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Exploring the Opportunities and Threats of Artificial Intelligence (AI) in Academia: A Quantitative Analysis

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Abstract

This study explores academic stakeholders' perceptions, usage patterns, and ethical considerations regarding Artificial Intelligence (AI) in higher education. With the rise of Generative AI tools like ChatGPT, understanding their influence on teaching, research, and governance is critical. A quantitative, cross-sectional survey design was employed, involving participants across faculty, students, staff and administrators. Descriptive and inferential statistics revealed that the perceived impact of AI on research and teaching significantly predicted AI usage. Ethical concerns varied significantly by academic role, with undergraduates and early-career researchers expressing greater apprehension. Strong correlations between ethical concern and support for regulation further emphasized the demand for institutional policies. The findings suggest that functional value drives AI adoption more than ethical or demographic factors. This research underscores the need for tailored policies, AI literacy training, and stakeholder-specific strategies to guide AI's responsible integration into academia.

Keywords: Artificial Intelligence; Higher Education; Generative AI; Ethics; Institutional Readiness; Academic Roles; Technology Adoption; Teaching and Research; AI Perceptions; Educational Technology; AI Adoption.

1. Introduction

This section introduces the growing role of Artificial Intelligence (AI) in higher education, focusing on its usage, perceptions, and ethical considerations among academic stakeholders. As AI tools become increasingly integrated into research, teaching, and administration, understanding how faculty, students, and staff perceive and engage with these technologies is crucial. The section outlines the background, significance, and aims of the study, while identifying the research gap related to attitudes, readiness, and institutional governance concerning AI in academia.

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1.1 Research Background

The 21st century has seen the widespread application of artificial intelligence, which is being heralded as a tool to improve and progress all aspects of our lives [1]. Artificial Intelligence (AI) has become an indispensable component of modern higher education, transforming both pedagogical and administrative practices. AI is transforming the way educational institutions operate, from research-assisting language models and adaptive learning platforms to intelligent tutoring systems and plagiarism detection technologies. These technologies promise increased efficiency, enhanced personalization, and broader access to educational resources. Alongside these advancements come substantial concerns about ethics, accountability, and the evolving nature of academic work [2,4]. This dual character of AI as both opportunity and threat necessitates rigorous empirical and theoretical exploration. Using a machine learning (ML) model "to learn the patterns and relationships in a dataset of human-created content," artificial intelligence (AI) is defined as "the use of AI to create new content, like text, images, music, audio, and videos." Then, the model "uses the learnt patterns to generate new content." GenAI is distinct from earlier iterations of artificial intelligence (AI) technology that use machine learning (ML) algorithms and data prediction based on historical behavior [5].

Among the most transformative innovations in this space is Generative Artificial Intelligence (GenAI), GenAI focuses on using large language models (LLMs), art-based models, and video-based models to create new textual and multimodal content. Popular GenAI tools include ChatGPT, GPT-4, Playground, DALL·E 3, and Sora from OpenAI, Claude from Anthropic, the Gemini (formerly Bard) from Google, the Stable Diffusion 3 from Stability AI, and the Gen-2 from Runaway [5]. and other large language models (LLMs) are increasingly being deployed in research environments, offering new possibilities for data synthesis, literature review generation, and even qualitative coding. While some skeptics dismiss GenAI as a product of a passing hype cycle, its remarkable progression and growing adoption suggest otherwise [4,5]. These technologies are influencing not only how knowledge is produced but also how it is consumed and validated.

In today's globalised society, when successful communication and cross-cultural understanding are critical for academic, professional, and personal success, language instruction and learning are crucial. Being capable of communicating, navigating a variety of cultural contexts, and participating in significant relationships are all made possible by language proficiency. Language educators have historically served as the main agents of language learning and growth in the educational setting, teaching students the fundamentals of the language and evaluating their progress through both spoken and written components [5,7]. On the other hand, uncritical adoption poses risks to research integrity, authorship, and peer review standards. As institutions place increasing emphasis on productivity and global rankings, the pressure to integrate AI tools may inadvertently compromise the ethical fabric of scholarly work. Questions regarding what constitutes legitimate intellectual labor, how to attribute credit, and how to maintain academic rigor are more pressing than ever [8].

According to recent research, artificial intelligence (AI) has demonstrated effectiveness across a wide range of fields. These industries include e-commerce, AI-powered smart applications, healthcare, education (particularly Natural Language Processing), autonomous vehicles and drones, and finance. Over the past two years, the global spread of COVID-19 a severe and highly contagious disease affected approximately 18.2 million people between

2020 and 2021. Every facet of daily life, including travel, education, healthcare, and transportation, was significantly disrupted. Researchers struggled to contain the pandemic due to a lack of comprehensive understanding of the virus's characteristics and behavior [9]. AI is now impacting many dimensions of modern life, including education. In higher education, AI holds the potential to revolutionize teaching and learning through increased accessibility, efficiency, and personalization.

One Natural Language Processing (NLP) model that has the potential to revolutionize higher education is ChatGPT from OpenAI. For open-ended prompts like questions, assertions, or prompts about academic content, this generative language model, or ChatGPT, can produce human-like responses [10]. A lot of ESL students have trouble with coherence, lexical variety, and grammar in their academic writing. Consequently, they seek help from AI-based tools. however, have been noted in earlier research. These include its incapacity to evaluate the reliability of sources, its propensity to produce ambiguous or deceptive content, and its potential to encourage plagiarism if students rely too much on AI-generated text without exercising critical thought [11].

Despite the rising prominence of AI in higher education, current research often remains fragmented. Many studies focus on single variables—such as AI's impact on academic writing or teaching efficiency—without exploring the broader ecosystem of familiarity, perceptions, ethics, and institutional readiness. Furthermore, much of the literature lacks empirical, theory-driven analysis based on diverse academic roles and demographics. For instance, while Aguilos and Fuchs highlight ChatGPT's potential in language learning, few studies explore how perceptions vary between students, faculty, and administrators, or how institutional culture influences the adoption of AI [10]. Applications of AI have become essential in educational establishments, including colleges and universities, since they are currently required to keep pace with technological development through the creation of new methods of education and teaching. This study addresses that gap by offering a comprehensive, quantitative analysis of stakeholder perceptions regarding the opportunities and threats of AI in academia. Drawing on a structured survey and SPSS-based statistical analysis, the research investigates how variables such as AI familiarity, perceived usefulness, ethical concerns, and readiness are distributed across demographic categories like age, gender, and academic role.

1.2 Research Objectives

1. To assess the level of familiarity and usage of AI tools among academic stakeholders.
2. To examine whether gender and age influence perceptions or usage of AI in academic settings.
3. To evaluate the impact of AI on research and teaching, and how this perception predicts AI usage.
4. To explore how academic roles, influence ethical concerns about AI in academia.
5. To investigate the relationship between ethical concerns and support for AI regulation and responsibility frameworks.
6. To determine whether AI-related perceptions, ethical concerns, and regulation attitudes predict institutional readiness for AI adoption.

1.3 Significance of the Study

Artificial Intelligence (AI) integration in higher education represents a multi-faceted occurrence, where the convergence of adoption of innovations, the institutional context, and individual motivations exists. In examining this complexity, this paper uses three well-established theoretical frameworks: The Diffusion of Innovations Theory [12], Technological Determinism, and the Uses and Gratifications Theory (UGT). Each framework offers a unique lens, outlining meaningful inquiries on AI perception by the academic stakeholders and it how it may influence research, teaching, ethics, and institutional preparedness.

2. Theoretical Framework

The incorporation of Artificial Intelligence (AI) into higher education is a multi-faceted phenomenon that intersects with innovation adoption, institutional contexts, and personal motivations. To examine this complexity, this study uses three notable theoretical perspectives: Diffusion of Innovations Theory [12], Technological Determinism, and the Uses and Gratifications Theory (UGT). Each perspective uniquely informs our understanding of how AI is perceived and adopted by individuals and organizations in academia and how the introduction of AI affects research, teaching, ethics, and institutional readiness.

