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Artificial Intelligence in Higher Education: Challenges and Managerial Risks

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Abstract: Generative artificial intelligence (GenAI) has become a near-universal part of students' academic practice, confronting universities with challenges that reach beyond technology to the core of teaching and assessment. This article is an integrative narrative review of peer-reviewed studies, preprints and policy documents published mainly between 2023 and 2026. It examines the crisis in the validity of knowledge assessment and the unreliability of AI detectors; cognitive dependence, metacognitive laziness and the erosion of critical thinking; digital inequality; the meta-analytic evidence on learning effects; and the regulatory framework set by UNESCO, the OECD and the EU Artificial Intelligence Act. The cross-cutting theme is the "performance–learning gap": GenAI reliably improves task performance, but genuine learning gains depend on teacher support, pedagogical guardrails and the way students use the tool, and they often disappear when knowledge is assessed without AI. Particular attention is given to Georgia, where AI uptake is already high while the institutional response remains fragmented. The article proposes structural reform of assessment, a five-stage institutional pilot model for Georgian universities, a practical formula for students ("think first, ask AI, then evaluate critically") and a research agenda of six priority directions.

Keywords: generative artificial intelligence, higher education, assessment validity, academic integrity, cognitive offloading, AI literacy, digital inequality, Georgia.

INTRODUCTION

The mass adoption of generative artificial intelligence (GenAI), above all ChatGPT, DeepSeek and Claude, confronts education systems with an unprecedented challenge. Studies from the United Kingdom, the United States, India and international bodies (including HEPI/Kortext and UNESCO) show that unless universities change their approaches to teaching and assessment, AI creates systemic risks for the quality of education. Gagnidze's lecture course *Artificial Intelligence in Education* [1] states that "the main aim of education is not the transfer of information but the development of critical, independent thinking". Protecting this aim has become the central challenge of the present moment.

By 2026 the question is no longer whether students use AI, but *how* they use it and whether they learn while doing so. The OECD *Digital Education Outlook 2026* summarises the shift: when tasks are handed over to GenAI without pedagogical guidance, performance quality rises and completion time falls, but genuine learning outcomes do not improve; GenAI supports learning only when it follows clear pedagogical principles [2]. This "performance–learning gap" is the cross-cutting theme of the article.

The literature is growing rapidly. In a PRISMA-based systematic review of 37 empirical studies published in 2023, Batista, Mesquita and Carnaz [3] grouped research into the use of GenAI technologies, stakeholder acceptance and perceptions, and specific situations of use (assessment, writing and academic integrity), identifying assessment practice, institutional strategy and academic integrity as the main challenges. Early syntheses [4, 5] relied mainly on theoretical and illustrative arguments, whereas since 2025 randomised experiments and meta-analyses have allowed many claims to be tested empirically.

Methodological note: This article is an integrative narrative review of peer-reviewed journals, leading conference proceedings (e.g., ACM CHI), preprint archives (arXiv, SSRN) and documents of international organisations (UNESCO, OECD and the EU), mainly from 2023–2026. Preprints and reports not yet peer reviewed are marked with an asterisk (*), and their findings should be treated as preliminary. Journalistic and blog sources (Times Higher Education, Nature News, LSE Blogs, The Guardian and Geotimes) illustrate the institutional context only and are not used as empirical evidence.

Section 2 examines the crisis in assessment validity; Section 3 cognitive dependence and its Georgian manifestations; Section 4 digital inequality; Section 5 the meta-analytic evidence; and Section 6 the regulatory framework. Section 7 proposes changes to assessment and a pilot model for Georgian universities, Section 8 a practical formula for students and Section 9 a discussion of restrictive and integrative approaches. Section 10 sets out the limitations of the evidence and a Georgian research agenda, and Section 11 concludes.

THE CRISIS IN THE CREDIBILITY OF KNOWLEDGE ASSESSMENT

Generative models blur the boundary between a student's independent work and algorithmically generated text, making it ever harder for teachers to tell where a student's real knowledge ends.

The Scale of Use: From "Novelty" to Universality

In January 2023, only months after ChatGPT appeared, over a third of more than a thousand surveyed American students were already using it for assignments, and 75% of them regarded this as cheating [4]. The annual HEPI/Kortext surveys of around one thousand UK undergraduates provide the most consistent monitoring. The share of GenAI users rose from 66% in 2024 to 92% in 2025, and use in assessed work from 53% to 88%; 18% admitted inserting AI-generated text directly into their work [6]. In the 2026 wave (1,054 respondents), 95% used AI in some form and 94% for assessed work [7].

The picture is nevertheless polarised: only 49% of students believe AI has improved their learning, some using it to deepen learning and others to outsource it. University provision of AI tools rose from 9% to 38% between 2024 and 2026, yet institutional practice still lags behind student behaviour [7]. Staff are concerned too: in the 2024 EDUCAUSE study, 64% expected academic dishonesty to increase and 60% believed students trust AI tools too much [8, as cited in 9].

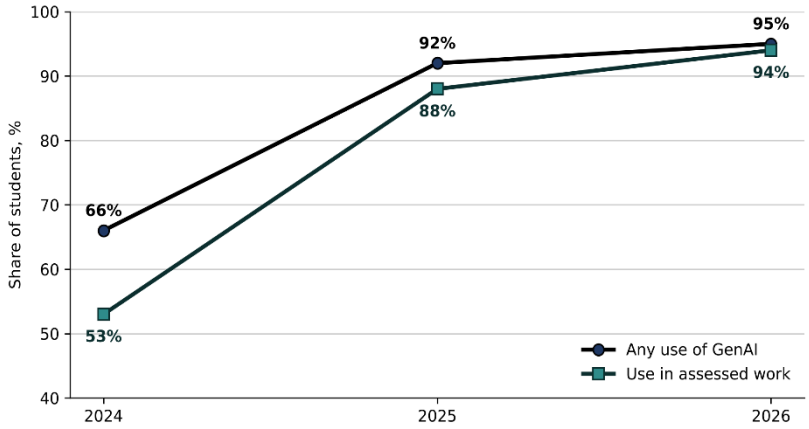


Figure 1: Use of GenAI among UK undergraduates, 2024–2026. Source: Authors' illustration based on Freeman [6] and Stephenson and Armstrong [7].

