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AI-Assisted Learning and Moral Disengagement in Mathematics Tasks

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Abstract
The integration of AI tools in mathematics education raises pressing concerns about academic integrity and ethical cognition. This study examined the relationship between AI-assisted tool usage frequency and moral disengagement in mathematics tasks among Filipino tertiary students, with differences analyzed across socioeconomic groups. A quantitative, cross-sectional correlational design was employed with 209 BSE–Mathematics students selected through stratified random sampling. Data were collected via two validated self-report instruments — the AI-Assisted Tool Usage Frequency Questionnaire and the Moral Disengagement Scale in Mathematics Tasks — alongside a demographic form capturing sex and household monthly income. Pearson correlation, independent samples t-test, and one-way ANOVA were used for analysis. Students reported moderate-to-frequent AI use ($M = 2.53$), primarily for answer verification and exam preparation. Moral justification was moderately endorsed ($M = 2.55$), while displacement of responsibility was largely rejected ($M = 2.47$). Significant positive correlations were found between AI use frequency and both moral justification ($r = .629$, $p < .001$) and displacement of responsibility ($r = .474$, $p < .001$). No significant differences were observed across sex or household income groups in either AI usage frequency or moral disengagement levels. Higher AI usage frequency is associated with greater cognitive rationalization of ethically ambiguous academic behavior. The absence of socioeconomic and sex-based disparities suggests these ethical risks are uniformly distributed, underscoring the need for institution-wide ethical AI frameworks and reflective pedagogical interventions in mathematics education.

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

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) [18, 1]. 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 [22]). 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 [21]; 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 [3], 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) [4]. 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). 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) [20]. 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). 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) [18, 1] and moral disengagement in academic contexts (Bartolo *et al*., 2019 [4]; 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) [22]. 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; 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) [3] 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 examine the relationship between students' frequency of AI-assisted tool use and levels of moral disengagement in completing mathematics tasks, with differences analyzed across socioeconomic groups. 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 sex; and
   1.2 household monthly income?
2. How may the students' AI-assisted tool usage frequency be described in terms of:
   2.1 Extent of use in mathematics tasks; and
   2.2 Types of tasks assisted?
3. How may the students' levels of moral disengagement be described in terms of:
   3.1 Moral justification mechanisms; and
   3.2 Displacement of responsibility?
4. Is there a significant relationship between students' AI-assisted tool usage frequency and levels of moral disengagement in mathematics tasks?
5. Is there a significant difference in AI-assisted tool usage frequency across socioeconomic groups?
6. Is there a significant difference in levels of moral disengagement across socioeconomic groups?

Methodology

Research Design

This study adopts a quantitative, cross-sectional correlational research design with comparative and moderation analyses to examine the relationship between students' frequency of AI-assisted tool usage and levels of moral disengagement in completing mathematics tasks, with differences analyzed across socioeconomic groups. This design is particularly suited to investigating naturally occurring phenomena through statistical analysis without manipulating variables, thereby ensuring methodological rigor and ethical integrity.

A quantitative approach is appropriate as the study seeks to measure variables numerically and analyze their relationships using inferential statistical techniques. Quantitative research enables the objective examination of patterns, associations, and differences among variables, contributing to generalizable and empirically grounded findings (Creswell & Creswell, 2018) [9]. Given the study's emphasis on measurable constructs—AI usage frequency, moral disengagement, and socioeconomic status—the use of structured instruments and statistical analyses ensures precision and replicability.

The research employs a cross-sectional design, wherein data are collected from respondents at a single point in time. This approach is widely used in educational and social science research to assess prevailing attitudes, behaviors, and relationships efficiently and economically (Cohen *et al.*, 2018). In the context of this study, the cross-sectional method allows for the timely assessment of students' AI usage behaviors and ethical cognitions within contemporary educational environments where artificial intelligence is rapidly evolving.

At its core, the study utilizes a correlational research framework to determine the extent to which students' frequency of AI-assisted tool usage is associated with their levels of moral disengagement in mathematics tasks. Correlational designs are suitable for identifying relationships among variables without implying causation, thereby providing insights into predictive trends and theoretical linkages (Fraenkel *et al.*, 2019) [11]. This approach aligns with Bandura's Social Cognitive Theory of Moral Agency, which posits that moral behavior is influenced by cognitive processes and environmental factors (Bandura, 1999) [3].

In addition to examining relationships, the study incorporates comparative analyses to determine whether significant differences exist in AI-assisted tool usage frequency and levels of moral disengagement across socioeconomic status (SES) groups. Comparative methods, such as Analysis of Variance (ANOVA), enable researchers to assess variations among distinct populations and are widely employed in educational research to explore disparities related to access, behavior, and outcomes (Field, 2018) [10]. By disaggregating data based on SES, the study advances equity-oriented inquiry into the ethical implications of AI-assisted learning.

Sample and Sampling Techniques

The target population of this study comprises of tertiary students enrolled in BSE - Mathematics within selected educational institutions in the Philippines. For the purpose of this study, a total population of four hundred fifty-three students were considered in determining the two hundred nine respondents that were considered as samples of the study. This population is deemed appropriate since the students in this level and programs frequently engage with artificial intelligence (AI)-assisted tools—such as large language models, generative AI platforms, and specialized mathematical solvers—in completing academic tasks. Their experiences provide valuable insights into the ethical and cognitive implications of AI use in mathematics 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, comparative, and moderation analyses. According to Cohen (1992) [7], 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.

Sampling Technique

This study employed a stratified random sampling technique in identifying 209 respondents of the study, which is widely regarded as one of the most effective methods for ensuring representativeness when a population is heterogeneous (Creswell & Creswell, 2018) [9]. Stratification was based on socioeconomic status (SES)—categorized into 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 AI tools and variations in ethical decision-making.