2.1 Diffusion of Innovations Theory (DoI)

The study of how innovations spread is a well-established field that was pioneered and popularized by Everett Rogers. He first articulated this theory in his book, "Diffusion of Innovations," published in 1962. Rogers continued his research in this area and released the fifth edition of the book in 2003. Diffusion of Innovations Theory was created to explain how, why and how new technologies spread throughout cultures, communities, or institutions [12]. Rogers establishes that the rate of adoption is based on five key factors: relative advantage (a perceived benefit over the current practice), compatibility (alignment with existing values and practices), complexity (ease of use), trialability (testing and modifying the technology before fully committing to it), and observability (being able to see the results).

Historically, in higher education, various types of AI tools such as ChatGPT, automated grading systems, or plagiarism detection software are new inventions whose implementation or adoption depends, among other things, on levels of understanding. Faculty, students, and administrative staff represent the various adopter categories or characteristics of adoption trends, such as innovator, early adopters, early majority, late majority, and laggard, according to their willingness to adapt to a technological change [12]. In this study, the categories of AI familiarity and engagement, as well as academic position (seeking students, faculty, and administrators), are informed directly by DoI. These kinds of category variables indicate the degree to which AI is known and used, and whether demographic or institutional position influences the attitudinal approach to adopting AI. DoI also provides a context for understanding the different rates of AI adoption and explains why some institutions or individuals appear to adopt AI technology much more rapidly than others [13].

2.2 Technological Determinism

Technological Determinism is a theory that attributes human society changes mainly to technology and shifts in culture and society to technology, perhaps with little regard for intentional human agency or institutional influence Reference [14]. In educational contexts, this theory holds that AI is more than a tool; it's a fundamental change agent that reorganizes the structure and practices of the academy, from knowledge production to evaluation to delivery. The role of AI that is now expanding in terms of producing and sustaining research outputs, grading, curriculum design, content production, and, although not described as such, the impending role of AI as a tutor raises significant concerns for academic integrity, authorship, job encroachment, and the authenticity of teaching and learning [4,8]. The ethics and integrity variables in this study are connected to this theory. These variables measure participants' concerns, hesitations, or resistance to AI possibly displacing human judgment, resulting in a loss of agency over control of the academic process.

For instance, applications such as ChatGPT and DALL·E 3 can generate written or visual materials that appear to have been produced by humans; hence, there is confusion over originality and authorship. This is congruent with one of the primary concerns of Technological Determinism, the extent to which technology could fundamentally transform existing academic roles with little attention to regulation or ethics [5]. Thus, the theory is especially helpful in understanding participants’ anxieties about academic standards, concerns about automation, and broader implications of AI on teaching and research.

2.3 Uses and Gratifications Theory (UGT)

The Uses and Gratifications Theory, which originated in the field of media studies, highlights how the role of users as active and intentional in both technology selection and technology use is based on specific needs [15]. In contrast to Technological Determinism, UGT does not engage individuals in a passive relationship but rather as agents who use technology to try and fulfill specific needs or wants (such as wanting to learn, solve a problem, be productive, or for entertainment). In the context of the study, UGT is used to help explain why students or faculty ultimately utilize AI tools. For instance, students may utilize an AI-powered writing tool to help with grammar checking, generate ideas, or aid in time management. Faculty members may use AI for literature reviews or support for data analysis or grading [6,10]. These use cases may pertain to the variables regarding AI familiarity and usage in the survey.UGT is also especially useful in understanding motivations for the use of AI within user groups. It also accounts for the differences in satisfaction, use, and self-directed use of AI in the academic sphere. For example, ESL learners might be motivated to use AI tools to improve linguistic accuracy or coherence in their writing [11]. These motivations affect how users perceive the benefits and limitations of AI, which is important considering how motivations inform regulations and ethics.

2.4 Conceptual Framework

The conceptual framework shows how role, readiness, usage, age, and gender influence AI-related perceptions, impact, ethics, and regulatory views in academia.

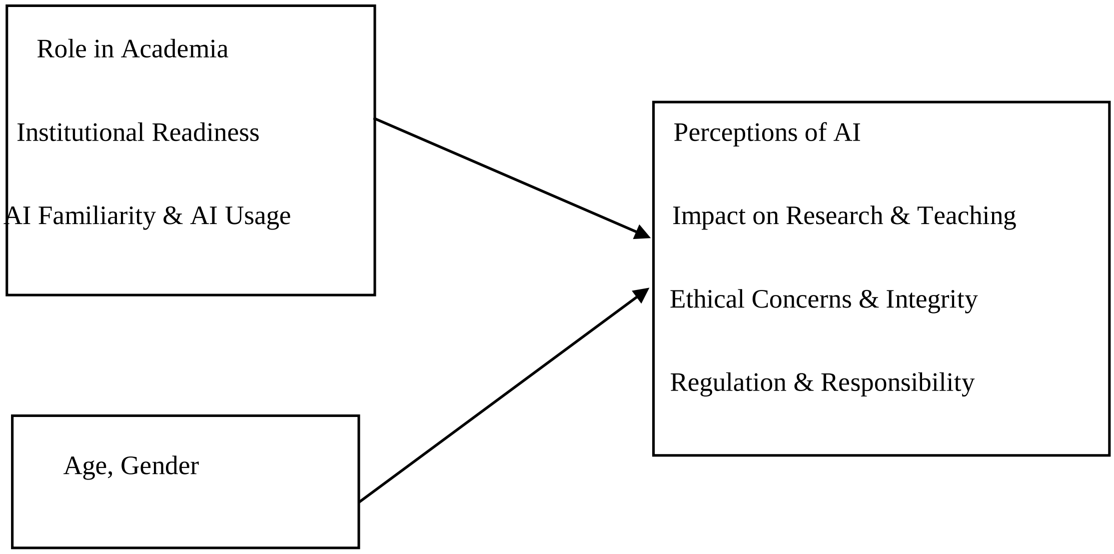

Figure 1

2.6 Research Hypothesis

H_1: Familiarity with AI significantly predicts perceptions of AI's impact on academic research and teaching.

H_2: Age and gender do not significantly influence perceptions, usage, or ethical attitudes toward AI in academic contexts.

H_3: Perceived impact of AI on research and teaching significantly predicts AI usage among academic stakeholders.

H_4: Academic role significantly predicts ethical concerns about AI in academic contexts.

H_5: Higher ethical concern is positively associated with support for AI regulation and responsibility frameworks.

H_6: Perceptions of AI, ethical concerns, impact, and regulation attitudes do not significantly predict institutional readiness.

3. Literature Review

This chapter explores existing literature on the integration of Artificial Intelligence (AI) in higher education, focusing on key themes such as AI familiarity and usage, perceptions of AI, ethical concerns, academic integrity, and institutional readiness. It examines how demographic factors, such as age and gender, influence attitudes toward AI and assesses both the opportunities and challenges of AI implementation in research and teaching. The review also considers governance frameworks and ethical responsibilities associated with AI use in academic contexts.

3.1 AI Familiarity and Usage Trends

The integration of artificial intelligence (AI) into education has prompted growing scholarly attention, particularly around how familiarity influences usage behavior among students, educators, and professionals. Familiarity—defined as prior knowledge, awareness, or hands-on experience with AI tools—is widely regarded as a critical determinant of technology adoption in academic contexts.

Elhassan and his colleagues [16] found that medical students familiar with ChatGPT and other chat-based AI tools were more likely to accept and utilize these applications, demonstrating a strong link between prior exposure and acceptance. Similarly, Apriyadi and Juwitasary [17] observed that familiarity with generative AI significantly influenced the intention to use such tools in academic environments, suggesting that experience fosters confidence and readiness.

Nikoulina and Caroni [18] reported that familiarity enhanced perceptions of usefulness, ease of use, and relevance among students and faculty, stressing the importance of institutional support in building AI fluency. This was echoed by Topsakal [19], who found that familiarity, combined with trust and usability, positively impacted the acceptance of AI systems—even in non-educational sectors like travel planning—highlighting parallels in how users engage with new technologies.

