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Governing the Intelligent University: An Empirical Analysis of Artificial Intelligence (AI) Integration Challenges in Smart City Knowledge Systems

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Universities serve as vital knowledge generation hubs within serious smart city strategies. However, the empirical integration of artificial intelligence into Egyptian academic research practices remains largely unexamined. This study surveys 105 researchers across four distinct core dimensions: awareness, workflow utilization, perceived barriers, and expected impact. The results demonstrate that general awareness is wide but shallow, while actual tool adoption is low. Operational and ethical challenges scored highest across the survey, with 85.7% of participants explicitly citing insufficient professional training as the primary bottleneck. Expected impact scores lean positive, particularly regarding efficiency, but skepticism about output accuracy limits overall optimism. Ultimately, this study frames artificial intelligence (AI) integration within higher education as an institutional smart city knowledge governance challenge. Fulfilling Egypt's national digital transformation agenda requires strategic policy intervention, structured governance frameworks, and systemic investment in human capacity, rather than focusing on technological infrastructure acquisition and deployment alone.

1. Introduction

The introduction of artificial intelligence (AI) marks one of the most consequential technological shifts in the history of higher education. From automating literature searches and data analysis to generating academic text and facilitating peer review processes, AI tools are profoundly altering the research landscape at universities worldwide. This transformation is no longer confined to technologically advanced nations. It is increasingly reshaping academic institutions in the Global South, including Egyptian universities, which face distinctive socioeconomic, infrastructural, and policy-related challenges in embracing these technologies.

Egypt, as the most populous Arab country and a major hub of higher education in Africa and the Middle East, hosts over 60 public and private universities enrolling millions of students. The country has in recent years pursued ambitious digital transformation agendas, making it an important and yet under-studied context for examining AI adoption in academic research. Understanding how Egyptian universities interact with AI its opportunities, adoption barriers, and ethical implications is critical for policymakers, academic administrators, faculty, and students.

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This literature review aims to map the existing body of knowledge on AI in academic research with particular attention to the Egyptian and broader MENA context. It proceeds through five thematic sections, culminating in a synthesis of research gaps and recommendations for future study.

1.1 Conceptual Framework

This study is guided by an integrated conceptual framework that maps the structural and thematic dimensions of AI integration in academic research within Egyptian universities. The framework draws on three foundational pillars: (1) Technology Acceptance Theory (TAM and UTAUT), which explains the cognitive and social factors driving AI adoption; (2) Sustainable Development Goals (SDGs), specifically SDG 4 (Quality Education) and SDG 9 (Innovation and Infrastructure), which situate AI adoption within a broader agenda of equitable and sustainable development; and (3) Institutional Theory, which addresses the organizational, policy, and cultural contexts that mediate AI diffusion in higher education settings.

The framework flows through five interrelated thematic domains, as follows: The first domain, Global AI Landscape, provides the macro-level context of AI development and adoption in higher education worldwide. The second domain, AI Adoption in MENA and Egypt, narrows focus to regional and national patterns, examining tool usage, institutional readiness, and socioeconomic constraints specific to Egyptian universities. The third domain, Research Methodology Applications, examines how AI tools are deployed across qualitative, quantitative, and mixed-methods research stages. The fourth domain, Ethics and Academic Integrity, explores how AI reshapes scholarly norms, plagiarism risks, and institutional policy requirements. The fifth domain, Barriers to Sustainable Integration, identifies structural impediments including infrastructure gaps, digital literacy deficits, and cultural factors that hinder equitable AI adoption.

These five domains feed into a synthesis layer that identifies research gaps and formulates recommendations for policy, practice, and future research. The framework is visually represented below as a sequential-integrative model: each domain builds cumulatively on the prior one, ultimately converging on actionable guidance for sustainable AI governance in Egyptian higher education. This approach is consistent with Sahar et al. [38], who advocate for thematically structured bibliometric and content analysis as a basis for future research agendas in AI and higher education, and with Nikolopoulou [37], who calls for empirically grounded frameworks linking generative AI to sustainable educational outcomes.

Theoretical Foundations

TAM / UTAUT | Sustainable Development Goals (SDG 4, SDG 9) | Institutional Theory

▼

Five Thematic Domains

[1] Global AI Landscape → [2] MENA / Egypt AI Adoption → [3] Research Methodology Applications → [4] Ethics & Academic Integrity → [5] Barriers to Sustainable Integration

▼

Synthesis Layer: Research Gaps, Policy Recommendations & Sustainable AI Governance for Egyptian Higher Education

Fig. 1. Conceptual Framework: AI Integration in Academic Research Egyptian Universities

1.2 The Global Landscape of AI in Higher Education and Research

1.2.1 AI in higher education: scope and evolution

The application of AI in higher education has grown substantially over the past decade. Bond et al. [10] conducted a comprehensive meta-review of secondary literature on AI in higher education, synthesizing 66 systematic reviews published between 2018 and 2023. Their analysis revealed that the predominant AI applications in higher education center on adaptive learning systems, personalized learning, and profiling and prediction. Crucially, they identified significant methodological and ethical gaps in existing research, including inadequate interdisciplinary approaches and insufficient attention to contextual factors findings that underscore the need for region-specific investigations such as the Egyptian case.

