western Europe remain the most attractive host regions for internationally mobile students, together accounting for 46 per cent of the global market share in 2021 (UNESCO, 2024b). Taken together, these indicators underscore the close relationship between funding levels and the quality of higher education.

If the aim is to widen access to higher education of high quality, substantial and sustained investment is required. This entails the expansion of institutional capacity through the establishment of additional universities, whether physical or virtual, the development and upgrading of infrastructure, and the recruitment and professional development of academic and support staff. In the absence of adequate funding, commitments to widening access to quality higher education risk remaining largely rhetorical. Of course, financial investment alone does not guarantee broader access or improved quality, even though it constitutes a necessary precondition. Equally critical is the capacity of higher education stakeholders to exercise agency in pursuing these goals, including their ability to mobilize contextual affordances and to deploy emerging technologies, such as AI, in ways that are pedagogically and socially meaningful. It is against this backdrop that this paper examines whether AI can meaningfully address systemic dysfunction in higher education by breaking the iron triangle of access, quality, and cost (Daniel et al., 2009).

What can AI potentially do to transform higher education for the better?

An earlier study (Xiao, 2024a) synthesizes the affordances of AI for open and distance education into four broad categories: personalization, automation, cost effectiveness, and virtual learning environments. It argues that, insofar as these affordances can be realized, they are “hardly distinguishable from those associated with campus-based higher education” (p. 18). Put differently, the application of these AI affordances is often presented as a means through which higher education, more generally, might be transformed for the better.

Personalization in higher education refers to how “AI tailors the educational process to each student’s individual learning pace and assigns tasks of increasing complexity” according to learners’ performance, mastery of knowledge and skills, and other idiosyncratic characteristics (Hamilton, 2020). It also involves recommending what are presented as optimal learning pathways, namely what to learn, when to learn, and how to learn. In this sense, personalization overlaps with adaptation and customization (Taylor et al., 2021) and is used in this paper as an umbrella term encompassing both for the sake of analytical convenience. It is widely argued that AI can address the lack of personalized attention to individual learners in large-scale educational settings (Lodge et al., 2023), thereby enhancing educational quality. AI-enabled personalization is said to cover a wide range of activities, including but not limited to:

- personalizing learning support (Wang et al., 2023), instruction and feedback (Paskevicius, 2024), and assessment (Naidu & Sevnarayan, 2023);
- enabling learning at one’s own pace (Crompton & Burke, 2023);
- customizing instructional content based on individual students’ needs and actual level of competence (Howard & Ulferts, 2025);
- offering one-on-one tutoring (Zawacki-Richter et al., 2019).

Automation is increasingly normalized on administrative fronts, integral to routine university businesses (Xiao, 2023). A typical case in point is the “invisibility” of learning management systems, which are becoming increasingly intelligent and can provide more and more “automated” services.

Closely related to automation is the promise of cost effectiveness. The primary rationale for automation in education is to reduce manual input by institutions and to increase efficiency, thereby lowering costs. It is often further claimed that automated outputs can match, or even surpass, the work of education professionals. For instance, Naidu and Sevnarayan (2023, p. 3) argue that “AI powered assessment tools can provide more accurate and objective assessments compared to human assessors, at a fraction of the cost.” This line of reasoning suggests that cutting-edge technologies such as AI make it possible to provide quality education to larger numbers of learners without increasing expenditure, thereby widening access to quality education. A similar logic underpins UNESCO’s (2019) Beijing Consensus on Artificial Intelligence and Education, which, in its Preamble, reaffirms the commitment first articulated in the Qingdao Declaration in 2015 to harness emerging technologies “to strengthen education systems, access to education for all, quality and effective learning, and equitable and more efficient service provision” (Article 3). The document further “reaffirm[s] that technological breakthroughs in the field of AI in education are an opportunity to improve access to education for the most vulnerable groups” (Article 22). Taken together, these claims reflect a broader narrative advanced by national governments and international and global organizations, in which technology-enabled cost effectiveness is presented as a means of simultaneously expanding access and enhancing quality in higher education (Marín et al., 2022; Munro, 2018; World Bank, 2020).

