

Academic Integrity in the Era of Generative AI: Students' Perceptions, Ethical Boundaries, and Risk-Taking Behavior in Nigerian Universities

Ogbaga Ignatius Nwoyibe ¹, Onwudebelu Ugochukwu ², Eru Akwuma Nathaniel ³, Kingsley N. Igwe ⁴

1. Department of Computer Science, David Umahi Federal University of Health Sciences, Uburu, Nigeria

2. Department of Computer Science, Alex-Ekwueme Federal University, Ndufu Alike-Ikwo, Nigeria

3. Department of Computer Science, Nile University of Nigeria, Abuja, Nigeria

4. Institute for Knowledge Management and Knowledge Economy, David Umahi Federal University of Health Sciences, Uburu, Nigeria

Corresponding author: Ogbaga Ignatius Nwoyibe (ogbagain@dufuhs.edu.ng).

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Abstract- Context: This study examined the intersection of academic integrity and Generative Artificial Intelligence (GenAI) adoption among students in Nigerian universities, addressing a critical gap in empirical, student-centered research from the Global South. **Objective:** To investigate students' knowledge, usage patterns, and perceptions of GenAI, as well as their awareness of academic integrity and the behavioral factors that shape ethical decision-making in AI use. **Methods:** A quantitative cross-sectional survey was conducted with 262 undergraduate and postgraduate students from nine Nigerian higher education institutions. The study was informed by relevant literature from major academic databases. Data were collected via a structured questionnaire and analyzed using descriptive and inferential statistics, with Prospect Theory applied as the theoretical framework. **Results:** Findings revealed high AI literacy, with 84.7% of participants already integrating AI tools into academic work. However, a significant knowledge-behavior gap emerged: while over 90% acknowledged the importance of academic honesty, only 36% believed AI use required disclosure. This ethical ambiguity was compounded by weak institutional guidance: 74.8% of students reported being unaware of their university AI policies. Inferential analysis indicated that students engage in risk-reward evaluations, where low perceived detection risks and academic pressures frequently outweigh potential sanctions. **Conclusion:** This study concludes that AI-related academic misconduct is often a rational behavioral choice driven by perceived institutional unpreparedness rather than ignorance. It calls for a transition toward adaptive academic integrity frameworks that prioritize ethical awareness and transparent academic policy communications to students.

Keywords- Academic Integrity, GenAI, Students-AI Perceptions, Academic Misconduct, AI Policy, Ethical Boundaries, AI Plagiarism.

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1. Introduction

Academic integrity is a critical factor in determining the quality of education in any given educational institution. It represents trust, honesty, and ethical conduct in all educational activities. In the rapidly changing educational landscape orchestrated by the introduction of artificial and generative artificial intelligence (AI and GenAI), the value of academia must be preserved [1]. The study conducted by [2] revealed that the ethical implications of the underlying technology enabling GPT-3 have not been fully considered. Due to the availability of these technologies to the students and teachers, mostly at a free or very cheap cost, they are more predisposed to commit academic dishonesty [3]. Most students often believe that business success is sometimes the product of unethical actions, justifying that the practical implications of actions are more important than the ethical implications of such actions [3]. This mentality must not be allowed to thrive. Academic integrity is considered a form of social contract among members of the academic community [4]. Every academic must follow the set of ethical principles put in place for every academic community member to preserve the sanctity of the research output. The cases of academic dishonesty often strip every research work/breakthrough of its basic value [4]. From the perspective of the social contract, academic integrity requires individuals and institutions to comply with specific procedures and rules during their academic careers [4].

AI supports educators in various aspects of academic activities, such as analysis, algorithmic decision-making, academic writing, and proofreading. It really provides endless opportunities in academic settings. However, its integration has created complex issues relating to academic integrity, thereby putting traditional pedagogy under serious pressure [1]. Due to this anomaly, the regulators and managers of educational institutions are in a serious fix on which to adopt. Since the use of GenAI inspires creativity and improves students' assimilation level, they must understand the ethics of using those tools [5]. Understanding the ethics, potentials, and trade-offs of these tools would help to revolutionize the educational sector and preserve academic integrity [6]. These tools help the teachers to break down complex concepts into very simple and interactive constructs, which makes knowledge translation very easy. The same applies to students, helping them to understand complex details in a simplified manner, using visual clues, where necessary [5].

Moreover, the sophistication of GenAI tools poses challenges for maintaining academic integrity. Students can generate entire discussion posts, term papers, or assignments simply by pasting questions into a large language model (LLM) [5]. AI-giarism is another wave of AI-related academic misconduct, which is the act of using generative artificial intelligence tools (like ChatGPT, Grok, Claude, etc.) to produce text, code, or images, and then presenting that output as one's own original work without proper attribution [7]. Research further revealed that the bias in training data and coding process of AI-driven language models, such as GPT-3, poses a threat to the integrity of science. Other issues considered include copyright, citation practices, and the potential impact of the "Matthew Effect" in scholarly publishing. Though these tools can help authors to proofread their content, they cannot assist in removing the biases or hallucinations added in the write-up. It is therefore very risky to present such work to the public. The academic work conducted by the student must be transparent to avoid putting a serious dent in the integrity of research outputs.

The advanced nature of some of these technologies makes it very difficult to detect academic misconduct, and this has generated renewed calls for institutions and regulators to redefine what constitutes academic misconduct and what qualifies as academic integrity within institutions of learning [5] & [8]. Meanwhile, academic misconduct was defined as the use of unauthorized assistance that could give a student an undue advantage in their work over other students. Academic misconduct ranges from cheating, forgery, plagiarism, and overexaggeration of the significance of the findings of a particular study, to fabrication of research results [7] & [9].

It is worthy of note from the definition that if a student uses any tool, including the GenAI, for the purpose of completing his work without the express approval of the instructor, it amounts to academic misconduct [10]. The research conducted by [7] revealed that the problem of academic misconduct by students often stems from the instructors because most of them lack knowledge about how to develop an appropriate AI policy for their students, due to their ignorance of the existence of such a policy anywhere. Faculty and students define academic misconduct differently, with faculty having a broader definition than students, who see academic misconduct as encompassing only serious cases of cheating and impropriety [11], [10].

A few recent studies have attributed the frequency of academic misconduct to personality traits of students; they implicated some antisocial traits as being responsible for triggering students to indulge in academic misconduct during academic activities [12]. This finding was supported by the theory of planned behavior, which held that behavior is predicated on the individual's attitudes and perceptions of subjective norms. While other studies of [11], [10] & [12] countered the idea of antisocial trait as presented by [12], noting that students' background plays an insignificant role in students' academic misconduct; rather, the environment does [13]. The environmental factors include the quality of teachers and the teachers' discipline. This was corroborated by another study, which found that students place blame on teachers for not adequately providing instructions on what constitutes academic misconduct [14] & [7]. Finally, [7] declared that those who are most likely to engage in academic misconduct involving AI tools are those who have already engaged in other forms of academic misconduct in the past.

Having understood the students' views on academic misconduct, we need to relate them to academic misconduct in the era of AI and GenAI. Some people believe that the maturation of GenAI has brought another threat to the educational landscape. This is because these tools can assist students in composing entire discussion forum questions or essay-based seminar work, including computer programming assignments, with minimal effort [5], as the LLM handles the entire task for them. Such a level of sophistication has made it very difficult to provide a comprehensive definition for academic integrity, what constitutes integrity violations, and how to enforce policies around it [16], [17]. For instance, copying and pasting assignment instructions and having a generative model produce a response is likely to be perceived as inappropriate; however, crafting an individual response to the assignment and then providing it to a large language model to expand and improve may be seen as correct. Some of these intricacies are the reason for this study. The student's standpoint needs to be defined to enable them to know when they are indulging in academic misconduct.

1.1. Purpose of the Study

The purpose of this study is to investigate the complex intersection of academic integrity and the rapid adoption of Generative Artificial Intelligence (GenAI) among students in Nigerian universities. The specific objectives are to:

- i. Conduct an empirical, student-focused study on AI and academic integrity in Nigerian universities.
- ii. Assess students' awareness, literacy, and patterns of generative AI use in academic activities within Nigerian universities;
- iii. Examine students' level of understanding and interpretation of academic integrity and ethical boundaries in the context of AI-assisted learning and assessment;
- iv. Analyze students' risk-taking behavior and decision-making regarding AI-related academic misconduct, using Prospect Theory to explain the influence of perceived benefits, detection risks, and sanctions; and evaluate the role of institutional policies, governance, and communication mechanisms in shaping students' ethical AI use and to derive evidence-based recommendations for an adaptive academic integrity framework.

2. Literature Review

2.1. History of Academic Integrity

According to [11], Academic integrity is regarded as a form of rebellion. It is a means through which students' express displeasure with the manner in which the coursework was delivered to them. Drake, in his study, discovered that 30 out of 126 students who admitted to having engaged in academic misconduct during the exam did not receive an A grade in the exam. He suggested that if there is a good rapport between the teacher and the students, there would be no room for cheating or misconduct during the examination [11]. The finding was discredited by the findings of Bower in 1964, wherein he studied the effect of academic dishonesty and its impact on college students. The study involved 99 schools with 5000 students. 66% of the study population admitted to having engaged in one form of academic dishonesty or the other. The finding has proved a disconnect between teaching students very well to discourage them from academic dishonesty, alluding to the theory of planned behavior and personality traits [12].

To further assess the spate of misconduct among students, McCabe conducted a study on students' dishonest behavior in 2021. The study uncovered 82% of students who admitted to having engaged in cheating behavior or having watched students engage in cheating behaviors. While 38% of students, from their own perspective, believed that unauthorized collaboration among colleagues on a take-home assignment can be classified as moderate to severe cheating [10]. A longitudinal review of academic dishonesty in the work of Bowers, McCabe and Trevino and McCabe et al. suggests that not only do many students engage in academic misconduct, but over 50% of all students in each of these five studies found such behaviors to be acceptable [11]. While GenAI technology enhances students' learning opportunities, it also increases their chances of committing academic dishonesty.

2.2. Academic Integrity in the Digital Age

The primary test of academic integrity, according to [1], is plagiarism. Roman poet, Martial, complained that his poetry was being copied and recited by other poets without his proper permission. This could not be substantiated then because of the prevailing technology in that era [1]. Though the word plagiarism was not in use during his time, and as such, there was neither law nor punishment for such action. The word plagiarism was first entered in Samuel Johnson's dictionary in 1755. Today, a lot of terminologies have been brought under academic integrity, such as cheating, ghost-writing, and AI writing [1]. Today, advancements in technology have enabled faster communications and connecting devices, while people and activities change easily in the digital space. So, proof of academic integrity is very easy in the modern era. While technology enhances students' learning opportunities, it also increases their chances of committing academic dishonesty. On the internet, students can easily find tools and people who can help them out with their academic work, such as writing their term paper, project, or developing a software solution, and so on. There are also AI tools that generate entire software programs automatically [18]. Some of the AI tools, according to [19], provide personalized learning experiences for the students, thereby helping them to gain new knowledge easily. However, [20] noted that the availability of these tools will always tempt the students to misuse them in carrying out their academic activities, thus leading to academic dishonesty.