This technique ensures equitable representation of all socioeconomic groups, enhances the precision of statistical comparisons, and supports moderation analysis. Stratified sampling also improves the external validity of the study by producing findings that are more reflective of the broader population (Cohen *et al*., 2018).

Inclusion and Exclusion Criteria

To ensure the appropriateness and consistency of the sample, the following criteria was applied:

Inclusion Criteria:

- Students currently enrolled in tertiary mathematics courses;
- Students who have used AI-assisted tools for academic purposes;
- Students willing to provide informed consent to participate in the study;
- Students with access to digital devices and internet connectivity.

Exclusion Criteria:

- Students not enrolled in mathematics courses during the data collection period;
- Students who have no prior experience using AI-assisted tools;
- Incomplete or invalid survey responses;
- Participants who withdraw from the study.

Research Instruments & Validation

The primary instruments are two self-report questionnaires: (1) AI-Assisted Tool Usage Frequency Questionnaire (AI-UFQ) for the independent variable, and (2) Moral Disengagement Scale in Mathematics Tasks (MDS-Math) for the dependent variable. Both use a 4-point Likert scale (1 = Strongly Disagree/Never, 4 = Strongly Agree/Always) for consistency and reliability. Socioeconomic status (SES) is assessed via a demographic form with established indicator like sex and household monthly income, validated in educational equity studies.

Content validity was ensured by adapting items from domain-specific validated scales (e.g., Bandura's MD mechanisms, AI usage surveys) and tailoring to math tasks via expert review (e.g., aligning with AI cheating in STEM). Construct validity is supported by factor analysis in source scales (Cronbach's $\alpha > 0.80$), high loadings (>0.70), and AVE > 0.50 in adaptations, confirming they measure intended constructs without overlap.

Data Analysis

The design was operationalized through a structured survey administered to secondary and/or tertiary students enrolled in mathematics courses. Stratified sampling techniques was employed to ensure adequate representation across socioeconomic groups, thereby enhancing the external validity of the findings. Data were collected using validated instruments measuring:

1. **AI-Assisted Tool Usage Frequency** – assessing the extent of use and types of AI tools utilized in mathematics tasks;
2. **Moral Disengagement** – evaluating cognitive mechanisms such as moral justification and displacement of responsibility, grounded in Bandura's theoretical framework; and
3. **Socioeconomic Status** – determined through indicators such as sex and household monthly income.

The study used a 4-point Likert scale in determining the extent of use of AI tools in mathematics tasks and moral disengagement of students in terms of moral justification mechanisms and displacement of responsibility.

Table 1: Four-point Likert Scale

Mean	Description
3.26 – 4.00	Strongly Agree / Always
2.51 - 3.25	Agree / Often
1.76 – 2.50	Disagree / Rarely
1.00 – 1.75	Strongly Disagree / Never

The collected data was analyzed using the following statistical techniques:

Table 2: Guide for Data Analysis

Research Objective	Statistical Treatment
Describe AI-assisted tool usage frequency	Mean, standard deviation, frequency, and percentage
Describe levels of moral disengagement	Mean and standard deviation
Determine differences across socioeconomic groups	One-Way Analysis of Variance (ANOVA)
Examine relationships between AI use and moral disengagement	Pearson Product–Moment Correlation

These statistical methods ensure comprehensive, valid, and reliable analysis of the relationships and differences among variables.

Results & Discussion

1. Socio – economic profile of the respondents

1.1 Sex

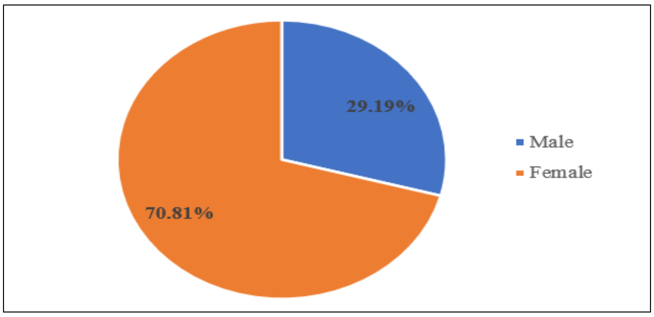

Fig 1: Distribution of Respondents According to Sex

Fig 1 illustrates the distribution of respondents according to sex in the present study. Female students constituted the majority of the sample (70.81%), while male students represented 29.19%. This female-dominated profile is consistent with patterns observed in recent educational research involving student populations, where female respondents frequently predominate in surveys on academic behaviors, attitudes, and technology integration (Sicuan, 2024). Such distributions often reflect higher female enrollment and participation rates in higher education programs, particularly in contexts like the Philippines where women lead in educational attainment metrics.

The sample composition enables robust subgroup analysis of sex-based differences in the frequency of AI-assisted tool use and levels of moral disengagement during mathematics tasks. Prior research has established that sex is a relevant variable in moral disengagement processes among adolescents and young adults, with observable trends in how males and females endorse or reject disengagement mechanisms (Thornberg, 2023).

1.2 Household monthly income

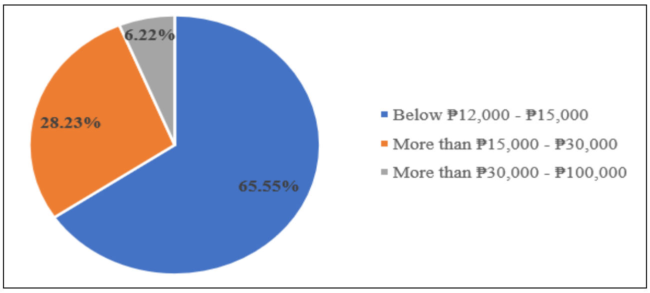

Fig 2: Distribution of Respondents According to Household Monthly Income

Fig 2 presents the distribution of respondents according to household monthly income. The majority of participants (65.55%) belonged to households earning below ₱12,000 – ₱15,000 per month (low-income group). This was followed by 28.23% from households earning more than ₱15,000 – ₱30,000 (middle-income group), while only 6.22% came from households with more than ₱30,000 – ₱100,000 (high-income group). This distribution, heavily skewed toward the low-income category (65.55%), reflects broader national patterns documented in the Philippine Family Income and Expenditure Survey (FIES), where a large proportion of households continue to fall into low- to lower-middle income brackets despite gradual middle-class expansion (Philippine Statistics Authority [PSA], 2024; Albert, 2024). Such concentration in lower socioeconomic strata is common in studies conducted in provincial or public higher education institutions in the Philippines. Socioeconomic status, operationalized via household income, has been consistently identified as a significant factor influencing technology access, ethical decision-making, and academic behaviors in adolescent and young adult populations (Rakesh *et al.*, 2024; Tan, 2025; Yigiter, 2025).