Beyond students, Kurshumova [20] noted that although Bulgarian teachers had rising awareness of AI, actual implementation remained low due to limited support and training. This finding underscores that while familiarity is essential, it must be paired with infrastructural readiness and capacity building. Omarzai and Kulkurni [21] similarly found high awareness but low practical usage among dental students and professionals, pointing to persistent gaps in AI integration in niche academic fields.

In the fields of retail and media education, Arce-Urriza and his colleagues [22] and Narayan [23] demonstrated that repeated exposure to generative AI tools leads to sustained intentions to adopt these tools, as well as greater perceived academic usefulness. Complementing this, Flavián and his colleagues [24] emphasized an important relationship of technology readiness based on exposure to technology, that increasing familiarity with technology relates to increased likelihood of use. Gabor and his colleagues [25], describe a group of veterinary professionals with high AI familiarity levels as overall more positive, engaged, and open to adopting the tools. Their study considered not only that the group exhibited higher familiarity and greater likelihood of use, but that familiarity with technology may influence not only helpful behaviors but attitudes toward innovations.

3.2 Perceptions of AI: Opportunities vs Risks

Pedro and his colleagues [26] have described AI as a transformative phenomenon for education and sustainable development, emphasizing that AI has the potential to personalize learning experiences for students, automate administrative activities, and facilitate improved degrees of student engagement. However, research into the integration of AI into education has revealed significant challenges associated with its application. For instance, Luckin [27], describes AI systems as posing risks for relationships, human contact, the quality of teaching and learning, and the invasions into the privacy of everyone involved in education (i.e., educators and learners). He also suggests that students' sense of belonging and general well-being may be sacrificed so that they develop specific skills while neglecting the overarching goals of education. While there are claims that AI can improve access and equity in education, possibly reducing educational inequality, especially in contexts of under-resourced and inequitable access, AI will not resolve educational concerns for students in schools. Saputra and his colleagues Reference [28] highlight this positive outlook, defining AI as a catalyst for innovation in assessment, adaptive instruction, and real-time feedback. Similarly, Eden and his colleagues [29] reference the potential of AI to facilitate data-informed practice and predictive analytics, preventing learning disabilities, and improving student success. Ethical considerations, in terms of data privacy, algorithmic bias, or inappropriate use of AI content in the classroom can be established via a regulatory framework. Guidelines should lay out a minimum set of polices surrounding higher ed AI and create accountability in terms of ethical standards, transparency, and responsible use of AI in all aspects of academic duty.

Nonetheless, even with possibilities available, many researchers warn against a thoughtless embrace of AI in education. Davis [30] addresses the limits of AI in higher education, focusing on issues related to overreliance on algorithms, the depersonalization of learning, and worries about privacy with one's data. While AI could increase scaling, it could also lessen human-centered learning experiences. In addition, Bartoletti [31] takes this a step further by discussing that AI systems generally are opaque in their functioning and applications, particularly with data and decision making within the gate of education. Opacity generates distrust of stakeholder groups and raises ethical questions of bias and fairness. Alwaqdani [32] explores several issues stating that AI systems may be viewed as suspect regarding their purposes and what is prioritized. Within the educational context, AI algorithms and systems could further generate unfairness, social injustices, and negative stereotypes. A further concern is also the abuse of data privacy, scope and scale of AI systems, ethics, limited recommendations in practice for teachers, and limited number of AI practitioners and specialists. Throughout all this process and understanding, there needs to be more research on how to understand the challenges of AI in education through the lens of instructors.

Blodgett and Madaio [33] discuss the risks of using foundation models in education, stressing that AI systems on a large scale can be biased or unfiltered and can reinforce existing inequalities and cultural stereotypes. Similarly, Vincent-Lancrin and Van der Vlies [34] argue that when trust in AI systems is compromised, their fairness, accountability, and explainability are critical components. Without those conditions, the dependencies on, and potential educational malpractice with AI tools, add risk to AI systems and have the potential to compromise educational value altogether due to distrust and ethical dilemmas. Zaman [35] takes a more balanced viewpoint, categorizing AI's benefits and risks into three categories or domains: pedagogical, ethical, and social. Zaman [35] suggests that while AI can afford us the benefits of efficiency and personalization, the design would need to have caveats to lessen the risk of misuse, over-dependence, and diminished academic integrity standards. Özer [36] similarly delves into a clear divide between the possible AI promise of increased teacher effectiveness and AI as possible displacement or dilution of educator roles.

3.3 AI's Impact on Research and Teaching

According to Al-Zahrani [37], GenAI tools are transforming research work by increasing the speed of literature review, improving clarity around academic writing tasks, and more efficiently organizing data and information. Such advancements increase research speed while also democratizing scholarly resource access, especially for early-career researchers. Similarly, Hanafi, Al-Mansi, and Al-Sharif [38] identified the growing role of GenAI throughout the research lifecycle - from idea conception and draft writing to editing and generating hypotheses - that acknowledges and emphasizes GenAI's place in reducing repetitive work and allows researchers to focus on analysis and innovation. In education, GenAI has led to a re-evaluation of teaching practices. Chiu [39] mentions that technology promotes instructional efficiency and creativity but requires institutions to update policies around the topics of authorship, assessment, and academic integrity. While educators must provide some assurance that student use of AI promotes student achievement of learning outcomes and does not erode necessary cognitive processes. Wood and Moss [40] discuss GenAI in the context of students and how the use of GenAI has forced institutions to revisit their assessment practices. Due to the potential for the misuse of AI to facilitate academic dishonesty, institutions are requiring stricter policies with the introduction of detection tools. Rather than banning AI, an increasing number of institutions are developing ethical policy frameworks for responsibly using AI. Khalifa and Albadawy [41] note that there are significant advantages of AI-powered writing tools for academic writing, including coherence, structure, time pressure, and interdisciplinary academic writing. These tools are being adopted to assist students with writing problems related to grammar, organization, and academic conventions. The emergence of these tools are being adopted as time-saving tools and may promote quality of academic writing if used properly. According to Nikolic and his colleagues [42], while many educators are apprehensive, there is developing hope for GenAI's capacity to support inclusive education. Educators underline its worth in their work to create custom learning materials, as well as automate mundane tasks. Additionally, it advocates for future research into best practices for AI integration, stressing the importance of aligning GenAI adoption with educational values. ‘

3.4 Ethical Concerns and Academic Integrity

According to Ugwu and his colleagues [43], the academic community faces an important ethical dilemma with the use of AI tools in the research writing process. Some in the academy advocate the use of AI tools in research writing as an acceptable practice, while some scholars oppose its use due to the potential threat to the integrity of the research process itself. Because of this, researchers who wish to publish face contradictory policies. Some respected outlets for publishing research, such as Elsevier, Taylor & Francis, and Sage, as well as others, potentially encourage the use of AI in research projects and writing research articles, while journals like Science just outright refuse to accept articles that include substance about AI. Ugwu and his colleagues [43] go on to describe the confusion about differences in policies around the use of AI in research and academic publishing. It might be difficult to separate AI systems' contributions from human ones already as they have developed to assist in research work such as writing. Inconsistent authorship, in the absence of standards, could not only harm the integrity and transparency of the academic record, but also disincentivise researchers and undermine their careers. Therefore, to assist writers with clear guidance on how to best move forward, clear definitions of authorship standards are required. As AI systems become more capable of assisting research tasks, understanding whether the answer came from a human or machine is increasingly challenging. If there are no clear policies on authorship, it misrepresents the potential that the author completed the work, and scholarly publications could become compromised by conflict and questionable results. Ugwu and his colleagues [43] assert that ambiguity in attribution may influence motivation for researchers to continue their field, raise questions regarding academic accountability, and damage academic careers in general. This will ensure that researchers understand their responsibilities and obligations related to authorship and the need to maintain the integrity and transparency of the research processes. Furthermore, it is still unclear whether text produced by an AI could be considered plagiarism. Ugwu and his colleagues [43] mention that at this time, there is controversy about the distinction between repurposing ideas from training materials and generating original human work. Regarding the application of AI to research writing, there are two opposing viewpoints. An AI system's drafts are sometimes viewed as plagiarising from the original texts that were used to train the system. In some circumstances, a set of suggested ethical governance principles addresses the social and ethical issues reviewed by Schiff (2022).