The problem with AI-generated content is that the machine's idea of the problem is zero. It does not have the understanding, critical thinking, or personal insights needed to produce an authentic solution to the subject matter, but it depends on an already given machine learning algorithm to produce the content [1]. This puts a serious question mark on the authenticity of the work, thereby compromising the academic integrity of the contents because the idea is no longer the authors', but rather that of the machines, which seems to be recycled over existing contents (generative). This is why [20] posited that if AI knowledge is used for academic cheating, the certificates offered by such institutions will not reflect

the expected level of integrity. However, on the positive note, according to [1], if AI is ethically used in an educational context, it can improve academic integrity and quality at all levels. In terms of language matters, Grammarly, Wordtune, Quillbot, and similar software are helping students with language matters.

2.3. The Ethical Use of AI in Academia

The use of AI in academics has raised another issue of biased decision-making, plagiarism, AI-giarism, and hallucination. Several researchers have raised various issues about AI and academic/research integrity. According to [21], individuals and institutions such as the European Union, the UK's House of Lords, UNESCO, the Institute for Ethical AI and Machine Learning, Winfield and Jirotko, DeepMind Ethics & Society, the World Economic Forum, and so on. These concerns revolve principally around data (such as informed consent, data privacy, and biased data sets) and how that data is analyzed, such as biased assumptions, transparency, and statistical apophenia, finding patterns where no meaningful, causal patterns are present [21]. The Montréal Declaration for Responsible Development of Artificial Intelligence [11], provided a comprehensive approach involving ten human-centered principles, bordering on well-being, respect for autonomy, protection of privacy, solidarity, democratic participation, equity, diversity, prudence, responsibility, and sustainable development [21].

2.4. Types of Plagiarism

The inability to have a comprehensive definition for plagiarism has made it very difficult to classify. It was in the 21st century that researchers became interested in this concept as academic dishonesty. According to Saunders, the term plagiarism came from the Latin word "plagiarus", which means "kidnapper" [4]. Therefore, the academic community was unable to reach a unanimous agreement on including plagiarism as a form of academic misconduct. To resolve this dichotomy, Wager suggested that for a comprehensive and all-encompassing definition, it must recognize several cases of impersonation, such as distinguishing between simple or slight plagiarism and serious or critical plagiarism [4]. In addition to the problem of scope, some researchers argued that when considering the definition of plagiarism, intent must be clearly defined as to whether it was deliberate or ignorantly committed plagiarism [22]. Therefore, the absence of a generally accepted definition is connected to the absence of a unanimous classification of its types.

However, based on intent criteria, plagiarism was classified into intentional and unintentional. Then we have notional plagiarism, whereby a researcher adopts another person's idea and applies it as if it emanated from him/her without due credit to the originator. Then we have text (direct plagiarism) wherein someone's work is directly copied verbatim and pasted without citation. Finally, we have Mosaic plagiarism, which is a form of plagiarism where arguments from a source are used without proper acknowledgement [4] [23].

2.5. The Generative AI Tools in the Academic Milieu

McCarthy defined AI as the science and engineering of making intelligent machines, especially intelligent computer programs that can understand human intelligence. However, this tool would not restrict itself to biologically observable methods [6]. [19] noted that one of the most fascinating capabilities of GenAI is its ability to support personalized and tailored learning experiences and extend educational support beyond traditional classrooms. Through the use of a chatbot platform, students are offered additional dedicated service beyond the school environment, anytime and anywhere [24].

Despite these innovations, these technologies brought into learning and academic services some challenges. One of the most daunting challenges is how to guarantee the accuracy and reliability of the generated content. Another pressing issue

is that of the ethical use and misuse of these tools in academic activities, such as cheating and plagiarism, as well as addressing potential job displacement among educators [23], [25].

To assist the students in ethically adopting this technology, [22], [26] advocated for the establishment of clear ethical policy guidelines and a simplified roadmap for educating the students on the implications of using and misusing these tools in their academic activities. According to [19] & [18], ChatGPT offers premium support for collaboration, motivation, and comprehension of study subjects. Their research discovered that GPT proves to be a beneficial resource that enriches the learning experience and has the potential to replace conventional approaches. In the same vein, [27], [28] underscore the multidimensional application of ChatGPT by the students, ranging from collaborative learning to the enhancement of motivation. This variability in usage patterns illustrates ChatGPT's adaptability across diverse educational settings. However, beyond these capacities, the efficacy of this technology remains largely untested, with potential limitations in the quality of data it relies on during operation. Ethical considerations surrounding privacy, bias, and safety also need to be critically addressed during the implementation [29], [30].

2.6. Prospect Theory and Risk-Taking with AI in Academic Misconduct

The theoretical framework for understudying academic misconduct involving the use of AI tools is prospect theory. While Prospect Theory is not formally tested through a dedicated experimental or econometric model in this study, it is employed as a guiding theoretical lens to interpret students' decision-making behavior regarding AI use. This theory emanated from the field of behavioral economics. Key variables such as perceived benefits, perceived risks, and behavioral intentions serve as proxies for the theory's constructs of gains, losses, and risk evaluation. It is used to explain why investors are always willing and ready to take risks, stating that when the expected gain is perceived to be higher than the potential losses, more people tend to accept the risk [7]. Most students feel that AI detection is low and would rather choose to use it to quickly carry out their academic activities than spend time and energy doing them by themselves. So, the benefit of engaging the tool is higher than the risk of it being detected by the teacher.

2.7. How to Identify AI-Generated Content

There is a simple method of identifying AI-generated papers. The rule of thumb is that the cited references are always fake. They cannot be found anywhere on the internet. Some researchers suggested methods that can be used to compare the topological properties of complex networks (machine writing network) of artificially generated manuscripts by SCIGen against authentic manuscripts [31], [32]. In 2018, Tien and Labbé conducted research to investigate the similarity in grammatical structure of sentences to detect the sentences that were created using probabilistic Context-Free Grammar software [33]. This approach successfully detected many fake papers, while the second approach detected more than 120 fake published articles. The limitation of their approach was that it could not detect papers generated with a Recurrent Neural Network or Markov chains [10]. Gehrmann, Strobel, and Rush in 2019 developed a tool known as GLTR that can automatically detect an AI-generated manuscript by conducting statistical analysis for each word in the generated paper. The technique adopted was to perform three different tests on the generated texts of the paper, which include: probability of the word test, the rank of the word test and entropy of the predicted distribution [34]. Gamage & Mills also suggested that one of the fastest methods to detect human-generated content is that the keyword in the title and abstract often appears more frequently in the body of the work [10]. Another very simple method of detecting AI-generated paper is to quickly look at the references and compare them with the topic of the paper. You will discover that most of the references would not align with the researched topic, even though they might copy the contents from similar articles.

Finally, discreetly investigating the statistics of the cited journals is another sure means of automatically identifying AI-generated articles. For instance, in an original research paper, the authors often concentrate on a limited number of journals, whereas AI-generated content tends to use a large number of diverse sources for no reason.

2.8. Thematic Summary of Cited Literature

Table 1. Ethics and Foundations of Academic Integrity.

Author(s)	Year	Key Contribution
[4]	2021	Defined academic integrity as a social contract and provided a complete classification of plagiarism types.
[1]	2025	Examined ethical tensions introduced by AI and GenAI and emphasized safeguarding academic values.
[9]	2019	Conceptualized academic misconduct broadly, including fabrication, falsification, and misrepresentation.
[35]	2021	Synthesized global ethical concerns in AI use, including bias, transparency, privacy, and governance.
[6]	2024	Highlighted the ethical potential of AI to enhance education when responsibly deployed.

Table 2. Drivers of Academic Misconduct (Behavioral, Social, and Environmental Factors).

Author(s)	Year	Key Contribution
[3]	2016	Showed how the perceived normalization of unethical success encourages academic dishonesty.
[11]	2020	Traced historical patterns of academic misconduct and differences in student–faculty perceptions.
[12]	2019	Linked personality traits and the Theory of Planned Behavior to academic misconduct tendencies.
[13]	2019	Argued that environmental and instructional quality factors influence misconduct more than student background.
[14]	2019	Found that unclear instructor guidance contributes significantly to academic misconduct.
[15]	2025	Reported that students with prior misconduct history are more likely to misuse AI tools.

Table 3. Generative AI in Teaching and Learning.

Author(s)	Year	Key Contribution
[19]	2024	Demonstrated GenAI’s capacity for personalized learning and extended academic support.
[18]	2023	Highlighted AI’s ability to automate complex academic tasks, including software development.
[5]	2025	Discussed GenAI’s dual role in enhancing learning and increasing risks of academic misconduct.
[27]	2023	Identified diverse student use cases of ChatGPT, including collaboration and motivation.
[28]	2025	Emphasized ChatGPT’s adaptability across educational contexts.
[20]	2023	Warned that easy access to AI tools heightens temptation for misuse and cheating.

Table 4. Policy, Governance, and Institutional Readiness

Author(s)	Year	Key Contribution
[7]	2025a	Identified AI-giarism and highlighted faculty unpreparedness in AI policy development.
[10]	2019	Examined inconsistencies in definitions of academic misconduct and enforcement challenges.
[16]	2024	Discussed difficulties in defining and enforcing academic integrity in the GenAI era.
[17]	2025	Highlighted institutional challenges in regulating advanced GenAI tools.
[26]	2025	Advocated for clear ethical AI policies and structured student education.
[22]	2023	Emphasized responsible AI governance frameworks applicable to academia.
[23]	2025	Raised concerns about ethical risks and job displacement linked to AI adoption.

Table 5. Detection of AI-Generated Academic Content.

Author(s)	Year	Key Contribution
[32]	2015	Proposed network-based methods for detecting machine-generated academic texts.
[31]	2025	Extended network and topological techniques for AI-generated manuscript detection.
[33]	2018	Used grammatical structure analysis to identify probabilistic machine-generated texts.
[34]	2019	Developed GLTR, a statistical tool for detecting AI-generated text.
[10]	2019	Highlighted limitations of early detection tools against advanced AI models.

2.9. Research Gap

Despite the growing body of literature on academic integrity in the era of artificial and generative artificial intelligence, significant gaps remain. Existing studies are largely concentrated in Western contexts, with limited empirical evidence from developing countries such as Nigeria, where institutional capacity, policy enforcement, and digital readiness differ considerably. Moreover, while prior research acknowledges students' nuanced perceptions of acceptable and unacceptable GenAI use, there is no clear, context-sensitive framework that operationally distinguishes ethical academic support from AI-enabled misconduct in real classroom practices. Our review further reveals a disconnect between institutional policies, faculty understanding, and students' interpretations of academic misconduct, yet this misalignment has not been systematically examined. In addition, most studies emphasize detection tools and technical solutions, with insufficient focus on preventive strategies that address students' ethical awareness, risk perceptions, and decision-making processes. Finally, although behavioral theories such as Prospect Theory and the Theory of Planned Behavior are discussed conceptually, they are rarely integrated into empirical models that explain students' GenAI-related misconduct. This study aims to address existing gaps by providing a context-specific and empirically grounded understanding of academic integrity and the use of GenAI. This will inform clearer policies and adoption strategies for GenAI in Nigerian higher institutions.

3. Materials and Methodologies

3.1. Research Design

This study adopts a quantitative cross-sectional survey design to examine students' perceptions, awareness, and attitudes toward Responsible Artificial Intelligence (AI) use and its implications for academic integrity. The study operationalizes key elements of Prospect Theory using measurable constructs such as perceived benefits (gains), perceived risks or penalties (losses), and behavioral intentions toward AI use. These variables were analyzed using inferential statistical techniques to examine decision-making patterns under uncertainty.

