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Environmental Burden and AI Ethics: Developing Quality Education

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Abstract
Generative AI tools such as ChatGPT are rapidly integrating into higher education, reshaping how students are learning, yet their misuse is raising concerns about learning quality, fairness and academic integrity. This study aimed to inspect the frequency and patterns of AI misuse among undergraduate students in Bangladesh and assess its impact on the educational environment and learning outcomes. A quantitative, cross-sectional survey design was used and data were collected from 1700 Bangladeshi undergraduates to measure AI misuse, AI consumption intensity, learning outcomes, ethical awareness, and educational environmental burden. To portray AI misuse as a systemic burden rather than just an isolated misconduct, the study applied an adapted IPAT framework (Population × AI Consumption × Technological Strength). Findings indicate that AI use is rigorous and normalized, however, misuse happens at a moderate level. Regression results partially support H1: AI Misuse increases Educational Environmental Burden., while results partially support H2: Higher AI Consumption predicts weaker Learning Outcomes. However, the H3 got rejected, giving new insights on education and ethics. In effect, the study recommends ethical AI literacy, assessment redesign, clear AI use guidelines, and selective monitoring to reduce AI-driven educational burden and protect learning integrity.

***Keywords**:* Generative AI, Academic Integrity, AI Misuse, Learning Outcomes, Ethical Awareness, IPAT Model, Educational Environmental Burden, AI Ethics

1. Introduction

Generative artificial intelligence (AI) technologies like ChatGPT are quickly being adopted in higher education and are changing the way students learn and perform academic tasks. These technologies enhance efficiency and inclusivity but their pervasive and often unregulated use poses risks to learning outcomes, academic integrity and assessment fairness. These concerns are particularly relevant in Bangladesh, given the rapid uptake of these tools by students and the lag in institutional policies and assessment practices. This paper explores the prevalence and patterns of AI misuse and consumption among undergraduate students in Bangladesh, and its associations with learning outcomes and educational environmental burden. To understand misuse as a systemic risk rather than individual misconduct, the study uses a modified IPAT model (Population × AI Consumption × Technological Strength) to describe how misuse prevalence, intensity, and technological invisibility can amplify institutional risk. Through a large cross-sectional survey of Bangladeshi undergraduates, the study assesses associations between AI misuse, intensity of AI consumption, learning outcomes (memory, understanding, originality, and academic ownership), and educational environmental burden (integrity and fairness erosion, institutional strain), while examining ethical awareness as a potential moderator. The results will inform evidence-based recommendations for ethics education, assessment reform, and balanced governance to ensure responsible co-existence of AI in higher education.

2. Adapted IPAT – A data driven model

The IPAT model was created by Paul Ehrlich and John Holdren in the early 1970s, with Environmental Impact (I) defined as: $I=P\times A\times T$. This research extends IPAT to model AI misuse as an educational risk, where P is the prevalence of misuse (number of students misusing AI), A is the intensity of AI use in academic work, and T is technological strength (undetectability, the proportion of AI-generated work that cannot be detected). National data supports a multiplicative approach: in 2023-4, nearly 7,000 cases of proven AI cheating were reported (approximately 5.1 per 1,000 students), and survey findings show 88% of students use AI tools, and up to 94% of AI-written work is undetected, demonstrating the compounding effect of prevalence, intensity, and invisibility. Using the Westbridge case, we set $P=6980$, $A=0.88$, and $T=0.94$, and define a unitless Educational Impact (EI) score as $EI=P\times A\times T$. Plugging in these values, we get $EI=6980\times0.88\times0.94=5770$, which is the compounding effect of a high-risk population, high AI use, and poor detection of AI-written academic work.