George et al. [18] conceptualized the emergence of "smart universities" as the next evolutionary stage for higher education, powered by AI and quantum technologies. They argued that while AI integration promises personalized learning, enhanced accessibility, and greater operational efficiency, it also introduces risks related to educational quality, job displacement, algorithmic bias, and data privacy. Their analysis, which notably considered historically marginalized institutions, is directly relevant to Egyptian universities navigating analogous challenges of resource constraints and digital equity.

1.2.2 AI and research productivity

Beyond teaching and learning, AI has begun reshaping the research function of universities. Rolnik [30] documented how AI enhances data analysis, automates repetitive research tasks, and enables entirely new research methodologies across disciplines. Similarly, Oyelude [27] reviewed AI tools as applied across multiple stages of academic research from literature review and data collection to writing and proofreading concluding that such tools significantly augment research efficiency and output quality, while simultaneously raising methodological and ethical concerns about authorship and accountability.

Ekundayo et al. [17], using focus group methodology with researchers from multiple disciplines and institutions, found that AI has positively influenced research methodologies, knowledge creation, and overall research productivity. However, participants also raised concerns about over-reliance on AI and the risk of diminishing the distinctly human cognitive contribution to scholarly inquiry. These findings are consistent with Perkins et al. [29], who examined the application of generative AI in both qualitative and quantitative research, demonstrating practical utility in transcription, thematic coding, statistical analysis, and visual analytics, while highlighting challenges of replicability and consistency in AI-assisted research.

1.2.3 AI tools in academic writing and literature review

The use of large language models (LLMs), particularly ChatGPT, in academic writing has attracted intense scholarly attention. Burger et al. [11] provided guidelines for using AI in systematic literature reviews, arguing that AI has the potential to make researchers' work faster and more reliable, particularly in handling unstructured data and automating repetitive tasks. Khlaif et al. [21] empirically evaluated ChatGPT-generated research articles, finding that with detailed prompting, ChatGPT can produce text of sufficient quality for high-impact journals, though its contribution to methodological development and data analysis remains limited. Nguyen et al. [26], in a study of doctoral students' interactions with AI writing tools, found that iterative, highly interactive engagement with AI produced superior academic writing outcomes compared to using AI merely as a supplementary information source.

1.3 AI Adoption in Arab and Egyptian Universities

1.3.1 The MENA Regional Context

The MENA region presents a heterogeneous landscape for AI adoption in higher education. Alzahrani et al. [7] conducted a comprehensive mixed-methods study across 508 participants from 259 institutions in 19 MENA countries, finding that 43.9% of institutions were still at early stages of AI adoption. Adaptive Learning Platforms (29.6%) and AI-enhanced research tools (26.9%) were the most commonly implemented technologies. Significant disparities in adoption were observed across income groups, with high-income countries demonstrating far greater integration. Key barriers identified in lower-income countries included financial constraints (17.9%), infrastructure deficiencies (17.1%), and the absence of clear institutional policies.

Khlaif et al. [22] surveyed 358 faculty members across Middle Eastern countries to examine factors driving the adoption of generative AI in student assessment. Using the UTAUT model, they found that performance expectancy, effort expectancy, social influence, and hedonic motivation significantly shaped educators' behavioral intentions. The study stressed the importance of institutional policies as a prerequisite for responsible and equitable AI integration a finding with direct implications for Egyptian higher education governance.

1.3.2 ChatGPT adoption among Arab university students

A multinational study by Abdaljaleel et al. [1] surveyed 2,240 university students in five Arab countries Iraq, Kuwait, Egypt, Lebanon, and Jordan using the validated TAME-ChatGPT instrument. The study found that 46.8% of respondents were aware of ChatGPT, and 52.6% had used it prior to the survey. Positive attitudes were associated with perceived ease of use, perceived usefulness, social influence, and low anxiety levels. Crucially, the study identified country of residence, age, university type, and recent academic performance as significant moderators of ChatGPT adoption, suggesting that policy responses should be context-sensitive rather than uniform across the region.

Strzelecki & ElArabawy [34] compared ChatGPT adoption among university students in Poland and Egypt across six universities, applying the extended UTAUT framework. The findings indicated that performance expectancy, effort expectancy, and social influence significantly influenced behavioral intention to use ChatGPT. Importantly, the study revealed that gender and academic year moderated several of these relationships, underscoring the need for targeted training programs and awareness initiatives tailored to specific student demographics in Egyptian universities.