Schiff [44] "Almost no research has been undertaken, no guidelines have been provided, no policies have been developed, and no regulations have been enacted to address the specific ethical issues raised by the use of Artificial Intelligence in Education," Schiff [44] noted in the context of AIED. The fact that the vast majority of national policy initiatives contain specific parts addressing AI ethics is, therefore, quite interesting. The substantial scientific and popular attention given to AI ethics over the past 10 years may help to explain this startling fact.

According to Elkhatat and his colleagues [45], Open AI classifier techniques are now used to differentiate between content created by AI and human writers, guaranteeing text authenticity in a variety of applications. According to tests conducted by the creators, the classifier properly classifies 26% of AI-written text (true positives) as "likely AI-generated" while misclassifying 9% of human-written text (false positives) as such. Copyleaks is an AI content detection approach with a 99% accuracy rate that can be embedded in dozens of Learning Management Systems (LMS) and API modules. Edward Tian's Open AI classifier program GPTZero identifies AI-generated language in students' submissions in order to deter the use of AI for plagiarism in education.

3.5 Regulation, Governance, and Responsibility

According to the Institute for AI Acceleration's [46] study, it's important to balance innovation with responsibility in terms of AI use in higher education. By enabling innovation, institutions can harness the transformative potential of AI technology to the benefit of research, teaching, and administration. Responsible AI use will address ethical issues and safeguard privacy, and reduce biases. This balance might be established with solid governance frameworks to enable accountability, transparency, and a culture of ethical AI research and use. A report published by Ruffalo Noel Levitz [47] states that only 20 percent of universities have a policy, or are in the process of developing a policy, to formally govern AI on their campuses. The lack of policies creates several risks. Without policies in place, institutions can begin to adopt AI tools without thoroughly evaluating them, leading to wasted resources, dependency on vendors, and duplication of systems. Furthermore, without proper governance in place, it is difficult for institutions to set ethical boundaries for the use of AI in teaching and assessment, risking academic integrity. Chan [48] connects educational AI governance to issues around AI policy in broader society. He indicates that privacy invasion, algorithmic discrimination, and harmful AI behavior are not unique to education and are becoming societal barriers that need to be addressed by governments. Therefore, when considering these issues in the context of universities, we must orient around existing national and international frameworks for responsible AI development.

4.6 Influence of Demographics on AI Attitudes

Both age and gender influence people's perception of AI. With growing understanding and usage of AI internationally, it is important to consider these demographic trends to formulate effective policy, educational as well as ethical frameworks. Shum and his colleagues [49] claim that people are aware of AI, becoming users, and judging its impacts, making this a favorable time to analyze opinions toward public sentiment about it. Assessing people’s perceptions of the technology provides valuable insights into what portions of the population AI adoption is aimed towards, which can tremendously benefit decision makers and developers from the industry. Schepman and Rodway [50], in their research, brought to light the relationship between individual personality traits and the perception of AI. They discovered that conscientiousness and agreeableness were the factors that showed a greater degree of patience with AI shortcomings. It was surprising to notice in the study that introverted individuals were more positive about the use of AI. Additionally, trust was a very important factor: High general institutional trust led to a positive AI outlook, and mistrust in a corporate setting was associated with the manifestation of skepticism and resistance. Age and gender differences are also quite frequently the subjects of discussion in this area of research. Lobera, along with coauthors [51] revealed in a Spanish national survey that the disapproval of AI was most commonly present among the female and older groups. These groups have also shown more contraction of technological awareness, distrust in scientific progress, and inclination for the egalitarian world order. Another work in the field of artificial intelligence, titled "No More Waiting for a Better Tomorrow: Technology Use Among Children With Disabilities," pointed out a similar trend for older and women, as they had lower optimism than younger and male respondents did. Consistently, however, Shandilya and Fan [52] observed that a larger number of younger people had more frequent experiences and brighter prospects in respect to AI. In contrast, as shared by Holder and his colleagues [53], elderly people could probably struggle in engaging with AI due to their limited experience with and rapid changes in technology

4. Method

4.1 Research Design

In this study, a quantitative, cross-sectional survey design was adopted in order to examine the extent to which academic stakeholders understand, engage with, and react to artificial intelligence (AI) within higher education. Quantitative was the preferred approach since it enables measurement of relationships between variables through statistical analysis [54]. In like manner, a cross-sectional design was suitable since the study sought to measure existing attitudes and behaviors within a given period of time and change over time. Lastly, this design also enabled comparisons among stakeholders' responses based on their demographics, such as age, gender, and position in the academic system.

4.2 Population and Sample

The study population comprised university stakeholders such as students, professors, and administrative staff. 35 valid responses were collected. The sampling strategy used was non-probability convenience sampling, which was considered adequate owing to practical limitations in reaching a random sample from various institutions

Reference [55]. Participants were invited using academic networks, institutional mailing lists, and online platforms like WhatsApp academic groups and university forums.

Efforts were made to obtain a representative sample by sampling across multiple disciplines and obtaining representation across age groups and academic positions. The participation was voluntary, and the inclusion criteria were being a member of a higher education institution and having basic awareness of AI. Informed consent was obtained from all participants prior to data collection, and ethical guidelines concerning anonymity and confidentiality were strictly maintained.

4.3 Instrumentation

The research tool was a self-administered, structured questionnaire designed by the researcher following an in-depth literature review [37,38,56].

The questionnaire had multiple sections aligned with the study's main constructs, including AI familiarity and usage, perceptions of AI benefits and risks, ethical concerns, regulation and responsibility, perceived institutional readiness, and demographic information.

Except demographic controls, all main constructs were assessed with a set of Likert-scale items on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree). Items were taken from the literature but were tailored to the academic environment of AI. For instance, measures of usage of AI included "I use AI tools in my studies regularly" for usage; for perception, an example item was "AI helps me become more efficient in academics."

To ensure the reliability of the instrument. Cronbach's alpha was calculated for each scale. The values ranged from 0.74 to 0.88, which indicated acceptable to strong internal consistency [57]. The AI familiarity and usage scale yielded a Cronbach's alpha of 0.81, affirming its reliability for the main study.

4.4 Data Collection Procedure

Data were collected over a period of four weeks using an online survey platform. The survey link was distributed through email invitations and academic social media networks. A brief explanation of the study's purpose, along with a consent form, was included at the beginning of the survey. Participants were informed that participation was voluntary and that their responses would remain anonymous and confidential.

The online format facilitated a broader reach and convenience for respondents, especially given the busy schedules typical in academic settings. No incentives were offered for participation. Ethical approval was not required due to the anonymous nature of the data and the minimal risk involved, but the study adhered to the ethical principles outlined in the Declaration of Helsinki [58].

4.6 Data Analysis

Data were analyzed using IBM SPSS Statistics Version 27. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were first computed to summarize participant characteristics and responses across key variables. This provided a general understanding of how academic stakeholders interacted with AI and their attitudes toward its use.

The research hypotheses were tested using inferential statistics. Independent samples t-tests were used to analyze differences in AI usage and perception based on binary variables, such as gender. One-way analysis of variance (ANOVA) was conducted to analyze mean differences based on several groups, such as academic roles and age groups. Pearson's correlation coefficients were used to find the strength and direction of associations among continuous variables, such as familiarity with AI, ethics concerns, or benefits of AI.

We used multiple regression analysis to determine significant predictors of the key dependent variables (e.g., AI usage or support for regulation). All analyses were done at a significance level of $p < .05$. Assumptions for each test (i.e., normality, linearity, and homogeneity of variance) were tested prior to interpreting results. When ANOVA tests showed significant differences, Tukey's HSD post hoc tests were used to evaluate which groups differed.

4.7 Ethical Considerations

The research followed established ethical protocols in the field of social science research. Participants were made aware that participation was voluntary and informed consent was obtained before participants participated, in line with the guidance from the Declaration of Helsinki [58]. No personal data were collected and responses were anonymized, in keeping with protecting anonymity as per the British Educational Research Association [59].