Academic Integrity and Hallucinations

Academic dishonesty is becoming systemic. Batista et al. [3] identify integrity risks and the need to adapt assessment as a central challenge, stressing that the problem is institutional and ethical, not merely technical. One fundamental cause is that "GenAI creates some things that do not exist in real life", often called AI "hallucination" [1, Chapter 10]. Mellado [5] cites a study in which 21% of GPT-3's answers were incorrect despite appearing coherent and persuasive, and models rarely indicate their sources. Bobula [4] singles out fabricated references: plausible titles and authors that do not exist. The threat to assessment is practical. In early 2023 tests summarised by Bobula [4], ChatGPT averaged C+ on University of Minnesota Law School examinations, showed competence in case analysis on an MBA operations management final, reached the 91st and 99th percentiles on standardised micro- and macroeconomics tests, and performed at the level of a third-year medical student on USMLE questions. Current models are considerably more capable. Many traditional forms of assessment, such as tests, standard essays and take-home examinations, can therefore no longer confirm that the result reflects the student's own knowledge.

Why AI Detectors Do Not Solve the Problem

Technical detection is unreliable. Testing 14 AI-text detectors, Weber-Wulff et al. [10] found none sufficiently accurate, and manual editing or paraphrasing reduced accuracy further. Liang et al. [11] showed that GPT detectors are biased against non-native English writers, misclassifying more than half of human-written TOEFL essays as AI-generated, and that they can be evaded by changing the prompting strategy. Some methods perform only slightly better than chance [4]. For Georgian students, who often write in English, false positives can harm innocent students and undermine trust; a detector result can only be a reason to start a conversation, not evidence of a violation.

Validity Matters More than "Catching Cheats"

Assessment theory increasingly holds that the central problem is not detecting cheating but the *validity* of assessment, that is, whether it measures what it intends to measure [12]. If

AI can complete a task without the student's thinking, the assessment loses validity whether or not a rule is broken. Corbin, Dawson and Liu [13] distinguish "discursive" changes (rules and warnings whose observance cannot be verified) from "structural" changes to the task itself, arguing that only the latter ensure trustworthy assessment in the GenAI era. The stakes include the value of the degree: if AI widens the gap between what is assessed and what is learned, employers will discover that graduates lack the skills their degrees certify, damaging the reputation of all graduates [14]. The devaluation of the degree is thus first and foremost a problem of assessment design.

COGNITIVE DEPENDENCE AND THE EROSION OF CRITICAL THINKING

When students replace independent reading and analysis with AI, both critical thinking and writing skills suffer. This "cognitive outsourcing" is the habit of turning immediately to AI for a ready-made answer and accepting it uncritically. Mellado [5] links it to an "illusion of knowledge": students may believe they have understood material to which they have merely gained access.

Knowledge Workers: Trust in AI and Critical Effort

A Microsoft Research and Carnegie Mellon study presented at CHI 2025 analysed 936 real examples of GenAI use by 319 knowledge workers [15]. Greater trust in AI was associated with less critical thinking, and greater self-confidence with more critical scrutiny. Cognitive effort *shifted* from information gathering to verification, from problem solving to integrating AI output, and from execution to task "stewardship". The data are self-reported and do not support causal conclusions.

Cognitive Offloading, Age and Academic Outcomes

At a Swiss business school (666 participants), frequent AI use was negatively related to critical thinking scores, partly through cognitive offloading; the effect was stronger among younger participants, while higher education was partially protective [16]. The design is correlational, so people with weaker critical thinking may simply be more prone to dependence. Among students, workload and time pressure increase ChatGPT use, and frequent use is associated with procrastination, self-reported memory loss and lower performance [17]. Comparing LLMs with conventional search, Stadler, Bannert and Sailer [18] found that LLM users experienced less mental load but produced shallower reasoning, the "cost of cognitive ease".

Metacognitive Laziness and Neurophysiological Evidence

In a randomised experiment with 117 students, those using ChatGPT scored higher on essay revision but gained no advantage in knowledge acquisition or transfer, and engaged less in planning, monitoring and evaluation, a pattern termed "metacognitive laziness" [19]. In an MIT Media Lab EEG study (54 participants), brain network connectivity during essay writing was weakest with an LLM, intermediate with a search engine and strongest without aids; LLM users also recalled less of their own text and felt less ownership of it, described as

"cognitive debt" [20*]. As a small, not yet peer-reviewed study, it should be interpreted with caution.

Performance ≠ Learning: Field Experiments

The most convincing causal evidence comes from a field experiment with about a thousand pupils at a Turkish secondary school, comparing a standard ChatGPT-like interface ("GPT Base") with a tutor equipped with pedagogical guardrails that withholds direct answers ("GPT Tutor"). Practice performance improved by 48% and 127% respectively, but once access was removed the Base group performed 17% worse than controls, while in the Tutor group the negative effect was largely neutralised [21]. Without guardrails, pupils use AI as a "crutch". Similarly, programmers who learned a new library with AI showed poorer conceptual understanding and debugging skills [22*]. A 2026 *Nature* feature notes that research mostly captures easily measured outcomes, while the erosion of metacognition and independent skills remains understudied [23].

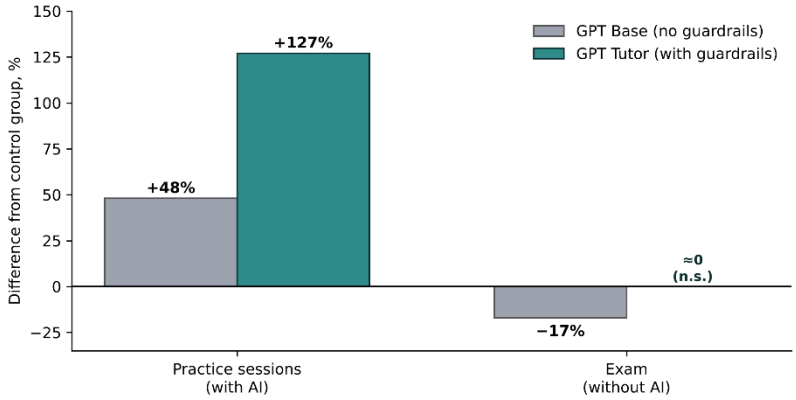


Figure 2: The "performance-learning gap" in a field experiment: results achieved with AI and knowledge without AI. Source: Authors' illustration based on Bastani et al. [21].

Offloading or Substitution? A Synthesis

Contrary evidence also exists. In a 12-week quasi-experiment with 240 first-year students writing English essays, delegating only lower-order operations (grammar, citation formatting and initial idea gathering) reduced extraneous cognitive load by 32%, increased germane load by 28% and deepened argumentation [24]. Cognitive offloading is in itself normal and often rational, as with notes, calculators and calendars [25]. What matters is *which cognitive operation* is handed over. Delegating mechanical operations frees resources, whereas delegating operations that constitute the learning goal (constructing an argument, solving a problem, synthesis) harms learning, consistent with the concept of "desirable difficulties" [26]. Figure 3 summarises this logic: depending on the operation and pedagogical conditions, the same technology either strengthens learning or produces a performance–learning gap.