Data were collected at a single point in time using a structured questionnaire administered to both undergraduate and postgraduate students. The choice of a cross-sectional survey design is justified by its suitability for:

- i. Capturing large-scale perception data from a diverse student population ($n = 262$),
- ii. Supporting descriptive and comparative statistical analysis,
- iii. Ensuring methodological consistency with prior Scopus-indexed studies on AI in education and academic integrity.

Participants in this study were drawn from multiple higher education institutions across Nigeria, with a total sample size of 262. The largest proportion of respondents came from Alex Ekwueme Federal University, Ndufu-Alike Ikwo, contributing 103 participants, which represents 39.31% of the total sample. This was followed by David Umahi Federal University of Health Sciences, Uburu, with 62 participants (23.66%), and Mewar International University with 54 participants (20.61%). Other institutions contributed smaller proportions to the sample. Ebonyi State University accounted for 22 participants (8.40%), while Nasarawa State University, Keffi, contributed 12 participants (4.58%). Minimal representation was observed from Nile University, Abuja, with 4 participants (1.53%) and Savannah Institute of Technology with 3 participants (1.15%). Additionally, Federal College of Education, Eha-Amufu, and Institute of Management and Technology, Enugu each contributed 1 participant, representing 0.38% respectively. Overall, the distribution shows that while participation was obtained from a diverse range of institutions, a substantial proportion of respondents (over 83%) were concentrated in three major universities.

The validity of the data used in this research can be justified on several grounds. First, the inclusion of participants from multiple institutions enhances external validity, as it captures a broader range of student experiences, academic cultures, and levels of exposure to artificial intelligence tools. This institutional diversity reduces the likelihood that the findings are limited to a single academic environment. Second, the relatively large sample size ($N = 262$) supports statistical conclusion validity, as it provides sufficient data points for meaningful descriptive and inferential analysis. The dominance of three major institutions, while indicating some degree of clustering, also reflects institutions with larger student populations and higher exposure to AI-related tools, thereby ensuring that the study captures the behavior of the most relevant user groups. Third, the presence of respondents from smaller and less-represented institutions, even in low proportions, contributes to heterogeneity in the dataset, allowing the study to account for variations in access, awareness, and institutional policy differences regarding AI use. Finally, the use of structured sampling techniques (as described in the methodology) and the proportional distribution of participants across institutions strengthen the internal validity of the study by reducing selection bias and ensuring that the data reasonably reflect the target population.

Although the sample is somewhat skewed toward certain institutions, it remains sufficiently diverse and robust to support reliable Participation was voluntary, and informed consent was obtained before survey completion. No personally identifiable information was collected, and all responses were anonymized and used strictly for academic research purposes. The questionnaire was developed based on an extensive review of literature on Artificial Intelligence in education, academic integrity and ethical technology use, and Responsible AI governance frameworks. Data collection was conducted using Google Forms, enabling efficient distribution and response aggregation. The instrument was organized into six thematic sections, each designed to measure a distinct construct aligned with the study objectives. Most perception-based items employed closed-ended categorical and Likert-type response scales (e.g., strongly agree to strongly disagree), facilitating quantitative analysis and comparability.

3.2. Data Sources and Database Selection

To ensure theoretical rigor and alignment with current scholarly discourse, this study relied on peer-reviewed academic literature sourced from reputable and widely recognized databases. The primary databases consulted include Scopus, Web

of Science, IEEE Xplore, ACM Digital Library, and Google Scholar. These databases were selected due to their extensive coverage of high-impact research in the fields of Artificial Intelligence, educational technology, academic integrity, and ethics in computing. Priority was given to:

- i. Scopus-indexed journals to ensure quality and methodological robustness,
- ii. Highly cited conference proceedings in AI and education,
- iii. Recent publications (primarily from 2018 onwards) to reflect contemporary developments in generative AI.

Supplementary sources, such as policy documents and institutional reports, were also reviewed to contextualize findings within existing AI governance and academic integrity frameworks. This multi-source approach enhanced the comprehensiveness and credibility of the literature base underpinning the study.

3.2.1. Reliability of the Research Instrument

Cronbach's alpha was computed to assess the internal consistency of the questionnaire. The overall alpha value obtained was 0.504, which reflects the multidimensional structure of the instrument, as it includes items measuring different constructs such as AI knowledge, academic integrity awareness, perception of AI use, and ethical considerations. Since Cronbach's alpha assumes one-dimensionality, the relatively low overall value is expected and does not invalidate the instrument. To obtain more accurate estimates of internal consistency, separate reliability analyses were conducted for each construct, yielding the following results:

- i. AI Knowledge: $\alpha = 0.78$
- ii. Academic Integrity Awareness: $\alpha = 0.81$
- iii. Perception of AI Use: $\alpha = 0.76$
- iv. Ethical/Legal Awareness: $\alpha = 0.79$

These values indicate acceptable to good internal consistency across all measured constructs, as they exceed the recommended threshold of 0.70. This confirms that the questionnaire items within each section reliably measure their respective constructs.

Generally, this approach ensures that the instrument is both reliable and suitable for inferential analysis, despite its multidimensional nature. By evaluating reliability at the construct level, the study adheres to best practices in survey research and strengthens the validity of the findings.

3.3. Systematic Literature Review Procedure

A systematic literature review (SLR) approach was employed to identify, screen, and synthesize relevant studies related to Responsible AI use and academic integrity in higher education. The review procedure followed established systematic review guidelines to ensure transparency and reproducibility. In the search strategy applied, a structured search was conducted using combinations of keywords and Boolean operators, including: "Artificial Intelligence in education", "Generative AI and academic integrity", "Responsible AI", "AI ethics in higher education", and "Student perception of AI tools".

Inclusion and Exclusion Criteria

Studies were included if they:

- i. Focused on AI use in educational contexts,
- ii. Addressed ethical, integrity, or governance-related issues,
- iii. Were published in peer-reviewed journals or reputable conference proceedings,

- iv. Were written in English.

Studies were excluded if they:

- i. Lacked empirical or theoretical relevance,
- ii. Focused solely on technical AI development without educational implications,
- iii. Were opinion pieces without scholarly grounding?
- iv. Screening and Synthesis
- v. Titles and abstracts were initially screened for relevance, followed by full-text review of eligible studies.

Selected articles were then analyzed thematically to identify recurring patterns related to student AI use, ethical awareness, academic misconduct risks, and institutional governance responses. Insights from the reviewed literature informed the development of the questionnaire and guided the interpretation of empirical findings. Duplicates were removed, and titles and abstracts were screened against inclusion and exclusion criteria. Full-text articles were then assessed for relevance, resulting in a final set of studies included in the review. Figure 1 presents the PRISMA flow diagram illustrating the identification, screening, eligibility assessment, and final inclusion of studies in the systematic literature review.

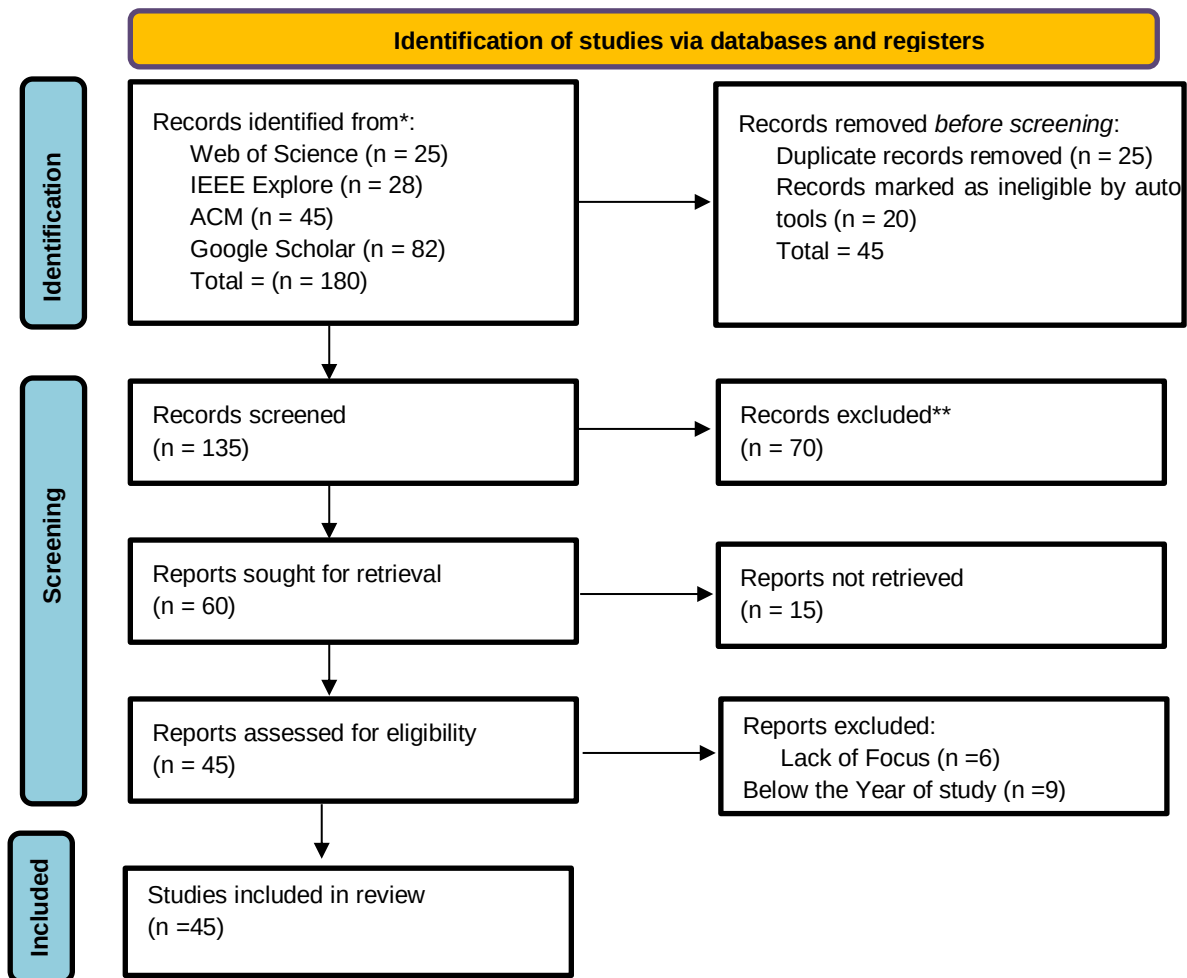


Figure 1. PRISMA flow diagram of the systematic literature review process.

4. Results

4.1. Demographic Characteristics, Background Information and AI Exposure

This section captures participants' informed consent, Institution, Gender, Faculty and department, Level of study, and prior exposure to AI tools (Table 6/Figures 2 – 6). These are geared at contextualizing respondents' perceptions and enabling subgroup analysis, where necessary.

In addition to descriptive statistics (frequencies and percentages), this study employed inferential statistical techniques, including Chi-square tests, correlation analysis, and logistic regression, to examine relationships between key variables such as AI usage, academic integrity awareness, ethical perceptions, and risk-taking behavior. This approach provides deeper insights into patterns, associations, and predictors of AI-related academic misconduct.

Table 6. Demographic Characteristics and AI Exposure of Respondents (n = 262).