2. Students' AI-assisted tool usage frequency

2.1 Extent of use in mathematics tasks

Table 3: Extent of AI-Assisted Tool Usage of Students

S. No	Statements	WM	Verbal Interpretation
1	I use AI tools to generate solutions for mathematics homework problems.	2.64	Often
2	I rely on AI for step-by-step explanations in mathematics assignments.	2.67	Often
3	AI helps me complete mathematics tasks multiple times a week.	2.55	Often
4	I use AI for mathematics practice quizzes or exam preparation.	2.82	Often
5	Compared to peers, I use AI more for complex mathematics problems.	2.58	Often
6	My AI use in mathematics increases during deadlines or difficult units.	2.69	Often
7	I input mathematics problems into AI tools (e.g., photo/voice) instead of solving manually.	2.27	Rarely
8	Frequency varies by my family's access to devices/internet.	2.56	Often
9	I use AI tools more than once a day for basic mathematics problems.	2.23	Rarely
10	AI assists me in mathematics calculations or data interpretation.	2.74	Often
11	I turn to AI first for mathematics problems before trying manual methods.	2.22	Rarely
12	My AI usage spikes for mathematics tasks requiring logical setup.	2.38	Rarely
13	I use AI to check my mathematics answers, even after attempting them myself.	2.90	Often
14	AI tools are my go-to for mathematics problems involving patterns or simulations.	2.56	Often
5	Compared to my socioeconomic group, I use AI more due to time constraints at home.	2.37	Rarely
16	I rely on AI for mathematics review sessions shared via school or family devices.	2.36	Rarely
	Grand Mean	**2.53**	**Often**

Table 3 presents the extent of AI-assisted tool usage among students in completing mathematics tasks. The computed grand mean of 2.53, interpreted as "Often," indicates a moderate to frequent level of engagement with AI tools in mathematics-related activities. This suggests that while AI is not used pervasively, it has become a regular component of students' learning processes. The highest-rated indicators reflect functional and supportive applications of AI. Students reported frequently using AI to verify their answers after independently attempting problems (WM = 2.90), to prepare for quizzes and examinations (WM = 2.82), and to obtain step-by-step explanations (WM = 2.67) as well as solutions for assigned tasks (WM = 2.64). These patterns imply that AI is primarily utilized as a supplementary learning aid that reinforces understanding and accuracy rather than replacing cognitive effort. Such findings are consistent with studies highlighting AI's role as a scaffolding tool that enhances procedural understanding and supports self-regulated learning in mathematics (e.g., Holmes *et al*., 2019; Zawacki-Richter *et al*., 2019 [22]).

Moderately high engagement is also evident in situational usage, particularly during periods of academic pressure such as approaching deadlines or when dealing with challenging topics (WM = 2.69). Meanwhile, the relatively lower mean for multimodal input methods, such as photo or voice-based problem entry (WM = 2.27), suggests that although these features are available, they are not yet fully integrated into students' routine practices. This reflects findings in recent literature indicating that students' adoption of advanced AI functionalities tends to lag behind more straightforward text-based interactions (Kasneci *et al*., 2023).

Conversely, lower-rated behaviors reveal limited dependence on AI as a primary problem-solving strategy. Students reported rarely using AI as their first approach before attempting problems manually (WM = 2.22), engaging with AI multiple times daily for basic tasks (WM = 2.23), or relying on shared devices for access (WM = 2.36). These results indicate a pattern of selective and intentional usage rather than habitual over-reliance, aligning with research suggesting that learners tend to integrate AI tools in a controlled manner to complement, rather than substitute, traditional learning practices (Luckin *et al*., 2016; Holmes & Tuomi, 2022). The findings are consistent with emerging empirical evidence showing that students increasingly incorporate AI tools for explanation, practice, and verification in mathematics, while maintaining moderate levels of use (Kasneci *et al*., 2023; Zawacki-Richter *et al*., 2019 [22]).

2.2 Types of tasks assisted

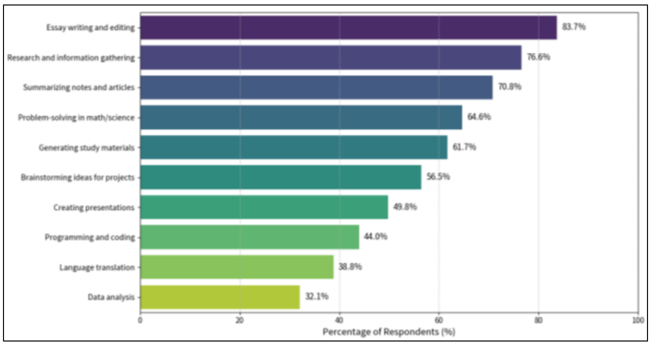

Fig 3: Types of Tasks Assisted by AI

Fig 3 presents the types of academic tasks assisted by AI tools as reported by the student respondents. The findings indicate that AI usage is most prevalent in language-intensive and cognitively supportive tasks. Essay writing and editing recorded the highest usage rate (83.7%), followed by research and information gathering (76.6%) and summarizing notes and articles (70.8%). These results highlight the strong alignment between students' AI usage patterns and the advanced natural language processing capabilities of generative AI systems. In relation to tasks central to the present study, problem-solving in mathematics and science was supported by AI among 64.6% of respondents, while generating study materials accounted for 61.7%. This suggests that although AI is widely utilized in mathematically oriented tasks, its role is more complementary than dominant. Meanwhile, relatively lower adoption rates were observed in brainstorming ideas for projects (56.5%), creating presentations (49.8%), programming and coding (44.0%), language translation (38.8%), and data analysis (32.1%). These variations imply that students selectively engage AI tools depending on task complexity, perceived usefulness, and familiarity with specific functionalities.