Using AI to create virtual learning environments can enhance the learning experience by allowing “students to explore and revise more complex phenomena in ways that traditional methods of teaching may not address” (Rajan et al., 2025, p. 1; also see Papaioannou et al., 2023). Such environments are also presented as a means of addressing safety concerns and accessibility constraints, as they enable learning in contexts that are “inherently

dangerous, costly to access, or logistically impractical for students to visit in person" (Hanna, n.d.). Virtual learning environments are therefore considered particularly relevant for off-campus learners. They can, for example, support virtual field trips to museums or historical sites, facilitate the acquisition of hands-on skills in simulated settings, and enable collaboration across multiple remote locations (Lee et al., 2021; Ryan & Knight, 2023). One illustrative example is the use of 360-degree virtual learning environments, which allow engineering students working remotely to access sites that would otherwise be unavailable to them (Shih et al., 2022).

Can AI cure higher education "illnesses"?

In this section, we examine how and to what extent AI can widen access to quality higher education. More specifically, we ask whether AI-enabled personalization, automation, and virtual learning technologies can enhance educational quality and, at the same time, contribute to broader access to higher education, and if so, to what extent.

(AI-enabled) personalization

"One to one human tutoring has long been thought to be the most effective approach to teaching and learning (since at least Aristotle's tutoring of Alexander the Great!)" (Luckin et al., 2016, p. 24). Bloom's (1984) seminal "2 sigma" study further intensified enthusiasm for personalization as the putative holy grail of education and has since become a key theoretical reference point for AI-enabled personalization. Bloom (1984) compared student achievement under three instructional conditions. In the conventional model, a teacher taught a class of approximately thirty students and assessed learning through periodic tests. In the mastery learning model, conventional instruction was supplemented with feedback, alongside "corrective procedures and parallel formative tests to determine the extent to which the students have mastered the subject matter" (Bloom, 1984, p. 4). The tutoring model closely resembled mastery learning, except that students studied the subject matter individually or in very small groups under the guidance of a tutor. Bloom's findings showed that students in the tutoring and mastery learning conditions performed approximately two standard deviations and one standard deviation higher, respectively, than those in the conventional classroom. However, Bloom also noted that one-to-one tutoring "is too costly for most societies to bear on a large scale" (Bloom, 1984, p. 4), giving rise to what later became known as the "2 sigma" problem. Today, AI-driven personalization is frequently promoted as a solution to this problem. As Sam Altman (2024), founder of OpenAI, has suggested, "our children will have virtual tutors who can provide personalized instruction in any subject, in any language, and at whatever pace they need."

Is one-on-one tutoring the most effective pedagogy across subject matters and levels of education? The one-on-one tutoring referred to by Bloom (1984, p. 4) involved "students at grades four, five, and eight and with two different subject matters, Probability and Cartography." The intervention lasted just over three weeks and comprised eleven instructional sessions. Although the study was replicated with four student samples, it remains unclear whether the reported learning gains reflected durable learning or were partly attributable to novelty effects associated with the short duration of the intervention. Moreover, a pedagogy that proves effective for particular subject areas at the elementary or secondary level may not translate equally well to other disciplines or to university-level education. The question may, therefore, be reframed as follows: Is one-on-one tutoring the most universally effective pedagogy? Evidence suggests otherwise. A recent meta-analysis indicates that individualized instruction is not among the most effective approaches, with effect sizes reported as follows: "individual instruction $d = 0.24$, one-on-one laptops $d = 0.16$ compared to cooperative learning $d = 0.55$, and collaborative learning $d = 0.46$ " (Hattie & O'Leary, 2025, p. 16). In light of these findings, one-on-one tutoring appears to yield mixed outcomes at best, with no clear consensus regarding its overall effectiveness (Linderoth et al., 2024).

Should learning be conceived as an obstacle-free, linear, and sequential journey, as implied by models of one-on-one tutoring? As Farthing (2025) argues, "education, at its best, is about exploration, freedom, and the messy, often non-linear journey of learning. Mistakes, detours, and curiosity are not inefficiencies to be optimized away; they are the substance of learning itself" (see also Konstantinidis, 2025). This view is particularly pertinent in the context of higher education. By contrast, one-on-one tutoring as conceptualized in Bloom's (1984) work tends to optimize away such "inefficiencies", a move that risks infantilizing education (Hillman & Couldry, 2025). As a resul-

-t, it sits uneasily with the aims of higher education, which include the cultivation of adaptive, autonomous, and agentic learners.