Participants were informed of their right to withdraw from the study at any time without reason and without consequence. The data the participants provided were stored securely in password-protected digital files and used only for educational research. Ethical transparency was maintained to ensure that the participants were fully aware of the purpose of the study and how their answers would be managed [60].

All ethical considerations were developed to be consistent with best practices in education and behavioral research to ensure participants were treated with dignity and respect during the research [61]. The research also conformed to institutional standards and ethical principles on human subject research and data protection.

5. Data Analysis

This chapter presents the results of the statistical analysis conducted on the data collected from academic stakeholders to examine their familiarity with, usage of, and perceptions regarding Artificial Intelligence (AI) in academia. The primary objective of this chapter is to provide empirical evidence that addresses the research objectives and tests the hypotheses formulated in Chapter 1. The analysis begins with descriptive statistics to outline the demographic characteristics of the respondents. These include independent samples t-tests, one-way analysis of variance (ANOVA), Pearson correlation coefficients, and multiple linear regression analyses. These tests were used in accordance with the research hypotheses and were aimed at examining differences across demographic groups and predicting dependent variables based on the independent constructs. The findings reported in this chapter are intended to offer insights into how AI is currently perceived and utilized in higher education environments and whether significant variations exist based on demographic or institutional contexts. The structure of this chapter corresponds directly to the study's hypotheses, all statistical procedures were carried out using SPSS software.

5.1 Frequency Distribution and Pie Charts

Table 1: Frequency Distribution of Demographic Characteristics of Participants (N = 35)

Variables	Category	f(%)
Age		3.51± 1.597
Under 25		7(20%)
25-34		2(5.7%)
35-44		5(14.3%)
45-54		11(31.4%)
55-64		7(20%)
65+		3(8.6%)
Gender		1.51±0.507
Male		17(49.6%)
Female		18(51.4%)
Academia Role		2.2±1.41
Faculty		19(54.3%)
Staff		1(2.9%)
Administrator		5(14.3%)
Undergraduate Student		9(25.7%)
Researcher		1(2.9%)

Note. *M* = mean, *SD* = standard deviation. Frequencies (*f*) and percentages (%) are reported for each category.

Table 1 presents the demographic characteristics of the participants (N = 35). The majority of respondents were between the ages of 45 and 54 (31.4%), followed by participants aged under 25 (20%) and those aged 55 to 64 (20%). The mean age score was (3.51± 1.597), indicating a mid-range age distribution. Gender representation was relatively balanced, with 51.4% identifying as female and 49.6% as male, and a mean gender score of (1.51±0.507). In terms of academic role, over half of the participants identified as faculty members (54.3%), followed by undergraduate students (25.7%), administrators (14.3%), staff (2.9%), and researchers (2.9%). The mean score for academic role was (2.2±1.41), suggesting that most participants occupied teaching or student positions within academic institutions.

5.2 Correlations and Reliability Estimates

Table 2: Intercorrelations and Reliability Estimates (Cronbach's Alpha) for Study Variables

Scales	1	2	3	4	5	6
1. AI Familiarity & Usage	**.784**					
2. Perceptions of AI	.087	**.789**				
3. Impact on Research & Teaching	.533**	.423*	**.868**			
4. Ethical Concerns & Integrity	-.329	-.136	-.230	**.841**		
5. Regulation & Responsibility	-.164	-.338*	-.233	.459**	**.736**	
6. Institutional Readiness	-.026	-.088	-.125	.007	0.085	**.781**

Note. Values on the diagonal (in bold) *represent Cronbach's alpha for each scale, indicating internal consistency reliability.* Significance levels: * *$p < .05$. ** $p < .01$.

Table 2 presents the intercorrelations among the study variables along with the internal consistency reliability (Cronbach's alpha) for each scale. All six constructs demonstrated acceptable reliability, with alpha values ranging from .736 to .868. The strongest positive correlation was observed between AI Familiarity & Usage and Impact on Research & Teaching ($r = .533$, $p < .01$), suggesting that greater familiarity with AI is associated with a stronger perceived impact on academic work, this supports Hypothesis 5, indicating that higher ethical concern is associated with greater support for AI regulation. Perceptions of AI also showed a moderate positive correlation with Impact on Research & Teaching ($r = .423$, $p < .05$). Ethical Concerns & Integrity was significantly correlated with Regulation & Responsibility ($r = .459$, $p < .01$), indicating that those more ethically concerned were more likely to support regulatory measures. Other relationships were weak or non-significant, including the correlation between Institutional Readiness and all other variables, which were notably low. These findings suggest distinct dimensions of attitudes and readiness toward AI within academic contexts.

5.3 Independent T-Test

Table 3: Gender-Based Comparison of Perceptions and Attitudes Toward AI in Academic Settings

	Male (n=17)		Female (n=18)				95% CI		
Gender	*M*	*SD*	*M*	*SD*	*t(df)*	*P*	*LL*	*UL*	*Cohen's d*
Perceptions of AI	2.47	0.87	2.33	.8	.48 (32.35)	.63	-.44	.72	.16
Impact on Research & Teaching	2.63	1.01	2.26	.71	1.24 (28.58)	.22	-.24	.98	.43
Ethical Concerns & Integrity	2.27	.7	2.13	.5	.70 (28.85)	.49	-.28	.57	.24
Regulation & Responsibility	2.4	.47	2.52	.53	-.71 (32.90)	.48	-.47	.22	-.24

Note. M = *mean;* SD = *standard deviation;* t*(df) = t-test value with degrees of freedom;* p = *significance value; CI = confidence interval; LL = lower limit; UL = upper limit; Cohen's* d = *effect size.*

Table 3 displays the results of independent samples t-tests comparing male and female participants across four key constructs: Perceptions of AI, Impact on Research and Teaching, Ethical Concerns and Integrity, and Regulation and Responsibility. In relation to Hypothesis 2, which posits that stakeholders' age and gender significantly predict their perception of AI's impact on research and teaching, the results show no statistically significant gender differences ($t(28.58) = 1.24$, $p = .22$). Although males reported a slightly higher mean score ($M = 2.63$, $SD = 1.01$) compared to females ($M = 2.26$, $SD = .71$), this difference did not reach significance, indicating that gender alone does not significantly predict perception of AI's academic impact.

Similarly, for Perceptions of AI, the mean difference between males ($M = 2.47$) and females ($M = 2.33$) was not significant ($t(32.35) = .48$, $p = .63$). For Ethical Concerns and Integrity, the difference was also non-significant ($t(28.85) = .70$, $p = .49$). Lastly, no significant gender-based difference was observed in Regulation and Responsibility scores ($t(32.90) = –.71$, $p = .48$). These findings support Hypothesis 2, suggesting that gender does not significantly influence AI-related attitudes or usage in Table 3.

Table 4: Age Differences by Gender in Perception, Impact, Ethics, and Regulation of AI in Academia

Age	Under 25 *(n=7)* *M(SD)*	25-34 *(n=2)* *M(SD)*	35-44 *(n=5)* *M(SD)*	45-54 *(n=11)* *M(SD)*	55-64 *(n=7)* *M(SD)*	65+ *(n=3)* *M(SD)*	*F*	*p*	η^2
Regulation & Responsibility	2.66 (.25)	1.90 (.42)	2.44 (.61)	2.67 (.48)	2.37 (.53)	1.87 (.12)	2.41	.06	.002
Perceptions of AI	2.29 (.95)	3.00 (.00)	2.50 (.79)	2.50 (.95)	2.29 (.70)	2.00 (1.00)	0.41	.83	.018
Impact on Research & Teaching	2.18 (.57)	2.63 (.53)	2.85 (.80)	2.4(1.06)	2.54 (1.13)	2.17 (.52)	0.4	.84	.029
Ethical Concerns & Integrity	2.76 (.42)	2.00 (.47)	1.80 (.18)	2.21 (.56)	2.10 (.81)	1.89 (.38)	2.28	.07	.006

Note. M = Mean, SD= Standard Deviation, *F* = ANOVA statistic; *p* = significance level; η^2 = effect size

Table 4 summarizes the differences in perceptions, ethical concerns, regulatory attitudes, and perceived impact of AI across different age groups. This table primarily relates to Hypothesis 2, which suggests that age and gender predict the perception of AI’s impact on research and teaching.