The observed distribution of AI-assisted tasks is consistent with prior research in educational technology, which emphasizes that generative AI is most effectively leveraged for writing, content generation, and summarization due to its strengths in natural language processing (Zawacki-Richter *et al*., 2019 [22]; Kasneci *et al*., 2023). In contrast, applications in mathematics and scientific problem-solving tend to focus on providing explanations, procedural guidance, and step-by-step solutions rather than complete task automation, thereby supporting conceptual understanding while still requiring learner engagement (Holmes *et al*., 2019; Luckin *et al*., 2016). Furthermore, emerging studies in higher education contexts indicate that students increasingly adopt AI tools to support a wide range of academic tasks, including writing, paraphrasing, and problem-solving, often integrating these tools as part of their self-regulated learning strategies (Kasneci *et al*., 2023).

3. How may the students' levels of moral disengagement be described in terms of:

3.1 Moral justification mechanisms

Table 4: Level of Moral Disengagement in Terms of Moral Justification Mechanisms

S. No	Statements	WM	Verbal Interpretation
1	Using AI in math is justified as mastering efficient problem-solving for real-world success.	2.70	Agree
2	AI use honors the goal of high grades, serving educational progress.	2.51	Agree
3	Relying on AI for math solutions is just "smart leveraging of technology," not cheating.	2.53	Agree
4	AI-assisted math work is "enhanced learning," not shortcutting.	2.78	Agree
5	Math AI use causes less harm than traditional copying from peers.	2.55	Agree
6	Compared to worse cheating like buying answers, AI is minor.	2.49	Disagree
7	Teachers expect AI use in math, so it's their responsibility to detect it.	2.54	Agree
8	AI companies promote tools for homework, shifting blame from me.	2.31	Disagree
	Grand Mean	**2.55**	**Agree**

Table 4 presents the level of students' moral disengagement in terms of moral justification mechanisms in the context of AI use in mathematics. The overall grand mean of 2.55, interpreted as "Agree," indicates that students moderately endorse justifications that frame AI-assisted academic behavior as acceptable or beneficial. This suggests the presence of moral reasoning processes that allow students to cognitively reframe AI use in ways that reduce perceived ethical conflict. Among the indicators, the highest-rated statements emphasize the perceived academic value of AI. Students agreed that AI-assisted math work enhances learning (WM = 2.78) and contributes to efficient problem-solving for real-world success (WM = 2.70). They also viewed AI as supporting educational goals such as achieving high grades (WM = 2.51) and interpreted its use as "smart leveraging of technology" rather than cheating (WM = 2.53). These responses reflect a tendency to morally justify AI usage by aligning it with desirable educational outcomes, thereby framing the behavior as constructive rather than unethical. This aligns with the concept of moral justification, where individuals cognitively reconstruct questionable actions as serving socially or personally valuable purposes.

Students also agreed that AI use causes less harm than traditional forms of academic dishonesty, such as copying from peers (WM = 2.55), and that teachers implicitly permit AI use by expecting it (WM = 2.54). These findings suggest additional layers of justification, including comparative reasoning and diffusion of responsibility, where accountability is partially shifted to institutional expectations. However, disagreement with statements such as AI being minor compared to more severe cheating (WM = 2.49) and blaming AI companies for promoting tool usage (WM = 2.31) indicates that students do not fully externalize responsibility nor completely trivialize AI-related academic misconduct. The pattern of responses suggests that students engage in selective moral disengagement, particularly through justifications that emphasize efficiency, academic success, and technological advancement. This is consistent with established theoretical perspectives on moral disengagement, which posit that individuals rationalize ethically ambiguous behaviors by construing them as acceptable within a given context (Bandura, 2016). In educational settings, recent studies have shown that the integration of digital and AI tools can blur traditional boundaries of academic integrity, leading students to reinterpret what constitutes acceptable assistance (Zawacki-Richter *et al*., 2019 [22]; Kasneci *et al*., 2023).

3.2 Displacement of responsibility

Table 5: Level of Moral Disengagement in Terms of Displacement of Responsibility

S. No	Statements	WM	Verbal Interpretation
1	In group math projects, AI use is shared, so no one is fully accountable.	2.40	Disagree
2	Everyone uses AI for math; individual fault is diluted.	2.47	Disagree
3	AI in math doesn't really harm learning; it builds familiarity with tools.	2.71	Agree
4	Detection is rare, so consequences are overstated.	2.57	Agree
5	Students who complain about AI users in math are just poor performers blaming others.	2.20	Disagree
6	Strict no-AI rules dehumanize math as rote, ignoring tech reality.	2.45	Disagree
7	AI decides the math solutions, so I have little personal control or blame.	2.44	Disagree
8	Mathematics tasks are mechanical; AI autonomy minimizes my ethical role.	2.51	Agree
	Grand Mean	**2.47**	**Disagree**

Table 5 presents the level of students' moral disengagement in terms of displacement of responsibility in the use of AI for mathematics tasks. The computed grand mean of 2.47, interpreted as "Disagree," indicates that, overall, students do not strongly endorse shifting responsibility for their academic actions to external agents such as AI systems, peers, or institutional conditions. This suggests a generally retained sense of personal accountability despite the increasing availability of AI tools. Students disagreed with statements implying shared or diminished accountability, such as the notion that AI use in group work diffuses responsibility (WM = 2.40) and that widespread AI usage reduces individual fault (WM = 2.47). Similarly, they rejected the idea that AI determines solutions to the extent that personal control or blame is minimized (WM = 2.44). These responses indicate that students largely recognize their active role in the learning process and do not fully attribute their academic outputs to the technology itself.