1.3.3 AI in Egyptian Higher Education: Policy and Practice

Several studies have begun to address the Egyptian context specifically. Negm [25] surveyed 405 faculty members at Egyptian universities, examining intentions to adopt AI in line with United Nations Sustainable Development Goals. The study found that AI adoption is perceived as beneficial for achieving quality education (SDG 4), environmental sustainability (SDGs 7, 9, and 12), and institutional efficiency. Perceived usefulness emerged as the dominant driver of adoption, mediated by job relevance, output quality, and subjective norms. These findings suggest that AI adoption at Egyptian universities is increasingly framed within broader institutional development agendas.

El Baradei & Abdulkarim [16] examined AI from a public policy perspective, analyzing how AI can address systemic challenges in Egyptian higher education. While specific findings were not fully available, the study's framing highlights the growing recognition among Egyptian policymakers of AI as a transformative tool for educational reform. Complementing this perspective, Salem et al. [31] assessed AI competency and readiness among medical educators in the Middle East, including Egypt, finding that AI competency and readiness are primary drivers of sustainable adoption, and that ethical perspectives on AI integration varied notably between Middle Eastern and South Asian educators reflecting culturally embedded attitudes toward technological governance.

1.4 AI Applications in Academic Research Methodology

1.4.1 Qualitative research methods

AI tools have found significant application in qualitative research. Christou [13] outlined how AI is used in literature and systematic reviews, conceptualization, thematic analysis, and content analysis. He cautioned that AI-assisted qualitative research risks producing unreliable and biased outputs if not rigorously overseen, proposing five guiding principles for responsible AI use, including cross-referencing AI-generated information and maintaining visible cognitive input from the human researcher throughout the process.

Akman et al. [4] conducted a comparative study of human versus AI-supported qualitative data analysis, using a hybrid prompt engineering strategy with ChatGPT. The findings indicated that well-designed AI prompts can significantly enhance the efficiency and accuracy of thematic coding and categorical analysis. However, human oversight remained essential to prevent systematic errors and prompt-induced biases.

1.4.2 Quantitative research and data analysis

In the domain of quantitative research, AI tools are automating statistical analysis, predictive modeling, and data visualization. Zhang et al. [36] examined the factors influencing the adoption of AI-based data analysis tools among academic researchers, finding that perceived utility and ethical concerns interact in complex ways to shape adoption decisions, with significant variation across academic disciplines and research contexts. Adeniran et al. [3] further documented how the integration of data analytics encompassing AI-driven approaches at academic institutions can enhance research productivity, optimize resource allocation, and improve institutional decision-making, though they also flagged concerns about data privacy, technical capacity, and financial barriers.

1.4.3 AI and Research Infrastructure

The broader integration of AI into institutional research infrastructure is mediated by Learning Management Systems (LMS) and research support platforms. Alotaibi [6], in a PRISMA-guided review of 60 studies, found that AI-LMS integration significantly enhances student engagement, personalizes learning pathways, and improves institutional performance metrics. However, algorithmic bias, data privacy, and the need for comprehensive faculty training were consistently identified as critical challenges. These infrastructure-level considerations are particularly relevant for Egyptian universities, many of which are in early stages of LMS adoption and lack the technical workforce to manage AI systems effectively.

1.5 Ethical Dimensions, Academic Integrity, and Institutional Policy

1.5.1 AI and Academic Integrity in Higher Education

The proliferation of AI tools particularly generative models such as ChatGPT has intensified concerns about academic integrity in universities worldwide. Cotton et al. [14], in a widely cited analysis, examined how ChatGPT enables novel forms of academic dishonesty, including sophisticated AI-generated submissions that evade traditional plagiarism detection tools. The authors recommended that universities adopt a multi-pronged strategy combining updated institutional policies, faculty training, and diversified assessment methods that prioritize critical thinking over text production.

Perkins [28] argued that the ethical classification of student use of LLMs in formal assessments depends fundamentally on institutional policy frameworks rather than on any inherent property of the AI tool itself. He concluded that transparency of use, rather than blanket prohibition, should be the cornerstone of academic integrity policies in the AI era. Song [32], analyzing higher education institutions globally, found that most institutions lack formal AI use guidelines, creating ambiguity for both students and faculty and contributing to increased academic misconduct incidents.

1.5.2 Institutional policy frameworks

The technological arms race between AI content generation and AI detection has profound implications for research integrity. Bing et al. [9] analyzed the effectiveness of AI-powered plagiarism detection systems, finding that while such systems significantly improve detection accuracy for paraphrased and AI-generated content, they also raise concerns about false positives and the ethical dimensions of automated student surveillance. Balalle et al. [8] conducted a systematic review concluding that AI presents both opportunities and threats to academic integrity, and that a balanced approach preserving human judgment while leveraging AI's analytical power is essential for maintaining scholarly standards.

Alawad et al. [5] examined AI-generated content and plagiarism rates in student writing submissions in an academic context proximate to Egypt, finding average AI-usage rates of 38–49% in student essays submitted to Turnitin. The study noted that student attitudes toward AI were divided: while many valued academic integrities in principle, there was genuine ambiguity about whether AI assistance constitutes academic misconduct highlighting the urgent need for clear, institutionally communicated policies.

