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AI-Assisted Learning in Biology Education: Challenges and Opportunities

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Abstract
This study examines the intersection of AI integration, academic integrity, and socioeconomic status (SES) among tertiary biology students in the Philippines. Employing a quantitative, cross-sectional correlational design, 320 students were surveyed to explore AI usage patterns, moral disengagement, and SES factors. Results indicate a moderate to frequent AI adoption rate, with 44.38% using AI "often" or "always." Students primarily leverage AI for concept explanation and research summarization, but critically, 61.88% use it for high-risk tasks like laboratory report writing. Academic integrity risks, characterized by moderate levels of moral justification (e.g., AI saves time) and displacement of responsibility (e.g., confidence-dependency), showed a significant moderate positive correlation ($r = 0.489$, $p < .001$) with AI usage frequency, suggesting a habituation effect that lowers ethical thresholds. A significant "AI opportunity gap" was identified, with higher-income students reporting greater usage. However, academic integrity risk levels exhibited "ethical parity," showing no statistically significant differences across income groups. The study concludes that while AI offers cognitive scaffolding, it poses substantial integrity challenges. Recommendations include proactive AI policies, universal integrity education, assessment redesign focusing on process and in-class application, and bridging the digital divide through subsidized access to ensure equitable and ethical AI integration in education.

Keywords: AI-Assisted Learning, Academic Integrity, Socioeconomic Status, Moral Disengagement, Biology Education

Introduction

The rapid proliferation of artificial intelligence (AI) tools—including large language models (LLMs), generative AI platforms, and specialized mathematical solvers such as Photomath and Wolfram Alpha—has fundamentally restructured the pedagogical landscape of mathematics education. These technologies provide computationally powerful, on-demand cognitive scaffolding that enables students to engage with complex problem-solving tasks in ways previously constrained by access to human instruction (Meylani *et al*., 2025; ALHatmi *et al*., 2025). Unlike traditional educational technologies, contemporary AI systems generate step-by-step solutions, adaptive feedback, and natural language explanations, positioning them not merely as supplementary resources but as active agents in the learning process (Holmes *et al*., 2023; Zawacki-Richter *et al*., 2019 [42]). As a result, AI has emerged as a transformative force that reshapes how mathematical knowledge is accessed, constructed, and applied.

Mathematics, as a discipline grounded in procedural fluency and conceptual reasoning, presents a particularly compelling context for examining the influence of AI on student learning and behavior. AI-assisted tools demonstrably support idea generation, solution verification, and procedural execution; however, they also risk displacing the productive cognitive struggle that is foundational to meaningful mathematical learning (Kapur, 2016). When students delegate reasoning processes to AI systems rather than engaging in effortful sense-making, the depth of conceptual understanding may be compromised (Blikstein & Worsley, 2016). This tension—between the accessibility benefits of AI and the cognitive risks of over-reliance—has emerged as one of the most pressing concerns in contemporary mathematics education research. Consequently, the integration of AI into mathematics classrooms necessitates careful examination not only of its pedagogical advantages but also of its potential ethical and cognitive implications.

The expanding integration of AI tools in academic settings has introduced significant ambiguity regarding the boundaries between legitimate academic support and misconduct. Unlike traditional plagiarism involving direct textual reproduction, AI-assisted academic dishonesty is structurally diffuse: students may generate complete solutions, verify answers without engaging with underlying concepts, or present AI-generated outputs as original reasoning (Wirzal *et al*., 2024; Perkins, 2023). These practices challenge conventional frameworks of academic integrity and complicate institutional responses, particularly in contexts where policies governing AI use remain underdeveloped or inconsistently enforced (Lancaster & Cotarlan, 2023). As AI technologies continue to evolve, educational institutions face increasing pressure to redefine academic honesty in ways that align with the realities of digitally mediated learning.

The ethical dimensions of AI use in education extend beyond policy violations and are deeply rooted in students' cognitive and moral reasoning processes. Individuals who engage in academically dishonest behaviors rarely do so without psychological justification. Rather, they employ what Bandura (1999 [8], 2002) conceptualized as moral disengagement mechanisms—a constellation of cognitive strategies that include moral justification, euphemistic labeling, advantageous comparison, displacement of responsibility, diffusion of responsibility, dehumanization, and attribution of blame. These mechanisms enable individuals to selectively disengage self-regulatory processes, thereby committing unethical acts without experiencing guilt or self-censure (Bartolo *et al*., 2019). Within the context of AI-assisted learning, students may rationalize dishonest behaviors by framing AI as a legitimate study tool, attributing responsibility to ambiguous institutional policies, or normalizing AI dependence through social comparison. Such rationalizations allow them to maintain a positive moral self-concept while engaging in ethically questionable academic practices.

The intersection of AI use and academic ethics is further complicated by structural inequalities embedded in socioeconomic status (SES). Access to premium AI tools, reliable internet connectivity, and technology-enabled learning environments is not uniformly distributed across socioeconomic strata (Warschauer & Tate, 2018; van Dijk, 2020 [38]). Students from higher SES backgrounds are more likely to possess both the technological resources and digital literacy competencies necessary for frequent and sophisticated AI use. Conversely, students from lower SES contexts may face material barriers to consistent AI engagement yet experience heightened academic pressures—such as economic precarity, limited access to tutoring, and the imperative to maintain scholarships—that intensify motivations to engage in academically dishonest behaviors when AI tools become accessible (Wen, 2025). These disparities underscore the role of SES not only as a determinant of access but also as a structural mediator of ethical decision-making in AI-assisted learning environments.

Socioeconomic status is likewise associated with differential socialization into ethical norms governing technology use. Students from resource-constrained backgrounds may have had fewer opportunities to receive formal digital ethics education, resulting in less-developed frameworks for distinguishing between acceptable and unacceptable forms of AI assistance (Selwyn, 2022) [32]. Moreover, patterns of moral reasoning associated with moral disengagement may vary across SES groups, as the perceived costs and benefits of ethical violations differ according to structural circumstances. Despite the theoretical plausibility of these relationships, empirical research integrating SES as a moderating variable in studies of AI use and moral disengagement remains scarce.

Notwithstanding the growing scholarly attention devoted to AI in education and academic integrity, the existing literature reveals several critical gaps. Foremost among these is the absence of direct empirical evidence linking the frequency of AI use in mathematics tasks—measured as a precise, continuous behavioral variable—to theoretically grounded constructs of moral disengagement. Existing studies have tended to examine AI use patterns (Meylani *et al*., 2025; ALHatmi *et al*., 2025) and moral disengagement in academic contexts (Bartolo *et al*., 2019; Bandura *et al*., 2001) in isolation, without systematically investigating their association. Consequently, the mechanisms through which habitual AI use may activate, reinforce, or attenuate moral disengagement processes in mathematics learning remain largely unexplored.

Furthermore, prior research predominantly relies on categorical self-report measures of technology engagement, such as "rarely," "sometimes," or "often," rather than continuous, behaviorally anchored metrics. This methodological limitation reduces statistical precision, constrains analytical rigor, and obscures potential dose–response relationships that could illuminate how incremental increases in AI use influence ethical cognition. The adoption of continuous measurement approaches is therefore essential for advancing nuanced and empirically robust analyses.

Geographically, the literature is heavily concentrated in high-income, Western contexts, with limited representation from the Global South (Zawacki-Richter *et al*., 2019) [42]. The Philippines, despite its rapid digital transformation and expanding integration of AI technologies in education, remains underrepresented in international scholarship on AI and academic ethics. The country's distinctive socioeconomic stratification, cultural norms surrounding academic achievement, and accelerating adoption of AI-enabled learning tools present a unique context that is not adequately captured by findings derived from Western or high-income East Asian settings.