However, some items received agreement, reflecting nuanced perspectives. Students agreed that AI use does not necessarily harm learning and may even enhance familiarity with technological tools (WM = 2.71), and that concerns about detection may be overstated (WM = 2.57). They also showed moderate agreement with the idea that the mechanical nature of mathematics tasks may reduce their perceived ethical role when AI is involved (WM = 2.51). These findings suggest that while students maintain responsibility, they may simultaneously normalize AI use by downplaying its potential academic or ethical implications. Lower-rated statements further reinforce this pattern. Respondents disagreed that critics of AI use are merely underperforming students shifting blame (WM = 2.20) and that strict no-AI rules are inherently unrealistic or dehumanizing (WM = 2.45). This indicates that students do not strongly externalize blame onto others nor fully reject institutional regulations, reflecting a balanced, rather than extreme, stance on accountability.

The findings suggest limited engagement in displacement of responsibility as a mechanism of moral disengagement. According to social cognitive theory, displacement of responsibility occurs when individuals attribute their actions to external authorities or systems, thereby reducing personal accountability (Albert Bandura, 2016). In this case, students appear to resist fully attributing their academic behavior to AI, maintaining a sense of agency over their work. These results are consistent with emerging research in AI-integrated learning environments, which indicates that while students adopt AI tools for support, they often remain aware of their responsibility for learning outcomes and academic integrity (Olaf Zawacki-Richter *et al*., 2019 [22]; Enkelejda Kasneci *et al*., 2023).

4. Test of Significant Relationship between Students' AI-assisted tool usage frequency and levels of moral disengagement in mathematics tasks

Table 6: Test of Relationship between AI-assisted tool usage frequency and levels of moral disengagement in mathematics tasks

Correlations				
		Extent of use in mathematics tasks	Moral justification mechanisms	Displacement of responsibility
Extent of use in mathematics tasks	Pearson Correlation	1	.629**	.474**
	Sig. (2-tailed)		.000	.000
	N	209	209	209
Moral justification mechanisms	Pearson Correlation	.629**	1	.750**
	Sig. (2-tailed)	.000		.000
	N	209	209	209
**. Correlation is significant at the 0.01 level (2-tailed).				

The Pearson correlation analysis presented in Table 5 revealed statistically significant positive relationships between the extent of students' AI-assisted tool usage frequency in mathematics tasks and their endorsement of moral disengagement mechanisms, based on a sample of 209 respondents. Specifically, a strong positive correlation emerged between AI tool usage and moral justification mechanisms ($r = .629$, $p < .001$), indicating that students who reported higher frequencies of AI-assisted engagement in mathematical problem-solving were substantially more likely to rationalize such usage through mechanisms that reframe the behavior as ethically acceptable (e.g., viewing AI outputs as legitimate extensions of personal effort). A moderate positive correlation was likewise observed between AI usage frequency and displacement of responsibility ($r = .474$, $p < .001$), suggesting an association whereby frequent users tended to externalize accountability to the technology itself rather than assuming personal ownership of the learning process. Additionally, the two moral disengagement dimensions exhibited a strong intercorrelation ($r = .750$, $p < .001$), consistent with their theoretical interdependence within Bandura's social cognitive framework of moral disengagement.

These findings underscore the potential ethical tensions accompanying the integration of generative AI into mathematics education, wherein elevated tool usage frequency appears to co-occur with diminished internal moral regulation. In an era of rapid AI adoption, such patterns may reflect students' adaptive strategies for reconciling academic demands with evolving technological affordances, yet they also signal risks to academic integrity and authentic skill development. The results highlight the necessity for targeted pedagogical interventions—such as explicit ethical scaffolding, reflective prompts on AI attribution, and curriculum redesigns that emphasize process-oriented assessment—to mitigate moral disengagement while harnessing AI's pedagogical benefits.

5. Test of Significant Difference in AI-assisted tool usage frequency across socioeconomic groups

Table 7: Test of Difference in AI-assisted tool usage frequency when grouped according to sex

Independent Samples Test										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Extent of use in mathematics tasks	Equal variances assumed	.081	.777	.685	207	.494	.06005	.08760	-.11265	.23275
	Equal variances not assumed			.665	102.320	.508	.06005	.09035	-.11916	.23926

Table 7 shows the result of the independent samples t-test was conducted to examine whether significant differences existed in the extent of AI-assisted tool usage frequency in mathematics tasks between male and female students ($N = 209$). Levene's test for equality of variances indicated no violation of the homogeneity of variance assumption ($F = 0.081$, $p = .777$). Consequently, the equal variances assumed row was interpreted. Results revealed no statistically significant difference in the mean frequency of AI tool usage between the two sex groups, $t(207) = 0.685$, $p = .494$ (two-tailed). The mean difference was minimal (0.06005), with a 95% confidence interval ranging from −1.1265 to 2.3275, which includes zero and further confirms the lack of meaningful difference.

These findings suggest that male and female students in the sample engaged in AI-assisted mathematics tasks with comparable frequency. This absence of sex-based differences contrasts with some prior literature on technology adoption in education, where gender gaps in digital tool usage have occasionally been reported. The result implies that the integration of generative AI tools in mathematics learning may be relatively gender-neutral within this higher education context, potentially reflecting the widespread accessibility and perceived utility of such tools across demographic groups. However, the small mean difference and wide confidence interval warrant cautious interpretation, as they may also indicate limited statistical power or homogeneity in the sample's exposure to AI technologies.