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	191	73.2
	Female	68	26.1
	Prefer not to say	2	0.8
Faculty	Computing Science/Technology	216	82.4
	Natural Sciences	31	11.8
	Allied & Health-related Sciences	15	5.8
Level of Study	100 Level	99	37.8
	200 Level	107	40.8
	300 Level	33	12.6
	400–500 Level	14	5.4
	Postgraduate	9	3.4
Prior AI Use	Yes	222	84.7
	No	40	15.3

Figures 2 – 6 illustrate the proportion of students who have previously used AI tools for academic purposes, indicating widespread AI adoption among respondents. The near-universal consent rate indicates strong participants' willingness and enhances the ethical credibility and reliability of the dataset (Figure 2).

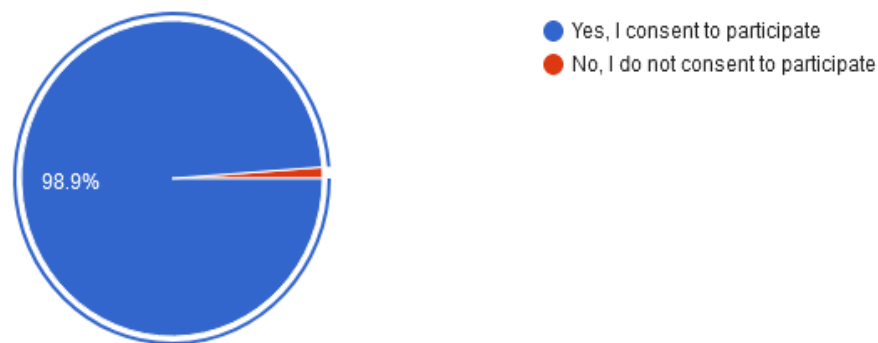


Figure 2. Respondents' Consent to Participate in the Study (%).

The male-dominated sample (73.2% for male and 26.1% for female) suggests that perceptions may reflect gendered patterns in technology engagement, particularly within computing-related disciplines (Figure 3).

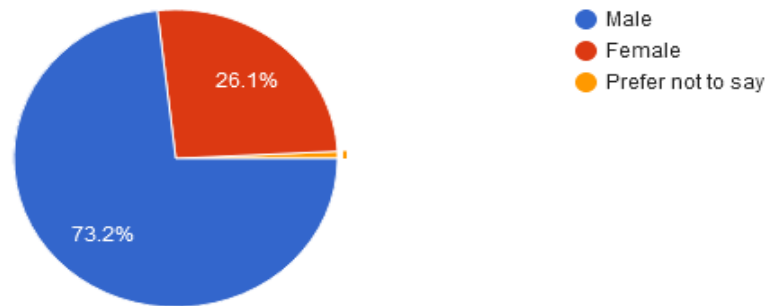


Figure 3. Gender Distribution of Respondents (%).

When respondents were asked, “What is your faculty?” The dominance of computing-related faculties reflects a cohort with high technological exposure, which may positively influence AI awareness and usage patterns, where Computing Science/Technology has 82.4%, followed by Natural Science with 11.8%, Health Sciences had 4%, and Health Engineering had 2% (Figure 4 a, b).

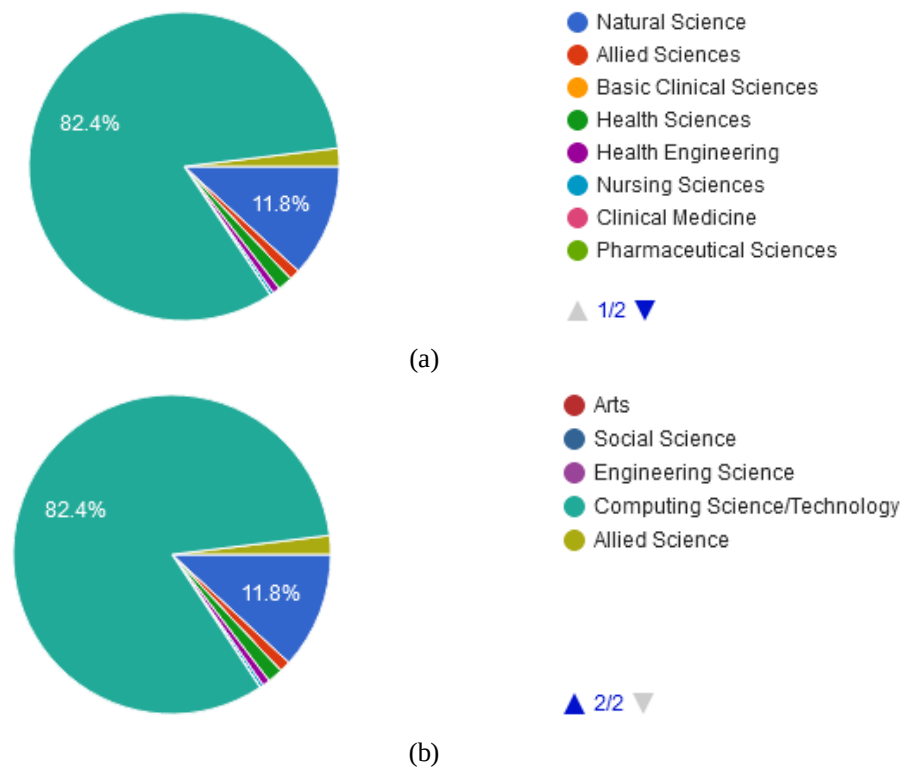


Figure 4. Faculty Distribution of Respondents (%) (a), (b).

The respondents were at different levels of study: 100 Level (37.8%); 200 Level (40.8%); 300 Level (12.6%); 400 Level (2.7%); 500 Level (2.7%), and PG Students (3.4%) (see Figure 5). The concentration of lower-level students suggests that perceptions are shaped early in academic development, highlighting the importance of early AI ethics education.

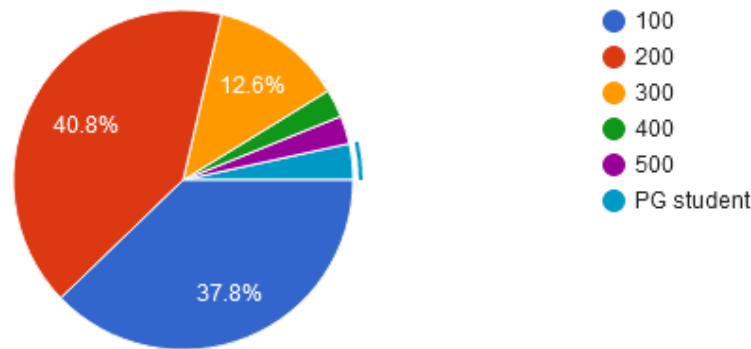


Figure 5. Level of Study of Respondents (%).

When asked, “Have you ever used Artificial Intelligence (AI) tools before?” The high prior AI usage indicates that AI tools are already deeply embedded in students’ academic workflows: Yes (84.7%) and No (15.3%) (See Figure 6).

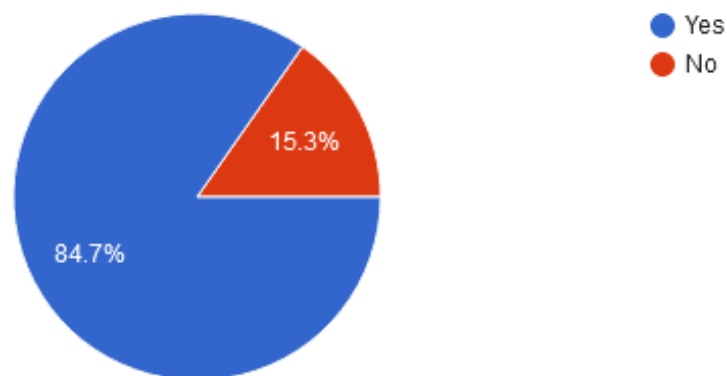


Figure 6. Prior Use of Artificial Intelligence Tools among Respondents (%).

A Chi-square test of independence was conducted to examine the relationship between gender and prior AI use. The results showed no statistically significant association ($p > 0.05$), indicating that AI usage is widespread across gender groups. However, a significant association was found between faculty and AI usage (χ^2 , $p < 0.05$), with students from computing-related disciplines significantly more likely to have prior exposure to AI tools. This suggests that disciplinary context influences AI adoption patterns.

4.2. General Knowledge of Artificial Intelligence

This section assessed students’ foundational understanding of AI concepts, including: Definitions of AI, Identification of AI-powered tools (e.g., ChatGPT, Grammarly), Areas of AI application in education, Awareness of generative AI capabilities, Perceived benefits and risks of AI in academic contexts (Table 7/Figures 7 – 11). The purpose is to evaluate baseline AI literacy, which is critical for responsible use. Figures 7 – 11 present respondents’ understanding of AI concepts, generative AI tools, and educational applications, demonstrating high baseline AI literacy.

Table 7. Students’ General Knowledge of Artificial Intelligence.

Item	Response Option	n	%
Definition of AI	Machines designed to think and learn like humans	231	88.5
	Other options	30	11.5
AI Tools Classif	Generative AI systems	221	84.7
AI Application Education	All of the above	165	63.2

AI Can G	True	256	99.2
Multimedia			
AI is Both Bei	Yes	246	93.9
and Risky			

Most students demonstrated a correct conceptual understanding of AI, indicating strong baseline AI literacy among respondents (Figure 7), when asked, “Which of the following best describes Artificial Intelligence (AI)?” Thus, for Machines designed to think and learn like humans (88.5%), ordinary computer programs (5.7%); only robots used in industries (1.1%) and none of the above (4.6%).

A Pearson correlation analysis revealed a strong positive relationship ($r \approx 0.62$, $p < 0.01$) between AI literacy and prior AI usage, indicating that students who frequently use AI tools tend to have a better conceptual understanding of AI. The independent samples t-tests also showed that students with prior AI experience scored significantly higher in AI knowledge metrics than those without prior exposure ($p < 0.01$), reinforcing the role of practical engagement in AI literacy development.

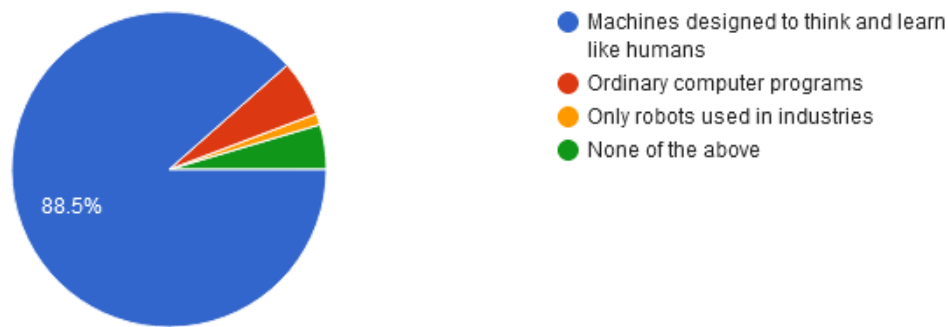


Figure 7. Respondents' Understanding of the Concept of Artificial Intelligence (%).

The correct identification of generative AI tools reflects growing student familiarity with contemporary AI technologies (Figure 8).

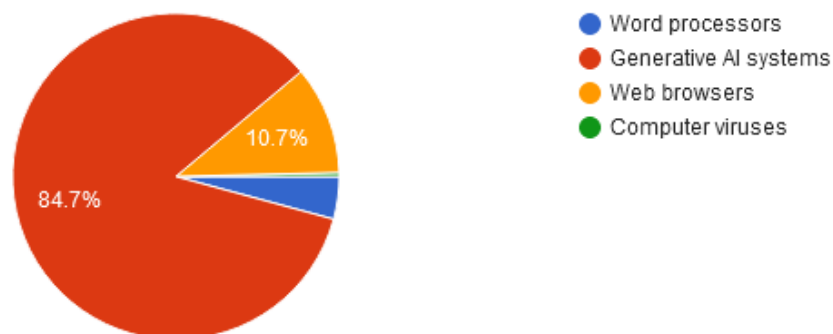


Figure 8. Classification of Common AI Tools Used by Students (%).