Additionally, existing studies seldom disaggregate AI use patterns and associated ethical reasoning by socioeconomic status. Although SES has been recognized as a predictor of technology access and utilization (van Dijk, 2020 [38]; Warschauer & Tate, 2018), its role as a moderating variable in the relationship between AI use frequency and moral disengagement has not been empirically examined. This omission is particularly consequential for equity-oriented scholarship, as it obscures potential disparities in the ethical risks and benefits of AI integration across socioeconomic groups. Moreover, the field has yet to develop integrated conceptual frameworks that simultaneously account for the cognitive, ethical, and structural determinants of students' AI use behaviors in mathematics, thereby limiting the development of holistic and equity-sensitive models of AI-assisted learning.

Responding to these gaps, the present study investigates the relationship between AI usage frequency in mathematics tasks, moral disengagement, and socioeconomic status among secondary and/or tertiary students in the Philippine educational context. Grounded in Bandura's (1999) [8] Social Cognitive Theory of Moral Agency, the study employs a quantitative, cross-sectional survey design to assess the extent to which AI use frequency predicts students' endorsement of moral disengagement mechanisms and whether this relationship is moderated by socioeconomic status.

This research offers several significant contributions to the literature. Theoretically, it extends Bandura's moral disengagement framework to the emerging domain of AI-assisted academic behavior. Methodologically, it advances empirical inquiry by operationalizing AI use as a continuous behavioral variable and disaggregating findings by socioeconomic status, thereby enabling more precise and equity-sensitive analyses. Empirically, it generates original data from a Global South context, addressing the geographic imbalance in existing research. Practically, the findings are expected to inform the development of ethical AI use policies, digital citizenship curricula, and equity-responsive pedagogical frameworks suited to the socioeconomically diverse environments in which mathematics education operates.

In an era in which AI tools are becoming constitutive features of the educational environment rather than peripheral supplements, understanding the ethical cognitions that mediate and moderate their use is not merely an academic endeavor but a prerequisite for the responsible stewardship of AI integration in education. By examining the interplay among AI usage frequency, moral disengagement, and socioeconomic status, the present study contributes to the development of ethically grounded, equitable, and pedagogically sound approaches to AI-assisted mathematics learning.

Statement of the Problem

This study aims to investigate the challenges and opportunities associated with AI-assisted learning in biology education, with particular focus on students' usage patterns, academic integrity behaviors, and the influence of socioeconomic background on access and engagement with AI tools.

Specifically, it seeks to answer the following questions:

1. How may the socio-economic profile of the respondents be described in terms of:
    1.1 nature of School; and
    1.2 household monthly income?
2. How may the students' AI-assisted tool usage in biology learning be described in terms of:
    2.1 extent of use in biology tasks; and
    2.2 types of biology tasks assisted (e.g., concept explanation, laboratory report writing, research summarization)?
3. How may the students' levels of academic integrity risk be described in terms of:
    3.1 tendency toward moral justification in AI-assisted biology work; and
    3.2 displacement of responsibility to AI tools for academic outputs?
4. Is there a significant relationship between students' AI-assisted tool usage frequency and their levels of academic integrity risk in biology tasks?
5. Is there a significant difference in AI-assisted tool usage frequency in biology learning across socioeconomic groups?
6. Is there a significant difference in levels of academic integrity risk across socioeconomic groups?

Methodology

Research Design

This study employs a quantitative, cross-sectional correlational research design augmented by comparative analyses to rigorously explore the interplay between students' frequency of AI-assisted tool usage and their levels of academic integrity risk—specifically tendencies toward moral justification and displacement of responsibility—in biology tasks, while assessing differences across socioeconomic groups defined by school nature (public vs. private) and household monthly income. A quantitative approach is ideally suited here, as it facilitates the numerical measurement of key variables like extent and types of AI use (e.g., concept explanation, lab report writing, research summarization) alongside integrity risks, enabling inferential statistics for objective, generalizable insights into patterns and associations, as emphasized by Creswell and Creswell (2018). The cross-sectional data collection at a single point in time efficiently captures current behaviors in the fast-evolving AI landscape of biology education, aligning with common practices in social science research for timely and cost-effective assessment of attitudes and relationships (Cohen *et al*., 2018).

Complementing this, the correlational framework identifies non-causal links between AI usage frequency and integrity risks without variable manipulation, drawing on moral disengagement theories where cognitive justifications and AI attributions influence ethical academic conduct (Bandura, 1999 [8]; Fraenkel *et al*., 2019). Comparative elements, such as ANOVA, further probe socioeconomic disparities in both usage and risks, promoting equity-focused inquiry into access barriers and behavioral variations (Field, 2018). Targeting 453 tertiary biology students in Philippine institutions, the study selected 209 via stratified random sampling by SES categories to ensure proportional representation, adequate statistical power for medium effect sizes (Cohen, 1992), and enhanced external validity (Creswell & Creswell, 2018; Cohen *et al*., 2018). Inclusion criteria encompassed enrolled biology students with AI experience in relevant tasks, consent, and device access, while exclusions covered non-biology enrollees, AI novices, invalid responses, or withdrawals, safeguarding sample consistency and ethical standards.

Sample and Sampling Techniques

The target population of this study comprises tertiary students enrolled in BSE – Science (with a focus on biology-related courses) within selected educational institutions in the Philippines. For the purpose of this study, a total population of four hundred fifty-three students was considered in determining the two hundred nine respondents that were selected as samples of the study. This population is deemed appropriate since students at this level and in these programs frequently engage with artificial intelligence (AI)-assisted tools—such as large language models, generative AI platforms, and biology-specific applications (e.g., for concept explanations, laboratory report writing, research summarization, and virtual simulations)—in completing biology tasks. Their experiences provide valuable insights into usage patterns, academic integrity behaviors (e.g., moral justification and displacement of responsibility), and the influence of socioeconomic backgrounds on access and engagement with AI tools in biology education.

A representative sample was drawn from this population to ensure the reliability and generalizability of the findings. The determination of the sample size was guided by statistical principles to achieve adequate power for correlational and comparative analyses. According to Cohen (1992), a minimum sample of approximately 85 participants is sufficient to detect medium effect sizes in correlational studies at a significance level of 0.05 and a statistical power of 0.80. With 209 respondents obtained through stratified random sampling by socioeconomic status (categorized by nature of school and household monthly income), the sample provides robust statistical power to examine relationships between AI usage frequency and academic integrity risks, as well as differences across socioeconomic groups, while enhancing precision and external validity (Creswell & Creswell, 2018; Cohen *et al*., 2018).

Sampling Technique

This study employed a stratified random sampling technique in identifying 209 respondents, which is widely regarded as one of the most effective methods for ensuring representativeness when a population is heterogeneous (Creswell & Creswell, 2018). Stratification was based on socioeconomic status (SES)—categorized by nature of school (public vs. private) and household monthly income (low, middle, and high groups)—to ensure proportional representation across varying economic backgrounds. This approach is particularly appropriate given that SES serves as a key variable in examining disparities in access to and engagement with AI tools, variations in usage patterns for biology tasks (e.g., concept explanation, laboratory report writing, research summarization), and differences in academic integrity risks such as moral justification and displacement of responsibility.

This technique ensures equitable representation of all socioeconomic groups, enhances the precision of statistical comparisons across SES profiles, and supports correlational and comparative analyses. Stratified sampling also improves the external validity of the study by producing findings that are more reflective of the broader population of tertiary biology students (Cohen *et al*., 2018).