Is AI-enabled personalization the solution to Bloom's (1984) "2 sigma" problem in terms of educational quality? To address this question, it is first necessary to clarify how AI-enabled personalization currently operates. Put simply, such personalization relies on patterns of typicality, large-scale data, and predictive algorithms. Individual learners' knowledge and competencies are matched against established patterns, on the basis of which recommendations are generated. Unlike human teachers, however, an AI tutor is not "a relational partner" (Sidorkin, 2025, p. 1218), as it cannot bring its own experiences, emotions, or social understanding to the learning process (p. 3). Learning, as Prinsloo (2025) argues, should involve "a range of formal but also serendipitous inter- and intra-actions with human and non-human actors and networks" (p. 72). By contrast, AI-enabled personalized learning tends to operate within calculable frameworks that reduce learners "to objects within calculable frameworks, stripping away opportunities to engage with and learn to manage real-world complexities" (Hillman & Couldry, 2025, p. 1). Moreover, genuine personalization, as exemplified by human tutoring, is inherently idiosyncratic and involves bespoke support tailored to individual learners. AI-enabled personalization, by contrast, amounts at best to mass customization (Mamlok, 2021) or what has been described as generic personalization (Xiao, 2024b). While AI tutors may take on some functions associated with human tutors, they are no substitute for them.

At present, there is little robust evidence that AI can perform as well as, let alone better than, educators, particularly at scale and over the long term (Holmes, 2023; Porayska-Pomsta et al., 2023). Much of the existing research in this area falls short of the methodological rigor required to support firm conclusions. For instance, Weidlich et al. (2025) show that common methodological weaknesses, including "loosely defined treatments, mismatched or opaque controls, and outcome measures with unclear links to durable learning", render many claims about the effectiveness of ChatGPT unfounded (p. 1). In this sense, the evidence base currently available is not one that can be relied upon with confidence. This assessment is echoed by Tuomi (2025), who argues that existing empirical research on AI in education "should not be used to guide policy or practice" because of persistent methodological and conceptual shortcomings (p. 1). In a similar vein, Mochizuki et al. (2025) contend that there is "no plausible explanation" for why AI should or could be expected to fix an outmoded education system (p. 11). Taken together, these critiques suggest that substantially more rigorous research is required before it is possible to determine whether, and if so how and to what extent, AI-enabled personalization can meaningfully contribute to the quality of higher education.

Automation

Automation can generate high levels of productivity, albeit often in the short term. However, efficiency should not be conflated with effectiveness. In education, efficiency is not always a desirable goal. For students, one of the most consequential paradigm shifts associated with automation is cognitive offloading, defined as "the use of physical action to alter the information processing requirements of a task so as to reduce cognitive demand" (Risko & Gilbert, 2016, p. 676). From the perspectives of neuroscience, cognitive psychology, and learning theory, extensive offloading of declarative and procedural cognitive activities to AI risks undermining students' reasoning, critical thinking, creative problem-solving, and productivity over time. This is because genuine expertise and insight develop through the internalization of knowledge, specifically through its progression from the declarative system to the procedural system (Gerlich, 2025; Oakley et al., 2025; Walter, 2024; Zhai et al., 2024). Persistent reliance on external tools for cognitive work can result in what has been described as cognitive debt, which "defers mental effort in the short term but results in long-term costs, such as diminished critical inquiry, increased vulnerability to manipulation, [and] decreased creativity" (Kosmyrna et al., 2025, p. 141). These concerns are reinforced by empirical evidence from a study of 348 students, many of whom reported that AI made them less independent and less critical in their thinking, more comfortable with automation, and more susceptible to algorithmic bias (Mohammadkarimi & Omar, 2025).

Moreover, AI systems remain vulnerable to misinformation, error, and bias, with responsibility for identifying and correcting these problems frequently shifted onto learners themselves. Universities often instruct students to "think critically about GenAI and carefully evaluate, fact check, and verify the information from GenAI" because

“the output of GenAI models may be inaccurate, misleading, biased, and even fictitious” (An et al., 2025, p. 18). Yet this expectation is difficult to justify. If students are required to take responsibility for verifying the accuracy and reliability of what they learn from AI systems, the rationale for the continued central role of universities as epistemic authorities becomes increasingly unclear.