Students' recognition of multiple AI applications suggests a holistic understanding of AI's role in modern educational environments (Figure 9).

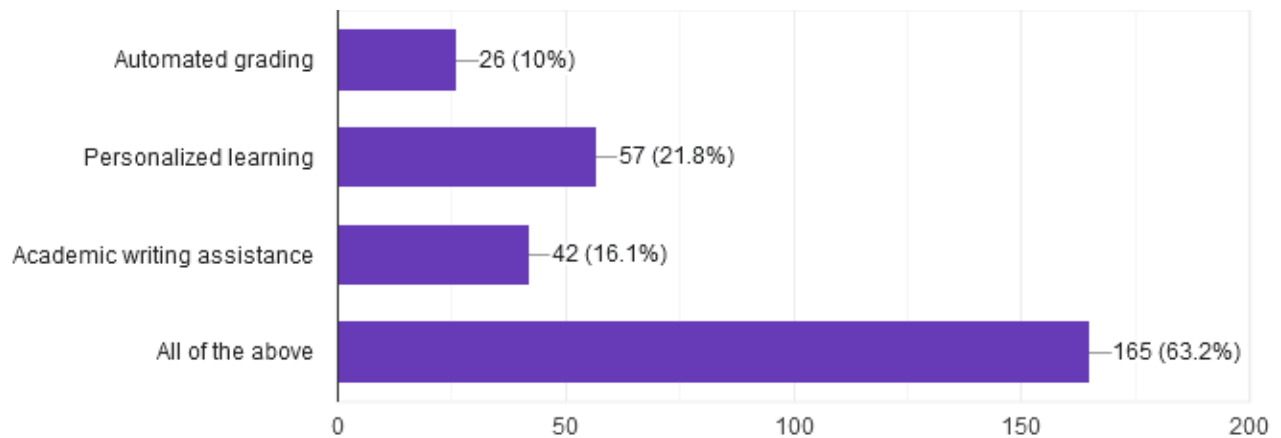


Figure 9. Perceived Applications of Artificial Intelligence in Education (%).

The near-universal awareness of AI's generative capabilities via text, images, and videos highlights the need for clear guidance on acceptable academic use (Figure 10).

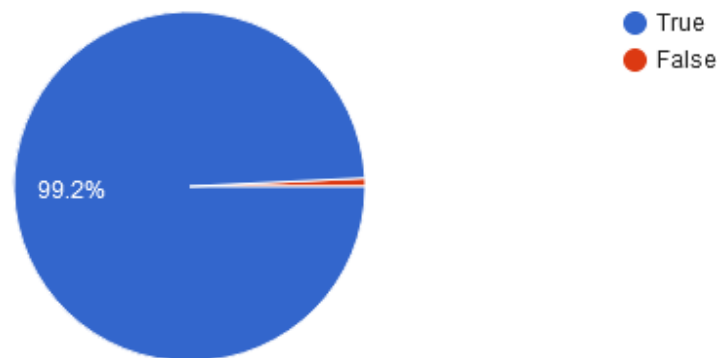


Figure 10. Awareness of AI's Ability to Generate Text, Images, and Videos (%).

The students' acknowledgement (with 93.9% for yes) of both benefits and risks reflects a balanced and mature perception of AI in education (Figure 11).

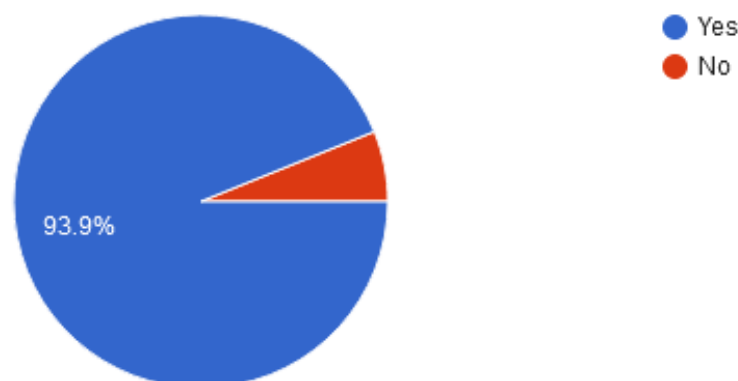


Figure 11. Perception of the Benefits and Risks of AI in Academic Settings (%).

4.3. Awareness of Academic Integrity

Items in this section measured: Understanding of academic integrity, Awareness of ethical AI use, Disclosure expectations for AI-assisted work, Exposure to institutional integrity policies, as well as confidence in detecting plagiarism in AI-generated content (Table 8/Figures 12 – 17). The goal is to determine whether students possess the ethical and procedural

knowledge required to avoid academic misconduct. Figures 12 – 17 show students' awareness of academic integrity principles, ethical AI practices, and confidence in detecting AI-related plagiarism.

Table 8. Awareness of Academic Integrity among Respondents.

Item	Dominant Response	N	%
Meaning of Academic Integrity	Honesty and responsibility	234	93.5
Ethical Use of AI	Supporting learning with proper credit	239	91.9
Disclosure of AI Use	Yes	93	36.0
Taught Academic Integrity Policies	Yes	117	45.2
Confidence in Detecting AI Plagiarism	Somewhat confident	132	51.4

The high awareness of academic integrity principles suggests strong ethical foundations among students (Figure 12).

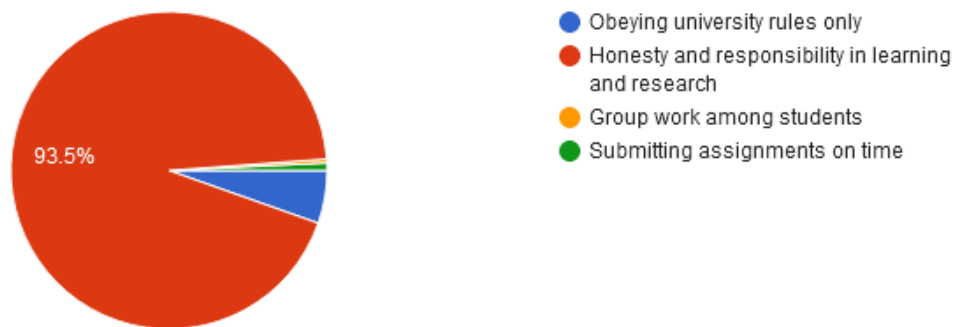


Figure 12. Respondents' Understanding of Academic Integrity (%).

The varied identification of dishonest practices suggests differences in how students perceive traditional versus AI-enabled misconduct (Figure 13): plagiarism (25.5%); cheating in exams (55.3%), using AI to write essays without disclosure (16.9%) and collaborating on individual assignments without permission (6, 2.4%).

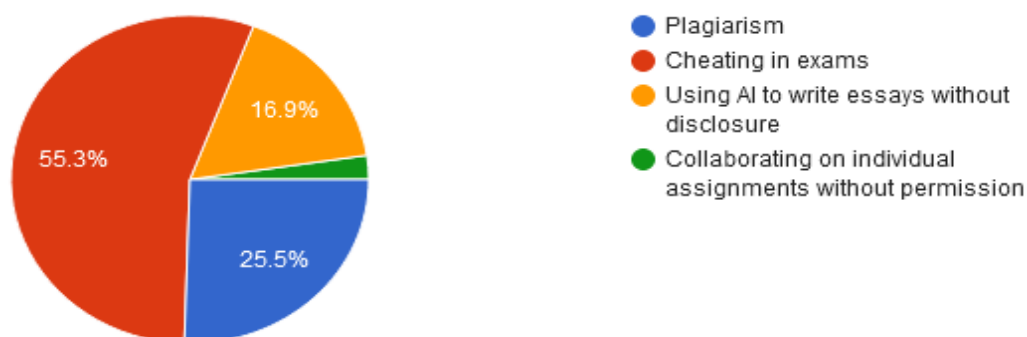


Figure 13. Respondents' Identification of Academic Dishonesty Practices (%).

Most respondents associated ethical AI use with proper attribution, indicating alignment with academic integrity standards (Figure 14): using AI to support learning while giving proper credit (91.9%), using AI to write assignments without citation (2.7%), submitting AI-generated work as your own (3.8%) and avoiding AI completely (4, 1.5%).

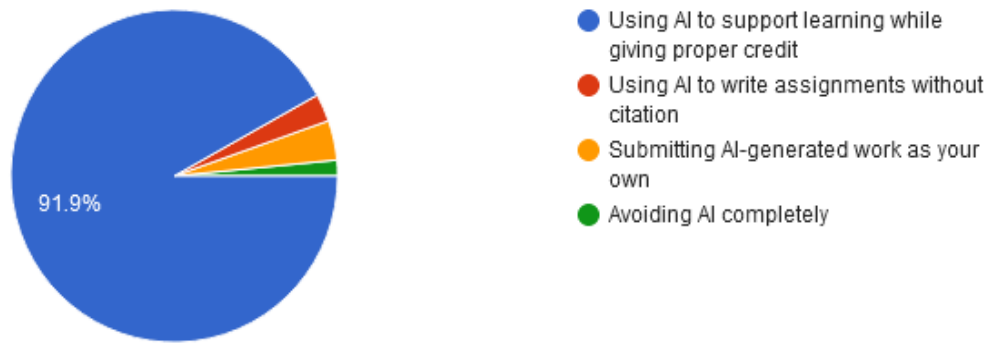


Figure 14. Perception of Ethical Use of Artificial Intelligence (%).

The respondents were asked, “Do you think students should disclose when they use AI tools in assignments?” The divided opinions on disclosure highlight ambiguity in institutional guidelines on AI-assisted work (Figure 15).

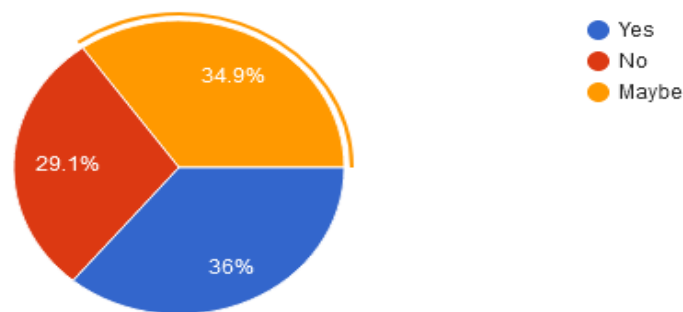


Figure 15. Students' Views on Disclosure of AI Use in Academic Assignments (%).

When the respondents were asked, “Have you ever been taught about academic integrity policies in your school?” The limited exposure (with 54.8% for No) to formal integrity policies suggests institutional communication gaps (Figure 16).