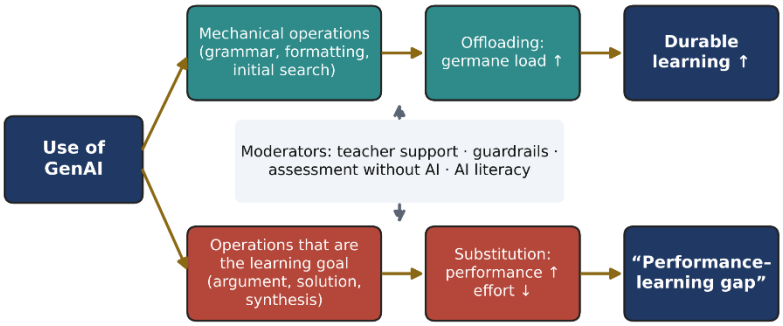


Figure 3: A conceptual model of cognitive offloading and substitution. Source: Authors' elaboration based on Sections 3.1–3.5.

The Emotional and Social Dimension

GenAI use also has an emotional and social dimension that policy largely overlooks. In Zhang's [27] action research at Beijing Normal University, high AI dependence reduced classroom discussion and collaboration, and students reported loneliness, anxiety and lower motivation, especially when AI-generated work proved unusable; teacher guidance only partly helped. In UK focus groups with psychology students [28], one member's submission of AI text in group assignments provoked a sense of unfairness, and students preferred human to AI feedback, associating it with care and recognition of effort. Moreover, 15% of UK undergraduates turn to AI for loneliness, advice or "friendship" [7], raising questions about students' psychosocial wellbeing that academic policy rarely addresses.

A Summary Typology of Risks

Cognitive risks occur alongside technical, ethical and organisational ones. Mellado [5] identifies unreliable information, embedded and algorithmic bias, weakened critical thinking, privacy and security threats and the "black box" nature of models, recommending education-specific models ("EdGPT"). Bobula [4] adds copyright, disinformation and equity, diversity and inclusion (EDI), and Ali [9] institutional risks: high implementation costs for small universities, insufficient staff training, resistance to change and fears of losing the "human touch". Table 1 summarises these interrelated risks and mitigation strategies.

Table 1: Risks of GenAI in higher education and mitigation strategies

#	Risk	Description	Source(s)	Mitigation strategy
1	Hallucinations / unreliable information	Convincing but factually incorrect answers and fabricated sources	[4, 5, 27]	Critical verification, cross-checking of sources, AI literacy in the curriculum
2	Bias and discrimination	Reproduction and amplification of social stereotypes	[4, 5]	Bias audits, transparency, discussion of bias in teaching

3	Cognitive dependence	"Outsourcing" of thinking; weakening of independent analysis	[15, 16, 18, 21]	Tutors with guardrails; process-oriented assessment
4	Metacognitive laziness	Reduced self-regulation (planning, monitoring, evaluation)	[19]	Reflective journals; teaching metacognitive strategies
5	Academic dishonesty	Presenting AI text as one's own; unclear rules	[3, 4, 28]	Structural assessment reform; oral defence; AIAS scale
6	Unreliable detectors	False positives; bias against non-native writers	[10, 11]	Detector as a conversation starter only, not evidence
7	Privacy and security	Storage of student data and third-party access	[4, 5, 9]	Data protection policy, anonymisation, informed consent
8	Lack of transparency ("black box")	The logic behind answers is opaque to users	[5]	Explainability, education-specific models, audits
9	Digital inequality	Paid versions, devices and competence are unequally distributed	[7, 28, 29]	Institutional access; AI literacy programmes
10	Emotional and social deficit	Loneliness, anxiety, less group interaction, sense of unfairness	[27, 28]	Group and face-to-face activities; human feedback
11	Uncertainty about the teacher's role	Fear of replacement, lack of training, resistance	[9, 28]	Professional development; positioning AI as an assistant
12	Copyright	Protected material in training data; unintentional plagiarism	[4]	Awareness raising; choice of transparent providers

Source: Authors' synthesis.

The Georgian Context

The literature on cognitive dependence is based mainly on Western and East Asian contexts, but recent Georgian data show similar patterns. In an April–May 2025 online survey of 950 students, lecturers, researchers and professionals from five leading universities (Ivane Javakhishvili Tbilisi State University, Georgian Technical University, Tbilisi State Medical University, Ilia State University and the University of Georgia), 72.6% of respondents used AI tools, mainly for research and information retrieval (75.0%), writing and editing (44.9%) and curiosity-driven exploration (38.8%). The main benefits were time saving (91.4%) and reduced routine work (54.6%); the main concerns were over-reliance (62.6%), data accuracy (53.8%) and the erosion of intellectual skills (37.2%) [30*].

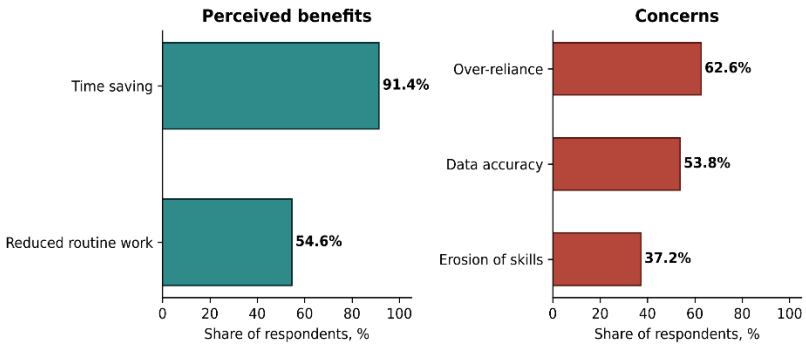


Figure 4: Perceived benefits of and concerns about GenAI in the Georgian academic community (n = 950). Source: Authors' illustration based on Kancheli and Kancheli [30*].

Time-saving use combined with fear of over-reliance is exactly the combination described by Lee et al. [15] and Gerlich [16]. Respondents are aware of the performance–learning gap, yet institutional mechanisms to address it are lacking (Section 6.3), an "awareness–action gap". Caution is needed: the sample is mixed, recruited via institutional e-mail and not yet peer reviewed, so the 72.6% figure is not directly comparable with the UK undergraduate figure of 95%. Kikoria [31] shows that peer encouragement and institutional support are the strongest drivers of ChatGPT use, meaning that norms are formed collectively and that institutional policy, or its absence, can reinforce either critical or uncritical use. Given that without teacher support the learning effect approaches zero [32], institutional passivity is not a neutral position. A linguistic factor may add to the risk: Georgian academic text is probably under-represented in LLM training data, which may increase inaccuracies and hallucinations and the verification burden on Georgian students, a hypothesis that remains to be tested (Section 10.1, Direction 3).