1.5.3 Plagiarism detection and AI-generated content

The development of institutional AI policies has emerged as a critical imperative. Spivakovsky et al. [33], drawing on the experience of Kherson State University, developed a model for institutional AI governance applicable to diverse higher education contexts. They proposed differentiated policy guidelines for students, faculty, and researchers, specifying both recommended and proscribed uses of AI. Their framework is particularly instructive for Egyptian universities, which largely lack formal AI governance structures.

Khatri et al. [20] synthesized evidence on AI's dual role in higher education enhancing productivity and learning while simultaneously challenging academic integrity and scholarly originality. They concluded that preserving scientific research integrity in the AI era requires placing human critical thinking at the forefront of academic work, suggesting that assessment reforms and AI literacy training should be institutionalized across Egyptian universities. Crawford et al. [15] further argued that institutional leadership is indispensable for cultivating an ethical AI culture, emphasizing character development and authentic assessment as structural antidotes to AI-enabled academic misconduct.

1.6 Barriers to AI Integration in Developing-Country Academic Environments

1.6.1 Structural and infrastructural barriers

The integration of AI at universities in developing countries faces a distinctive cluster of barriers that differ in nature and intensity from those in high-income academic environments. Gkrimpizi et al. [19], in a systematic literature review, identified 20 distinct barriers to digital transformation in higher education, classified into six broad categories: environmental, strategic, organizational, technological, people-related, and cultural. Infrastructure-related and financial barriers were found to be particularly salient in lower-income country contexts.

Alzahrani et al.'s [7] MENA-wide study confirmed that financial constraints and infrastructure deficiencies are the primary impediments to AI adoption in the region's lower-income institutions a profile that applies to many Egyptian public universities, which face significant resource constraints relative to the scale and demands of their student populations.

1.6.2 Human capital and digital literacy

Beyond infrastructural barriers, deficiencies in AI literacy among both faculty and students represent a critical bottleneck. Mah et al. [23], studying faculty attitudes toward AI across higher education institutions, found that lack of AI literacy was among the greatest challenges, with a majority of faculty expressing interest in professional development opportunities. The study identified four distinct faculty profiles optimistic, critical, critically reflected, and neutral underscoring the heterogeneity of attitudes that policy interventions must address.

Titko et al. [35], in a multi-country European study of academic staff, found that only about 40% of respondents reported using AI tools, attributing low adoption partly to inadequate skills and the absence of structured training programs. Faculty were generally supportive of AI for information searches and teaching material preparation but resistant to AI use in research and thesis writing, reflecting concerns about research authenticity. These findings resonate with the situation in Egyptian universities, where digital skills training has historically received insufficient institutional investment.

1.6.3 Cultural and Policy Factors

Cultural attitudes toward technology adoption, combined with the absence of national-level AI policy frameworks for education, constitute additional barriers. Mohamad et al. [24], studying computer engineering educators across the MENA region, identified the alignment of AI investments with national vision statements as crucial for sustaining adoption momentum. They also noted that excessive AI reliance risks undermining critical thinking a pedagogical concern with deep resonance in Egyptian academic culture, where traditional lecture-based and memorization-focused teaching methods remain prevalent. Abulibdeh et al. [2] added that the ethical challenges of Industry 4.0 technologies, including AI, necessitate curriculum redesign and strategies for continuous learning imperatives that Egyptian higher education institutions have only begun to address in any systematic fashion.

1.7 Barriers to AI Integration in Developing-Country Academic Environments

1.7.1 Synthesis and Research Gaps

The foregoing review reveals a dynamic and rapidly expanding literature on AI in academic research, with a growing body of evidence from the MENA region, including Egypt. Several important patterns emerge from this synthesis:

- First, AI adoption in Egyptian and MENA universities is real but uneven, concentrated in larger and better-resourced institutions, and still at early stages for many public universities. Adoption is driven by perceived usefulness, social influence, and institutional policy clarity factors that can be deliberately shaped by policy interventions.
- Second, AI tools offer demonstrable benefits for academic research at Egyptian universities particularly in literature synthesis, data analysis, writing support, and research productivity but these benefits are contingent on adequate AI literacy training, infrastructure, and clear institutional governance frameworks.
- Third, ethical and academic integrity challenges are acute and insufficiently addressed. Egyptian universities, like their counterparts elsewhere, lack robust policy frameworks for AI use in research, creating ambiguity and facilitating academic misconduct. The

development of culturally appropriate, contextually adapted AI governance policies is an urgent priority.

- Fourth, significant research gaps remain. There is a paucity of Egypt-specific empirical research on: (a) the actual prevalence and patterns of AI tool use in research by Egyptian academics; (b) the perceived impacts on research quality and productivity; (c) the specific barriers and enablers at Egyptian institutions; and (d) the development and evaluation of AI governance policies tailored to the Egyptian higher education system. These gaps represent important opportunities for future primary research.