Future studies should consider larger, more diverse samples and explore potential moderating variables such as academic major, year level, or prior AI familiarity to determine whether sex differences emerge under specific conditions. From a pedagogical perspective, the lack of gender disparity supports the development of inclusive AI integration strategies in mathematics education that do not require sex-specific tailoring, while still addressing the broader ethical concerns surrounding AI usage identified in related analyses of moral disengagement.

Table 8: Test of Difference in AI-assisted tool usage frequency when grouped according to household monthly income

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Extent of use in mathematics tasks	Between Groups	.291	2	.146	.443	.643
	Within Groups	67.810	207	.329		
	Total	68.101	209			

Table 8 shows the result of the one-way analysis of variance (ANOVA) performed to determine whether statistically significant differences existed in the frequency of AI-assisted tool usage in mathematics tasks across different household monthly income groups among the 209 student respondents. The analysis yielded a non-significant result, $F(2, 207) = 0.443$, $p = .643$. The between-groups sum of squares was 291 (mean square = 146), while the within-groups sum of squares was 67,810 (mean square = 329), resulting in a total sum of squares of 68,101. These findings indicate that students from varying household income levels reported comparable frequencies of AI tool engagement in their mathematics learning activities.

The absence of significant differences based on socioeconomic status (as proxied by household monthly income) suggests that the adoption of generative AI tools for mathematics tasks in this sample was not strongly stratified by economic background. This result is noteworthy in the context of the digital divide literature, which has historically documented disparities in technology access and utilization across income levels. The current findings may reflect the increasing democratization and affordability of AI-powered applications (many of which are freely available or low-cost), thereby reducing traditional socioeconomic barriers to their educational use.

Nevertheless, the relatively small between-groups variance and non-significant F-value should be interpreted cautiously. It is possible that the income categories used were too broad to capture nuanced differences or that other unmeasured factors—such as parental education, urban/rural residence, or institutional access to AI resources—play a more decisive role than monthly household income alone.

From an educational equity perspective, these results are encouraging as they imply that AI integration in mathematics education may not be exacerbating existing socioeconomic inequalities in tool usage within this population. However, to ensure responsible and inclusive implementation, institutions should continue monitoring access patterns and provide targeted support for students from lower-income households if subtle disparities emerge in larger or more diverse samples. Future research employing more granular income measures or mixed-methods designs could further clarify the relationship between socioeconomic factors and AI-assisted learning behaviors.

6. Test of Significant difference in Levels of moral disengagement across socioeconomic groups

Table 9: Test of Difference in Levels of moral disengagement when grouped according to sex

Independent Samples Test										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Moral justification mechanisms	Equal variances assumed	.138	.711	.107	207	.915	.00899	.08421	-.15703	.17501
	Equal variances not assumed			.103	101.069	.918	.00899	.08740	-.16438	.18236
Displacement of responsibility	Equal variances assumed	2.547	.112	.318	207	.751	.02679	.08426	-.13932	.19291
	Equal variances not assumed			.335	121.984	.739	.02679	.08009	-.13176	.18535

Table 9 shows the result of an independent samples t-test conducted to determine whether significant differences existed in two mechanisms of moral disengagement—moral justification and displacement of responsibility—between male and female students in a sample of 209 Filipino university respondents. Levene's test confirmed homogeneity of variances for both variables (Moral Justification: $F = 0.138$, $p = 0.711$; Displacement of Responsibility: $F = 2.547$, $p = 0.112$). Thus, results assuming equal variances are interpreted.

The analysis revealed no statistically significant sex differences in moral justification, $t(207) = 0.107$, $p = 0.915$ (two-tailed), with a negligible mean difference of 0.00899 (95% CI [−0.15703, 0.17501]). Likewise, no significant difference emerged for displacement of responsibility, $t(207) = 0.318$, $p = 0.751$ (two-tailed), with a mean difference of 0.02679 (95% CI [−0.13932, 0.19291]). The small effect sizes and confidence intervals straddling zero indicate virtual equivalence in these mechanisms across sexes.

These null findings diverge from much of the international literature, which consistently documents higher overall moral disengagement among males than females, particularly during adolescence and young adulthood (Gini *et al*., 2014; Thornberg, 2023; Tabares, 2024). Meta-analytic evidence has shown that males tend to endorse moral disengagement mechanisms more readily, including cognitive restructuring processes such as moral justification—reframing unethical acts as serving a higher purpose—and agency-related mechanisms like displacement of responsibility, whereby personal accountability is shifted to external authorities or circumstances (Gini *et al*., 2014; Bandura, 1999 [3]; Piccardi *et al*., 2023). Such patterns are frequently linked to elevated involvement in aggressive, bullying, or unethical behaviors among males (Killer *et al*., 2019; Martínez-Bacaicoa *et al*., 2024).

Several culturally and contextually grounded explanations may account for the observed equivalence in the present Philippine sample. In collectivist societies like the Philippines, where strong family-oriented values, religious (predominantly Catholic) socialization, and communal norms emphasize shared responsibility and empathy, traditional gender disparities in moral self-regulation may be attenuated (consistent with cross-cultural nuances noted in Luo, 2023). Moreover, the specific mechanisms examined here—moral justification and displacement of responsibility—may be less gender-differentiated than others (e.g., dehumanization or distortion of consequences), especially among university students whose educational experiences and exposure to egalitarian ideals could narrow gaps seen in younger or more heterogeneous samples (Thornberg, 2023; Tabares, 2024). Evolving gender roles in contemporary Philippine higher education, alongside widespread digital tool use (including AI-assisted academic tasks), may further homogenize moral cognition across sexes.

The results align with studies indicating that sex differences in moral disengagement are not invariant but are moderated by contextual factors such as age, educational level, cultural norms, and situational demands (Gini *et al*., 2014; Killer *et al*., 2019; Romera *et al*., 2021, as cited in Thornberg, 2023). Importantly, the absence of significant differences does not suggest negligible moral disengagement overall; rather, it implies that these two mechanisms function comparably for male and female students in everyday academic and social decision-making.