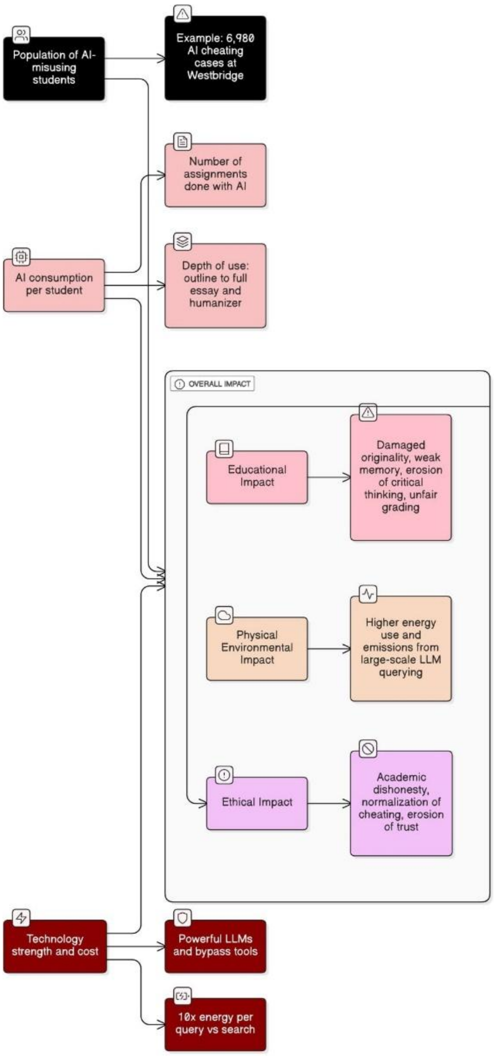

Fig.1 Adapted IPAT

3. Hypothesis & Conceptual Model

• H1: AI Misuse increases Educational Environmental Burden.
• H2: Higher AI Consumption predicts weaker Learning Outcomes.
• H3: Ethical Awareness moderates AI Misuse (protective influence).

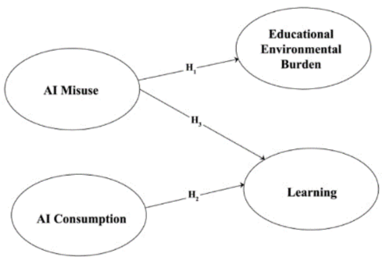

Fig.2 Conceptual Model

4. Design & Methodology

A convenience sampling method will be used for the survey and sample size will be 1700 (N=1700). The target population will be undergraduate students of private universities in Bangladesh due to their relevant exposure and unlimited access to technology (LLMs). The survey will contain Likert questions (eg; 1-5, where 1 represents strongly disagree and 5 represents strongly agree). The process will be done through Google forms and responses will be analyzed by SPSS software. Variables to be used are: Ai misuse (AIM), Ai consumption intensity (AICI), Learning outcome (LO), Educational Environmental Burden (EEB) and Moderating factors like Ethical awareness (EA). The educational environmental impact will be computed by an adapted IPAT model: EI = P x A x T where EI = Environmental Impact and environment means (Educational environment), P = Ai misusing student population, A = Consumption of LLMs and T = the strength of technology. The study will also run sensitivity analysis by testing how EI will shift under alternative assumptions of T (low/medium/high vulnerability).

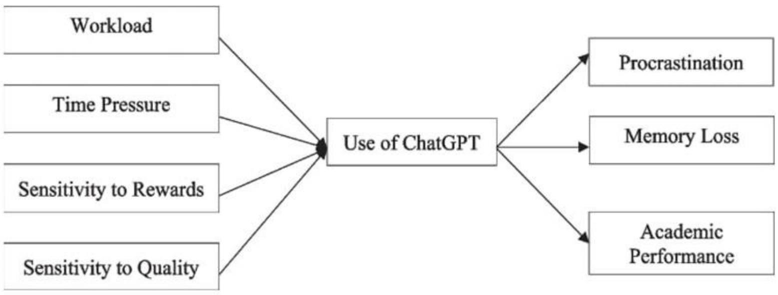

Fig.3 Current state of students (model)

5. Analysis

5.1 Reliability Analysis

All constructs demonstrated good to excellent internal consistency, confirming the reliability of the measurement scales.

