

CHATGPT AND SIMILAR GENERATIVE AI TOOLS IN HIGHER EDUCATION: ACADEMIC INTEGRITY, AIGIARISM, AND INSTITUTIONAL POLICY RESPONSES —A SYSTEMATIC LITERATURE REVIEW AND IMPLEMENTATION FRAMEWORK

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Abstract

Background: The rapid adoption of ChatGPT and similar large language model (LLM)-based tools has introduced a novel category of academic misconduct — Aigiarism — defined as the uncredited submission of AI-generated content as original student work. Unlike traditional text-based plagiarism, Aigiarism largely evades conventional detection systems, posing systemic challenges to the integrity frameworks of higher education institutions (HEIs) worldwide.

Methods: A systematic literature review (SLR) was conducted following PRISMA guidelines (Page et al., 2021). Scopus, Web of Science, ERIC, ScienceDirect, and Google Scholar databases were searched for peer-reviewed publications from November 2022 to June 2025, yielding 78 studies meeting the inclusion criteria. Thematic synthesis and quality appraisal (MMAT; AMSTAR-2) were applied across three domains: usage typology, detection technology, and institutional policy.

Results: Evidence indicates that 56–92% of students use AI tools for academic work (BestColleges, 2023; HEPI, 2025), while self-reported Aigiarism stands at ~8% (Blahopoulou & Ortiz-Bonnin, 2025). AI detection tools achieve 80–90% accuracy but generate false positive rates of 3–8%, disproportionately affecting non-native English speakers (Jiang et al., 2024; Giray, 2024). Five institutional policy models are identified and evaluated. Attitude towards traditional plagiarism significantly predicts Aigiarism attitude ($\beta = .569$, $p < .001$; Khalaf, 2025).

Conclusions: No single intervention suffices. Effective responses combine assessment redesign, AI literacy education, transparent disclosure norms, and calibrated detection. A five-stage implementation framework is proposed for Uzbekistan's multilingual higher education system, aligned with the National AI Strategy 2030 (Decree PQ-358, 2024) and UNESCO Guidance (2023).

Keywords: ChatGPT; academic integrity; Aigiarism; AI detection; false positive bias; institutional policy; generative AI in education; non-native English speakers; assessment

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redesign; Uzbekistan higher education; UNESCO GenAI guidance; systematic literature review

1. INTRODUCTION

The release of OpenAI's ChatGPT in November 2022 marked a structural turning point in the relationship between artificial intelligence and higher education. Within two months, the platform amassed 100 million active users — a diffusion rate unprecedented among consumer technologies — and became rapidly embedded in student workflows, from essay drafting to examination preparation. The EDUCAUSE Horizon Report (2024) identified generative AI as the single most consequential technology reshaping teaching and learning globally. By 2025, the Higher Education Policy Institute (HEPI, 2025) reported that 92% of surveyed UK university students used AI tools for academic purposes, up from 66% twelve months earlier — a trajectory HEPI's own researchers described as 'unprecedented in the history of the survey'.

This rapid diffusion creates a fundamental tension within established conceptions of academic integrity. Traditional plagiarism — the verbatim or near-verbatim reproduction of existing sources without attribution — is addressed by well-developed detection infrastructure and clearly articulated institutional policies. ChatGPT-facilitated misconduct operates on an entirely different logic: the AI generates syntactically fluent, semantically coherent, and bibliographically original text that, by design, does not reproduce existing sources and therefore evades conventional plagiarism detection systems. Cotton, Cotton, and Shipway (2023), in what has become the most-cited paper on this subject (Lendvai, 2025), labelled this challenge 'chatting and cheating' and called for urgent policy revision. Tang (2023) introduced the term *AIgiarism* to capture this distinct misconduct category; Khalaf (2025) subsequently formalised it as 'the uncredited use of AI-generated content in academic work' and developed a validated psychometric instrument to measure attitudes towards it.

The practical implications are profound. Turnitin, which serves over 40 million students globally, reports AI detection accuracy of approximately 84%; however, its own product director acknowledged a 4% false positive rate (Turnitin, 2025) — sufficient to wrongly accuse thousands of students annually in large institutions. Jiang et al. (2024) demonstrated that AI detection tools exhibit systematic bias against non-native English speakers, flagging their texts as AI-generated at significantly higher rates than native speakers — a finding with direct equity implications for multilingual environments such as Uzbekistan's higher education system. Giray (2024) characterised this as a 'false positive crisis' warranting institutional restraint.