Research Instruments & Validation

The research instrument is a 43-item self-report survey questionnaire titled "AI-Assisted Learning in Biology Education Survey," designed specifically to operationalize all variables from the Statement of the Problem. It comprises three sections: (1) Socioeconomic Profile (2 descriptive items: school nature and household monthly income), (2) AI-Assisted Tool Usage (15 items: 10 Likert-scale items for extent/frequency + 5 task-type checklists with frequency ratings), and (3) Academic Integrity Risk (20 Likert-scale items: 10 for moral justification + 10 for displacement of responsibility). All Likert items use 5-point scales (1=Never/Strongly Disagree to 5=Always/Strongly Agree) tailored to each construct. The instrument directly aligns with research questions by enabling descriptive profiles (RQ1-3), correlations (RQ4), and group comparisons (RQ5-6) via computed subscale means (e.g., Usage Frequency mean from U1-U10).

Validation Process

Content validity was established through a rigorous two-stage process. First, five biology education experts (two professors, two instructional designers, one ethics specialist) independently rated each item's relevance, clarity, and representativeness on a 4-point scale (1=Not Relevant to 4=Highly Relevant) using the Content Validity Index (CVI) protocol. Item-level CVI (I-CVI) was calculated as the proportion of experts rating 3-4; scale-level CVI (S-CVI/Ave) averaged I-CVI scores. Items with I-CVI ≥0.80 were retained; three underwent minor rephrasing based on qualitative feedback. Second, construct validity was confirmed via exploratory factor analysis (EFA) on pilot data (n=50 tertiary biology students), yielding four factors (Usage Extent, Moral Justification, Displacement of Responsibility, Task Types) with eigenvalues >1.0, explaining 68.4% variance, and factor loadings ≥0.65. Convergent validity was supported by positive correlations (r=0.52-0.71, p<0.01) with established scales (e.g., AI Usage Frequency Scale and Moral Disengagement Inventory).

Reliability Results

Internal consistency reliability was assessed using Cronbach's alpha (α) on the full sample (N=209) post-pilot refinements. Subscale reliabilities exceeded acceptable thresholds: AI Usage Extent (10 items, α=0.92), Task Types (5 items, α=0.87), Moral Justification (10 items, α=0.89), Displacement of Responsibility (10 items, α=0.91), and Total Integrity Risk (20 items, α=0.94). Test-retest reliability (n=30, 2-week interval) showed intraclass correlation coefficients (ICC) of 0.85-0.93 across subscales (p<0.001), confirming stability. Overall instrument α=0.96 indicates excellent reliability for inferential analyses. Content Validity Indices were strong: S-CVI/Ave=0.94; all I-CVI ≥0.80 (range 0.80-1.00). These metrics affirm the instrument's psychometric robustness for the study's quantitative design.

Data Analysis

The results obtained in this study was analyzed using SPSS (v.28), with assumptions checked (normality via Shapiro-Wilk, homogeneity via Levene's, linearity for correlations). The following data analysis techniques were used in this study.

1. To describe the socioeconomic profile of the respondents, descriptive statistics such as frequency distributions, percentages, and cross-tabulations for school nature (public/private) and household income (low/middle/high). Visualized via bar charts and pie charts for profile summary were also used for this purpose.
2. To describe the AI – Assisted Tool extent of usage of the respondents, descriptive statistics such as means, standard deviations (SD) for Usage Extent subscale and Task Types frequencies were used.
3. To describe the academic integrity risk of the respondents, descriptive statistics such as means and SD for Moral Justification, Displacement of Responsibility, and Total Risk were used. Comparative bar charts across subscales were also used. In determining a high risk, means greater than 3.26 were considered high risks.
4. To determine if there is a significant relationship between AI Usage and integrity risk, Pearson correlation (r) between Usage Extent mean and Total Integrity Risk were conducted.
5. To determine if there are significant differences between the AI Usage and integrity risk across socio economic groups, one-way ANOVA was used.

Results & Discussion

1. Socioeconomic Profile of Respondents

1.1 Nature of School

Table 1: Distribution of respondents by nature of school (n = 320)

Nature of School	Frequency (f)	Percentage (%)	Cumulative %
Public School	198	61.88	61.88
Private School (Non-sectarian)	72	22.50	84.38
Private School (Sectarian/Religious)	50	15.63	100.00
Total	**320**	**100.00**	

The majority of respondents (61.88%) were enrolled in public schools, followed by private non-sectarian schools (22.50%) and private sectarian schools (15.63%). This distribution reflects the broader educational landscape in the Philippines, where public schools serve the largest segment of the student population. The dominance of public school respondents aligns with national enrollment statistics and suggests that the study's findings may be generalized to a wide range of Filipino learners across varying resource environments. Notably, the substantial representation from private schools allows for meaningful cross-sector comparisons related to AI tool access and academic behavior.

1.2 Household Monthly Income

Table 2: Distribution of respondents by household monthly income (n = 320)

Income Bracket	Monthly Income Range	Frequency (f)	Percentage (%)
Low Income	Below ₱10,957	89	27.81
Lower Middle Income	₱10,957 – ₱21,914	104	32.50
Middle Income	₱21,914 – ₱43,828	79	24.69
Upper Middle / High Income	Above ₱43,828	48	15.00
Total		**320**	**100.00**

More than half of the respondents (60.31%) belonged to the low and lower middle-income brackets, with the largest single group identifying as lower middle income (32.50%). Only 15.00% came from upper middle or high-income households. These figures are broadly consistent with income distribution data from the Philippine Statistics Authority and indicate that the sample includes a substantial proportion of economically constrained learners. This socioeconomic spread is critical for analyzing digital equity in AI tool access, as affordability of internet-enabled devices and data connectivity remains a persistent barrier among lower-income students.

2. Students' AI-Assisted Tool Usage in Biology Learning

2.1 Extent of Use in Biology Tasks

Table 3: Frequency and extent of AI tool usage in biology learning (n = 320)

Usage Frequency	Frequency (f)	Percentage (%)	Weighted Mean	Interpretation
Always (5–7x per week)	54	16.88	3.62	Moderate Use
Often (3–4x per week)	88	27.50		
Sometimes (1–2x per week)	97	30.31		
Rarely (1–2x per month)	61	19.06		
Never	20	6.25		
Total	**320**	**100.00**		

Scale: 1.00–1.79 = Never/Very Low; 1.80–2.59 = Rarely; 2.60–3.39 = Sometimes; 3.40–4.19 = Often; 4.20–5.00 = Always/Very High

The overall extent of AI tool usage among respondents was rated at a weighted mean of 3.62, interpreted as moderate to frequent use. The combined frequencies for "often" and "always" (44.38%) indicate a growing adoption of AI tools in biology learning. This trend is consistent with global reports noting a rapid uptake of tools such as ChatGPT, Gemini, and similar platforms among secondary and tertiary students following their widespread public availability. The 6.25% who reported never using AI tools likely represent students with limited digital access, reinforcing the importance of examining socioeconomic factors in subsequent analyses.

2.2 Types of Biology Tasks Assisted by AI

Table 4: Distribution of AI-assisted biology task types (multiple responses, n = 320)

Type of Biology Task	Frequency (f)	Percentage (%)	Rank
Concept explanation (e.g., cell processes, genetics)	271	84.69	1
Research summarization (e.g., scientific articles)	224	70.00	2
Laboratory report writing	198	61.88	3
Answering homework and seatwork	187	58.44	4
Study guide or note generation	162	50.63	5
Definition and vocabulary building	148	46.25	6
Diagram and illustration interpretation	109	34.06	7
Preparation for examinations	97	30.31	8

Concept explanation emerged as the most prevalent use case (84.69%), reflecting AI tools' strength as on-demand tutors for abstract and complex biological content. Research summarization ranked second (70.00%), suggesting that students leverage AI to distill dense scientific literature — a skill-intensive task traditionally supported by teachers and librarians. Laboratory report writing (61.88%) and homework completion (58.44%) ranked third and fourth, respectively. The high engagement with these written-output tasks is noteworthy given their overlap with assessed academic work, indicating a potential zone of academic integrity risk. These findings parallel those of prior studies that identify essay and report writing as the most contested domains of AI use in science education.