DIGITAL INEQUALITY

Access to paid versions of neural networks (e.g., ChatGPT Plus at $20 per month, or Claude Pro), to powerful devices and to stable internet connections is unequally distributed. Students who can afford advanced tools gain an advantage in the speed and quality with which they complete assignments. Gagnidze's lecture course (Chapter 10) links this risk to "digital poverty" and distinguishes three dimensions of it:

- **Access poverty:** there is no internet connection or device at all.
- **Quality poverty:** there is internet access, but it is too slow or too expensive for using GenAI.
- **Competence poverty:** the technology is available, but the skills to use it effectively are lacking.

UNESCO's 2023 global guidance states directly that GenAI may further deepen digital inequality and worsen "digital poverty". The document advises governments to introduce age limits and mandatory data protection standards so that the technology does not become a new instrument of discrimination [29].

Recent data broadly confirm this claim. According to the 2026 HEPI survey, male students from more affluent backgrounds use AI more actively than less affluent female students, and only 38% receive AI tools from their university; the rest rely on their own, often free and limited, versions [7]. According to the OECD, GenAI uptake is fastest in high-income countries, which risks deepening the digital divide between countries. The organisation therefore calls on governments to ensure digital infrastructure that is as equitable as possible: devices, connectivity, digital resources and professional development for teachers [2].

"Competence poverty" may prove to be the least visible but most important dimension: as Section 5 shows, the learning effect of AI depends to a large extent on teacher support and on the strategy of use (see Section 5.4). Institutional investment in AI literacy should therefore be regarded as part of equity policy.

The equity question cuts both ways. In the study by Cena et al. [28], neurodivergent students (e.g., those with dyslexia or attention deficit) and students with English as a second language described GenAI as a "transformative" aid: it simplifies difficult texts, improves grammar and reduces language anxiety. For some students it also compensates for a lack of academic support at home. The same study shows the reverse side as well: students noted that if some have access to paid versions and additional tools while others use only an outdated free version, this is not equality, and that a university that encourages AI use should also ensure equal access. Thus, a technology that can potentially reduce inequality may also amplify it if institutional policy does not provide for equal access.

THE OBJECTIVE BENEFITS OF AI: META-ANALYTIC EVIDENCE

Despite the risks, recent meta-analyses confirm a *statistically significant positive effect* of GenAI on learning outcomes, particularly when interventions are well designed (Table 2).

Table 2: Meta-analyses of the learning effects of GenAI and AI (2024–2026)

Study	Sample	Effect size	Main moderator / note
Tlili et al. [33]	28 studies, n = 2,765 (computer science)	g = 1.36	ITS: g = 1.45; effects of intervention duration and geography
Wang & Fan [34]	51 studies (ChatGPT)	g = 0.867	Learning perception g = 0.456; higher-order thinking g = 0.457
Gu & Yan [32]	19 studies, 24 effects (K-12 and university)	g = 0.683	With teacher support g = 1.426; without it g = 0.077
Liu, Zuo & Lu [35]	37 studies (ChatGPT)	g = 0.577	No difference across educational levels
Han, Peng & Liu [36]	68 studies, 337 effects (2022–2025)	SMD = 0.45	Effect depends on level, subject and form of use
Deng et al. [37]	69 experimental studies (ChatGPT)	Positive	Academic performance, motivation and higher-order thinking ↑; mental effort ↓; self-efficacy unchanged
Maier et al. [38*]	10 studies, 11 effects (programming education)	g = 0.14 (n.s.)	Exam without AI: g = −0.06; exam with AI: g = 0.76

Note: * Not peer reviewed. g = Hedges' g; SMD = standardised mean difference; ITS = intelligent tutoring systems; n.s. = not significant. Source: Authors' synthesis.

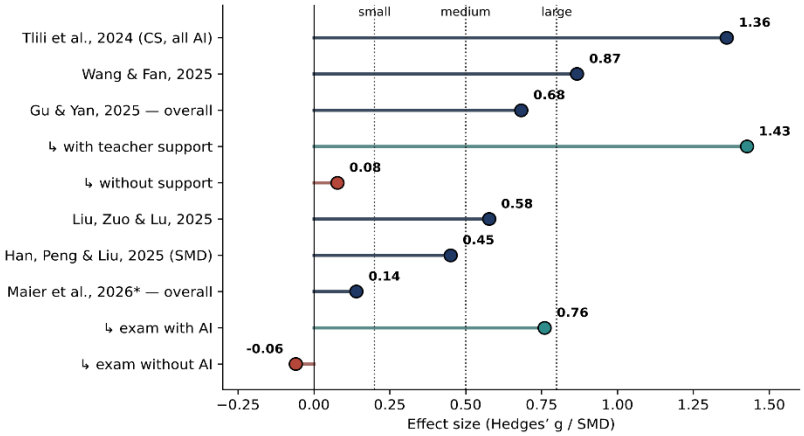


Figure 5: Effect sizes and main moderators in the meta-analyses. Note: Point estimates; dotted lines mark Cohen's conventional thresholds. Source: Authors' illustration based on the studies listed in Table 2.

Overall Effects and the Role of the Teacher

A meta-analysis of 68 experimental and quasi-experimental studies (337 effect sizes) found a moderate but significant positive effect (SMD = 0.45) that varies by level, subject and form of use [36]. ChatGPT-focused syntheses report g = 0.577 across 37 studies [35] and g = 0.867 for learning performance and 0.457 for higher-order thinking across 51 studies [34]; a synthesis of 69 experiments found gains in performance, motivation and higher-order thinking with reduced mental effort and unchanged self-efficacy [37]. In computer science education the effect of AI is very large (g = 1.36), especially for intelligent tutoring systems (g = 1.45), although this meta-analysis covers all forms of AI, not GenAI alone [33]. The most important finding concerns the teacher: across 19 studies the overall effect was g = 0.683, but students with teacher support gained far more (g = 1.426) than those without it (g = 0.077) [32]. Without the teacher, the average learning effect of GenAI is practically zero.

Learning or Tool-Enhanced Performance?

A 2026 meta-analysis of programming education found no significant learning effect overall (g = 0.14). When AI was not allowed in the examination the effect approached zero (g = −0.06); when it was allowed, it was large (g = 0.76), reflecting tool-dependent performance rather than durable knowledge. Studies with a high risk of bias reported larger effects [38*]. Weidlich, Gašević, Drachsler and Kirschner [39] further showed that only a small minority of primary experiments in the Deng et al. meta-analysis precisely describe the intervention and the control condition and use a valid measure of learning, so the gains cannot yet be attributed to ChatGPT with full confidence. This is consistent with evidence that AI-assisted work is of high quality while its effect on overall academic performance is limited (as reviewed by Cena et al. [28]).