1.8 Conclusion

This literature review has demonstrated that AI is reshaping academic research globally, with growing but uneven penetration in Egyptian and MENA universities. The evidence establishes that AI tools can enhance research efficiency, expand methodological repertoires, and support academic writing benefits that are particularly valuable in resource-constrained environments where researchers face heavy teaching loads and limited access to research infrastructure. At the same time, the literature unequivocally establishes that AI integration without adequate governance, training, and institutional policy risks undermining research integrity, deepening digital divides, and homogenizing scholarly knowledge production.

For Egyptian universities, the path forward requires simultaneous action on multiple fronts: investment in digital infrastructure, structured AI literacy programs for faculty and researchers, the development of context-sensitive institutional AI policies, and the cultivation of a research culture that harnesses AI's capabilities while preserving the critical, creative, and ethical dimensions that define scholarly inquiry. The present review aims to provide a scholarly foundation for this agenda and to invite further empirical investigation of the Egyptian case.

2. Methodology

2.1 Research Design

This study adopted a quantitative descriptive survey design, which is well suited to investigating attitudes, perceptions, and self-reported behaviors across a defined population (Creswell & Creswell, 2018). The descriptive approach was selected because the study aimed to document the current state of AI use in academic research at Egyptian universities, assess awareness and challenges, and estimate the expected impact on research quality objectives that do not require experimental manipulation but benefit from systematic quantification of participant responses.

2.2 Population and Sample

The target population comprised academics and researchers affiliated with Egyptian universities, including faculty members at various academic ranks (lecturers, instructors) and postgraduate researchers. A convenience sampling procedure was employed, consistent with the online distribution method used. Participation was voluntary and open to all members of the academic community engaged in research activities. A total of 105 valid responses were collected and retained for analysis. Table 1 presents the distribution of respondents by academic role. As shown in Table 1, lecturers constituted the largest group (n = 50, 47.6%), followed by researchers (n = 40, 38.1%), instructors (n = 10, 9.5%), and students (n = 5, 4.8%). The predominance of lecturers and researchers is consistent with the study's focus on academic research practices in higher education institutions.

Table 1
Sample Characteristics by Academic Role

Role / Academic Position	Frequency (n)	Percentage (%)
Lecturer	50	47.6%
Researcher	40	38.1%
Instructor	10	9.5%
Student	5	4.8%
Total	**105**	**100%**

2.3 Instrument Development

Data were collected using a structured self-administered questionnaire designed specifically for this study and distributed electronically via Google Forms. The questionnaire comprised two parts. The first part recorded demographic information, specifically the participant's academic role. The second part consisted of 20 Likert-type items organized into four thematic dimensions, each comprising five items:

(1) Awareness of AI Applications in Academic Research: This dimension measured participants' self-reported knowledge of AI tools, their ability to follow recent AI developments, and their recognition of AI's potential benefits in research.

(2) Actual Use of AI Applications: This dimension assessed the extent to which participants actively employ AI tools in their research workflows, including data collection and analysis, academic writing, reference management, and research design.

(3) Challenges Associated with AI Use: This dimension explored barriers and concerns related to AI adoption, including technical difficulties, concerns about result accuracy, ethical reservations, potential impact on research originality, and insufficiency of professional training.

(4) Expected Impact of AI on Research Quality: This dimension examined participants' perceptions of AI's anticipated contribution to research output quality, efficiency, error reduction, creativity, and global research competitiveness.

All items were rated on a three-point Likert scale: Agree, Neutral, and Disagree. A three-point scale was selected to maximize response clarity and minimize ambiguity, which is appropriate for diverse academic populations with varying familiarity with survey methodology (Garland, 1991).

2.4 Content Validity

The instrument was developed based on a thorough review of relevant literature on AI adoption in higher education and academic research, drawing on established frameworks including the Technology Acceptance Model (TAM) and recent empirical studies on AI use in the MENA region and globally. Item content was aligned with the four thematic dimensions identified in the literature as most central to understanding AI integration in research contexts [7,27,35].

2.5 Data Collection Procedure

The questionnaire was distributed electronically through Google Forms during a defined data collection period. The link was circulated through academic networks, university departmental channels, and professional research groups accessible to the research team. Participation was entirely voluntary, anonymous, and not linked to any institutional affiliation requirement. Respondents were informed of the study's purpose at the start of the form. All submitted responses were automatically recorded and exported as a spreadsheet for analysis.

2.6 Data Analysis

Quantitative data were analyzed using descriptive statistical methods. For each item and each thematic dimension, the following statistics were calculated: (a) frequency distributions and percentages for the three response categories (Agree, Neutral, Disagree); (b) arithmetic means (M) and standard deviations (SD) per item and per dimension, treating the three-point scale as continuous following established practice in survey research (Norman, 2010). Mean scores were interpreted against a standardized scale: scores of 1.00–1.66 were classified as Low, 1.67–2.33 as Moderate, and 2.34–3.00 as High. Descriptive comparisons across academic role groups were also conducted to identify patterns in responses. All analyses were performed using Python (pandas library).