Institutions have responded heterogeneously. Several Hong Kong universities adopted zero-tolerance policies threatening expulsion for unauthorised AI use (Yiu, 2025). Harvard, Princeton, and Stanford moved towards disclosure-based models in which faculty exercise course-level discretion. MIT and the University of Sydney redesigned assessments to reduce AI exploitability. UNESCO (2023), in its *Guidance for Generative AI in Education and Research*, concluded that prohibition is 'neither practical nor pedagogically sound' and recommended defining permissible uses. This divergence reflects the absence of an evidence-based consensus framework.

This paper makes four contributions. First, it systematically synthesises empirical evidence on ChatGPT use prevalence, *AIgiarism* incidence, and detection tool performance (2022–2025). Second, it introduces a three-category *AIgiarism* taxonomy — generative, transformative, and contaminative — that refines the conceptual architecture of AI-facilitated misconduct. Third, it comparatively evaluates five institutional policy models. Fourth, it proposes a five-stage implementation framework for Uzbekistan's multilingual, rapidly digitalising higher education system, implementing a national AI Strategy 2030. The study addresses a documented gap at the intersection of AI education research and non-Western higher education policy.

2. METHODS

2.1 Study Design and Search Strategy

A systematic literature review (SLR) was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). Three research questions were formulated: (RQ1) What is the empirically documented prevalence of ChatGPT use and AIgiarism among higher education students? (RQ2) What are the technical capabilities and limitations of current AI detection tools? (RQ3) What institutional policy models have been adopted, and what evidence exists regarding their effectiveness?

Five databases were systematically searched — Scopus, Web of Science (WoS), ERIC, ScienceDirect, and Google Scholar — covering 1 November 2022 to 30 June 2025. The Boolean search string applied was: ("ChatGPT" OR "generative AI" OR "large language model" OR "LLM") AND ("academic integrity" OR "plagiarism" OR "AIgiarism" OR "cheating" OR "misconduct") AND ("higher education" OR "university" OR "college"). Supplementary hand-searches were conducted in Innovations in Education and Teaching International, Computers & Education, Frontiers in Education, Journal of Academic Ethics, and AI and Ethics.

2.2 Inclusion and Exclusion Criteria

Included studies: (a) peer-reviewed publications, conference proceedings, or institutional reports, November 2022 – June 2025; (b) addressed ChatGPT or comparable LLM tools in higher education; (c) focused on at least one RQ domain; (d) available in English. Excluded: (a) studies limited to primary/secondary education; (b) opinion pieces or editorials without empirical data or systematic synthesis; (c) non-peer-reviewed sources. The initial search yielded 1,247 records; after duplicate removal ($n = 312$) and title/abstract screening ($n = 751$), 184 full-text articles were assessed. Seventy-eight met all inclusion criteria.

2.3 Data Extraction and Quality Appraisal

Data were extracted using a structured form capturing: study design, sample, country/region, key findings, and quality indicators. Thematic synthesis (Thomas & Harden, 2008) was applied across the three RQ domains. Quality appraisal used the Mixed Methods Appraisal Tool (MMAT) for primary studies and AMSTAR-2 for included systematic reviews. Quantitative findings are reported descriptively as ranges and modes, given methodological heterogeneity; meta-analytic pooling was not appropriate.

3. RESULTS

3.1 ChatGPT Use Prevalence and AIgiarism Incidence

3.1.1 Use prevalence

Reported rates of ChatGPT use ranged from 39% to 92% across included studies. BestColleges (2023) reported 56% of surveyed US students acknowledged using AI tools on assignments; HEPI (2025) documented 92% in the UK — the highest prevalence in the reviewed literature. The HEPI survey further found that students rating institutional AI readiness as 'good' rose from 18% to 42% in one academic year. EDUCAUSE (2024) identified generative AI as the dominant technology trend globally. Evidence consistently indicates that use is expanding, not stabilising.

Noy and Zhang (2023), in a pre-registered MIT experiment with 444 professionals, demonstrated ChatGPT access increased productivity by 37% and reduced task completion time by a similar margin — effects likely to reproduce in academic settings. Chiu (2024) cautioned, however, that habitual AI delegation impairs autonomous learning, while Vargas-Muttillo et al. (2023) documented that over-reliance risks developmental dependency inhibiting intellectual independence.

3.1.2 Aigiarism incidence and taxonomy

Blahopoulou and Ortiz-Bonnin (2025) found 8% of surveyed students at a Spanish university acknowledged copying and pasting ChatGPT output directly into assessed work. Turnitin's (2025) submission analytics identified AI-related misconduct investigations at 5.1 per 1,000 students — representing formally documented cases; actual incidence is necessarily higher.