The ANOVA results show that there were no statistically significant age-based differences in any of the variables listed. For Perceptions of AI, the F-value was low ($F = 0.41$, $p = .83$), suggesting no meaningful variation across age groups. Similarly, Impact on Research & Teaching showed no significant difference ($F = 0.40$, $p = .84$), which means that age does not significantly predict how participants perceive AI's influence in research and academic instruction. Although Ethical Concerns & Integrity ($F = 2.28$, $p = .07$) and Regulation & Responsibility ($F = 2.41$, $p = .06$) approached significance, they did not meet the conventional threshold ($p < .05$). The η^2 (effect size) values for all variables were also very small, indicating negligible effects. Therefore, based on this data, therefore, Hypothesis 2 is supported, as perceptions and attitudes toward AI do not significantly differ across age groups.

5.5 Analysis of Variance (ANOVA)

Table 5: Analysis of Variance for AI Attitudes and Perceptions Across Academic Roles

	Faculty *(n=19)*	Staff *(n=1)*	Admin *(n=5)*	Undergrad *(n=9)*	Researcher *(n=1)*			
	M(SD)	*M*	*M(SD)*	*M(SD)*	*M*	*F*	*p*	η^2
Regulation & Responsibility	2.40 (.54)	2.20	2.48 (.54)	2.60 (.47)	2.60	0.31	0.872	.000
Perceptions of AI	2.42 (.85)	3.00	2.70 (.45)	2.28 (.91)	1.00	1.07	0.39	0.001
Impact on Research & Teaching	2.57 (1.01)	2.25	2.70 (.62)	2.22 (.59)	1.00	1.04	0.402	0.002
Ethical Concerns & Integrity	1.96 (.53)	2.33	2.20 (.18)	2.52 (.60)	3.67	3.81	0.013	.000

Note. M = Mean, SD= Standard Deviation, *(n = 1) unavailable standard deviation*, F = *ANOVA statistic;* p = *significance level; η^2 = effect size*

Table 5 presents the results of a one-way ANOVA conducted to examine differences in AI-related attitudes and perceptions across various academic roles: faculty, staff, administrators, undergraduate students, and researchers. These findings directly relate to Hypothesis 4, which posits that academic role significantly predicts support for AI regulation and responsibility frameworks. The results show that there were no significant differences across roles in Regulation & Responsibility ($F = 0.31$, $p = .872$), indicating that participants, regardless of their academic role, expressed similar levels of support for AI governance. Likewise, Perceptions of AI ($F = 1.07$, $p = .39$) and Impact on Research & Teaching ($F = 1.04$, $p = .402$) did not vary significantly across roles, suggesting consistent attitudes toward AI's academic benefits among different groups. However, a statistically significant difference was found in Ethical Concerns & Integrity ($F = 3.81$, $p = .013$), with $\eta^2 = .000$ indicating a small effect size. This suggests that the academic role has a modest but significant influence on participants' ethical concerns about AI. Notably, undergraduate students and researchers reported higher concern levels compared to faculty and administrative roles.

In summary, Hypothesis 4 is partially supported. While the academic role does not significantly influence perceptions of AI, its impact on research and teaching, or support for regulation, it does significantly influence ethical concerns. Specifically, undergraduate students and researchers expressed higher levels of ethical apprehension compared to faculty and administrative staff, suggesting that ethical sensitivity toward AI varies by academic position.

5.6 Multiple Regression

Table 6: Multiple Linear Regression Predicting AI Usage from Perceptions, Impact, Ethical Concerns, and Regulation

Predictor	B	SE	*β*	t	p	95.0% Confidence Interval for B	
						LB	UB
(Constant)	2.43	.73		3.34	.00	.94	3.91
Perceptions of AI	-.14	.13	-.18	-1.04	.31	-.41	.13
Impact on Research & Teaching	.42	.12	.56	3.38	.00	.16	.67
Ethical Concerns & Integrity	-.25	.18	-.23	-1.37	.18	-.62	.12
Regulation & Responsibility	.02	.23	.01	.07	.95	-.45	.48

Note. B = *unstandardized coefficient; SE = standard error; β = coefficient;* p = *significance level; CI = confidence interval; LB = lower bound; UB = upper bound.* R^2*=.355, Adjusted* R^2*=.269.*

A multiple linear regression analysis was conducted to examine whether perceptions of AI, its impact on research and teaching, ethical concerns, and attitudes toward regulation significantly predict AI usage among academic stakeholders. The overall model was statistically significant, $F(4, 30) = 4.142$, $R^2 = .355$, Adjusted $R^2 = .269$, indicating that approximately 27% of the variance in AI usage could be explained by the four predictors. Among the independent variables, only Impact on Research and Teaching was found to be a significant predictor, B = .42, SE = .12, β = .56, t = 3.38, p = .00, suggesting that individuals who perceive AI as beneficial for academic work are more likely to use AI tools. The 95% confidence interval for this effect ranged from .16 to .67, which does not include zero, further supporting its statistical significance. In contrast, Perceptions of AI (p = .31), Ethical Concerns and Integrity (p = .18), and Regulation and Responsibility (p = .95) were not statistically significant predictors of AI usage. These findings provide support for the hypothesis that the perceived academic value of AI plays a key role in determining actual usage behaviors in academic settings.

Table 7: Multiple Linear Regression Predicting Institutional Readiness from AI Perceptions, Impact, Ethical Concerns, and Regulation

						95.0% Confidence Interval for B	
Predictor	B	SE	*β*	t	p	LB	UB
(Constant)	2.49	.92		2.7	.01	.61	4.38
Perceptions of AI	-.02	.17	-.02	-.11	.92	-.36	.33
Impact on Research & Teaching	-.08	.16	-.11	-.54	.59	-.4	.23
Ethical Concerns & Integrity	-.06	.23	-.06	-.28	.78	-.53	.41
Regulation & Responsibility	.10	.29	.08	.37	.72	-.48	.69

Note. B = *unstandardized coefficient; SE = standard error; β = coefficient;* p = *significance level; CI = confidence interval; LB = lower bound; UB = upper bound.* R^2*=.22, Adjusted* R^2=108

A multiple linear regression analysis was conducted to examine whether perceptions of AI, impact on research and teaching, ethical concerns, and support for regulation significantly predict institutional readiness for AI adoption in academia. The regression model was not statistically significant, indicating that the predictors collectively did not explain a meaningful amount of variance in institutional readiness ($R^2 = .22$, Adjusted $R^2 = .108$)

None of the independent variables were significant predictors. Specifically, Perceptions of AI (B = –.02, SE = .17, β = –.02, t = –.11, p = .92), Impact on Research and Teaching (B = –.08, SE = .16, β = –.11, t = –.54, p = .59), Ethical Concerns and Integrity (B = –.06, SE = .23, β = –.06, t = –.28, p = .78), and Regulation and Responsibility (B = .10, SE = .29, β = .08, t = .37, p = .72) all yielded p-values above the conventional significance threshold of .05. The 95% confidence intervals for each coefficient included zero, indicating a lack of statistically reliable effects.

Based on these results, Hypothesis 1 is not supported. The findings suggest that institutional readiness for AI is not significantly influenced by stakeholders' perceptions, perceived impact, ethical concerns, or support for regulation.

6. Discussion

6.1 Results Discussion

This study presents to the growing scholarship on the role of AI in higher education, specifically in terms of use patterns, self-reported effectiveness, ethical matters, regulatory views, and institutional readiness. An overarching theme in this study was that the only statistical predictor of usage was the self-reported effectiveness of AI on academic performance, teaching and research in particular. This finding coincides with a number of recent findings that argue practical function is the strongest motivating factor for adoption among students and academics alike. For example, Batista, Mesquita, and Carnaz [62] state that users who believe that their productivity will be enhanced or learning will be improved are more likely to adopt AI tools. Systematic literature reviews consistently illustrate that people in higher education see functionality within the context of professional work as being the main motivator for adoption, not ethics, institutional factors or attitudes.