As for teachers, automation is often presented as a means of relieving them of labor-intensive and time-consuming tasks, thereby reducing workload and allowing greater focus on what is framed as more meaningful work. Common examples include the use of AI to mark assignments, generate feedback, prepare lesson plans, and create educational resources. Yet such claims invite closer scrutiny of both their necessity and effectiveness. Marking assignments, providing feedback, and designing lessons are core components of teachers’ professional responsibilities, for which they are employed and trained. What, then, are the more important tasks that would justify offloading these responsibilities to machines? Moreover, how frequently do teachers face student numbers so large that assessment and feedback become unmanageable without automation? Where such conditions exist, why should investment in AI be preferred over the employment of additional teaching staff? There is also limited evidence that AI can perform these tasks as well as human teachers, let alone better or at a lower cost. Finally, it is worth questioning whether the routine creation of instructional resources by individual teachers is always necessary, or whether alternative organizational solutions might address this issue more effectively.

Empirical evidence does not support the claim that automation saves time or reduces teachers’ workloads. Research indicates that substantial, and often invisible, manual input by teachers is required for AI-driven automation to function at all (Selwyn et al., 2025; Sperling et al., 2023). Teachers must continually reskill and upskill in order to use AI competently, while also reviewing, correcting, and in some cases reworking AI-generated outputs. Equally important are the implications for teachers’ professional practices and identities. Many of the so-called “mundane” and labor-intensive tasks targeted for automation are integral to teachers’ professional learning and development (Frelin, 2013). If teachers no longer engage in these practices, or are no longer capable of doing so, their professional status is fundamentally undermined. For example, marking and commenting on assignments play a crucial role in helping teachers understand their students and informing subsequent lesson planning. Without such engagement, it becomes unclear how teachers can judge whether AI-generated lesson plans are fit for purpose in specific educational contexts, or how they might meaningfully adapt and improve them. As Mutton et al. (2011, p. 399) observe, “it is through [lesson] planning that teachers are able to learn about teaching and through teaching that they are able to learn about planning.” From this perspective, the risk of deprofessionalizing education through automation cannot be overstated.

By comparison, investment in automating back-end administrative operations may be justified where it demonstrably reduces human input and workload (Xiao, 2024a). Even so, particular caution is warranted when automation is applied to high-risk functions with direct consequences for students, such as identifying potential dropouts, flagging at-risk learners, e-proctoring, plagiarism detection, student counseling, and career advising. Overall, there remains little conclusive evidence that automation has a positive impact on the quality of higher education. At present, its effects, whether beneficial or detrimental, remain largely conjectural rather than empirically established.

Virtual learning environment

Virtual learning environments are often presented as having significant potential to enhance educational quality. As noted earlier, such environments enable students to engage in activities that would otherwise be too dangerous, too costly, or impractical to undertake in physical settings. In doing so, they may contribute to more effective learning through increased engagement and, in some cases, improved learning outcomes. A synthetic review of the literature suggests that the use of virtual learning environments in higher education can indeed improve and enrich students’ learning experiences, albeit with important limitations (Rajan et al., 2025). According to this review, learning gains vary considerably depending on the specific environment or technology deployed (see Table 5 in Rajan et al., 2025). That said, these potential benefits are contingent upon a critical precondition, namely, whether universities are able

to afford the substantial costs associated with developing, implementing, and maintaining such environments.