Randomised Studies in Which AI Enhances Learning

When AI use follows sound pedagogical principles, the results are impressive. In a Harvard physics course, students working with a research-based AI tutor learned significantly more

in less time than in active-learning classes [40]. In Nigeria, six weeks of teacher-guided GPT-4 use improved English outcomes by about 0.3 standard deviations [41]. In both cases AI was embedded in a structured framework and did not provide ready-made answers. AI is thus neither "good" nor "bad": its effect depends on whether it *enriches* or *replaces* learning. Most studies, however, come from East Asia, North America and Western Europe, so effects cannot be transferred directly to Georgian-language courses and require local replication (Section 10.1).

Does Teaching Students How to Use AI Change Outcomes?

The studies discussed above concern mainly tool design: what happens to learning when AI is configured with pedagogical guardrails. For the integrative position (see Section 9), a second question is no less important: can students themselves be taught to use AI in such a way that even a standard, "unguarded" tool strengthens learning? The first experimental evidence in this direction appeared in 2025–2026 and can be divided into three groups.

The mode of use determines the outcome: In a randomised experiment by Contractor and Reyes [42*], 211 undergraduates studied an unfamiliar topic under supervision and wrote an analytical essay with or without AI, after which knowledge in both groups was assessed without AI, both immediately and one week later. Access to AI improved test scores by 0.27 standard deviations, and this gain persisted after one week. The form of use proved decisive: the delayed gain was larger among students working in "augmentation" mode, who used AI to explain concepts, whereas the short-term gain of those working in "automation" mode, for whom AI wrote the text, disappeared as soon as AI was removed. Yi et al. [43*] obtained a similar picture in a randomised experiment with 318 university students in which the final examination was taken without AI by all participants: better results were associated with active and critical engagement, namely independent attempts, verifying AI's answers and correcting its errors. Moreover, once this behaviour was taken into account, the relationship between students' initial advantage (university ranking, prior knowledge) and their outcomes weakened considerably: stronger students gain more from AI because they use it better. This implies that teaching students how to use AI could become an instrument for reducing "competence poverty" (Section 4).

Direct instructional interventions: In a randomised study by Huang, Xie and Bao [44] (N = 95), Chinese students completed a structured training session built on the self-regulated learning (SRL) cycle and subsequently outperformed the control group when working through electromagnetism problems with AI assistance. The training also weakened the influence of prior AI experience, that is, it narrowed the gap between experienced and inexperienced users. In a controlled study at a French secondary school (N = 116, pupils aged 13–15), a two-hour workshop explaining how LLMs work and how they err, combined with practical exercises, made pupils less uncritical towards AI: they refined their prompts more often, asked follow-up questions, judged the correctness of answers more accurately and, as a result, performed the tasks better. Self-assessed AI knowledge and metacognition, however, did not predict performance [45*]. Puppart and Aru [46*] obtained an opposite but equally informative result: a short educational text about how ChatGPT works and its limitations, given to final-year secondary school pupils in Estonia, did not reduce over-reliance; pupils accepted incorrect recommendations uncritically in about half of the cases, while rejection of correct recommendations increased. Comparing these studies leads to a

clear conclusion: passive information ("AI makes mistakes") is not enough and may even provoke the opposite extreme of unwarranted distrust, whereas specific behavioural habits acquired in practice (refining the prompt, verifying, correcting errors) change the outcome.

The time factor: In an experiment by Fischer, Rau and Rilke [47*] based on material from an introductory economics textbook (334 students), access to an AI tutor improved scores on a test taken without AI by 0.23 standard deviations. Unexpectedly, unrestricted access outperformed restricted access, which required compulsory independent reading before AI could be used, by 0.21 standard deviations. The unrestricted group turned to AI gradually, as difficulties arose, whereas the restricted group sent intensive bursts of requests as soon as access was granted, which disrupted the continuity of learning. Gains were greatest among students with low prior knowledge and strong self-regulation. This finding does not refute the formula in Section 8 but refines it: "think first" should be taught as a self-regulation skill rather than imposed as a mechanical time barrier.

Limitations and interim conclusion: This evidence is still early: some of the studies are not yet peer reviewed, the interventions are short (a single session or a two-hour workshop), two studies involved school-age participants, and Huang et al. [44] and Clerc et al. [45*] measured outcomes by performance with AI rather than by knowledge without AI. To the authors' knowledge, there is as yet no randomised study assessing the effect of a semester-long AI literacy course at university level on knowledge measured without AI and with a delay. The hypothesis that teaching students how to use AI changes learning outcomes is therefore partly supported but not yet established, and it is conditional: instruction must be practical, embedded in the discipline and focused on specific behaviours (attempt → verify → correct). Direction 6 of the Georgian research agenda is devoted to filling this gap (see Section 10.1).

GenAI and the Sustainable Development Goals

Within the framework of the social construction of technology, Jogezai, Koroleva and Ivanov [48] find that GenAI creates both opportunities and challenges for achieving SDG 4 on quality education, and that ethical AI guidelines are crucial for education for global citizenship and sustainable development (Target 4.7). Integrating GenAI is therefore connected to the global agenda of quality and equity, not only to pedagogy.

THE REGULATORY AND POLICY FRAMEWORK

UNESCO and the OECD

UNESCO's 2023 guidance on GenAI in education and research adopts a human-centred approach and recommends data protection, a minimum age of 13 for classroom use and the pedagogical and ethical validation of tools [29]; its 2024 AI competency frameworks for students and teachers treat AI literacy in technical, ethical and human-centred terms [49, 50]. The OECD's 2026 report distinguishes general-purpose chatbots from education-specific tools such as tutors and teacher assistants and urges governments to support the latter; in 2024, 37% of lower secondary teachers used AI, while 72% believed it threatens academic integrity [2].

The EU Artificial Intelligence Act

The EU AI Act (Regulation 2024/1689; [51]) classifies as high-risk (Annex III) AI systems used for admission, the assessment of learning outcomes, determining the appropriate level of education and proctoring, and has prohibited emotion recognition in educational institutions since 2 February 2025 (except for medical and safety purposes). The "Digital Omnibus" (Regulation 2026/1744; [52]), in force since 27 July 2026, postponed the Annex III obligations from 2 August 2026 to 2 December 2027 without changing the risk classification. Universities using automated assessment or proctoring should treat this as time to prepare human oversight, documentation and fundamental rights impact assessments.

The Georgian Context: An Institutional Gap

For Georgia, legislative approximation under the EU Association Agreement and participation in the Bologna Process make European standards a natural reference, yet as of 2026 there is no national AI framework for quality assurance in higher education. In July 2026 the Minister of Economy and Sustainable Development announced work on a national AI strategy and the creation of the country's first AI research centre at the Kutaisi Technology Hub [53]. Georgia was among the first signatories, on 5 September 2024, of the Council of Europe Framework Convention on Artificial Intelligence and Human Rights, Democracy and the Rule of Law [54]. The National Center for Educational Quality Enhancement (NCEQE) acknowledges the absence of a national framework and is developing an internal AI policy aligned with ENQA standards [55], while Ivane Javakhishvili Tbilisi State University and other universities are developing AI strategies based on the EU AI Act. Empirically, AI uptake is high [30*], and among 150 students the strongest predictors of ChatGPT use are peer encouragement (odds ratio 1.180) and institutional support (1.264), with male students using it more than female students, echoing the UK data; post-Soviet settings remain under-represented in technology adoption research [31].