Kohnke, Moorhouse, and Zou [63] further supported this conclusion in their case study of university language instructors, showing that teachers were far more inclined to adopt AI tools when they perceived direct pedagogical benefits, such as efficiency in creating teaching resources or providing feedback. These instructors often displayed a pragmatic orientation, one which prioritizes academic enhancement over theoretical or ethical hesitations. This parallels the regression analysis in the present study, where “Impact on Research and Teaching” emerged as the only statistically significant variable influencing AI usage, accounting for the majority of explained variance in the model.

In contrast to expectations, this study found that institutional readiness had no significant influence on AI usage among participants. Although many institutions globally have begun to draft policies and outline AI strategies, their practical influence on faculty and student behavior remains ambiguous. Akanzire, Nyaaba, and Nabang [64], studying educators’ attitudes in Ghanaian colleges of education, observed that although AI-readiness strategies existed at the administrative level, they rarely translated into classroom-level support or tool integration. The present findings echo this reality, suggesting that the presence of readiness policies may lack operational substance, and that end-user behavior is shaped more by individual or contextual motivators than by institutional declarations.

However, this perspective is not universally accepted. Lin, Chan, and Bista [65], examining global patterns of AI adoption in higher education, argued that institutional investment in AI literacy, infrastructure, and faculty development significantly affects adoption rates. Their research indicated that where institutions offer consistent training and resources, AI integration is more successful. The contrast between their findings and the results of the current study may be attributed to differences in institutional maturity, geographic scope, or sample characteristics. The current study's sample was limited and may have drawn from institutions where readiness was more nominal than active.

Another important outcome of this study was the non-significant influence of demographic variables such as age and gender on AI-related attitudes and behaviors. This finding aligns with the observations of Khlaif and his colleagues [66], who studied instructors and students across several Middle Eastern universities. They concluded that, once access and exposure are leveled, demographic distinction is often erased, and user behavior will converge in homogeneity. Jin et [67] also found slight generational divides within a global perspective study, with older faculty being more hesitant and resistant, particularly in Western locales. But, the generational divides largely disappeared in contexts having more institutional support and high exposure to technology, indicating access to AI tools and training likely outweighed people's inherent demographic differences.

One of the most interesting findings from this study was that ethical reservations were not a substantial deterrent to using AI, despite participant claims of ethical considerations such as academic dishonesty, or misuse of data. Even when they acknowledged ethical quandaries, participants did not correspondingly exhibit behavioral avoidance. Mireku, Abenaba and Kweku [68] identified a similar phenomenon in which ethical concerns were high among Ghanaian students, but so too was frequent use of tools like ChatGPT. The authors highlighted a sort of cognitive dissonance where students justified their use of something they criticized, by focusing on the tool's usefulness, and not the ethical consequences. Similarly, Ahmed and his colleagues [69] drew attention to this issue in a large-scale survey-based study of university students. Specifically, the survey results illustrated that while 74% of respondents agreed that generative AI tools pose serious ethical challenges, nevertheless, over 80% had used generative AI tools for homework, or plans, in the last six months.

This disconnection between ethical concern and behavior raises interesting questions about the relationship between awareness and practice. The current study provides support for the notion that ethical concern does not equal restraint, and instead seems to co-occur with frequent use. Nevertheless, there was a strong correlation between ethical concerns and support for AI regulation, suggesting that while users do not self-impose limits on their own behavior, they support institutions in attempts to establish boundaries and guidelines. This is congruent with a similar study by Barros and Saúde [70], which found people expressing high ethical concern about generative AI were also the strongest proponents for policy intervention. They determined ethical awareness is more likely to fuel political or policy preferences than personal behavioral change.

Another noteworthy result is the impact of academic role on the ethical considerations mentioned. The current study's undergraduate students and researchers expressed more ethical worry than faculty or administrators. Chan and Tsi [71] observed a similar pattern in their study of AI perceptions in East Asian universities, where students tended to express more concern about fairness, plagiarism, and transparency when it comes to AI use. They speculated this was due to students being more susceptible to consequences related to academic misconduct and being subjected to a greater level of institutional discourse surrounding AI ethics. The role-based variation could complicate the discussion further to suggest that perceptions of ethical risk may be somewhat rooted in institutional power relationships and accountability mechanisms.

Lower ethical concern among faculty members could indicate a somewhat more instrumental conception of the use of an AI tool, nonetheless, that may be concentrated among members with high levels of confidence about addressing issues of academic integrity. In contrast, students and researchers, who might often be more subject to scrutiny, might internalize institutional discourse about responsible AI use more thoroughly. This divergence in perception should inform any future institutional policies that are developed to address the differences in concerns and stakes, or roles

Finally, the findings of this study call into question the idea that comprehensive policies developed by an organization are adequate enough to influence user behavior. Participants in this study recognized the concept of institutional readiness, or regulatory structures, to which their behavior did not necessarily conform. Jin and his colleagues [67] identified this discrepancy in their global review of AI policies adopted in schools of higher education. While increased adoption of AI policy frameworks denotes progress, the implementation of policies remains minimal and superficial. At many institutions, policies are created without fundamental training, incentive structures, or feedback systems, which further separates organizational aspirations from user realities.

This disconnect can be further demonstrated by the finding that in the current study none of the variables—ethical concern, perceptions of AI, or attitudes towards regulation—were shown to be significant predictors of institutional readiness. This might suggest that institutional readiness is less a reflection of users' feelings and more a function of strategic leadership, policies being acted upon, and the available technology. Therefore, enhancing institutional readiness will require more than articulating policy; it will take embedding AI in the daily practices and workflows of academic staff and students.

6.1 Limitations

While the study offered valuable information, there are limitations to consider. First, the small sample size (N=35) limits generalizability to larger academic contexts. Liang and his colleagues [72] articulated that studies related to AI and higher education need larger and more diverse samples to account for the nuance of perspectives across institutional types and global regions. Second, the cross-sectional design does not allow for causal inferences. Longitudinal studies could tell us more about how perceptions and behaviors changed over time [73]. Third, given the nature of self-reported data, it may be biased as a result of social desirability or recall bias, which is a limitation in educational technology research [74]. Finally, the study focused mainly on perceptions of AI instead of specifying AI tools or platforms, which likely would provide a deeper insight into the differential adoption and trust of various AI technologies.

6.3 Implications

The results of this research have some significant implications for higher education institutions that are implementing AI processes. For instance, the impactful role of "Impact on Research & Teaching" as an indicator of AI usage implies that institutions might want to prioritize demonstrating academic utility to help move forward in adoption. Ott [75] mentions that if faculty and students interpret AI tools as productivity enhancers rather than an abstract technology, it could support engagement. Moreover, the weak correlation between institutional readiness and action shows a disconnect between institutional policies and institutional realities. As cited by Safiulina [76], it is important to move beyond declarative institutional policies and instead think about how to embed AI into pedagogical and administrative infrastructures. Finally, students and researchers raised ethical issues, and there seemed to be a lack of targeted ethics training and a space for open discussions addressing these issues. Institutions should differentiate their strategies for various academic stakeholders based on their anxieties and needs, appropriate to their AC role and where it might necessitate establishing trust and responsible usage.

6.4 Future Research Directions

Future studies should expand on this project via three important avenues. First, longitudinal studies to show how student perceptions and student behaviors change over time, as tools become increasingly advanced and inflected in college academic practices [77]. Second, comparative studies across different regions and types of institutions to see how differences in culture and socio-cultural differences facilitate or inhibit AI adoption in higher education

Reference [78]. These studies should pay particular attention to socio-cultural differences, as well as access to technology, training, and enforcement of policy. Third, ethics is highlighted as an area of study that certainly requires additional research, especially as generative AI is increasingly being used for student assessments and in content creation. Rehman and his colleagues [74] suggest conducting research focused not only on what people think or perceive the ethics to be, but also what institutions can do to articulate ethics through policies and pedagogy. Finally, I believe future studies should amplify student views more as part of this research agenda; in terms of users' acceptance of AI and its value, college students remain the population that is most directly impacted by policy decisions involving AI.