Cost

In policy documents issued by governments and international or global organizations, such as the OECD (2021, 2023), cost is rarely treated as a significant constraint (Xiao & Bozkurt, 2025). The prevailing assumption appears to be that the more cutting-edge a technology is, the more educationally useful it will be, and the more cost-effective education will become as a result. However, this “newer is better and cheaper” rhetoric runs counter to empirical realities (Chihi & Peral, 2022). In practice, the more advanced a technology is and the broader the range of use cases it supports, the more expensive it tends to be (Córdova-Esparza, 2025). As Likhadzed (2025) explains, the cost of AI is shaped by five interrelated factors: software type, data volume and quality, level of intelligence, algorithmic accuracy, and system complexity. Costs rise as demands across these dimensions increase. From the perspective of quality assurance, universities must ensure that AI systems are customized “to cater for the specificity and diversity of use cases, namely their courses and programs” (Xiao, 2024a, p. 17). This requirement places high demands on all five dimensions identified by Likhadzed (2025), rendering such systems far from cost-effective. Moreover, AI deployment is not a one-off investment. Beyond initial acquisition, institutions must account for supporting infrastructure, ongoing maintenance and updates, routine technical support, and recurring subscription fees, all of which pose substantial challenges to the large-scale use of AI in higher education (Rajan et al., 2025; Shete et al., 2024).

The demand for substantial financial investment also has direct implications for students, who must have access to stable internet connectivity and appropriate devices to benefit from AI-based solutions (Slegers et al., 2025). The University of South Africa provides a telling example. Many students were unable to use ChatGPT-4 because of its monthly subscription fee of USD 42, a sum that may be negligible for students in highly-developed contexts but constitutes a significant barrier elsewhere (van Wyk et al., 2023). Similarly, Kouam and Muchowe (2025) identify “the high cost of premium AI platforms, internet accessibility issues, and potential social skills deficits” as major obstacles to “mitigating the equity gap in educational access in Zimbabwe” (p. 154). Taken together with the continuing and substantial financial demands placed on universities, these realities raise a critical question: are AI-enabled personalization, automation, and virtual learning environments genuinely cost-effective approaches to widening access to quality higher education?

Conclusion

The imperative to fundamentally rethink the relationship between education and technology

Can AI cure higher education “illnesses”? In terms of educational quality, despite the rapid and widespread adoption of AI across higher education, “our comprehension of how these tools should be effectively integrated remains limited, and their impact is still insufficiently explored and mapped. This shortfall in understanding poses inherent risks to their implementation in higher education” (Noroozi et al., 2025, p. 1425). Put simply, the jury remains out on whether AI can meaningfully enhance higher education quality. Moreover, like all technologies, AI is a double-edged instrument. While it may address certain problems, it is also likely to introduce new ones. For example, tools such as ChatGPT are promoted as a means of automating the marking and commenting on written assignments and reducing teachers’ workloads, yet they simultaneously function as powerful instruments for plagiarism. More broadly, the use of AI in higher education is associated with a wide range of risks, contested practices, and unresolved grey areas. This calls for caution regarding when, how, and at what scale AI should be deployed (Xiao et al., 2025). Given that education shapes the future of humanity, its transformation demands careful and responsible deliberation. Unless AI is used for the right purpose, in the right way, and in the right context, the damage done to higher education may be difficult, if not impossible, to undo.

In terms of widening access, AI is far from inexpensive, particularly when effective deployment requires customization to address the complexity, diversity, and contextual specificity of higher education. To date, there is little, if any, rigorous research examining whether and how AI can make higher education more cost-effective

and, by extension, more affordable and accessible. Determining whether AI can break the iron triangle of access, quality, and cost should therefore be a central focus of future research and praxis, much as open universities worldwide did from the 1970s to the 1990s when they sought to justify the use of technology to deliver distance education at scale (Daniel et al., 2009).

For decades, almost every new generation of technology, even when not developed with education in mind, has generated renewed hype about its capacity to disrupt and transform higher education by curing long-standing educational “illnesses”. The arrival of a new technology is frequently treated, explicitly or implicitly, as a once-and-for-all solution to whatever problems are perceived to be afflicting education at the time. As a result, education is often reshaped to fit technology, rather than the other way around, so that technology can be seen to deliver its purported curative effects. Put differently, innovation is framed as the imperative to ensure that a new technology is used, often by identifying, exaggerating, or even manufacturing problems for it to solve in order to demonstrate its educational value. This is what Selwyn (2012) famously described as a “solution in search of a problem”. Under such conditions, more attention is paid to sustaining hype around new technologies than to assessing whether they actually live up to their promises. Otherwise, it would be difficult to explain why the repeatedly lamented dystopia of higher education has yet to be transformed into the utopia so confidently promised by successive technological waves, or why greater realism has not emerged regarding the limits of technology in addressing deep-seated educational problems.