In the absence of a national framework, universities develop their own, divergent rules (Table 3). Shota Rustaveli Theatre and Film Georgia State University uses a detailed, permission-based model: AI use requires the supervisor's written consent and a declaration, AI-generated text must be cited or paraphrased, the methodology must state the tool, prompt and purpose, and generating original findings or copying whole works is prohibited [56]. Caucasus International University treats AI as a learning aid, defines uncited or uncritical use as a violation, requires students to sign a relevant document and holds information sessions [57]. Both models reflect the logic of the international literature: transparency, authorial responsibility and protection of the core of thinking. However, TAFU bases the permissible threshold on an anti-plagiarism system's "AI-use probability score", which, given the evidence in Section 2.3, risks false positives, especially for texts in Georgian, for which detector accuracy has not been established. Students at different universities thus face substantially different rules.

Infrastructure compounds the problem. According to Oxford Insights [59], Georgia's AI readiness is held back by the lack of a national strategy and by unstable rural internet and limited access to devices, with private initiatives such as the Business and Technology University's AI4Globe and Women in AI partly filling the gap. Digital poverty (Section 4) is thus a real barrier in Georgia. In sum, AI uptake in Georgian higher education is already high and is not waiting for regulation; the institutional response is fragmented; and both

infrastructural and competence gaps reduce the potential benefits of GenAI. Priorities therefore include not only institutional policy but also investment in digital infrastructure and AI literacy as part of equity policy.

Table 3: Examples of AI policies at Georgian universities compared with international benchmarks

Element	Shota Rustaveli Theatre and Film University [56]	Caucasus International University [57]	International benchmark
General approach	Permission-based, detailed regulation	AI as a learning aid; "improper use" prohibited	Differentiated permission by task type (AIAS; [58])
Permission	Written consent of supervisor; restrictions in the syllabus	No separate permission specified	The lecturer defines the role of AI for each task
Disclosure	Mandatory declaration; description of tool, prompt and date in the methodology	Citation of AI text; signed document with the academic contract	Transparency and authorial responsibility [29]
Prohibited	Generating conclusions/findings; copying entire papers; failing to correct errors	Use without citation or critical analysis	Delegating cognitive operations that constitute the learning goal (Section 3.5)
Detection	Anti-plagiarism system, including an AI-probability score	Anti-plagiarism software	Detector is not evidence [10]
Awareness	Lecturers inform students of the rules; academic writing courses	Information sessions on AI capabilities and limitations	AI literacy in the curriculum [49]

Source: Authors' analysis of publicly available university documents. The table is illustrative and does not cover all Georgian universities.

HOW THE ASSESSMENT SYSTEM SHOULD CHANGE

International research and policy recommendations, consistent with Gagnidze's lecture course, propose the following measures:

- **Transparency rules:** Only 36% of UK students felt their university clearly explains when AI use is acceptable [6]. Students describe the boundary as left to "personal judgement", fear unintentional plagiarism and ask for discipline-specific examples, introductory training and regularly updated guidance [28]. Unclear rules increase the risk of both violations and unfair accusations.
- **The AI Assessment Scale (AIAS):** A five-level scale, from "no AI" to "AI exploration", lets lecturers define the permitted role of AI for each task [58].
- **The "two-lane" approach:** The University of Sydney model separates secured assessment (supervised, oral or in class), which certifies attainment, from open assessment, in which AI use is permitted and directed towards learning, a typical "structural" change [13].
- **Oral defence and process assessment:** Oral defence supports academic integrity and engagement, while assessing drafts, records of dialogue with AI and reflective journals reveals the student's own contribution [4]. Australia's TEQSA principles

likewise require assessment to evidence the learning process and ethical engagement with AI [60].

- **Evaluative judgement and AI literacy:** Tasks such as critiquing AI responses, analysing one's own prompts or comparing AI-generated and original texts turn AI into an object of critical thinking [4, 28]. Since passive information does not change behaviour [46*] but practical training does [44, 45*], AI literacy should be taught through discipline-embedded exercises in independent attempts, using AI as an "explainer" rather than a "performer", verification and error correction [42*, 43*], with particular attention to less well-prepared students.
- **Tools with guardrails and a detector that is not evidence:** Institutional AI should be configured as a tutor that guides rather than answers [21] and used with active lecturer support [32]; detector output can justify a conversation, never a sanction [10, 11].

Institutional responses vary. Several Australian universities returned to "pen and paper" examinations in early 2023 [61], and by 2026 some UK universities were returning to closed, supervised, in-person examinations [62]. A HEPI analysis distinguishes "educational" from "detection-oriented" university policies, and some experts note that there is no evidence yet that students cheat more with AI than before [62]. A purely control-oriented response fails to address the structural side of the problem [13].

Institutional Piloting for Georgian Universities

For Georgian universities, with limited resources, fragmented policy and fast-changing technology, we propose a *staged pilot model* that can be implemented within one semester at modest cost:

- **Stage 1. Audit and baseline (1–2 weeks):** a short survey of staff and students based on Georgian instruments [30*, 31]; a review of integrity and assessment regulations; and the selection of two pilot courses, ideally one in the humanities and one in science or engineering, since patterns of use differ by discipline [27, 28].
- **Stage 2. Two-lane assessment (2–3 weeks):** at least one secured task (oral defence or in-class writing) confirming core knowledge without AI, plus an open task in which AI is permitted but the process (drafts, AI dialogue records and a reflective journal) is documented, with the role of AI set by the AIAS [13, 58].
- **Stage 3. A tool with guardrails (whole semester):** an institutionally configured assistant, such as a platform's learning mode or a model with a dedicated system prompt replicating the "GPT Tutor" logic [21]; a 2–3-hour pedagogical training for lecturers, given the decisive role of teacher support [32]; and a two-hour practical workshop for students on refining prompts, verifying answers and correcting errors [45*], reinforced in regular assignments [46*].
- **Stage 4. Evaluation (end of semester):** comparison with control groups, including tests without AI at the end of the semester and several weeks later; critical thinking and self-regulation measures [19]; lecturer experience; and behavioural indicators from anonymised AI logs [42*, 43*], summarised in a 5–10-page report.