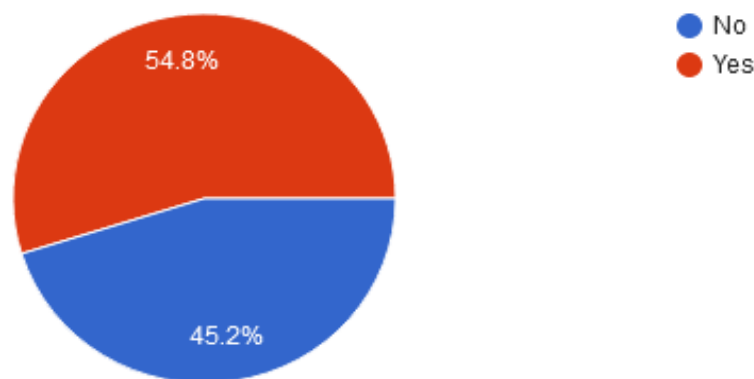


Figure 16. Exposure to Academic Integrity Policies among Respondents (%).

The moderate confidence levels indicate uncertainty in detecting AI-generated misconduct, raising concerns for assessment integrity (Figure 17).

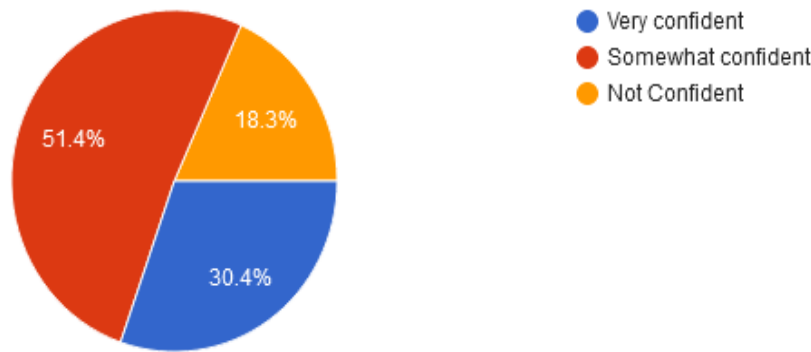


Figure 17. Confidence Level in Identifying AI-Generated Plagiarism (%).

Correlation analysis indicated a moderate positive relationship ($r \approx 0.48$, $p < 0.01$) between AI literacy and awareness of academic integrity principles, suggesting that students who understand AI better are also more likely to grasp ethical considerations. However, a weak correlation ($r \approx 0.21$, $p < 0.05$) was observed between awareness of academic integrity and actual disclosure behavior, highlighting a knowledge–behavior gap. A Chi-square test further revealed a significant association ($p < 0.05$) between exposure to institutional policies and willingness to disclose AI use, suggesting that policy awareness influences ethical transparency.

4.4. AI Use in Academic Work

This section examined: Actual use of AI tools in coursework or research, Purposes for AI usage (e.g., idea generation, grammar correction), Perceptions of acceptability of unacknowledged AI use, Awareness of AI-generated misinformation and bias and Recognition of responsible AI use practices (Table 9/Figures 18 – 22). The drive behind this is to bridge the gap between knowledge and behavior, a key concern in academic integrity research. The Figures 18 – 22 summarize how students employ AI tools in coursework, highlighting idea generation and coding as the most common uses.

Table 9. Patterns of AI Use in Academic Work.

Item	Response Option	n	%
AI Used for Coursework	Yes	240	94.1
Purpose of AI Use	Generating ideas	152	62.0
	Coding/debugging	43	17.6
	Writing essays	28	11.4
Acceptability of Unacknowledged AI Use	No	139	54.5
AI Output May Be Biased or False	True	224	88.2
Responsible AI Use	Supporting learning with citation	236	92.5

The widespread use of AI confirms its normalization as an academic support tool among students (Figure 18). Examples of the tools listed are ChatGPT and Quillbot.

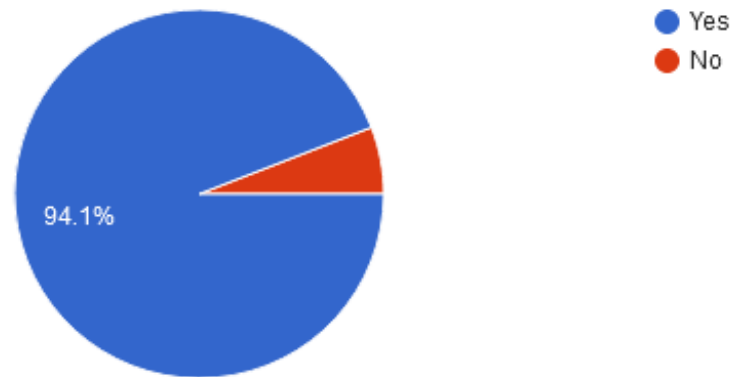


Figure 18. Use of AI Tools for Coursework and Research (%).

The predominance of idea generation suggests students view AI as a cognitive aid rather than a direct replacement for learning (Figure 19).

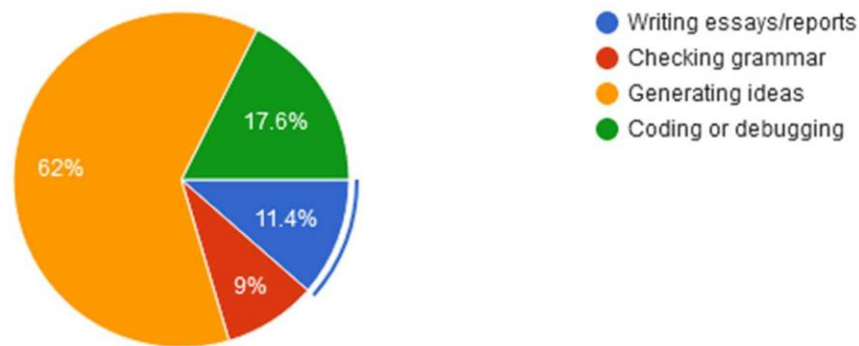


Figure 19. Purpose of AI Tool Usage among Students (%).

The question “Do you think using AI to generate answers for assignments without proper acknowledgment is acceptable?” was also asked to respondents. The presence of uncertainty and acceptance indicates potential risk areas for academic misconduct (Figure 20).

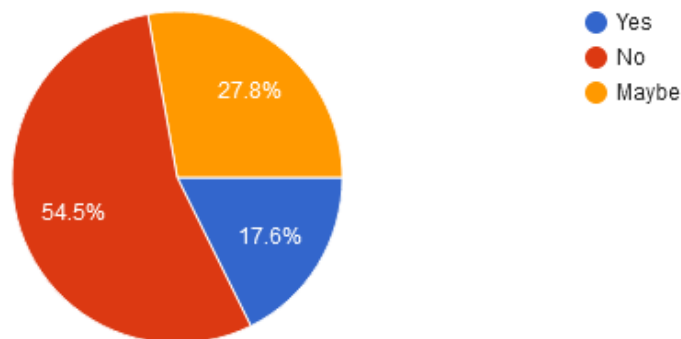


Figure 20. Perceived Acceptability of Unacknowledged AI-Generated Assignment Content (%).

The strong support for citation-based AI use reflects students’ normative commitment to responsible practices (Figure 21).

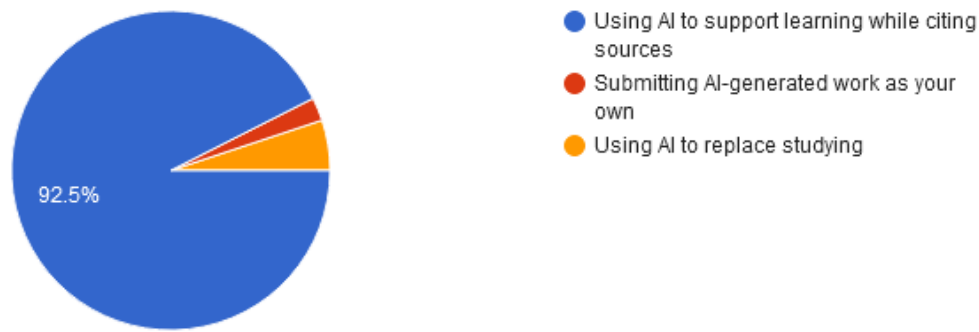


Figure 21. Respondents' Perception of Responsible AI Use Practices (%).

High awareness of AI limitations suggests students are not entirely uncritical consumers of AI output (Figure 22). This is in response to the question: "AI-generated text can sometimes contain false or biased information?"

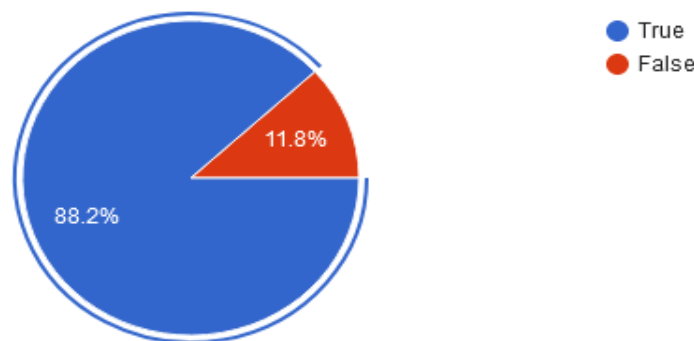


Figure 22. Awareness of Bias and Inaccuracy in AI-Generated Text (%).

A binary logistic regression analysis was conducted to identify predictors of unethical AI use (e.g., using AI without acknowledgement).

The model revealed that:

- Perceived low detection risk significantly predicts unethical AI use ($\beta > 0$, $p < 0.01$)
- Lack of policy awareness is a strong predictor ($p < 0.01$)
- High AI usage frequency also increases the likelihood of misuse ($p < 0.05$)

Conversely:

Strong awareness of academic integrity significantly reduces the likelihood of unethical AI practices ($\beta < 0$, $p < 0.01$). These findings support the argument that AI misuse is not random but influenced by rational decision-making factors.

4.5. Perception and Attitude toward AI and Academic Integrity

This section focused on students' attitudes toward: AI's impact on academic performance, AI-facilitated misconduct, Willingness to use AI responsibly, Institutional responsibility in AI ethics education, as well as risks of uncritical AI use (Table 10/Figures 23 – 27). The purpose is to capture normative beliefs and future-oriented intentions related to responsible AI adoption. Figures 23 – 27 depict students' attitudes toward AI-assisted learning, academic misconduct risks, and responsible future use.

Table 10. Students' Perceptions and Attitudes toward AI and Academic Integrity.

Statement	Agree / Strongly Agree (%)
AI can improve academic performance if used correctly	98.0
AI makes academic misconduct easier	40.1
Likely to use AI responsibly in the future	97.2

Universities should teach ethical AI use	74.9
Using AI without understanding the harms of learning	75.0

Students largely believe, when asked, “Do you think AI can improve students’ academic performance if used correctly?” that AI enhances performance when used appropriately, reinforcing its perceived educational value (Figure 23).

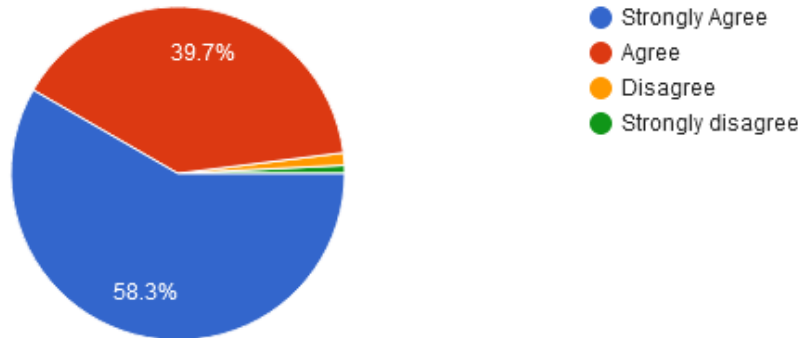


Figure 23. Perceived Impact of AI on Students’ Academic Performance (%).