Many higher education stakeholders appear not to have moved beyond the fantasy sustained by recurring technological hype. As Selwyn (2025b) sharply observes, a prevailing “sense of digital resignation” characterizes dominant narratives, grounded in the belief “that there are no feasible alternatives to current dominant forms of digitization, and that education simply needs to respond to any new technology (such as Generative AI) as best as possible” (p. 6). Digital resignation is, in effect, another expression of technological determinism. As argued earlier, cutting-edge technologies are not inevitable for higher education, not least because they have yet to demonstrate an ability to break the iron triangle of access, quality, and cost. Indeed, many educational problems “are often non-technological in nature and require no technological fixes”, given that “students’ lack of privileged access to frontier technologies is no barrier to learning success”, as educators from open universities committed to widening access to quality higher education attest convincingly (Lim et al., 2024, p. 282). At the same time, digital resignation reinforces a logic in which educational innovation becomes a race toward ever newer technologies, creating a self-perpetuating cycle of addressing old problems while generating new ones. This dynamic may help explain why the educational transformations repeatedly promised by successive technological waves have yet to materialize.

AI will, in time, be superseded by newer technologies, much as it has itself outperformed its predecessors. This raises a fundamental question: what is gained by entering yet another “digital revolution”, namely the AI revolution, when we have yet “to come to terms with the sweeping social and educational implications of these earlier revolutions, which are still unfolding” (Giannini, 2023, p. 2)? At what point might the race toward ever newer technologies reach its limits? How can higher education problems be foregrounded over technological advancement in efforts to widen access to quality education? And how might emerging technological affordances be harnessed in ways that genuinely serve the purposes of higher education? These questions are far from exhausted and point to a broader agenda for sustained inquiry.

The relationship between education and technology, therefore, requires fundamental rethinking. Technology should serve education, not the reverse. Technology does not, in itself, empower higher education; rather, it is the education stakeholders who must exercise agency in directing technology toward the goals of quality and access. Technology is never the determining driver of higher education outcomes. Put differently, expanded access to quality higher education does not automatically follow from the adoption of new technologies. What ultimately matters is not the affordances of technology per se, but whether and how a particular technology is educationally beneficial within a given context. When reform is driven primarily by technological affordances, technology-led or technology-centric approaches risk doing more harm than good. A salient example is the use of AI, which may, in practice, reduce access to higher education by re-marginalizing learners who already struggle to afford tuition, let alone those who are excluded from higher education altogether.

Towards a technology-agnostic, future-proof approach

For the betterment of higher education, a technology-agnostic, future-proof approach is needed to address its persistent “illnesses”. Higher education should remain open to technological innovation, but its future should not

hinge on any particular technology, regardless of how advanced or intelligent it may appear. In this regard, minimal computing offers useful insights into how technology might be deployed to ameliorate structural weaknesses in higher education. Minimal computing is described as “a mode of thinking about digital humanities praxis that resists the idea that ‘innovation’ is defined by newness, scale, or scope” (Risam & Gil, 2022, para. 3). Instead, it emphasizes contextualized decision-making, whereby “only the technologies that are necessary and sufficient for developing digital humanities scholarship in such constrained environments” are adopted (Risam & Gil, 2022, para. 4).

Informed by minimal computing thinking, we propose a fundamental principle to guide the choice and use of technology in higher education: new technology should be adopted only when it can do what educators are incapable of doing, or when it can do better than educators at an affordable cost, or when it can perform as well as educators at a lower cost. This principle can be operationalized through a set of heuristic questions to support decision-making. What problems within the current higher education system require attention? What are the underlying causes of these problems? Can they be addressed by educators alone? Where this is not the case, which technologies, if any, are capable of addressing them? If multiple technological options are available, which is preferable in terms of effectiveness, affordability, and accessibility? Where both educators and technology are capable of addressing a problem, which intervention offers greater educational benefit across these same criteria? In short, problem-solving should be centered on higher education itself, rather than on reshaping higher education to fit a particular new technology (Xiao & Bozkurt, 2025).