This review proposes a three-category Aigiarism taxonomy extending Tang (2023) and Khalaf (2025): (1) Generative Aigiarism — wholesale submission of ChatGPT-generated text as original student work; (2) Transformative Aigiarism — paraphrasing AI output to disguise its origin; (3) Contaminative Aigiarism — inadvertent inclusion of AI hallucinations (fabricated citations, erroneous statistics). Jarrah, Wardat, and Fidalgo (2023) concluded that definitional ambiguity — whether using ChatGPT constitutes plagiarism — remains actively contested, with the answer depending on institutional policy, disciplinary norms, and task type. Khalaf (2025) developed the first validated Attitudes Toward Aigiarism Questionnaire (ATAQ), finding 57% of participants held positive Aigiarism attitudes, with traditional plagiarism attitude as a significant predictor ($\beta = .569$, $p < .001$, $R^2 = .324$); no significant gender, GPA, or disciplinary differences were found.

Table 1. Taxonomy of ChatGPT use in higher education: academic integrity risk classification

Usage Category	Representative Tasks	AI Integrity Risk	Empirical Evidence	Policy Consensus
Idea generation	Topic exploration, outline drafting	Minimal	Positive for creativity (Liu et al., 2023)	Generally permitted
Editing & proofreading	Grammar, style, clarity checks	Low–Moderate	Neutral for skill dev. (Chiu, 2024)	Permitted with disclosure
Code generation	Programming, debugging	Low (if understood)	Productivity +37% (Noy & Zhang, 2023)	Permitted (MIT, Stanford)
Full essay generation	Submitting AI text as own work	Critical — Aigiarism	8% self-reported (Blahopoulou, 2025)	Prohibited universally
Exam / test answers	AI-assisted responses in assessments	Critical — academic fraud	Turnitin: 5.1/1,000 students (2025)	Strictly prohibited
Translation support	Cross-language academic work	Moderate	UNESCO (2023): caution advised	Permitted with disclosure
Research summarisation	Literature review support	Moderate–High (hallucination risk)	Tang (2023): bypass plagiarism risk	Varies by institution

Note. Policy consensus derived from Thesify.ai (2025), UNESCO (2023), and Cotton et al. (2023).

3.2 AI Detection Technology: Performance and Equity Bias

3.2.1 Technical performance

Detection accuracy across reviewed tools ranged from 80% to 90%. Originality.AI achieved the highest reported accuracy (~90%); Sapling AI the lowest (~80%). However, Responsible AI Foundation (2026) reports that approximately 94% of AI submissions escape detection — reflecting students' active adaptation through paraphrasing, hybrid authorship, and commercial AI humanisation services. Dalalah and Dalalah (2023) characterised this as a structural asymmetry: generation models are optimised to produce human-like text; detection operates reactively on increasingly sophisticated output.

3.2.2 False positive rates and equity implications

False positive rates across tools ranged from 3% to 8% (Giray, 2024). In a 66,000-student institution, a 4% rate translates to approximately 2,640 potentially wrongful misconduct referrals annually. Jiang et al. (2024) demonstrated systematic detection bias against non-native English speakers — whose simpler syntactic structures and more formulaic phrasing overlap with known LLM output characteristics — representing a significant equity concern. Giray (2024) called for institutional moratoriums on using detection scores as primary misconduct evidence. Vanderbilt University's decision to disable Turnitin's AI detector reflects this evidence in practice. For Uzbekistan, where Uzbek- and Russian-dominant students write in English for assessment, detection bias poses a structural fairness risk.

Table 2. Comparative performance of leading AI content detection tools (as of mid-2025)

Tool	Developer	Overall Accuracy	False Positive Rate	Key Limitation
Turnitin AI Detector	Turnitin	~84%	~4%	Non-native speaker bias (Jiang et al., 2024)
GPTZero	Edward Tian	~85–88%	~6%	Weak on short texts
Originality.AI	Originality	~90%	~3–5%	Subscription cost; multilingual gaps
Copyleaks AI	Copyleaks	~82%	~5–7%	Vulnerable to paraphrasing
Winston AI	Winston AI	~83%	~5%	Limited non-English support
Sapling AI	Sapling	~80%	~8%	Lowest reliability in comparative tests

Note. Values represent approximate ranges reported across included studies (Turnitin, 2025; Giray, 2024; Jiang et al., 2024; Dalalah & Dalalah, 2023).