- **Stage 5. Institutional policy (after the pilot):** AI roles by task type (AIAS), institutionalised oral defence and process assessment, clear discipline-specific guidance for students as requested by Cena et al. [28], and AI literacy aligned with UNESCO's competency frameworks [49, 50], with detector results serving only as grounds for a follow-up conversation.

The model is modular, measurable, evidence-based and generates local data that currently do not exist. Its main risks can be mitigated: staff resistance [9] through voluntary participation and training; unequal access [28] by making the institutional assistant free for all; privacy risks [5] through anonymisation, informed consent and restrictions on third-party data transfer; and, where AI is used for assessment or proctoring, by meeting the EU AI Act's high-risk requirements. Such pilots are a *mechanism of institutional learning*, moving universities from general debate to evidence-based policy in line with student demand [28] and international recommendations [2, 49], and can form part of the empirical basis for national policy.

THE STUDENT'S FORMULA: HOW TO USE AI WITHOUT LOSING ONE'S MIND

Researchers and the author of the lecture course agree in proposing a practical model of behaviour that helps students preserve their own thinking when working with neural networks:

> *"First think for yourself, then ask the artificial intelligence, then reflect on and critically evaluate its answer."*

This procedure turns the neural network from a substitute for the mind (likened in the lecture course to a "genie in a bottle") into an instrument of success. In UNESCO's view, the main task of education is to teach people "to think together with artificial intelligence and not to hand over the function of thinking to it".

Empirical support: The steps of the formula have empirical backing. "Think first": according to Lee et al. [15], confidence in one's own abilities increases critical scrutiny, whereas blind trust in AI reduces it. Students say the same: respondents in Cena et al. [28] noted that an AI error can be spotted only if one already has a "basic understanding" of the topic, and that without it reliance on AI can sink an entire piece of work. "Reflect and evaluate": structured, critical use of AI reduces extraneous cognitive load and deepens argumentation [24]. At the institutional level, the same logic is built into the design of the "GPT Tutor", which makes students work through their own steps before receiving an answer and neutralises the negative effect of dependence [21]. Critical dialogue with AI, not blind acceptance, is therefore the key.

The formula has to be taught: New experimental data (Section 5.4) show that knowing the formula is not sufficient in itself; it must be acquired in practice. Short written information does not reduce over-reliance [46*], whereas a practical workshop in which pupils practise refining prompts and evaluating answers improves the quality of AI use [45*]. At the same time, "think first" does not mean artificially delaying recourse to AI: in an experiment based on economics teaching material, compulsory independent reading before using AI produced worse results than unrestricted access, under which students turned to AI gradually as difficulties arose [47*]. The essence of the formula is thus not a strict temporal sequence but keeping one's own thinking active throughout the whole process.

DISCUSSION: RESTRICTIVE AND INTEGRATIVE APPROACHES

Two positions in the literature both oppose and complement each other. A clear example of the restrictive (conservative) position is Ali [9], who, after reviewing the benefits and risks of AI, sets out the author's personal view: AI should be avoided in schools and, in higher education, by undergraduate and master's students in the process of learning and completing assignments, while in research its use is acceptable only with critical verification of the accuracy and appropriateness of the results. The logic of this position is partly supported by the negative effect of use "without guardrails" [21, 22*] and by the fact that in many cases the gains disappear when knowledge is assessed without AI [38*].

The integrative position [2, 4, 5, 28] argues that a ban is unrealistic when 95% of students already use the technology, and that the university's task is to teach its responsible use, which is also essential for graduates' employability. This position is supported empirically by evidence that pedagogically structured AI significantly improves learning outcomes [40, 41] and that gains are particularly large with teacher support [32]. Guardrails neutralise the negative effect, although they do not in themselves improve learning [21]. The latest experiments give this position an additional argument: practical training in AI use changes the student's own behaviour, and behaviour changes the learning effect ([45*]; [42*]; see Section 5.4). Both positions rest on a common premise: learning requires mental effort. The decisive difference lies not in a choice between being "for or against AI" but in *how* the technology is used: as a substitute for thinking or as its enrichment. In practice this means a differentiated approach: restricting AI at the stage of forming basic skills and in secured assessment, and integrating it in a structured, critical and transparent way at more advanced stages. This tension reflects well the central thesis of this article on the "performance–learning gap" and explains why pedagogical design is decisive.

LIMITATIONS OF THE EVIDENCE BASE AND A RESEARCH AGENDA

Several limitations must be considered. First, heterogeneity is high and control conditions weak: interventions and control activities are often vaguely described and learning measures of questionable validity [39]. Second, interventions are short and the technology changes rapidly, so long-term effects on retention, transfer and skill erosion are understudied, and some data relate to older models [4, 28]. Third, the main evidence on cognitive dependence relies on self-reports and correlational designs [15–17], and qualitative studies on small, specific samples [27, 28]. Fourth, several widely cited results are not yet peer reviewed [20*, 22*, 30*, 38*], studies at high risk of bias report larger effects, and some reviews (e.g., [9]) rely largely on blogs and institutional reports. Fifth, representative and experimental data from the post-Soviet region, and Georgia in particular, are almost absent [30*, 31]. Finally, few experiments evaluate training students rather than changing tools, and none yet tests a semester-long university course on knowledge measured without AI [44, 45*].

A Georgian Research Agenda: Six Priority Directions

The following six directions respond both to gaps in the global literature and to the needs of the Georgian system. National monitoring could serve as an "umbrella" project for the other five (Figure 6).

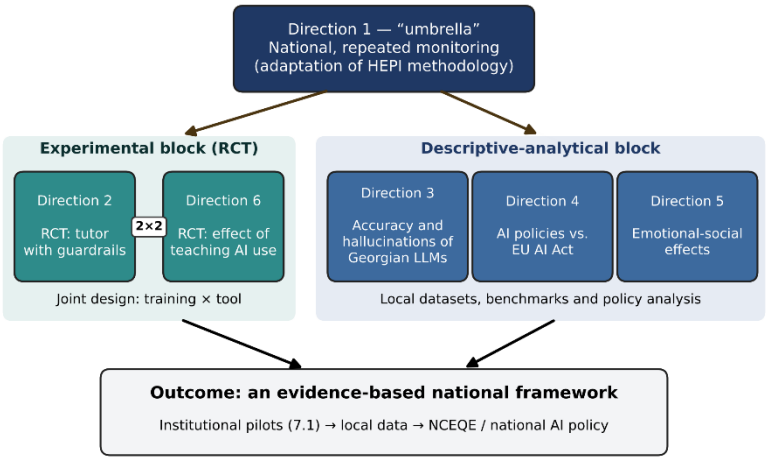


Figure 6: The structure of the Georgian research agenda. Source: Authors' elaboration.

Direction 1. National, repeated monitoring of students' AI behaviour.