“Successful technology-based learning cannot be guaranteed, and when it does occur results from careful planning and sustained teacher support (not all of which can be computerized)” (Selwyn, 2025a, p. 37). From pedagogical and contextual perspectives, no technology is inherently outmoded; what matters instead is fitness for purpose. By adopting a technology-agnostic approach, higher education can avoid being driven by the hype surrounding successive waves of emerging technologies. Technology should be employed only “where it demonstrably supports student learning and development” without compromising “academic integrity or sound pedagogy” (Rudolph et al., 2025b, p. 6). Ultimately, higher education should be defined by what universities are intended to do, rather than by what any particular technology is claimed to enable. Without such restraint, the sector risks remaining trapped in an endless race toward ever newer technologies, often at the expense of its own educational purposes.

Key takeaways for policymakers and institutional leaders

1. AI is not a cure for structural problems in higher education.

The two persistent “illnesses” of higher education remain uneven quality and inequitable access. These challenges are rooted primarily in structural underfunding rather than technological absence. AI cannot compensate for chronic investment gaps in infrastructure, staffing, and institutional capacity.

2. The “iron triangle” remains unbroken.

There is currently no robust evidence that AI simultaneously improves quality, expands access, and reduces cost at scale. Claims that AI can break the iron triangle of access, quality, and cost remain largely aspirational rather than empirically demonstrated.

3. Personalization is not synonymous with educational quality.

AI-enabled personalization amounts largely to mass customization based on data patterns, not genuine relational tutoring. Evidence that one-on-one AI tutoring produces durable learning gains in higher education is inconclusive. Policymakers should avoid equating algorithmic optimization with meaningful learning.

4. Efficiency should not be mistaken for effectiveness.

Automation may increase short-term productivity, but efficiency does not automatically enhance educational quality. In some cases, automation risks:

- cognitive offloading and long-term “cognitive debt” in students;
- over-reliance on algorithmic outputs;
- erosion of teachers’ professional expertise and judgement.

5. Automation may deprofessionalize teaching.

Tasks often targeted for automation, such as assessment and lesson planning, are integral to teachers’ professional growth and pedagogical insight. Removing these functions without careful evaluation risks undermining academic professionalism and educational quality.

6. Virtual environments show promise but are resource-intensive.

AI-enabled virtual learning environments can enhance experiential learning, particularly where physical access is constrained. However, their effectiveness varies significantly by discipline and implementation, and they require substantial upfront and ongoing investment.

7. AI deployment is rarely cost-neutral.

Contrary to policy rhetoric, advanced AI systems are expensive to customize, maintain, and scale. Costs include:

- software development and licensing;
- infrastructure and technical support;
- continuous updates and maintenance;
- student access to devices and stable connectivity.

In lower-income contexts, subscription fees alone may constitute a barrier to access.

8. Technological hype risks policy capture.

Higher education repeatedly encounters waves of technological determinism in which each new innovation is framed as transformative. Policymakers should resist “digital resignation”, namely the belief that institutions must adapt uncritically to every emerging technology.

9. Many higher education challenges are non-technological.

Access gaps, quality disparities, and funding inequities are fundamentally socio-economic and political issues. Technological solutions cannot substitute for structural reform, sustained investment, and institutional agency.

10. Technology should serve education, not define it.

The future of higher education should not be contingent on any single technology, however advanced. Reform must remain problem-driven rather than technology-driven.

Strategic implications for decision-making

The transformation of higher education requires prudence, not technological accelerationism. Technology may contribute to reform, but it cannot substitute for institutional agency, sustained investment, and principled governance. Therefore, the proposed technology-agnostic, future-proof approach offers a more sustainable path forward. This approach carries several implications for making strategic decisions:

- Consider adopting a technology only if it meets at least one of the following conditions: (a) enabling educators to do what they otherwise cannot do, (b) performing demonstrably better than educators at an affordable cost, in other words, doing as well as educators while reducing costs.
- Invest first in structural capacity: funding, staffing, and infrastructure.
- Demand rigorous, long-term evidence before scaling technological solutions.
- Evaluate technology initiatives against educational purpose, not novelty.
- Protect academic professionalism and pedagogical integrity.
- Prioritize contextual, minimal, and sufficient technological use.

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