3. Result

This section presents the study's findings across four thematic dimensions of the questionnaire. Each subsection reports the quantitative results and situates them within the existing literature on AI in academic research and higher education, with particular attention to Egyptian and MENA contexts.

3.1 Awareness of AI Applications in Academic Research

Table 2 presents the frequency distributions and descriptive statistics for the five items constituting the Awareness dimension.

The overall mean for the Awareness dimension was M = 2.37 (SD = 0.77), which falls in the High range of the adopted interpretation scale. Participants, taken together, reported a reasonably positive level of awareness regarding AI tools in academic research though the variation across individual items complicates that picture.

The two highest-scoring items were Item 5 ("AI represents an indispensable future direction in scientific research"; M = 2.81, SD = 0.50; 85.7% agreement) and Item 3 ("I recognize the benefits that AI technologies can offer to researchers"; M = 2.76, SD = 0.53; 81.0% agreement). Both point to a strong normative orientation toward AI's future role in research. Alzahrani et al. (2025) found similar attitudes in their MENA study: most academics acknowledged AI's transformative potential even in institutions where formal adoption was still limited. Rolnik [30] made the same observation awareness of AI's potential benefits typically runs ahead of actual adoption rates.

Table 2

Descriptive Statistics for the Awareness of AI Applications Dimension

Item	Agree %	Neutral %	Disagree %	M	SD
1. I have sufficient knowledge of AI tools used in scientific research.	38.1%	38.1%	23.8%	2.14	0.78
2. I follow recent developments related to AI in research.	42.9%	33.3%	23.8%	2.19	0.80
3. I recognize the benefits AI technologies can offer to researchers.	81.0%	14.3%	4.8%	2.76	0.53
4. I can distinguish between different AI tools and their roles in research stages.	28.6%	38.1%	33.3%	1.95	0.79
5. AI represents an indispensable future direction in scientific research.	85.7%	9.5%	4.8%	2.81	0.50
Section Overall				**2.37**	**0.77**

Item 4 ("I can distinguish between different AI tools and their roles in the various stages of research") tells a different story. It recorded the lowest mean in the dimension (M = 1.95, SD = 0.79), with only 28.6% agreeing and 33.3% disagreeing. Participants broadly recognized AI as valuable but lacked the operational knowledge to use it purposefully at different research stages. This disconnect between positive macro-awareness and limited tool-specific knowledge is well documented in AI adoption studies from developing-country academic contexts [23,35]. Items 1 and 2, which measured self-reported knowledge sufficiency and engagement with recent AI developments, landed in the moderate range (M = 2.14 and 2.19, respectively), confirming that awareness exists but is neither comprehensive nor consistently current.

These results point to a real gap between recognizing AI's importance and actually knowing which tools to use for what. Salem et al. [31] identified exactly this as the primary AI integration challenge in Middle Eastern academic contexts bridging the distance between theoretical awareness and hands-on application competency.

3.2 Actual Use of AI Applications

Table 3 presents the results for the Actual Use of AI Applications dimension, which measures the extent to which participants engage with AI tools in their practical research activities.

Table 3

Descriptive Statistics for the Actual Use of AI Applications Dimension

Item	Agree %	Neutral %	Disagree %	M	SD
1. I regularly use AI tools in my research work.	33.3%	42.9%	23.8%	2.10	0.75
2. AI applications have helped me in data collection and analysis.	38.1%	38.1%	23.8%	2.14	0.78
3. I have used AI in writing or editing parts of my research.	23.8%	38.1%	38.1%	1.86	0.78
4. I use AI tools to organize references or manage sources.	23.8%	47.6%	28.6%	1.95	0.73
5. I use AI to suggest ideas or design research studies.	33.3%	28.6%	38.1%	1.95	0.85
Section Overall				**2.00**	**0.78**

The overall mean for this dimension was M = 2.00 (SD = 0.78), the lowest of the four dimensions, sitting at the boundary between Low and Moderate use. The pattern observed in the Awareness section repeats itself: participants hold positive views of AI without yet turning them into regular research practice.

Items 1 and 2 drew the most agreement. Item 1 ("I regularly use AI tools in my research work") yielded M = 2.10 (SD = 0.75), with 33.3% agreeing and 23.8% disagreeing indicating that regular AI use is still a minority practice. Item 2 ("AI applications have helped me in data collection and analysis") came in slightly higher (M = 2.14, SD = 0.78; 38.1% agreement), suggesting that data-related tasks tend to be the entry point for those who have tried AI. Ekundayo et al. [17] and Perkins et al. [29] both identified data analysis and synthesis as the areas where AI tools offer the most tangible efficiency gains.