TABLE 1 RELIABILITY STATISTICS

Variable	Cronbach's Alpha	Interpretation
AI Misuse (AIM)	0.770	Good
AI Consumption (AICI)	0.789	Good
Learning Outcomes (LO)	0.794	Good
Educational Environmental Burden (EEB)	0.852	Excellent
Ethical Awareness (EA)	0.785	Good

Overall, all scales met reliability thresholds, supporting the validity of subsequent analyses.

5.2 Regression Results: Educational Environmental Burden (H1)

Five regression models were estimated using Educational Environmental Burden (EEB) items as dependent variables and AI Misuse (AIM1–AIM5) indicators as predictors. Results show statistically significant models for integrity- and quality-related burden dimensions, while fairness-related burden is not significant.

TABLE 2 REGRESSION RESULTS FOR EDUCATIONAL ENVIRONMENTAL BURDEN (EEB): MODEL-LEVEL SIGNIFICANCE

EEB Dimension	Model p-value	Result
EEB1 (Unfair evaluation)	$p = 0.689$	Not significant
EEB2 (Integrity weakened)	$p = 0.004$	Significant

EEB3 (Institutional strain)	p = 0.099	Marginal
EEB4 (Honest students disadvantaged)	p = 0.059	Marginal
EEB5 (Threat to education quality)	p = 0.028	Significant

Interpretation: Overall, H1 is partially supported (weak): AI misuse predicts selected burden dimensions (especially integrity/quality-related outcomes), but the pattern is not consistent across all EEB dimensions.

5.3 Regression Results: Learning Outcomes (H2)

Learning outcome items (LO1–LO5) were regressed on AI misuse (AIM1–AIM5) and AI consumption (AICI1–AICI5) indicators. All models are statistically significant at the model level with small explained variance.

TABLE 3 REGRESSION RESULTS FOR LEARNING OUTCOMES (LO): MODEL-LEVEL SIGNIFICANCE AND FIT

Learning Outcome	R^2	Model p-value	Result
LO1 (Memory)	0.069	$p \approx 2.93 \times 10^{-22}$	Significant
LO2 (Understanding)	0.066	$p \approx 4.55 \times 10^{-21}$	Significant
LO3 (Originality)	0.047	$p \approx 9.20 \times 10^{-14}$	Significant
LO4 (Ownership)	0.038	$p \approx 1.32 \times 10^{-10}$	Significant
LO5 (Learning without AI)	0.025	$p \approx 2.51 \times 10^{-6}$	Significant

Interpretation: H2 is partially supported: learning outcomes are significantly associated with AI-related behaviors, but the incremental role of AI consumption alone is weaker and may vary when AI misuse is controlled.

5.4 Moderation Test: Ethical Awareness (H3)

To test whether Ethical Awareness (EA) moderates the effect of AI Misuse (AIM) (protective influence), AIM and EA were mean-centered and an interaction term (AIM×EA) was added. Moderation is evaluated using the interaction coefficient and ΔR^2.

TABLE 4 MODERATION RESULTS (H3): INTERACTION TERM (AIM×EA)

DV	Interaction B	p-value	R^2	ΔR^2
EEB_mean	−0.0011	0.9567	0.3408	0.0000
LO_mean	−0.0013	0.9578	0.1352	0.0000

Interpretation: The interaction term is not significant for either outcome, and ΔR^2 is effectively zero. Therefore, H3 is rejected / not supported: ethical awareness does not moderate the relationship between AI misuse and educational burden or learning outcomes.