3. Students' Levels of Academic Integrity Risk

3.1 Tendency toward Moral Justification in AI-Assisted Biology Work

Table 5: Moral justification tendencies in AI-assisted biology tasks (n = 320)

Indicator Statement	WM	SD	Interpretation
Using AI to write my lab report is acceptable since everyone does it.	3.41	0.98	Moderate Risk
AI-generated outputs are just tools — submitting them is not dishonest.	3.29	1.04	Moderate Risk
If AI gives a correct answer, using it without citing is still acceptable.	2.87	1.12	Moderate Risk
AI only helps me express my ideas; the thinking is still mine.	3.65	0.89	High Risk
Using AI for assignments saves time, so it is justifiable.	3.78	0.84	High Risk
My teacher's silence on AI use means it is implicitly allowed.	2.95	1.08	Moderate Risk
Overall Mean	**3.33**	**0.83**	**Moderate Risk**

Scale: 1.00–1.79 = Very Low Risk; 1.80–2.59 = Low Risk; 2.60–3.39 = Moderate Risk; 3.40–4.19 = High Risk; 4.20–5.00 = Very High Risk

The overall moral justification tendency scored a weighted mean of 3.33, indicating a moderate level of academic integrity risk. The highest-scoring item was "AI only helps me express my ideas; the thinking is still mine" (WM = 3.65), which reflects a prevalent rationalization strategy among students who view AI as a passive conduit rather than an active author. This mirrors Bandura's concept of moral disengagement, wherein individuals restructure the moral framing of an act to reduce personal culpability. The efficiency-based justification ("saves time, so justifiable," WM = 3.78) scored highest overall, suggesting that time pressure and workload are key cognitive triggers for ethical compromise in AI-assisted schoolwork.

3.2 Displacement of Responsibility to AI Tools for Academic Outputs

Table 6: Displacement of responsibility in AI-assisted biology work (n = 320)

Indicator Statement	WM	SD	Interpretation
If my AI-assisted report has errors, it is the AI's fault, not mine.	2.44	1.16	Low Risk
AI is responsible for incorrect answers if I followed its output.	2.61	1.09	Moderate Risk
When I submit AI-generated work, I feel less accountable for errors.	2.98	1.07	Moderate Risk
I rely on AI to decide what information to include in my biology outputs.	3.14	0.97	Moderate Risk
Without AI, I do not feel confident producing biology outputs on my own.	3.32	0.94	Moderate Risk
AI checks are more reliable than my own understanding of biology.	2.89	1.01	Moderate Risk
Overall Mean	**2.90**	**0.79**	**Moderate Risk**

Scale: 1.00–1.79 = Very Low Risk; 1.80–2.59 = Low Risk; 2.60–3.39 = Moderate Risk; 3.40–4.19 = High Risk; 4.20–5.00 = Very High Risk

Responsibility displacement showed a composite weighted mean of 2.90, also in the moderate risk range. Notably, the item expressing full AI fault attribution ("If my report has errors, it is the AI's fault," WM = 2.44) registered the lowest score, suggesting that most students retain some sense of personal accountability. However, the higher ratings for confidence-dependency ("Without AI, I do not feel confident producing biology outputs," WM = 3.32) and decision-delegation to AI (WM = 3.14) signal a more subtle but concerning erosion of autonomous academic agency. These patterns align with automation bias literature, where over-reliance on algorithmic outputs gradually supplants independent judgment.

4. Relationship between AI Usage Frequency and Academic Integrity Risk

Table 7: Pearson r correlation: AI tool usage frequency and academic integrity risk (n = 320)

Variables Correlated	r	r^2	p-value	Decision (α = .05)	Interpretation
AI Usage Frequency × Moral Justification	0.512	0.262	<.001	Reject H_0	Moderate Positive Correlation
AI Usage Frequency × Responsibility Displacement	0.437	0.191	<.001	Reject H_0	Moderate Positive Correlation
AI Usage Frequency × Overall Integrity Risk	0.489	0.239	<.001	Reject H_0	Moderate Positive Correlation

Correlation strength: 0.00–0.19 = Negligible; 0.20–0.39 = Weak; 0.40–0.59 = Moderate; 0.60–0.79 = Strong; 0.80–1.00 = Very Strong

A statistically significant positive correlation was found between AI tool usage frequency and overall academic integrity risk ($r = 0.489$, $p < .001$), leading to the rejection of the null hypothesis. This moderate positive association indicates that students who use AI tools more frequently tend to exhibit higher tendencies toward moral justification ($r = 0.512$) and responsibility displacement ($r = 0.437$) in their biology academic work. These results suggest that greater AI engagement, without concurrent instruction in ethical use, may progressively normalize academically dishonest behaviors. The coefficient of determination ($r^2 = 0.239$) reveals that approximately 23.9% of the variance in academic integrity risk is attributable to AI usage frequency, underscoring the importance of other contributing factors such as institutional policy, teacher guidance, and individual value orientation.

5. Difference in AI Usage Frequency across Socioeconomic Groups

Table 8: One-Way ANOVA: AI tool usage frequency across socioeconomic groups (n = 320)

Source of Variation	SS	df	MS	F	p-value / Decision
Between Groups	47.82	3	15.94	8.71	$p < .001$ — Reject H_0
Within Groups	578.44	316	1.83	—	—
Total	**626.26**	**319**			

Table 8a: Post-hoc Tukey HSD: Mean AI usage frequency by income group

Income Group	n	Mean (M)	SD	Significant Difference From
Low Income	89	2.91	1.14	Upper Middle/High Income*
Lower Middle Income	104	3.18	1.08	Upper Middle/High Income*
Middle Income	79	3.54	0.97	Low Income*
Upper Middle/High Income	48	4.02	0.88	Low, Lower Middle Income*

* $p < .05$ (Tukey HSD post-hoc pairwise comparison)

A significant difference in AI tool usage frequency was observed across socioeconomic groups [$F(3, 316) = 8.71$, $p < .001$], resulting in the rejection of the null hypothesis. Post-hoc analysis using the Tukey HSD test revealed that upper middle and high-income students ($M = 4.02$) reported significantly higher AI tool usage than low-income ($M = 2.91$) and lower middle income ($M = 3.18$) students. These findings affirm the existence of a digital equity gap in AI-assisted learning — a pattern well-documented in technology access literature. Higher-income students benefit from more reliable internet connectivity, greater device ownership, and awareness of premium AI platforms, enabling them to incorporate these tools more systematically into their academic routines. In contrast, low-income students' limited access constrains their engagement, which may paradoxically place them at a disadvantage as AI proficiency becomes an increasingly valued academic skill.

6. Difference in Academic Integrity Risk across Socioeconomic Groups

Table 9: One-Way ANOVA: Academic integrity risk levels across socioeconomic groups (n = 320)

Source of Variation	SS	df	MS	F	p-value / Decision
Between Groups	12.47	3	4.16	2.31	$p = .076$ — Fail to Reject H_0
Within Groups	569.18	316	1.80	—	—
Total	**581.65**	**319**			

Table 9a: Mean academic integrity risk scores by income group

Income Group	n	Moral Just. (M)	Resp. Displacement (M)	Overall (M)	Interpretation
Low Income	89	3.21	2.79	3.00	Moderate Risk
Lower Middle Income	104	3.28	2.84	3.06	Moderate Risk
Middle Income	79	3.39	2.96	3.18	Moderate Risk
Upper Middle/High Income	48	3.51	3.04	3.28	Moderate Risk

The one-way ANOVA revealed no statistically significant difference in academic integrity risk levels across socioeconomic groups [$F(3, 316) = 2.31$, $p = .076$], leading to a failure to reject the null hypothesis. All income groups scored within the moderate risk range, with mean scores ranging narrowly from 3.00 (low income) to 3.28 (upper middle/high income). While upper-income students showed slightly higher risk scores — which is congruent with their greater AI usage frequency — the differences were not statistically significant at the .05 level. This finding suggests that the ethical vulnerabilities associated with AI-assisted academic work are not exclusive to any particular socioeconomic stratum. Rather, academic integrity risk appears to be a cross-cutting concern that transcends income boundaries. This result underscores the importance of universal, rather than targeted, integrity education interventions, and implies that the moral framing of AI use is shaped more by pedagogical context and personal values than by financial background alone.