The lowest-scoring item was Item 3 ("I have used AI in writing or editing parts of my research"; M = 1.86, SD = 0.78), where 38.1% both agreed and disagreed. The disagreement rate is notable given that AI writing assistance through tools like ChatGPT is arguably the most publicized AI application in academic contexts globally. Two things are probably happening at once: ethical reluctance to use AI for academic writing, and insufficient familiarity with generative AI writing tools. Strzelecki and ElArabawy [34], in an Egypt-inclusive study, found that while ChatGPT awareness is growing among Arab university communities, actual integration into research writing remains limited by ethical concerns and digital literacy barriers.

Items 4 and 5 (reference management and research idea generation, respectively) also recorded low means (M = 1.95 each) with substantial disagreement. AI use in Egyptian university research appears nascent and concentrated in familiar, lower-stakes tasks rather than integrated across the full research lifecycle. Alzahrani et al. (2025) reported that 43.9% of MENA institutions are still at early stages of AI adoption, a figure that fits the pattern here.

3.3 Challenges Associated with AI Use in Research

Table 4 presents descriptive statistics for the Challenges dimension. Notably, this dimension produced the highest overall mean (M = 2.52, SD = 0.65), falling clearly in the High range, indicating that participants strongly endorsed the challenges associated with AI adoption in research.

Table 4
Descriptive Statistics for the Challenges Associated with AI Use Dimension

Item	Agree %	Neutral %	Disagree %	M	SD
1. I have difficulty understanding how AI applications work.	28.6%	38.1%	33.3%	1.95	0.79
2. I find that some AI tools lack accuracy in their results.	52.4%	47.6%	0.0%	2.52	0.50
3. I have ethical concerns about full reliance on AI in research.	71.4%	28.6%	0.0%	2.71	0.45
4. AI use may affect the originality of research work.	66.7%	28.6%	4.8%	2.62	0.58
5. Lack of training or professional awareness hinders effective AI use.	85.7%	9.5%	4.8%	2.81	0.50
Section Overall				**2.52**	**0.65**

Item 5 "Lack of training or professional awareness hinders effective AI use in research" was the highest-scoring individual item across the entire questionnaire (M = 2.81, SD = 0.50; 85.7% agreement). This is not a surprise. Multiple studies have identified AI literacy and professional training as the main barriers to meaningful AI integration in academic environments [7,23,35]. The near-unanimous endorsement here suggests a systemic gap in formal AI competency programs within the Egyptian higher education system, not just isolated cases of individual unfamiliarity.

Ethical concerns were prominent as well. Item 3 ("I have ethical concerns about full reliance on AI in research") recorded M = 2.71 (SD = 0.45; 71.4% agreement), and Item 4 ("AI use may affect the originality of research work") yielded M = 2.62 (SD = 0.58; 66.7% agreement). Not a single participant disagreed with Item 3, and only one in twenty-one disagreed with Item 4 figures that point to something close to consensus. This aligns with what the global literature shows: concern about AI threatening research originality and academic integrity is among the most consistent apprehensions in higher education [8,14,20]. The particular salience of these concerns in Egypt may reflect cultural values around scholarly authenticity, as well as institutional environments that have not yet developed clear norms for acceptable AI use in research.

Item 2 ("Some AI tools lack accuracy in results") was endorsed by 52.4% of participants (M = 2.52, SD = 0.50), with the rest neutral and none disagreeing. Every participant who formed a view on this item agreed that accuracy limitations are real. Khlaif et al. [21] documented this empirically: AI-generated research content, while often of acceptable quality, has notable limitations in methodological development and data analysis accuracy.

Item 1 ("I have difficulty understanding how AI applications work"; M = 1.95, SD = 0.79) was the only item with a notably divided distribution 33.3% of participants actually disagreed. The central barrier is not basic technical illiteracy. Rather, it is the absence of structured professional training to convert existing digital familiarity into research-grade AI competency. That distinction matters for how institutions respond.

3.4 Expected Impact of AI Applications on Research Quality

Table 5 presents the findings for the Expected Impact dimension. The overall section mean was M = 2.34 (SD = 0.71), placing this dimension at the lower boundary of the High range.

Table 5
Descriptive Statistics for the Expected Impact of AI on Research Quality Dimension

Item	Agree %	Neutral %	Disagree %	M	SD
1. AI contributes to improving the quality of research outputs.	42.9%	47.6%	9.5%	2.33	0.65
2. AI increases the efficiency of completing research stages.	57.1%	33.3%	9.5%	2.48	0.67
3. AI can reduce human errors in data analysis.	33.3%	47.6%	19.0%	2.14	0.71
4. AI enhances opportunities for creativity and innovation in research.	61.9%	19.0%	19.0%	2.43	0.79
5. AI use has become a necessity for research excellence per global standards.	47.6%	38.1%	14.3%	2.33	0.72
Section Overall				**2.34**	**0.71**

Item 2 ("AI increases the efficiency of completing research stages"; M = 2.48, SD = 0.67; 57.1% agreement) drew the strongest endorsement, followed by Item 4 ("AI enhances opportunities for creativity and innovation in research"; M = 2.43, SD = 0.79; 61.9% agreement). Participants are broadly optimistic about AI's capacity to improve efficiency and creative output a finding that mirrors the international literature. George et al. [18] argue that AI's primary promise in academic contexts lies in augmenting human creative and analytical capacity, and Oyelude [27] consistently identifies research efficiency as the most documented benefit of AI tool integration.