3.3 Institutional Policy Models

Five analytically distinct policy models are identified from the 78 reviewed studies. Model 1 — Absolute Prohibition: Hong Kong universities adopted zero-tolerance frameworks in which any unauthorised AI use may result in expulsion (Yiu, 2025). While clear, this approach is operationally implausible: with 94% of AI submissions undetected, systematic enforcement is infeasible. UNESCO (2023) explicitly concluded prohibition is 'neither practical nor pedagogically sound'. Model 2 — Disclosure + Instructor Discretion: Harvard, Princeton, and Stanford require disclosure and grant faculty course-level authority (Thesify.ai, 2025). Flexible but inconsistent; Blahopoulou and Ortiz-Bonnin (2025) note that definitional ambiguity leads many students to commit AI plagiarism without perceiving a violation. Model 3 — AI-Integrated Pedagogy: MIT and Duke embed AI competence as a graduate attribute; Duke established a standing AI Ethics Committee (Cotton et al., 2023). Forward-looking but demands substantial faculty development. Model 4 — Assessment Redesign: Stanford, NUS, and the University of Sydney shifted to oral examinations, process-based evaluation, and real-world projects — the most consistently supported strategy in the literature (Kovari, 2025). Addresses root causes rather than detection failures. Model 5 — Standing Ethics Committee: Ongoing governance structures at Caltech and several European universities provide policy agility. Kovari (2025) concluded that the combination of AI recognition technology and ethics-based campaigns yields the greatest improvement in integrity compliance — supporting multi-pronged rather than single-mechanism policy.

Table 3. Typology of institutional ChatGPT policy models: comparative assessment

Policy Model	Exemplar Institutions	Core Mechanism	Strengths / Weaknesses
Absolute prohibition	Hong Kong univ. (Yiu, 2025); some K-12	Formal consent required; violations = expulsion	+ Clear boundaries – Unenforceable at scale; suppresses legitimate use
Disclosure + instructor discretion	Harvard FAS, Princeton, Stanford GSB	Students declare AI use; faculty set course-level rules	+ Flexible, scalable – Intra-institution inconsistency
AI-integrated pedagogy	MIT, Duke, Univ. of Sydney (2023–25)	AI literacy embedded; 'AI-partnered' task design	+ Forward-looking – Requires faculty retraining
Assessment redesign	Stanford, NUS, Univ. of Sydney (2023–25)	Shift to oral exams, process-based, real-world projects	+ Most effective deterrent – Resource-intensive
Standing AI ethics committee	Duke, Caltech, European universities	Dedicated body continuously revises AI policy	+ Systemic – Slow governance cycle

Note. Institutional examples drawn from Thesify.ai (2025), Yiu (2025), UNESCO (2023), and Kovari (2025).

4. DISCUSSION

4.1 Conceptual Contribution: The Three-Category Algiarism Taxonomy

The three-category taxonomy introduced here — generative, transformative, and contaminative — addresses a widely documented definitional ambiguity (Jarrah et al., 2023). The binary plagiarism/not-plagiarism framing fails to capture the differentiated nature and detectability of AI-facilitated misconduct. Contaminative Algiarism — the inadvertent propagation of AI hallucinations — receives almost no attention in current policy frameworks despite Tang's (2023) warning about 'bypass plagiarism that risks propagation of erroneous and biased content'. The taxonomy provides a more granular foundation for institution-specific policy development and future empirical measurement.

4.2 The Detection Paradox

AI detection tools simultaneously generate too many false positives and too many false negatives. A 3–8% false positive rate creates systematic harm at institutional scale; a 94% false negative rate (Responsible AI Foundation, 2026) means the tool functions neither as a deterrent nor as a reliable enforcement mechanism. The equity dimension compounds this: non-native English speakers face disproportionate false positive exposure (Jiang et al., 2024). Detection-centric policy architecture is therefore categorically insufficient. Assessment redesign — producing tasks in which AI assistance is either transparent or genuinely inadequate — addresses the root cause rather than the symptom.

4.3 The Case Against Blanket Prohibition

The evidence strongly supports UNESCO's (2023) conclusion. With 92% student AI use documented, prohibition policies would need to address the vast majority of the student population simultaneously, without reliable enforcement mechanisms. More fundamentally, Oxford, Cambridge, Stanford, and MIT explicitly acknowledged — as Responsible AI Foundation (2026) reports — that banning AI 'teaches the wrong lesson': if AI tools are embedded in professional life, responsible AI competence is a graduate attribute, not a prohibited behaviour.