Table 10: Test of Difference in Levels of moral disengagement when grouped according to household monthly income

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Moral justification mechanisms	Between Groups	.074	2	.037	.121	.886
	Within Groups	62.719	207	.304		
	Total	62.793	209			
Displacement of responsibility	Between Groups	.028	2	.014	.047	.955
	Within Groups	62.863	207	.305		
	Total	62.891	209			

Table 10 shows the result of the one-way analysis of variance (ANOVA) conducted to examine whether levels of moral disengagement—specifically moral justification mechanisms and displacement of responsibility—differed significantly across household monthly income groups among the 209 student participants. For moral justification mechanisms, the results indicated no statistically significant differences between income groups, $F(2, 207) = 0.121$, $p = .886$. The between-groups sum of squares was minimal (0.074, mean square = 0.037), compared with the within-groups sum of squares of 62.719 (mean square = 0.304), yielding a total sum of squares of 62.793. Similarly, for displacement of responsibility, the analysis revealed a non-significant result, $F(2, 207) = 0.047$, $p = .955$, with between-groups sum of squares of 0.028 (mean square = 0.014) and within-groups sum of squares of 62.863 (mean square = 0.305), for a total of 62.891.

These non-significant findings suggest that students' tendencies to morally disengage when using AI-assisted tools in mathematics tasks do not vary meaningfully as a function of household monthly income. Both dimensions of moral disengagement—rationalizing AI use as acceptable and shifting accountability to the technology itself—appear to operate at comparable levels regardless of socioeconomic background in this sample. This homogeneity contrasts with some earlier studies on academic dishonesty that have linked lower socioeconomic status to higher moral disengagement due to perceived resource constraints or competitive pressures. The current results may indicate that the ethical challenges posed by generative AI in mathematics education transcend economic strata, possibly because AI tools have become widely accessible across income levels through free or low-cost platforms.

From a theoretical standpoint, the findings lend support to the notion that moral disengagement mechanisms in the context of AI-assisted learning may be more strongly driven by individual cognitive processes, peer norms, or institutional culture than by household income. Practically, the absence of income-based differences is encouraging for equity considerations, suggesting that interventions aimed at fostering ethical AI use (such as reflective assignments on authorship and responsibility) can be implemented uniformly without requiring socioeconomic targeting. Nonetheless, the extremely small between-groups variances highlight the need for caution in interpretation and call for replication with larger, more socioeconomically diverse samples or finer-grained income categorizations. Future research could also incorporate interaction effects with other demographic or psychological variables to provide a more nuanced understanding of the antecedents of moral disengagement in AI-supported academic tasks.

Conclusions

The study reveals that AI tool use in mathematics has become a regular, normalized practice among Filipino BSE-Mathematics students, with a grand mean of 2.53 indicating "often" frequency of use. Rather than replacing independent thought entirely, students primarily turn to AI for supplementary purposes — verifying answers, preparing for exams, and obtaining step-by-step explanations. The most common single behavior was using AI to check answers after attempting problems independently, suggesting that students generally preserve some degree of cognitive effort before delegating to technology. Nevertheless, the normalization of this pattern warrants attention, as routine reliance on AI for verification can gradually erode the productive struggle that is foundational to deep mathematical learning.

The most significant ethical concern emerging from the data is the endorsement of moral justification mechanisms, which yielded a grand mean of 2.55, interpreted as "Agree." Students tend to cognitively reframe their AI-assisted behavior as "enhanced learning" or "smart use of technology" rather than recognizing it as a potential breach of academic integrity. This form of rationalization allows students to maintain a positive moral self-image while engaging in ethically ambiguous academic practices. In contrast, students largely rejected displacement of responsibility — with a grand mean of 2.47, interpreted as "Disagree" — indicating that they do not strongly attribute their choices to AI systems, institutional ambiguity, or peer behavior. This retained sense of personal accountability is encouraging, though it coexists with the concerning tendency to normalize and justify AI dependence.

Perhaps the study's most consequential finding is the statistically significant positive relationship between AI use frequency and both dimensions of moral disengagement. The strong correlation with moral justification ($r = .629$, $p < .001$) and the moderate correlation with displacement of responsibility (r = .474, p < .001) point to a dose-response pattern: the more frequently students use AI, the more they rationalize doing so ethically. This dynamic poses a growing risk to academic integrity as AI tools become more capable and more embedded in everyday academic life.

Interestingly, neither sex nor socioeconomic status produced significant differences in either AI use frequency or moral disengagement levels. The absence of sex-based differences diverges from much of the international literature, which typically finds males more prone to moral disengagement, and may reflect the attenuating influence of collectivist and Catholic cultural values in the Philippine context. The absence of income-based differences, meanwhile, suggests that the widespread availability of free and low-cost AI platforms has effectively democratized access — but it also means that the ethical risks associated with AI use are distributed uniformly across socioeconomic groups rather than being concentrated in any particular stratum.

Recommendations

Educational institutions and policymakers should prioritize the development of clear, explicit AI use policies tailored to specific course types and assessment contexts. Because ambiguity in institutional rules is itself a driver of moral disengagement — giving students room to rationalize behavior when expectations are unclear — policies must go beyond general statements and define precisely what constitutes acceptable versus unacceptable AI assistance in homework, examinations, and collaborative projects. Alongside policy, institutions should embed digital ethics directly into mathematics curricula rather than treating academic integrity as a standalone module. Since moral justification is the dominant disengagement mechanism identified in this study, instruction should explicitly address what constitutes authentic intellectual effort and personal ownership of learning.