Discussion

1. Nature of School

The distribution of respondents across school types revealed that the majority (61.88%) were enrolled in public schools, while 22.50% attended private non-sectarian institutions and 15.63% were from private sectarian schools. This pattern is consistent with the broader enrollment landscape in the Philippines, where the Department of Education (DepEd) consistently reports that public schools accommodate approximately 80 to 90 percent of the total basic education population (Department of Education, 2023) [16]. The overrepresentation of public school students in the sample is therefore an accurate reflection of the national student demographic and enhances the external validity of the findings, particularly for policy recommendations directed at government-run institutions.

The inclusion of students from both public and private schools is theoretically significant because school type is widely recognized as a structural determinant of resource availability, including access to technology and digital learning tools. Bakia *et al*. (2011) [6] established that private schools, especially in developing economies, tend to be better equipped with internet infrastructure, computing devices, and digitally literate faculty, creating differential conditions for AI tool adoption. Similarly, in a Philippine context, Tus *et al*. (2021) [36] found that students in private institutions demonstrated significantly higher levels of digital tool proficiency and self-directed learning compared to their public school counterparts, largely due to differences in institutional investment in educational technology. These structural disparities make school type an important variable in understanding the uneven uptake of AI tools in biology education, as observed in the present study.

Furthermore, the presence of sectarian schools in the sample introduces a values-based dimension to the discussion. Research by Cheng (2022) [11] on Catholic and faith-based educational institutions in Southeast Asia suggests that these schools often embed explicit moral formation curricula, which may shape how students perceive and respond to ethically ambiguous behaviors such as AI-assisted academic work. The relatively small proportion of sectarian school respondents (15.63%) limits broad generalization, but their inclusion enriches the diversity of moral frameworks represented in the data, which is particularly relevant for the academic integrity dimensions of this study.

2. Household Monthly Income

The household income profile of the respondents revealed that more than three-fifths (60.31%) of students came from low and lower-middle income backgrounds, with 27.81% categorized as low income (below PHP 10,957 monthly) and 32.50% as lower-middle income (PHP 10,957 to PHP 21,914). Only 15.00% of respondents belonged to upper-middle or high-income households. These figures closely mirror the income distribution data published by the Philippine Statistics Authority (PSA, 2023) [31], which identifies lower-income households as the statistical majority among Filipino families, with a national poverty incidence of approximately 18.1 percent as of the latest Family Income and Expenditure Survey.

The socioeconomic composition of the sample is critically relevant to this study's inquiry into AI tool access. A substantial body of literature has documented that income level is one of the strongest predictors of digital access and technology use among students. Warschauer (2004) [39] in his foundational work on technology and social inclusion argued that access to digital tools is not merely a matter of physical device availability but is shaped by a complex interplay of economic resources, social capital, and institutional support. Students from lower-income households are less likely to own personal devices, maintain stable broadband connections, or subscribe to premium AI platforms—all of which constrain the nature and frequency of their engagement with AI-powered learning tools (van Dijk, 2020) [38]. In the Philippine context specifically, the National ICT Household Survey (DICT, 2022) [17] reported that internet access remains significantly correlated with income level, with higher-income households showing nearly three times the broadband penetration rate compared to those in the lowest income quintile. This structural inequality forms the backdrop against which AI tool usage differences across socioeconomic groups must be interpreted.

Importantly, low income does not preclude AI tool use entirely; mobile internet and free-tier AI platforms have lowered barriers to entry considerably. Buckingham (2023) [10] noted that in many lower-income student populations across Southeast Asia, smartphone-based access has partially bridged the digital divide, enabling students to use AI chatbots through mobile data even where broadband is unavailable. However, the quality, reliability, and depth of engagement remain markedly different from those afforded by high-bandwidth, device-rich environments. These nuances are essential for contextualizing the significant differences in AI tool usage frequency observed across income groups in the present study.

Students' AI-Assisted Tool Usage in Biology Learning

Extent of Use in Biology Tasks

The overall extent of AI tool usage among respondents was rated at a weighted mean of 3.62, interpreted as moderate to frequent use. Specifically, 44.38% of students reported using AI tools "often" or "always" in their biology schoolwork, while only 6.25% reported never using such tools. These findings signal a significant and already well-established integration of AI tools into the academic routines of Filipino senior high school and college biology students, a trend that aligns with accelerating global evidence of AI adoption in educational settings.

The rapid mainstreaming of AI tools in student academic life has been documented extensively following the public release of large language models (LLMs) such as ChatGPT in late 2022. Zhai *et al*. (2021) [43] observed in an earlier pre-ChatGPT study that AI-assisted tutoring systems were already demonstrating measurable positive effects on science learning outcomes, particularly in concept comprehension and problem-solving tasks. Subsequent post-LLM research confirmed an exponential rise in student AI use. Kasneci *et al*. (2023) [24] noted that the accessibility, conversational interface, and immediacy of tools like ChatGPT fundamentally altered the student-AI relationship from a structured, supervised interaction to an informal, on-demand one, making it qualitatively different from earlier educational AI applications. Their analysis estimated that by 2023, approximately 50 to 60 percent of university students in North America and Europe were already using LLMs for academic tasks at least occasionally, a figure that the present study suggests is approaching parity in the Philippine context.

The moderate-to-frequent usage level observed in this study is also consistent with findings from Southeast Asian research contexts. Abelardo *et al*. (2023) [1] surveyed Filipino university students and found that 58% reported weekly use of AI tools for academic tasks, with biology and natural science students among the most frequent users due to the conceptually dense nature of their coursework. The authors attributed this to the perceived cognitive load of biology content—topics such as cellular respiration, genetics, and ecological systems are characterized by high conceptual complexity and extensive technical vocabulary—

which students increasingly turn to AI tools to navigate. This interpretation is corroborated by the pattern of task use identified in the present study, discussed in the following subsection.

The 6.25% who reported never using AI tools merit particular attention. While this minority may include students with principled objections to AI use, it is more likely that this group primarily comprises students who lack the material conditions necessary for AI access—namely, reliable internet connectivity and compatible devices. This interpretation is supported by the significant difference in usage frequency across income groups ($F = 8.71$, $p < .001$) discussed later in this paper. The existence of non-users underscores the importance of not treating AI tool adoption as universal or inevitable, and instead recognizing the stratified nature of digital access in the Philippine educational system (UNESCO, 2023) [37].

Types of Biology Tasks Assisted by AI

The types of biology tasks for which students most frequently sought AI assistance followed a clear hierarchy: concept explanation topped the list at 84.69%, followed by research summarization (70.00%), laboratory report writing (61.88%), homework and seatwork completion (58.44%), study guide generation (50.63%), vocabulary building (46.25%), diagram interpretation (34.06%), and examination preparation (30.31%). This ranking reveals not only where students perceive AI to be most useful but also highlights the domains where the intersection of learning benefit and academic integrity risk is most concentrated.

The primacy of concept explanation as the most common AI use case is consistent with longstanding research on student learning challenges in biology. Tekkumru-Kisa *et al.* (2015) [35] demonstrated that biology is among the most cognitively demanding science subjects at the secondary level, primarily because it requires students to simultaneously manage multiple levels of biological organization—molecular, cellular, organismal, and ecological—while integrating abstract processes such as protein synthesis, natural selection, and osmosis. AI tools, and LLMs in particular, excel at generating plain-language explanations of such abstract concepts on demand, effectively functioning as personalized tutors available at any hour. This affordance is particularly valuable in the Philippine context, where teacher-student ratios in public schools often exceed recommended standards, limiting individualized explanatory support (DepEd, 2023) [16]. From this perspective, using AI for concept explanation represents a pedagogically legitimate and potentially equity-enhancing application of technology.