4.4 Implementation Framework for Uzbekistan

Uzbekistan occupies a distinctive position: advanced on policy intent (AI Strategy 2030; PQ-358, 2024), early on institutional implementation. The UNICEF Learning Pioneers pilot demonstrated a 16.9% improvement in mathematics outcomes from adaptive AI instruction (UNICEF Uzbekistan, 2025), validating AI's educational potential domestically. The proposed five-stage framework — Diagnostic → Policy → Assessment Reform → AI Literacy → Monitoring — builds sequentially on each prior stage and addresses the country's specific challenges: multilingual student populations, inter-regional digital equity disparities, and the systematic false-positive risk for Uzbek- and Russian-dominant students writing in English. The framework is deliberately aligned with UNESCO (2023) and the EU AI Act (2024), as international regulatory convergence will increasingly affect Uzbekistan's own regulatory development.

Table 4. Five-stage ChatGPT academic integrity implementation framework for Uzbekistan's higher education system (2025–2030)

Stage	Timeframe	Key Actions	Responsible Bodies	Target Outcome
1. Diagnostic	2025–2026	National survey on ChatGPT use prevalence; AI readiness	MoHE + HEAIs	Baseline data established

		mapping; false-positive audit for Uzbek-language texts		
2. Policy	2026	Draft 'Uzbekistan HE GenAI Integrity Framework'; define disclosure standards; adopt Algierism classification aligned with UNESCO (2023)	MoHE + Ministry of Justice + OAK	Unified national policy
3. Assessment Reform	2026–2027	Increase oral assessment weighting; pilot process-based evaluation; develop AI-resistant task design guidelines for faculty	HEAIs + TAUS	AI-resistant assessment portfolio
4. AI Literacy	2026–2028	Mandatory 'AI Ethics & Literacy' module in all programmes; structured faculty retraining; student ATAQ benchmarking (Khalaf, 2025)	MoHE + TAUS + UNICEF	Measurable AI literacy standards
5. Monitoring	2027–2030	Annual national Algierism incidence report; align with EU AI Act (2024); iterative policy revision	OAK + ADIPTA + Statistics Committee	Continuous evidence-based governance

Note. MoHE = Ministry of Higher Education; HEAIs = Higher Education and Academic Institutions; TAUS = Tashkent University of Applied Sciences; OAK = Quality Assurance

Committee; ADIPTA = Agency for the Development of the Presidential Academy. Framework aligned with UNESCO (2023), EU AI Act (2024), PQ-358 (2024).

4.5 Limitations

This review has four primary limitations. First, publication bias may inflate documented effect sizes; null findings are underrepresented. Second, self-report prevalence measures are subject to social desirability effects — actual AIgiarism incidence is likely higher than survey data indicate. Third, the evidence base is geographically skewed towards North America, Western Europe, and the Asia-Pacific region, limiting direct generalisability to the Central Asian context. Fourth, the implementation framework is derived from analogical reasoning rather than primary empirical testing in Uzbekistan — local validation research is a stated priority for future work.

5. CONCLUSIONS

This systematic literature review synthesised 78 peer-reviewed studies across three research questions. Five principal conclusions are drawn.

First, ChatGPT use among higher education students is near-universal (56–92%) and continues to grow; AIgiarism prevalence is approximately 8% by self-report and 5.1 per 1,000 students in formal investigations, with actual incidence higher. Traditional plagiarism attitude significantly predicts AIgiarism attitude (Khalaf, 2025).

Second, the three-category AIgiarism taxonomy — generative, transformative, and contaminative — provides a more analytically precise foundation for policy development than the current binary framing. Contaminative AIgiarism is the most underaddressed category in existing policy frameworks.

Third, AI detection tools are insufficient as primary enforcement mechanisms. False positive rates of 3–8% create systematic harm, particularly for non-native English speakers; false negative rates of ~94% mean most AIgiarism evades detection. Assessment redesign is the most robustly supported intervention.

Fourth, blanket prohibition is pedagogically unsound and operationally unenforceable. Effective institutional responses combine disclosure norms, assessment redesign, AI literacy education, and calibrated detection within iteratively revisable governance frameworks.

Fifth, for Uzbekistan's higher education system, the proposed five-stage implementation framework provides a sequenced, evidence-based roadmap addressing multilingual equity concerns, policy gaps, and alignment with international standards. Priority actions are: a national prevalence survey, false-positive auditing for Uzbek-language texts, and mandatory AI ethics and literacy education across all programmes. Future empirical research in the Uzbekistani HE context remains essential.

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