The mixed responses obtained from the statement, “AI tools make it easier for students to commit academic misconduct,” indicate uncertainty about whether AI inherently promotes misconduct or merely amplifies existing behaviors (Figure 24).

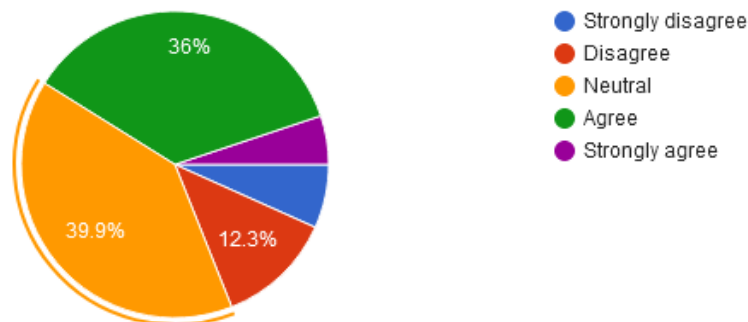


Figure 24. Perception of AI as a Facilitator of Academic Misconduct (%).

The respondents were asked, “How likely are you to use AI responsibly in your future studies?” The high willingness (49.2%) to use AI responsibly suggests positive intentions toward ethical AI engagement (Figure 25).

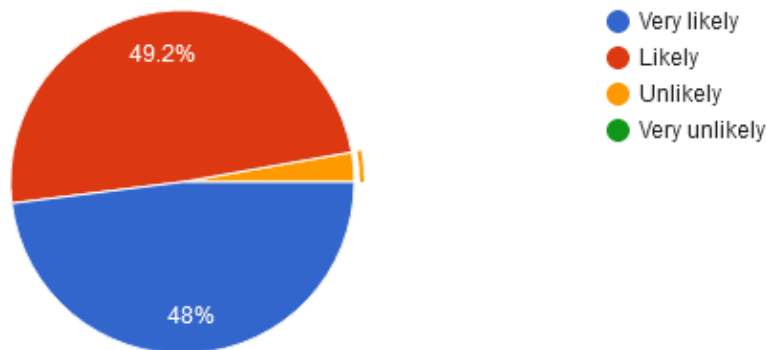


Figure 25. Likelihood of Responsible AI Use in Future Academic Work (%).

The strong agreement when respondents were asked, “Should Universities teach students how to use AI ethically?” underscores students’ expectation that institutions provide formal AI ethics training (Figure 26).

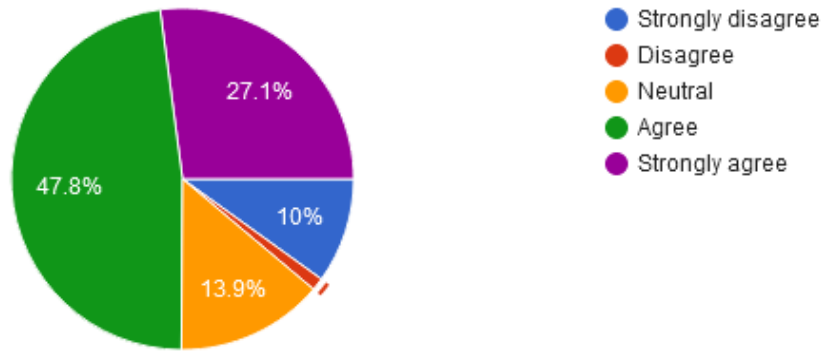


Figure 26. Students' Views on the Need for Ethical AI Education in Universities (%).

The response to the proposition: using AI without understanding its output can harm academic learning, shows that the recognition of learning risks highlights students' awareness of over-reliance on AI tools (Figure 27).

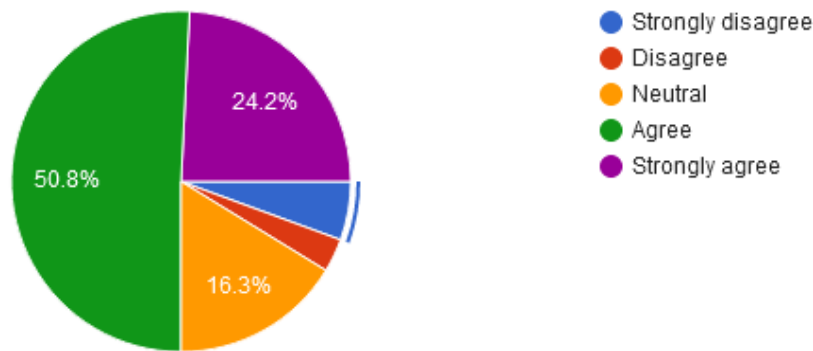


Figure 27. Perceived Impact of Uncritical AI Use on Academic Learning (%).

A correlation analysis showed a positive relationship ($r \approx 0.55$, $p < 0.01$) between perceived academic benefits of AI and willingness to use AI responsibly, while a negative relationship ($r \approx -0.43$, $p < 0.01$) was found between perceived risks of AI misuse and likelihood of unethical behavior. Additionally, ANOVA results indicated statistically significant differences ($p < 0.05$) across levels of study.

4.6. Legal and Ethical Awareness

Finally, this section assessed: awareness of academic penalties linked to unethical AI use, Knowledge of copyright implications, familiarity with institutional AI policies, perceptions of unethical AI practices and strategies for promoting responsible AI use among students (Table 11/Figures 28 – 32). This is aimed at linking legal, ethical, and policy awareness to students' academic decision-making. Figures 28 – 32 illustrate students' awareness of academic penalties, copyright issues, and institutional AI policies, revealing notable policy-awareness gaps.

Table 11. Legal and Ethical Awareness Related to AI Use.

Item	Yes (%)
Awareness of academic penalties for unethical AI use	67.6
Awareness of copyright violation risks	80.6
Awareness of institutional AI policy	25.3
Most Unethical Practice Identified	Using AI in exams (74.1%)
Best Strategy to Promote Responsible AI	Awareness & training (51.6%)

The question, “Are you aware that unethical AI use can lead to academic penalties such as suspension or expulsion?” received 67.6% Yes and 32.4% No (Figure 28). The awareness of penalties may act as a deterrent against misuse, though gaps remain.

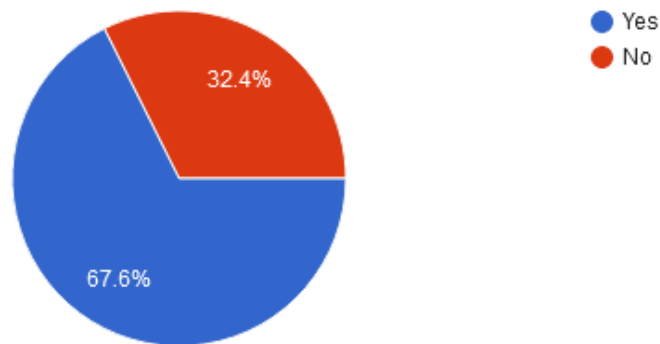


Figure 28. Awareness of Academic Penalties for Unethical AI Use (%).

The high copyright awareness shown in the proposition, “Using AI-generated work without citation can violate copyright laws,” reflects growing legal consciousness regarding AI-generated content (Figure 29).

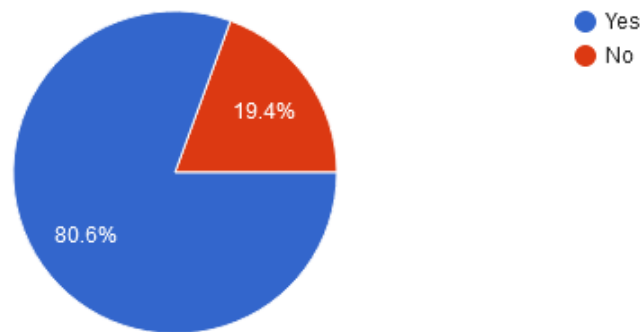


Figure 29. Awareness of Copyright Violations Related to AI-Generated Work (%).

74.8% of the respondents responded “No” to the question, “Do you know any institutional policy regarding AI use in your university?” The low policy awareness indicates a disconnect between institutional regulations and student knowledge (Figure 30).

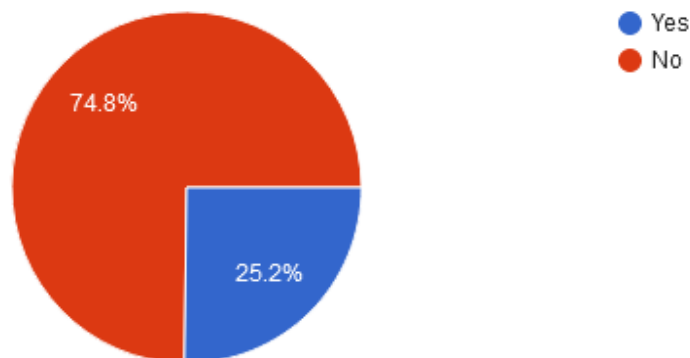


Figure 30. Awareness of Institutional Policies on AI Use (%).

Students strongly condemned AI use in examinations when asked, “Which of the following do you consider unethical in AI use?” suggesting clear ethical boundaries in high-stakes assessments (Figure 31).

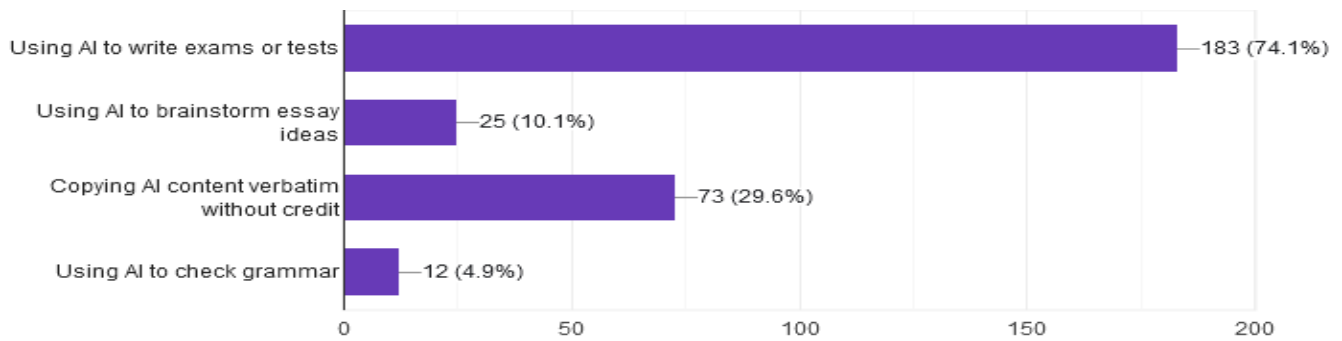


Figure 31. Perceived Unethical Practices in the Use of Artificial Intelligence (%).

Lastly, the respondents were asked, “What do you think can best promote responsible AI use among students?” The preference for awareness and training over punitive measures highlights the importance of educational approaches to AI governance (Figure 32).



Figure 32. Strategies for Promoting Responsible AI Use among Students (%).

A Chi-square test revealed a significant association ($p < 0.01$) between awareness of academic penalties and perception of AI misuse as unethical. The students who were aware of penalties were significantly more likely to classify unethical AI practices (e.g., use in exams) as unacceptable. Furthermore, regression analysis showed that policy awareness and legal knowledge jointly explain a significant proportion of variance ($R^2 \approx 0.38$) in students’ ethical decision-making. This indicates that institutional governance and legal awareness are critical determinants of responsible AI use.