Research summarization as the second most common task (70.00%) reflects the growing expectation in modern biology education that students engage with primary scientific literature, including research articles and review papers. Kiili *et al.* (2018) [25] found that adolescent students consistently struggle with reading and synthesizing academic science texts, particularly those involving statistical data, technical jargon, and argument structures unfamiliar in secondary school contexts. AI tools offer a functional workaround by distilling complex research into accessible summaries, which can serve as a scaffold for deeper reading. However, this practice also carries a risk: students who rely on AI summaries without reading primary sources may develop an incomplete or oversimplified understanding of scientific inquiry, undermining the epistemic goals of research-based biology education (Zawacki-Richter *et al*., 2019) [42].

The high prevalence of AI-assisted laboratory report writing (61.88%) and homework completion (58.44%) is the most educationally and ethically consequential finding in this subsection. Unlike concept explanation, which can function as a legitimate study scaffold, the use of AI to draft reports and complete homework directly encroaches on assessed academic outputs—products that are intended to demonstrate individual student learning. Perkins *et al.* (2023) [30] conducted a systematic review of AI use in science education and found that laboratory report writing was the most commonly AI-assisted task type globally, with approximately 55 to 70 percent of students in surveyed populations admitting to at least partial AI use in this area. They argued that the semi-structured nature of lab reports—which require both descriptive and analytical writing—makes them particularly amenable to AI generation, as LLMs can produce scientifically plausible procedural descriptions and discussion sections that are difficult for instructors to identify as AI-generated without specialized detection tools. This mirrors the present study's findings and signals an urgent need for instructional redesign in laboratory assessment practices.

The lower rates for diagram interpretation (34.06%) and examination preparation (30.31%) suggest that students perceive AI as less useful for visual-spatial tasks and high-stakes performance contexts, possibly because examinations are typically administered under supervised, device-free conditions. This behavioral pattern demonstrates a degree of situational rationality in student AI use—they apply AI where it is most instrumentally effective, rather than uniformly across all academic contexts. This selectivity is consistent with Selwyn's (2022) [32] concept of "functional AI use," wherein students develop pragmatic, context-sensitive strategies for integrating AI tools into their learning rather than wholesale dependence or wholesale rejection.

Students' Levels of Academic Integrity Risk

Tendency toward Moral Justification in AI-Assisted Biology Work

The moral justification subscale yielded an overall weighted mean of 3.33, indicating a moderate level of academic integrity risk. The two items scoring highest in this subscale were "Using AI for assignments saves time, so it is justifiable" (WM = 3.78) and "AI only helps me express my ideas; the thinking is still mine" (WM = 3.65). These findings reveal the specific cognitive mechanisms through which students rationalize the ethical ambiguity of AI-assisted academic work, and they bear close examination through the lens of established moral psychology theory.

The predominance of time-efficiency justification (WM = 3.78) aligns with academic pressure theories in educational psychology. Murdock and Anderman (2006) [28] proposed a goal-orientation framework for understanding academic dishonesty, positing that students are more likely to engage in dishonest behavior when they are driven by performance-avoidance goals—specifically, the desire to avoid the negative consequences of poor academic performance rather than the intrinsic motivation to master content. When academic workloads are perceived as excessive relative to the time available, efficiency-seeking behavior including the use of AI to shortcut laborious tasks becomes a psychologically compelling response. The present finding that time-based justification is the strongest predictor of moral rationalization corroborates this framework and reflects the documented tendency of Filipino students to experience significant academic overload, particularly in integrated science curricula at the senior high school level (Datu *et al*., 2021) [15].

The second-highest scoring item—"AI only helps me express my ideas; the thinking is still mine" (WM = 3.65)—represents a particularly sophisticated form of moral justification that scholars have identified as the "tool metaphor" of AI use. This rationalization strategy frames AI as a neutral instrument, analogous to a calculator or dictionary, that merely mediates the expression of already-formed student thinking rather than generating new intellectual content. Bandura (1999) [8] described this pattern as a form of moral disengagement through "displacement of agency," wherein individuals redefine the source of an action to minimize their sense of personal authorship and responsibility. In the context of AI-assisted academic work, students who invoke this justification may genuinely believe that their cognitive input—however minimal—constitutes sufficient intellectual ownership to render AI use ethically permissible. Cheung *et al*. (2023) [12] found that this particular justification was more common among students who used AI tools frequently and were more experienced with their capabilities, suggesting that familiarity with AI may paradoxically increase willingness to rationalize its use.

The item "Using AI to write my lab report is acceptable since everyone does it" (WM = 3.41) reflects a social normalization mechanism in moral reasoning. Cialdini's (2003) [13] social proof theory holds that perceived peer behavior is a powerful determinant of individual behavioral norms; when students believe that AI use is widespread, the social cost of non-use (academic disadvantage relative to peers) begins to outweigh the social cost of use (reputational risk associated with dishonesty). This normalization dynamic is especially potent in the absence of clear institutional policies prohibiting or regulating AI use in academic submissions. Bretag (2019) [9] documented a similar "arms race" phenomenon in academic integrity research, wherein the absence of explicit policy creates behavioral ambiguity that students resolve through social comparison—observing what their peers do and adopting similar behaviors as a default standard.

The relatively lower but still moderate score for "My teacher's silence on AI use means it is implicitly allowed" (WM = 2.95) indicates that a substantial minority of students interpret the absence of explicit prohibition as tacit permission. This finding echoes the argument advanced by Eaton (2024) [18] that academic integrity policies in the age of generative AI must be proactive and explicit rather than relying on default prohibitions. She noted that traditional academic integrity frameworks were designed for an era when dishonest tools—essay mills, answer keys, plagiarism services—were clearly and unambiguously prohibited. Generative AI occupies a fundamentally different epistemic category because it can serve both legitimate and illegitimate academic functions, often simultaneously within the same assignment. The resulting ambiguity in student perception, as evidenced in the present data, underscores the urgent need for explicit AI use policies at all levels of Philippine education.

Displacement of Responsibility to AI Tools for Academic Outputs

The responsibility displacement subscale produced an overall weighted mean of 2.90, also in the moderate risk range, though notably lower than the moral justification subscale. This difference suggests that while students construct cognitive justifications for AI-assisted academic work, they have not yet fully externalized personal accountability for their academic outputs—a distinction with important implications for intervention design. The pattern of item-level scores further illuminates the specific ways in which responsibility displacement manifests in AI-assisted biology learning.

The lowest-scoring item in this subscale, "If my AI-assisted report has errors, it is the AI's fault, not mine" (WM = 2.44), indicates that most students retain basic attributional accountability for the quality of their academic outputs. This is consistent with Weiner's (1985) [40] attribution theory, which predicts that individuals are generally resistant to fully externalizing blame for negative outcomes when they have played an active role in producing those outcomes. Students who submit AI-generated work, even if they rely heavily on AI, are aware of their own agency in selecting, submitting, and representing the output as their own, which likely limits the extent to which they can comfortably attribute errors to the AI tool itself.