TABLE 5 HYPOTHESIS TESTING SUMMARY (UPDATED)

Hyp.	Statement	Decision
H1	AI misuse increases educational environmental burden	Partially supported
H2	Higher AI consumption predicts weaker learning outcomes	Partially supported
H3	Ethical awareness moderates AI misuse (protective influence)	Rejected

6. Discussion & Recommendations

6.1 Discussion related to findings and literature

Generative AI is an everyday part of life in Bangladeshi universities, but the latest findings reveal the academic effects of generative AI are not a simple "good or bad" narrative. The results show a mixed but significant pattern: AI misuse is related to some aspects of educational environmental burden, learning outcomes are significantly related to AI usage with small effect sizes, and ethical awareness does not act as a statistical "shield" when AI misuse happens. This mix supports the theory that AI misuse is not just an individual ethics problem, it is a systemic problem when many students use AI frequently and universities do not have clear boundaries, assessment designs and governance. Theoretically and from a literature perspective, the findings support the idea that generative AI transforms misuse from plagiarism to "AI-authorship" that is difficult to detect, and causes institutional pressures and trust problems. Our partial support for H1 aligns with literature arguing integrity and degree value are the most obvious consequences of AI misuse. Students may not always perceive misuse as "unfair evaluation" because fairness is affected by other factors like grading leniency, teacher differences, peer ability, and workload. But the weakening of integrity and perceived threats to education quality are consistent with academic integrity theory: if AI misuse is widespread and hard to detect, then the institution's integrity and learning culture are damaged. Likewise, H2 being partially supported aligns with learning theory and recent research on cognitive offloading: AI can be time-saving but can undermine deep processing, originality, memory encoding and ownership if it substitutes for reading and thinking. The small effect sizes also indicate that learning is a complex process with many factors (teaching quality, motivation, time, assessment) influencing it, so AI is not the only factor. The failure to support H3 is a key finding. Many ethics models assume that increased ethical awareness leads to better behaviour. Our finding suggests a more realistic process: students can be aware of ethics, but it does not necessarily mitigate misuse effects under high academic pressure. Students can be aware of the rules, but misuse AI due to time constraints, fear of poor grades, competition, AI accessibility, and inconsistent enforcement. This finding confirms a common message in applied ethics and behavioural science: knowledge and attitudes are not always sufficient to change behaviour unless there are supports for ethical behaviour. For our model, it means that ethical knowledge is not enough, and structural interventions are required to make it easier to do the right thing and harder to misuse AI. In terms of implications, the study has several practical and policy implications. For higher education, the findings indicate that a detection-only strategy is insufficient. Given misuse is part of the integrity and quality problem, universities should aim to minimise "substitution use" (students using AI to replace their own thinking) rather than outlawing AI. The results endorse a hybrid governance model: education plus assessment redesign plus limited monitoring. For teachers, the message is to change assessment so that it focuses on process as well as product. Process grading, draft trails, reflection statements, oral assessment, in-class writing, and applied tasks can minimise misuse incentives and retain valid signals of learning. For policymakers and quality assurance agencies, the research supports the development of national guidelines on acceptable and unacceptable use of AI, with examples, disclosure standards and minimum standards for assessment integrity in universities.

6.2 Recommendations

Based on the findings, the following actionable and realistic recommendations are proposed:

Integrate Ethical AI Education: Universities should introduce compulsory AI ethics and literacy modules to clarify acceptable and unacceptable AI use.

Redesign Assessment Methods: Increase the use of in-class tasks, oral presentations, reflective journals, and process-based grading to reduce AI misuse.

Establish Clear AI Usage Policies: Institutions should publish transparent, student-friendly AI guidelines with concrete examples rather than vague restrictions.

Promote Responsible AI Use: Encourage supervised use of AI as a learning aid rather than a content generator to reduce cognitive offloading.

Adopt a Hybrid Governance Approach: Combine ethics education, assessment redesign, and selective technological monitoring instead of relying solely on detection software.

Continuous Policy Review: Regularly update institutional policies to keep pace with evolving AI capabilities and misuse patterns.

Collaboration between Institutions and AI companies: To save the learning environment and establish fairness, AI companies should collaborate with universities and educators to design LLMs for students' use that can limit misuse from the root.

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