At the classroom level, teachers and instructors are encouraged to design AI-aware learning tasks that transform AI from a shortcut tool into a thinking partner. Assignments that require students to document their reasoning process, identify errors in AI-generated solutions, or explain the logic behind AI outputs make passive delegation far less viable and reward demonstrated understanding over mere final answers. Instructors should also incorporate brief reflective prompts — such as asking students to articulate what they contributed that AI could not — as these can meaningfully disrupt moral justification rationalizations and reinforce a sense of intellectual agency. Particular vigilance is warranted during high-pressure periods such as approaching deadlines or difficult units, which the data shows are precisely the moments when AI use spikes and ethical risk is highest.

For researchers, the findings point to several productive directions. Longitudinal designs are urgently needed to track how AI use habits and associated moral reasoning evolve as students advance through their programs and as AI tools grow more powerful. Future studies should also measure the full spectrum of Bandura's eight moral disengagement mechanisms rather than only the two examined here, as mechanisms such as dehumanization and distortion of consequences may manifest in distinct ways within AI-assisted academic contexts. Socioeconomic status, moreover, should be operationalized more granularly in future work — incorporating parental education, urban or rural residence, and digital literacy alongside household income — to capture the nuanced structural factors that a single income variable cannot adequately represent.

Finally, students themselves benefit from awareness of the pattern this study has identified: that more frequent AI use tends to co-occur with greater cognitive rationalization of that use, representing a gradual and often unnoticed erosion of ethical self-regulation. Building metacognitive habits — regularly questioning one's own justifications, reflecting on the depth of understanding gained, and distinguishing between AI as a learning aid versus a substitute for thinking — is the most direct pathway toward responsible and integrity-preserving integration of AI in academic life.

References

1. ALHatmi B, Abdullah S, AlGabshi B. Evaluating the role of ChatGPT in mathematics education: Impact on student performance, academic integrity, and perceptions in higher education. International Journal For Multidisciplinary Research. 2025; 7(5). Doi: https://doi.org/10.36948/ijfmr.2025.v07i05.56338
2. Alvarez JI. Evaluating the Impact of AI-Powered Tutors Mathgpt and Flexi 2.0 in Enhancing Calculus Learning. Jurnal Ilmiah Ilmu Terapan Universitas Jambi. 2024; 8(2):495-508. Doi: https://doi.org/10.22437/jiituj.v8i2.34809
3. Bandura A. Moral disengagement in the perpetration of inhumanities. Personality and Social Psychology Review. 1999; 3(3):193-209. Doi: https://doi.org/10.1207/s15327957pspr0303_3
4. Bartolo MG, Palermiti AL, Servidio R, Musso P, Costabile A. Mediating processes in the relations of parental monitoring and school climate with cyberbullying: The role of moral disengagement. Europe's Journal of Psychology. 2019; 15(3). Doi: https://doi.org/10.5964/ejop.v15i3.1742
5. Bravo PAP, Velazco DJM, Hinostroza EMF, *et al*. Critical and correlational analysis of the use of artificial intelligence among teachers and students in online early childhood education programmes: Ethical, educational and technological challenges. AI Education and Research, 2025. Doi: https://doi.org/10.56294/ai2025415
6. Cohen L, Manion L, Morrison K. Research methods in education (8th ed.). Routledge, 2018. Doi: https://doi.org/10.4324/9781315456539
7. Cohen J. A power primer. Psychological Bulletin. 1992; 112(1):155-159. Doi: https://doi.org/10.1037/0033-2909.112.1.155
8. Cohen L, Manion L, Morrison K. Research methods in education (8th ed.). Routledge, 2018. Doi: https://doi.org/10.4324/9781315456539
9. Creswell JW, Creswell JD. Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications, 2018.
10. Field A. Discovering statistics using IBM SPSS Statistics (5th ed.). SAGE Publications, 2018.
11. Fraenkel JR, Wallen NE, Hyun HH. How to design and evaluate research in education (10th ed.). McGraw-Hill Education, 2019.
12. Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis (8th ed.). Cengage Learning, 2019.

13. Hayes AF. Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (3rd ed.). Guilford Press, 2022.
14. Isave SG. A study of the use of artificial intelligence by student-teachers. E-methodology, 2024, 123-134. Doi: https://doi.org/10.15503/emet2023.123.134
15. Lockwood A, Brown J. Mitigating AI bias in school psychology: Toward equitable and ethical implementation. OSF Preprints, 2025. Doi: https://doi.org/10.31234/osf.io/mh4rj_v2
16. Mahama I, Amadu P. You are the driver and AI is the mate: Exploring human-led creative and critical thinking in AI-augmented learning environments. F1000Research, 2025. Doi: https://doi.org/10.12688/f1000research.167988.1
17. Maska L, Vlachopanou P, Kalamaras D, *et al*. Psychometric network analysis of AI constructs related to students' academic motivation and basic psychological needs in Higher Education. Research Square, 2025. Doi: https://doi.org/10.21203/rs.3.rs-7665675/v1
18. Meylani R, Kutluca T, Meylani R. AI-powered discourse in mathematics education in support of SDG 4: A systematic review of contemporary research literature. Discourse and Communication for Sustainable Education, 2025. Doi: https://doi.org/10.2478/dcse-2025-0014
19. Tejada JJ, Punzalan JRB. On the misuse of Slovin's formula. The Philippine Statistician. 2012; 61(1):129-136.
20. Wen D. The impact of AI on teachers' math teaching and students' learning from diverse socioeconomic status. International Journal of Elementary Education. 2025; 14(3). Doi: https://doi.org/10.11648/j.ijeedu.20251403.12
21. Wirzal MDH, Nordin NAHM, Halim NSA, *et al*. Generative AI in science education: A learning revolution or a threat to academic integrity? A bibliometric analysis. Jurnal Penelitian dan Pengkajian Ilmu Pendidikan: E-Saintika. 2024; 8(3). Doi: https://doi.org/10.36312/e-saintika.v8i3.2127
22. Zawacki-Richter O, Marín VI, Bond M, Gouverneur F. Systematic review of research on artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education. 2019; 16(1):39. Doi: https://doi.org/10.1186/s41239-019-0171-0