6.5 Conclusion

This study explored the academic stakeholders in higher education perceive, think through, and act with artificial intelligence (AI). Ultimately, we found that perceived impact, and, importantly, the perceived impact in relation to research or teaching, had the greatest influence on participants' use of AI. Each participant reported different levels of ethical concern and ethical awareness, and these ethical determinants did not have a noticeable check on use. So, while ethics were certainly a consideration, utility and the furthering of perceived scholarship mattered much more. Conversely, institutional readiness, which is often a point of emphasis in policy discussions, was not a strong enough contributor to predictability of use or confidence in usage, revealing a mismatch between the ideals of policy creators and the reality of their use. The academic role attributed to shaping ethical sensitivity, especially more so for students and early-career researchers, is likely due to more awareness of academic misconduct as a result of greater vulnerability. Gender and age did not predict differences in attitudes or usage. This all complicates simple models of technology adoption and further emphasizes the contextualized nature of AI. This study deepens conversations about how function matters most in weighing whether to use AI, followed by awareness and demographic variables. Future directions for research and institutional initiatives should support function, address discipline specific needs, and increase ethical literacy for members in each academic role.

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7.Appendix

Table 1: Frequency Distribution of Demographic Characteristics of Participants (N = 35)

Variables Category	f(%)
Age	3.51± 1.597
Under 25	7(20%)
25-34	2(5.7%)
35-44	5(14.3%)
45-54	11(31.4%)
55-64	7(20%)
65+	3(8.6%)
Gender	1.51±0.507
Male	17(49.6%)
Female	18(51.4%)
Academia Role	2.2±1.41
Faculty	19(54.3%)
Staff	1(2.9%)
Administrator	5(14.3%)
Undergraduate Student	9(25.7%)
Researcher	1(2.9%)

Note. *M* = mean, *SD* = standard deviation. Frequencies (*f*) and percentages (%) are reported for each category.

Table 2: Intercorrelations and Reliability Estimates (Cronbach's Alpha) for Study Variables

Scales	1	2	3	4	5	6
7. AI Familiarity & Usage	**.784**					
8. Perceptions of AI	.087	**.789**				
9. Impact on Research & Teaching	.533**	.423*	**.868**			
10. Ethical Concerns & Integrity	-.329	-.136	-.230	**.841**		
11. Regulation & Responsibility	-.164	-.338*	-.233	.459**	**.736**	
12. Institutional Readiness	-.026	-.088	-.125	.007	0.085	**.781**

Note. Values on the diagonal (in bold) *represent Cronbach's alpha for each scale, indicating internal consistency reliability*. Significance levels: * *$p < .05$. ** $p < .01$.

Table 3: Gender-Based Comparison of Perceptions and Attitudes Toward AI in Academic Settings

	Male *(n=17)*		Female *(n=18)*				*95% CI*		
Gender	*M*	*SD*	*M*	*SD*	*t(df)*	*P*	*LL*	*UL*	*Cohen's d*
Perceptions of AI	2.47	0.87	2.33	.8	.48 (32.35)	.63	-.44	.72	.16
Impact on Research & Teaching	2.63	1.01	2.26	.71	1.24 (28.58)	.22	-.24	.98	.43
Ethical Concerns & Integrity	2.27	.7	2.13	.5	.70 (28.85)	.49	-.28	.57	.24
Regulation & Responsibility	2.4	.47	2.52	.53	-.71 (32.90)	.48	-.47	.22	-.24

Note. M = *mean;* SD = *standard deviation;* t(*df*) = *t-test value with degrees of freedom;* p = *significance value; CI = confidence interval; LL = lower limit; UL = upper limit; Cohen's* d = *effect size.*

Table 4: Age Differences by Gender in Perception, Impact, Ethics, and Regulation of AI in Academia

	Under 25 *(n=7)*	25-34 *(n=2)*	35-44 *(n=5)*	45-54 *(n=11)*	55-64 *(n=7)*	65+ *(n=3)*			
Age	*M(SD)*	*M(SD)*	*M(SD)*	*M(SD)*	*M(SD)*	*M(SD)*	*F*	*p*	η^2
Regulation & Responsibility	2.66 (.25)	1.90 (.42)	2.44 (.61)	2.67 (.48)	2.37 (.53)	1.87 (.12)	2.41	.06	.002
Perceptions of AI	2.29 (.95)	3.00 (.00)	2.50 (.79)	2.50 (.95)	2.29 (.70)	2.00 (1.00)	0.41	.83	.018
Impact on Research & Teaching	2.18 (.57)	2.63 (.53)	2.85 (.80)	2.4(1.06)	2.54 (1.13)	2.17 (.52)	0.4	.84	.029
Ethical Concerns & Integrity	2.76 (.42)	2.00 (.47)	1.80 (.18)	2.21 (.56)	2.10 (.81)	1.89 (.38)	2.28	.07	.006

Note. M = Mean, SD= Standard Deviation, *F* = ANOVA statistic; *p* = significance level; η^2 = effect size

Table 5: Analysis of Variance for AI Attitudes and Perceptions Across Academic Roles

	Faculty *(n=19)*	Staff *(n=1)*	Admin *(n=5)*	Undergrad *(n=9)*	Researcher *(n=1)*			
	M(SD)	*M*	*M(SD)*	*M(SD)*	*M*	*F*	*p*	η^2
Regulation & Responsibility	2.40 (.54)	2.20	2.48 (.54)	2.60 (.47)	2.60	0.31	0.872	.000
Perceptions of AI	2.42 (.85)	3.00	2.70 (.45)	2.28 (.91)	1.00	1.07	0.39	0.001
Impact on Research & Teaching	2.57 (1.01)	2.25	2.70 (.62)	2.22 (.59)	1.00	1.04	0.402	0.002
Ethical Concerns & Integrity	1.96 (.53)	2.33	2.20 (.18)	2.52 (.60)	3.67	3.81	0.013	.000

Note. M = Mean, SD= Standard Deviation, *(n = 1) unavailable standard deviation,* F = *ANOVA statistic;* p = *significance level; η^2 = effect size*

Table 6: Multiple Linear Regression Predicting AI Usage from Perceptions, Impact, Ethical Concerns, and Regulation

						95.0% Confidence Interval for B	
Predictor	B	SE	*β*	t	p	LB	UB
(Constant)	2.43	.73		3.34	.00	.94	3.91
Perceptions of AI	-.14	.13	-.18	-1.04	.31	-.41	.13
Impact on Research & Teaching	.42	.12	.56	3.38	.00	.16	.67
Ethical Concerns & Integrity	-.25	.18	-.23	-1.37	.18	-.62	.12
Regulation & Responsibility	.02	.23	.01	.07	.95	-.45	.48

Note. B = *unstandardized coefficient; SE = standard error; β = coefficient;* p = *significance level; CI = confidence interval; LB = lower bound; UB = upper bound. R^2=.355, Adjusted R^2=.269.*

Table 7: Multiple Linear Regression Predicting Institutional Readiness from AI Perceptions, Impact, Ethical Concerns, and Regulation

Predictor	B	SE	β	t	p	95.0% Confidence Interval for B	
						LB	UB
(Constant)	2.49	.92		2.7	.01	.61	4.38
Perceptions of AI	-.02	.17	-.02	-.11	.92	-.36	.33
Impact on Research & Teaching	-.08	.16	-.11	-.54	.59	-.4	.23
Ethical Concerns & Integrity	-.06	.23	-.06	-.28	.78	-.53	.41
Regulation & Responsibility	.10	.29	.08	.37	.72	-.48	.69

Note. B = *unstandardized coefficient; SE = standard error; β = coefficient;* p = *significance level; CI = confidence interval; LB = lower bound; UB = upper bound.* R^2=.22, *Adjusted* R^2=108