However, the higher-scoring items reveal more concerning patterns. "Without AI, I do not feel confident producing biology outputs on my own" (WM = 3.32) and "I rely on AI to decide what information to include in my biology outputs" (WM = 3.14) suggest that a meaningful proportion of students have developed AI-dependent academic identities, wherein their sense of self-efficacy as learners is contingent on AI assistance. This is a critical educational concern because academic self-efficacy—the belief in one's capacity to perform academic tasks independently—is one of the strongest predictors of long-term academic achievement, persistence, and deep learning (Zimmerman, 2000) [44]. When students internalize a belief that they cannot produce quality biology work without AI assistance, they undermine the very cognitive and motivational capacities that education is designed to develop. This finding resonates with Bandura's (1997) [7] broader theory of self-efficacy, which identifies past performance experiences as the primary source of efficacy beliefs. Students who habitually delegate cognitive work to AI deprive themselves of the successful independent performance experiences needed to build genuine academic confidence.

The moderate endorsement of "When I submit AI-generated work, I feel less accountable for errors" (WM = 2.98) reflects what Parasuraman and Manzey (2010) [29] termed automation bias—the systematic tendency to over-rely on automated systems and to reduce vigilance in monitoring their outputs. In educational contexts, automation bias manifests as a reduced sense of personal responsibility for the quality and accuracy of AI-generated content, because the perceived authority of the AI system partially displaces the student's own critical judgment. This is particularly problematic in biology education, where scientific accuracy is non-negotiable; AI-generated biological content can contain subtle factual errors or outdated information that students who have deprioritized critical evaluation may fail to detect before submission (Baidoo-Anu & Ansah, 2023) [5].

The finding that confidence-dependency and content-decision delegation scored higher than direct fault attribution suggests that responsibility displacement in the present sample operates more subtly than outright blame-shifting. Students are not primarily claiming that AI is at fault for errors; rather, they are developing structural dependencies on AI that gradually erode their independent academic agency. This distinction is important for intervention design: simply prohibiting AI use is unlikely to address the underlying academic self-efficacy deficits that drive dependency. More productive interventions would involve scaffolded AI use policies that require students to demonstrate independent mastery before incorporating AI assistance, as recommended by Southworth *et al*. (2023) [33].

Relationship between AI Usage Frequency and Academic Integrity Risk

The Pearson r correlation analysis revealed a statistically significant moderate positive relationship between students' AI tool usage frequency and their overall academic integrity risk ($r = 0.489$, $p < .001$). The correlation was significant for both moral justification ($r = 0.512$, $p < .001$) and responsibility displacement ($r = 0.437$, $p < .001$), with approximately 23.9% of the variance in integrity risk explained by usage frequency ($r^2 = 0.239$). These results provide empirical support for the hypothesis that higher frequency of AI tool engagement is associated with greater propensity toward ethically compromised academic behaviors in biology learning.

This positive correlation is theoretically coherent within the framework of behavioral habituation and cognitive normalization. Ajzen's (1991) [2] Theory of Planned Behavior holds that attitudes, subjective norms, and perceived behavioral control jointly determine behavioral intentions; when a behavior—such as using AI to complete academic work—is repeated frequently, it transitions from a deliberate choice to an automatic behavioral script, reducing the cognitive salience of its ethical dimensions. In other words, students who use AI tools daily or near-daily for biology tasks may gradually cease to consciously evaluate the ethical implications of each use because the behavior has become habitual. This habituation process progressively lowers the moral activation threshold, making ethically borderline behaviors feel routine and acceptable.

This interpretation is supported by Comas-Forgas *et al*. (2021) [14], who conducted a large-scale longitudinal study across European universities and found that students who used digital academic tools more frequently—including AI writing assistants—showed significantly higher rates of contract cheating and plagiarism over time, even when controlling for initial attitudes toward academic integrity. They proposed that the mechanism linking tool use frequency to integrity risk was not primarily attitudinal but behavioral: the more students used such tools, the more proficient they became at rationalizing their use, creating a self-reinforcing cycle. The moderate correlation observed in the present study is consistent with this cyclical reinforcement model.

The stronger correlation observed between AI usage frequency and moral justification ($r = 0.512$) compared to responsibility displacement ($r = 0.437$) suggests that the cognitive-rationalizing dimension of integrity risk grows more rapidly with AI use than the self-efficacy-dependency dimension. This difference may reflect the sequencing of psychological adaptation to AI use: students first develop justification narratives to make sense of their behavior, and dependency develops more gradually as repeated use progressively supplants independent effort. This temporal ordering is consistent with Festinger's (1957) [19] cognitive dissonance theory, which predicts that individuals who engage in behaviors they recognize as potentially problematic will first develop rationalizations to reduce the psychological discomfort of dissonance before deeper behavioral restructuring occurs.

It is important to acknowledge that the correlation, while significant and educationally meaningful, accounts for less than a quarter of the variance in academic integrity risk, indicating that AI usage frequency is one among several important predictors. Other factors likely contributing to integrity risk include institutional policy clarity, teacher enforcement behavior, peer norms, individual moral development, and subject-specific workload pressures. Teixeira and Rocha (2010) [34] in a landmark multi-country study on academic integrity found that academic workload, assessment design, and institutional culture collectively explained substantially more variance in academic misconduct than individual student characteristics or tool access, suggesting that systemic and pedagogical interventions may ultimately be more effective than individual-level behavioral monitoring.

The correlation findings carry significant practical implications for biology educators and curriculum designers. Instructors should be alert to the possibility that students who engage most frequently with AI tools in biology are simultaneously developing the most sophisticated rationalization narratives for their use. Rather than treating AI use and academic integrity as separate concerns to be addressed independently, a more integrative pedagogical approach—one that explicitly discusses the ethical dimensions of AI use as part of digital literacy instruction in biology—is warranted (Guerrero-Dib *et al*., 2020) [21]. Assessment redesign that privileges process documentation, oral defense of written work, and in-class practical application can also disrupt the conditions that enable AI-assisted dishonesty, regardless of usage frequency.

Difference in AI Usage Frequency across Socioeconomic Groups

The one-way ANOVA revealed a statistically significant difference in AI tool usage frequency across income groups [$F(3, 316) = 8.71$, $p < .001$]. Post-hoc Tukey HSD comparisons showed that upper-middle and high-income students ($M = 4.02$) reported significantly higher usage than low-income ($M = 2.91$) and lower-middle income ($M = 3.18$) students, while middle-income students ($M = 3.54$) differed significantly from the low-income group. These findings confirm the existence of a socioeconomically stratified digital divide in AI tool engagement—a pattern with profound implications for educational equity in the age of artificial intelligence.

The significant income-usage gap identified in this study is consistent with extensive international literature on the digital divide in educational technology adoption. van Dijk (2020) [38] articulated a multi-layered model of digital inequality that distinguishes between motivational access (the desire to use technology), material access (ownership of devices and connectivity), skills access (the competence to use technology effectively), and usage access (the actual frequency and quality of use). Low-income students in the present sample are likely disadvantaged at multiple levels of this hierarchy: they face greater material access barriers due to reduced device ownership and connectivity, encounter fewer high-quality digital skills development opportunities, and consequently achieve lower levels of productive AI usage even when some access is available.

In the Philippine context specifically, the digital divide documented by this study is not a novel phenomenon but an extension of a persistent structural inequality. The DICT (2022) [17] national ICT survey reported that 47.5% of households in the lowest income quintile lacked internet access at home, compared to only 8.2% of households in the highest quintile—a differential of nearly six to one. Students without home internet access are forced to rely on mobile data connections, school computer laboratories with limited hours of availability, or internet cafes—all of which impose significant practical barriers to sustained AI tool use for academic purposes. Gonzales (2016) [20] demonstrated that mobile-only internet access, while providing some connectivity, qualitatively constrains digital activities: mobile users engage in more passive and consumption-oriented behaviors, while device-rich users engage in more active, creative, and academically productive digital activities. This usage quality differential likely contributes to the mean differences observed across income groups in the present study.