- *Research questions:* How do the frequency, areas of and attitudes towards GenAI use among Georgian students change over time? What differences exist between public and private universities, disciplines and regions? How is AI use related to academic performance, wellbeing and self-assessed independent thinking?
- *Methodology:* Adaptation of the HEPI/Kortext methodology [6, 7]: an annual survey with a stratified sample (e.g., 1,500+ respondents) from authorised universities by discipline, level of study and region; quantitative indicators combined with open questions; public sharing of anonymised data for secondary analysis.
- *Expected results:* The first systematic, time-comparable dataset, which would replace the current episodic and non-representative studies [30*, 31] and allow international comparison.

Direction 2. Randomised studies with a tutor equipped with guardrails.

- *Research questions:* How effective is a tool built on the logic of the "GPT Tutor" of Bastani et al. [21] in Georgian-language courses? How does its effect differ from that of a standard chatbot? Is the decisive role of teacher support [32] confirmed in the Georgian context?
- *Methodology:* A randomised controlled trial in at least two universities and two disciplines with three groups: control (no AI), standard chatbot and tutor with guardrails. Measures: pre- and post-tests, standardised critical thinking instruments, interaction logs and focus groups. The final test is administered both with and without AI in order to measure the "performance–learning gap" [38*].
- *Expected results:* The first experimental evidence on whether guardrails work in the Georgian setting, and practical recommendations for configuring institutional AI tools.

Direction 3. Systematic evaluation of the accuracy and hallucinations of LLMs in Georgian.

- *Research questions:* How accurately do leading large language models process Georgian-language academic text? Which types of error (hallucinations, terminological inaccuracies, stylistic problems) predominate, and how do they differ across disciplines (e.g., law, medicine and engineering)? How reliable are AI-text detectors for Georgian?
- *Methodology:* Testing with a standardised task set (e.g., 200+ tasks from three disciplines) and double-blind evaluation by independent experts; classification of errors according to the risk typology of Mellado [5] and Bobula [4]; creation of an open Georgian-language benchmark.
- *Expected results:* The first systematic assessment of LLM reliability in Georgian; recommendations on the tasks for which AI can and cannot be used; a basis for developing Georgian-language models designed for education [5].

Direction 4. Comparing university AI policies with the categories of the EU AI Act.

- *Research questions:* To what extent do the AI policies of Georgian universities meet the high-risk requirements of the EU AI Act (transparency, human oversight and documentation)? What gaps exist in current policies, and how can they be harmonised with ENQA standards [55]?
- *Methodology:* Collecting and coding the public AI and academic integrity documents of authorised universities against the criteria of Annex III of the AI Act and the AIAS (an extension of the method used for Table 3); semi-structured interviews with quality assurance officers (e.g., at 10+ institutions); presentation of the results as a "compliance map".
- *Expected results:* The first systematic comparative analysis and specific recommendations for NCEQE on developing a national framework.

Direction 5. The emotional and social effects of GenAI among Georgian students.

- *Research questions:* How does GenAI use affect Georgian students' feelings of loneliness, anxiety and motivation? Do these effects differ for neurodivergent students and those studying in a non-native language? How do students perceive the role of AI in social relationships and group work?
- *Methodology:* Mixed methods: a quantitative survey (e.g., 500+ students) using validated scales of loneliness, anxiety and motivation, and qualitative focus groups adapting the approach of Cena et al. [28] and Zhang [27], with particular attention to groups that benefit most from GenAI and are at the same time most vulnerable to inequality.
- *Expected results:* The first empirical data on GenAI and students' psychosocial wellbeing, and recommendations for support services (psychological counselling and academic tutoring).

Direction 6. The effect of teaching AI use: a randomised study at university course level.

- *Research questions:* Does semester-long, discipline-embedded AI literacy instruction change Georgian students' knowledge when it is assessed without AI and with a delay? Which behaviours (independent attempts, using AI as an "explainer", verification and error correction) constitute the mechanism of the effect? Does instruction narrow the gap between better- and less-prepared students or, on the contrary, widen it? Does instruction induce unwarranted distrust of AI (rejection of correct answers)?
- *Methodology:* A cluster-randomised study (at the level of teaching groups) with a 2×2 factorial design that can be implemented together with Direction 2: student training (a practical AI literacy module embedded throughout the semester vs. standard information) × tool type (standard chatbot vs. tutor with guardrails). Such a design makes it possible to establish whether student training substitutes for or complements tool design. Measures: tests without AI at the end of the semester and 4–8 weeks later; a trust-calibration task with correct and incorrect recommendations (following the approach of [46*]); coding of anonymised interaction logs with a behavioural typology [42*, 43*]; and heterogeneity analysis by prior knowledge, self-regulation and socio-economic factors [47*].
- *Expected results:* The first causal evidence in higher education on whether teaching AI use changes durable knowledge, and a tested instructional module that can be integrated into institutional pilots (Section 7.1) and curricula. The result is valuable either way: if the effect is confirmed, universities will have an evidence-based route to integration; if not, the emphasis on structural changes to assessment and tools will be strengthened.

All six directions should share a common ethical framework of data protection, informed consent and public reporting, and should build replicable methods and open datasets that avoid the shortcomings identified by Weidlich et al. [39]. Georgian research could thus become an active participant in the global debate on GenAI rather than merely a recipient.

CONCLUSION

The integration of artificial intelligence into education is inevitable: by 2026 it has become a near-universal, everyday practice among students. In the approach set out in Gagnidze's lecture course, routine and standard tasks should be delegated to technology, while responsibility for conclusions, decisions and acquired knowledge must remain with the human being. Universities should assess not only the finished assignment but also the reasoning and process behind it. The best strategy is not prohibition (as New York City public schools attempted in 2023, only to reverse course within a few months) but teaching students to make the technology an intellectual assistant and interlocutor that stimulates mental activity and broadens the range of ideas, rather than a replacement for the brain.

The latest evidence refines this position. Meta-analytic studies show an on-average positive effect of AI use, but this effect depends largely on teacher support and pedagogical

design. When knowledge is assessed without AI, the gains often disappear, and use without guardrails may even harm learning. Moreover, the impact of AI is not only cognitive: it changes students' relationships, their sense of fairness and their psychosocial wellbeing, and its benefits and harms are unequally distributed. Three practical principles follow: **structural reform of assessment** (validity, oral defence and process assessment); **institutionally governed AI** (equal access, pedagogical guardrails and clear rules); and **AI literacy** as a new form of critical thinking, understood not as one-off information but as practical training in specific behaviours for working with AI (attempt, verify and correct), whose effect is already visible in early experiments but has yet to be confirmed in higher education. For Georgia these principles are particularly relevant: AI uptake is already high but the institutional response is fragmented, so evidence-based institutional pilots and local research are a necessary precondition for forming a national framework. The potential of AI will be realised only when the student remains the active subject of the thinking process.

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