Items 1, 3, and 5 produced more cautious agreement profiles, each in the M = 2.14–2.33 range. Item 1 ("AI contributes to improving the quality of research outputs"; M = 2.33, SD = 0.65) drew 42.9% agreement but a substantial 47.6% neutral response suggesting uncertainty rather than opposition. Item 3 ("AI can reduce human errors in analysis") recorded the lowest mean in this section (M = 2.14, SD = 0.71; 33.3% agreement, 19.0% disagreement), reflecting skepticism about AI's reliability for error reduction likely informed by the accuracy concerns documented in the Challenges dimension. Item 5 ("AI use has become a necessity for research excellence per global standards"; M = 2.33, SD = 0.72; 47.6% agreement) shows a view that is held by some but far from universal.

Taken together, the picture across this dimension is one of guarded optimism. Participants expect more from AI than their current adoption levels would suggest, but those expectations are tempered by concerns about accuracy, authenticity, and ethics documented in the Challenges dimension. Abulibdeh et al. [2] and Castro Benavides et al. [12] describe this same gap between positive expectations and cautious practice as characteristic of technology adoption in developing-country university systems.

3.5 Comparative Analysis by Academic Role

Table 6 presents mean scores for each of the four dimensions disaggregated by academic role.

Table 6
Section Mean Scores by Academic Role

Dimension	Lecturer (n=50)	Researcher (n=40)	Instructor (n=10)	Student (n=5)
AI Awareness	M=2.22	M=2.60	M=2.50	M=1.80
Actual AI Use	M=2.04	M=2.05	M=1.90	M=1.40
Challenges	M=2.46	M=2.58	M=2.70	M=2.40
Expected Impact	M=2.32	M=2.33	M=2.50	M=2.40

On the Awareness dimension, researchers recorded the highest mean (M = 2.60), followed by instructors (M = 2.50), lecturers (M = 2.22), and students (M = 1.80). This pattern makes sense: researchers' professional identities are built around research production, giving them more exposure to AI tools through publications, conferences, and research networks. The lower awareness among students likely reflects limited access to professional research communities and the absence of systematic AI literacy training. Abdaljaleel et al. [1], in a multinational study of Arab university students, documented significant variation in ChatGPT awareness across respondent groups, consistent with this finding.

For Actual AI Use, all groups scored near or below the midpoint (lecturers M = 2.04, researchers M = 2.05, instructors M = 1.90, students M = 1.40). Students' particularly low score may reflect restricted access to AI research tools and the different nature of their research activities relative to faculty. Across all groups, actual use lags behind awareness, reinforcing the finding that awareness-to-practice translation is the core adoption problem.

In the Challenges dimension, instructors reported the highest endorsement (M = 2.70), followed by researchers (M = 2.58), lecturers (M = 2.46), and students (M = 2.40). The elevated scores among instructors and researchers are worth noting. For instructors, greater direct exposure to AI-related difficulties in applied research contexts may be a factor. For researchers, heightened sensitivity to ethical and authenticity implications given that research is their core professional activity is a plausible explanation. All groups scored above the moderate threshold: perceived challenges are salient regardless of academic role.

Expected Impact scores were relatively uniform across groups (range: M = 2.32 to M = 2.50), with instructors and students reporting the highest expectations (M = 2.50 and 2.40 respectively). This convergence stands in contrast to the greater divergence in the Awareness and Actual Use dimensions suggesting that positive expectations about AI's potential are broadly shared across the Egyptian academic community, even where current adoption and awareness differ.

4. Conclusion

Four principal findings emerge from this study. First, awareness of AI's potential in academic research is relatively high among Egyptian university academics, though it remains concentrated in generalized recognition of AI's value rather than granular, tool-specific knowledge. Second, actual AI use in research is low to moderate and has not yet been integrated across core research activities such as writing, reference management, and study design suggesting that the awareness-to-practice gap documented in the MENA literature Alzahrani et al. [7] applies acutely to the Egyptian university context. Third, challenges to AI adoption are strongly felt across the sample, with insufficient professional training and ethical concerns about research originality and integrity emerging as the most universally endorsed barriers. Fourth, expectations regarding AI's positive impact on research quality are broadly positive but tempered, particularly regarding error reduction and output quality improvement, where a substantial proportion of participants remained neutral or skeptical.

Taken together, these findings suggest that Egyptian universities stand at an inflection point in their relationship with AI in academic research: positive orientation and aspirational acknowledgment of AI's importance are widespread, but structural barriers particularly inadequate training infrastructure and the absence of institutional ethical frameworks continue to constrain active, purposeful, and ethically grounded AI adoption in research practice.

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The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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