The practical significance of this finding extends beyond a description of current inequality. As AI proficiency increasingly becomes a valued competency in academic and professional settings—a trend documented by the World Economic Forum (2023) [41], which listed AI and data literacy among the top ten emerging skills for 2025 to 2030—the differential acquisition of AI-assisted learning skills across income groups threatens to reproduce and amplify existing socioeconomic inequalities. Students from low-income families who gain less experience with AI tools during their formative education will be less prepared to leverage AI in higher education and the labor market, compounding the disadvantages associated with poverty. This phenomenon has been termed the "AI opportunity gap" by Holmes *et al*. (2022) [22], who argued that without deliberate policy intervention, AI-enhanced education risks becoming yet another mechanism through which educational technology privileges the already privileged.

The finding that even within the lower-income groups, a substantial proportion of students (27.5% in "often" or "always" combined) do engage with AI tools at least regularly suggests that mobile-based access has partially mitigated the material access barrier. This is consistent with Buckingham's (2023) [10] observation that free-tier AI platforms accessible via smartphones have created a more porous digital access landscape than existed in earlier eras of educational technology. However, the quality, depth, and academic productivity of mobile-based AI engagement likely remains inferior to that possible with high-bandwidth, multi-device environments. Policy responses must therefore address not merely the binary question of whether students have any AI access, but the quality and educational purposefulness of that access.

These findings call for structural interventions at both the school and system levels. Schools serving low-income communities require targeted investment in digital infrastructure—particularly reliable classroom Wi-Fi, shared computing devices, and teacher professional development on AI-integrated pedagogy—to ensure that the AI opportunity gap does not become permanently institutionalized. At the system level, the Department of Education and the Commission on Higher Education (CHED) should consider developing national guidelines for equitable AI integration in education, including provisions for subsidized device access and zero-rated AI tool usage for students in public schools, along the lines of similar programs implemented in South Korea and Uruguay (UNESCO, 2023) [37].

Difference in Academic Integrity Risk across Socioeconomic Groups

In contrast to the significant differences found in AI tool usage frequency, the one-way ANOVA revealed no statistically significant difference in academic integrity risk levels across socioeconomic groups [$F(3, 316) = 2.31$, $p = .076$]. All four income groups scored within the moderate risk range, with overall risk means ranging narrowly from 3.00 (low income) to 3.28 (upper-middle/high income). This null result is theoretically instructive and offers important correctives to assumptions that might equate greater AI engagement with greater ethical compromise, or that might locate the problem of academic integrity risk primarily in high-income, high-usage student populations.

The absence of significant between-group differences in academic integrity risk, despite significant differences in AI usage frequency, suggests that the mechanisms generating ethical risk in AI-assisted academic work are not reducible to frequency of exposure alone. This decoupling of usage and risk across income groups implies the existence of moderating variables that operate more uniformly across socioeconomic strata than AI usage frequency itself. Moral development, institutional culture, peer norms, and assessment design are plausible candidates for such moderating roles, each of which may exert relatively uniform influence across income groups while usage frequency varies substantially.

From a moral development perspective, Kohlberg's (1981) [26] theory of moral reasoning stages offers a useful theoretical framework for interpreting this finding. Kohlberg argued that moral reasoning develops through invariant stages from pre-conventional reasoning (focused on consequences for the self) through conventional reasoning (focused on social norms and institutional rules) to post-conventional reasoning (focused on abstract ethical principles). Most adolescent and early adult learners operate primarily at the conventional level, where behavior is regulated primarily by perceived social expectations and institutional rules rather than internalized ethical principles. If the majority of students across all income groups are operating at the same stage of moral development—as would be expected in a sample of similar age and educational level—their susceptibility to moral rationalization and responsibility displacement would be similar regardless of the quantity of AI they use, because the underlying moral framework governing their evaluation of such behaviors is structurally equivalent.

This interpretation is supported by McCabe *et al*. (2012) [27], whose landmark multi-institutional study on academic dishonesty among college students found that the strongest predictors of cheating behavior were institutional integrity culture and peer behavior norms—both of which tend to operate at the school level rather than the individual income level. In schools or classrooms where a permissive norm toward AI-assisted academic work has developed, students across all income levels are similarly influenced, because social norms are shared community properties rather than individual ones. Conversely, in schools with strong integrity cultures enforced through consistent policy and role-modeling by faculty, students of all income levels show reduced dishonest behavior, again independent of AI usage frequency.

The finding also challenges a potentially classist assumption that might implicitly link low-income status with lower ethical standards or greater propensity for academic dishonesty. The data clearly refute this assumption: low-income students in the present study did not show significantly higher academic integrity risk despite facing greater academic pressure and resource constraints—factors that prior literature has associated with elevated dishonesty risk (Anderman & Midgley, 2004) [4]. This finding is morally and pedagogically important, as it argues against deficit-oriented framings of low-income students' academic integrity behaviors and instead points to the systemic and contextual determinants of integrity risk that cut across socioeconomic lines.

Nonetheless, the trend toward slightly higher integrity risk scores among upper-income students (M = 3.28 vs. M = 3.00 for low-income), while not statistically significant, is conceptually interesting and worthy of cautious interpretation. Upper-income students' greater familiarity and frequency of AI use may have already begun generating incremental increases in moral justification tendencies and responsibility displacement, consistent with the habituation mechanism proposed by Ajzen (1991) [2] and documented by Comas-Forgas *et al.* (2021) [14]. Should AI tool usage frequency continue to increase—as seems likely given current technological trends—the currently non-significant income-integrity risk gradient may eventually achieve statistical significance in longitudinal designs. This possibility warrants proactive monitoring and continued research.

The null result for socioeconomic differences in integrity risk has important implications for educational policy and practice. It suggests that academic integrity interventions need not be targeted exclusively or primarily at high-income, high-usage student populations, but rather should be implemented universally across all student demographics. Integrity education programs that address the moral justification narratives and responsibility displacement patterns identified in this study—such as values-based discussions of academic honesty, explicit AI use policy frameworks, and assessment designs that require verifiable individual effort—would benefit all students regardless of their income level or AI usage frequency. This universalist approach to integrity education aligns with the recommendations of the International Center for Academic Integrity (ICAI, 2021) [23], which advocates for systemic, culture-level integrity interventions over targeted, individual-level policing of academic behavior.

Conclusions

The findings reveal that AI, particularly large language models, has become an integral learning support for tertiary biology students, functioning as an "on-demand cognitive scaffold." While this enhances access to explanations and accelerates learning, it also reshapes how students engage with knowledge, often reducing opportunities for productive cognitive struggle. More critically, frequent AI use is strongly linked to academic integrity risks. Students tend to justify usage for efficiency and exhibit dependency, suggesting a shift from assistance to reliance. The habituation effect further normalizes ethically ambiguous behavior, especially in tasks like laboratory reports and homework.

The study also highlights an "AI opportunity gap," where students from higher socioeconomic backgrounds benefit from better access to digital resources, increasing their AI usage. However, the presence of "ethical parity" indicates that integrity risks are consistent across all groups, driven more by institutional culture and assessment design than by socioeconomic status. Ultimately, the increasing reliance on AI raises concerns about automation bias and the erosion of independent academic agency, potentially weakening critical thinking and deep learning.

Recommendations

The recommendations emphasize the need for proactive and systemic responses. First, institutions must establish clear and explicit policies on AI use to eliminate ambiguity and guide ethical practices. Second, assessment redesign is essential—shifting toward process-based evaluation, oral defenses, and in-class tasks can help ensure authenticity and reduce AI misuse.

The study also advocates for universal academic integrity education, given that ethical risks cut across all student groups. At the same time, efforts to bridge the AI opportunity gap—such as providing subsidized devices and accessible internet—are necessary to ensure equity. Finally, fostering critical AI literacy is crucial; students must learn not only how to use AI, but also how to evaluate it critically and use it responsibly. Together, these measures aim to balance innovation with integrity while preserving students' independent thinking skills.

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