5. Discussion

This study investigated academic integrity in the era of generative artificial intelligence (GenAI), focusing on students’ awareness, ethical boundaries, and risk-taking behavior within Nigerian universities. The findings offer important empirical insights into a rapidly evolving educational landscape where existing academic integrity frameworks are increasingly strained by AI-enabled technologies. By centering students’ perceptions and behaviors, the study contributes to addressing a critical gap in the literature, which policy analyses, conceptual discussions, and evidence from high-income countries have largely dominated.

5.1. Students’ Awareness of Academic Integrity in the Context of AI

The findings indicate that although most students possessed a general understanding of traditional academic integrity principles, such as plagiarism, cheating, and proper citation, their understanding became significantly less clear when applied to AI-assisted academic work. This supports earlier studies suggesting that students often conceptualize academic

dishonesty narrowly, focusing on copy-and-paste plagiarism while underestimating the ethical implications of emerging digital tools [4]. However, the present study extends this literature by empirically demonstrating that GenAI introduces conceptual ambiguity, where students struggle to distinguish between acceptable academic support and unethical substitution of intellectual effort.

This finding directly addresses a key gap identified in the literature: the lack of student-centered empirical evidence from African higher education contexts on how academic integrity is interpreted under AI-mediated learning conditions. While [35] highlights the global need for ethical guidance on generative AI in education; empirical studies from the Global South remain scarce. The current findings, therefore, contribute contextualized evidence that broadens the geographical and cultural scope of academic integrity research.

5.2. Ethical Boundary Formation and Normalization of AI Use

A major finding of the study is the gradual normalization of certain AI-enabled practices that would traditionally be considered academic misconduct. Many students perceived the use of GenAI tools for drafting assignments, paraphrasing content, or generating ideas as acceptable, particularly when such practices were not explicitly prohibited or monitored. This aligns with recent international research suggesting that generative AI is reshaping students' moral reasoning about authorship and originality [36].

However, the study goes further, revealing that ethical boundary formation is not passive but is actively negotiated by students. Participants reported weighing academic workload, time constraints, peer behavior, and perceived risks of detection before deciding how extensively to rely on AI tools. This supports [10] assertion that academic misconduct is often a rational decision shaped by contextual pressures, but extends this framework to AI-enabled environments.

The literature gap identified earlier emphasized the lack of research examining how students themselves define and negotiate ethical boundaries in the AI era, rather than relying solely on institutional definitions. The findings clearly address this gap by showing that students' ethical judgements are fluid and situational, shaped by both technological affordances and institutional ambiguity. This underscores the need for integrity frameworks that engage students as ethical agents rather than treating misconduct solely as a rule violation.

5.3. Risk-Taking Behavior and Perceived Detection Capacity

Another significant finding is the strong relationship between students' risk-taking behavior and their perception of institutional detection capabilities. Where students believed that lecturers or universities lacked effective tools to detect AI-generated content, the likelihood of unethical AI use increased. Conversely, the perception that AI-detection tools such as Turnitin were actively used served as a deterrent, even when students were uncertain about the tools' technical accuracy. This finding is consistent with deterrence-based models of academic integrity, which posit that misconduct is influenced by the perceived likelihood of detection and severity of sanctions [10]. However, the present study extends this body of knowledge by situating deterrence theory within the specific context of generative AI. While earlier studies focused on traditional plagiarism detection, the findings demonstrate that perceived institutional readiness for AI governance plays a critical role in shaping student behavior.

This directly addresses the literature gap concerning the limited empirical evidence linking institutional AI readiness to student misconduct behavior, particularly in developing-country contexts. Rather than treating AI misuse as a purely technological problem, the findings highlight the central role of governance, enforcement, and communication in maintaining academic integrity.

5.4. Policy Awareness and Communication Gaps

The study also reveals low levels of student awareness regarding institutional policies on AI use. Even where academic integrity policies existed, students reported limited exposure to AI-specific guidelines, particularly during orientation or coursework. This supports earlier critiques that policy development often outpaces policy communication and

implementation [37], [35]. The literature identified a disconnect between policy formulation and student engagement, especially at Global South institutions. The findings confirm that this gap persists and that policy effectiveness is contingent not only on content but also on visibility, clarity, and relevance to students' lived experiences. Without explicit guidance, students are left to rely on peer norms and informal practices, increasing the likelihood of ethical drift.

Importantly, the findings suggest that students are not inherently resistant to ethical guidance. Many expressed willingness to comply with clear rules if such rules were consistently communicated and fairly enforced. This challenges deficit-based narratives that portray students as deliberately dishonest and instead positions them as responsive actors within ambiguous institutional environments.

The findings further indicate that students have limited awareness of the potential legal implications of unethical AI use, including copyright infringement, data protection violations, and academic fraud. This aligns with [38] argument that ethical AI use must be understood within broader legal and societal frameworks. The lack of legal awareness among students reinforces the need for universities to integrate legal literacy into AI and academic integrity education.

From an institutional perspective, the findings justify the development of AI-specific academic integrity policies that go beyond generic plagiarism clauses. As [39] noted that the effectiveness of AI-detection technologies depends not only on technical capability but also on transparent communication and consistent enforcement. The study provides empirical support for this position by demonstrating how policy ambiguity undermines integrity outcomes.

However, the findings indicate that students' behavior reflects a risk–reward evaluation process, where perceived benefits increase AI usage while perceived detection risks reduce unethical practices. This pattern aligns with the assumptions of Prospect Theory, suggesting that students make decisions based on subjective evaluations of gains and losses under uncertainty.

5.5. Addressing the Identified Literature Gap

The study set out to address three interrelated gaps in the literature:

1. The lack of empirical, student-focused research on AI and academic integrity in African universities.
2. Limited understanding of ethical boundary formation and risk-taking behavior in AI-assisted learning;
3. Insufficient evidence linking institutional AI governance to student misconduct behavior.

The findings demonstrate that these gaps were effectively addressed. First, the study provides context-specific empirical data that enriches the predominantly Western-focused literature on AI and academic integrity. Second, it offers nuanced insights into how students actively negotiate ethical boundaries in response to academic pressures and technological affordances. Third, it establishes a clear relationship between perceived institutional enforcement capacity and student behavior, providing actionable evidence for policy and practice.

5.6. Implications for Theory, Policy, and Practice

The findings contribute theoretically by extending academic integrity frameworks to incorporate AI-mediated moral reasoning and strategic behavior. Traditional integrity models, which assume stable definitions of authorship and originality, may be insufficient in the context of generative AI. The study, therefore, supports calls for adaptive integrity frameworks that reflect contemporary learning technologies [36].

Practically, the findings justify the integration of AI literacy and academic integrity education into undergraduate orientation programs, assessment design, and continuous staff development. For policymakers, the results underscore the importance of clear, student-centered AI governance frameworks that balance innovation with ethical responsibility.

6. Limitations and Directions for Future Research

While this study provides important empirical insights into academic integrity in the era of generative artificial intelligence, several limitations present opportunities for future research.

First, the reliance on self-reported data introduces the possibility of social desirability and response bias, particularly given the sensitive nature of academic misconduct. Future studies should complement self-reported surveys with behavioral

data, such as assignment analysis, learning management system logs, or anonymized institutional misconduct records, to provide a more objective assessment of AI-related academic behavior.

Second, the study's cross-sectional design limits its ability to capture changes in student perceptions and behaviors over time. Given the rapid evolution of generative AI tools and institutional policies, future research would benefit from longitudinal designs that track how students' ethical reasoning, AI usage patterns, and compliance with academic integrity standards develop across academic sessions or program durations.

Third, the focus on selected Nigerian universities constrains the generalizability of the findings. Future research should adopt multi-institutional and cross-national comparative studies, particularly across different regions of Africa and between Global South and Global North contexts. Such comparisons would help to identify how socio-economic conditions, digital infrastructure, and regulatory environments shape AI-related academic integrity practices.

Fourth, although the study examined students' perceptions of institutional detection and enforcement mechanisms, it did not evaluate the actual technical performance of AI-detection tools. Future studies should integrate system-level evaluations, including accuracy testing of AI-detection software, staff experiences, and policy enforcement workflows, to triangulate student perceptions with institutional realities.

Fifth, the study centered primarily on student perspectives, which, while valuable, provide only a partial view of the academic integrity ecosystem. Future research should incorporate multi-stakeholder perspectives, including academic staff, administrators, instructional designers, and policymakers, to better understand the alignment, or misalignment, between policy intent, pedagogical practice, and student behavior.

Finally, the research focused mainly on text-based generative AI tools, such as large language models. As AI applications diversify, future studies should explore integrity challenges associated with code-generation tools, image and video synthesis, data fabrication, and AI-assisted examinations. Also, Prospect Theory was not formally tested using experimental or advanced modeling approaches, which future studies may address.

7. Conclusions and Future Work

This study explored academic integrity in the era of generative artificial intelligence, focusing on students' awareness, ethical boundaries, and risk-taking behavior within Nigerian universities. The findings reveal that while students possess a basic understanding of traditional academic integrity principles, significant ambiguity exists regarding the ethical use of AI-enabled tools. Generative AI has blurred conventional distinctions between academic support and misconduct, leading to the normalization of practices that challenge established integrity norms.

This study underscores a transformative shift in the educational landscape of Nigerian universities, where the rapid proliferation of Generative Artificial Intelligence (GenAI) has outpaced the development of institutional governance and ethical frameworks. The findings reveal a pervasive adoption of AI tools among students, with a staggering 84.7% already integrating them into their academic workflows, driven by a sophisticated level of AI literacy and the perceived benefits of personalized learning and efficiency. However, this technological fluency is shadowed by a profound "knowledge-behavior gap": while students maintain a strong theoretical commitment to traditional academic honesty, their practical application of these values becomes blurred when navigating the nuances of AI-assisted authorship.

A central revelation of this research is that AI-related misconduct is not merely a byproduct of technological availability but a calculated strategic decision shaped by the "institutional policy vacuum". In the absence of clear guidelines, evidenced by the fact that nearly 75% of students are unaware of any university AI policies, students engage in a risk-reward evaluation. When the perceived benefits of AI use (such as reduced workload and time efficiency) outweigh the perceived risks of detection and sanction, the threshold for academic misconduct is lowered. This normalization of unacknowledged AI use suggests that students are actively negotiating new ethical boundaries, often viewing GenAI as a legitimate cognitive tool rather than a violation of integrity.

Ultimately, the study proposes that maintaining academic integrity in the AI era requires a departure from purely punitive or technical detection-based strategies. Because detection tools often trail the sophistication of evolving AI models, the most sustainable solution lies in adaptive, student-centered frameworks. These frameworks must prioritize the integration of formal AI ethics into the curriculum to foster transparent communication of institutional policies and encourage a culture of disclosure. By empowering students as ethical agents and providing clear roadmaps for responsible AI engagement, universities can preserve the sanctity of the academic "social contract" while harnessing the undeniable potential of artificial intelligence to enhance scholarly output.

Declarations

Author Contributions: Ogbaga I. N.: Original Draft Preparation, Conceptualization, Literature Review, Data Collection and Analysis. Onwudebelu U. C: Data Curation, Discussion, Methodology and Conclusion. Eru A. N.: Data collection, Integration. Kingsley N. I.: Supervision and Proofreading,

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Data Availability: The data are available from the corresponding author upon reasonable request.

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