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Original article

Artificial Intelligence in Libyan Academia: Adoption, Ethics, and Institutional Responses: A Mixed-Methods Study

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Abstract
AI has quickly become an important technology for knowledge creation in academia; however, there is little information about AI adoption in the context of non-Western countries that feature linguistic diversity. The present paper employs a mixed methods approach (sequential explanatory design) to examine the use of artificial intelligence among 130 Libyan researchers who work in public universities and institutes across various career levels and disciplines (STEM, medical sciences, humanities, business, and environmental sciences). Quantitative data were analysed using exploratory factor analysis (EFA), hierarchical cluster analysis (HCA), structural equation modelling (SEM), random forest (RF) classification, and social network analysis (SNA), complemented by thematic analysis of open-ended responses. Key findings: (1) AI adoption is near-universal (96.2%, 95% CI [92.1, 98.6]), with ChatGPT as the preferred tool (85.5%). (2) Three distinct adopter clusters emerge: Enthusiastic Adopters (32%, daily use 76.2%, low ethical concern), Cautious Integrators (41%, strategic use, high verification), and Skeptical Minimalists (27%, minimal use, greatest ethical concern). (3) Despite widespread verification (73.8% always check AI output), only 11.5% consistently disclose AI assistance, a profound disclosure deficit. (4) Using SEM, we find that institutional policy clarity emerges as the most powerful predictor of disclosure ($\beta = 0.45$, $p < 0.001$), followed by individual ethical concern ($\beta = 0.25$, $p = 0.008$) and disciplinary norms ($\beta = 0.18$, $p = 0.04$). Productivity benefits have no significant effect on disclosure ($\beta = 0.09$, $p = 0.21$). (5) Finally, using random forest classification (accuracy = 78.4%), we find that policy clarity is the most important variable (importance = 0.32). Theoretical contribution: We present the Academic Technology Acceptance Model (ATAM), which builds upon existing TAM and TPB models by incorporating four novel variables: epistemic utility, disciplinary alignment, institutional legitimacy, and ethical compatibility, and illustrates how they impact the adoption intensity vs. disclosure. Practical implications: Training individual academics about the ethics of AI use is ineffective; what is needed are clearly defined, publicly available, and rigorously enforced institutional policies. Universities should develop comprehensive AI policies, make the disclosure process mandatory, and educate their students; journal editors should standardize disclosure templates and develop strict authorship policies; and researchers should adopt rigorous verification practices. Conclusion: AI is much more than just a tool; it is an epistemic infrastructure. Its responsible adoption necessitates institutional measures that ensure transparency, accountability, and ethical integrity across all stages of the research workflow. Without such structural safeguards, the disclosure deficit will persist regardless of individual awareness or productivity gains.
Keywords. Artificial Intelligence, Research Integrity, Technology Adoption, Institutional Policy.

Introduction

The incorporation of artificial intelligence into academic research represents an essential transformation in knowledge production. Unlike earlier digital tools that mainly affected distribution and storage, modern generative AI systems, specifically large language models, impact the generation, validation, and articulation of scholarly claims. This qualitative shift elevates crucial questions about epistemic agency and research integrity [1]. This represents what Collins and Evans [2] define as a wave-three shift in expertise. altering the basic mechanisms through which knowledge is created by way of computer enhancement. Following earlier digital transformations in scholarly communication [3], modern generative AI systems present unprecedented challenges and opportunities for academia's core functions of knowledge production, verification, and dissemination [4].

The large language models (LLMs) rapid growth [5] since 2020 has induced what Jasan [6] calls a socio-technical imaginary, a collective vision of AI-enhanced scholarship that concurrently guarantees efficiency gains while intimidating established norms of authorship, originality, and critical inquiry [7]. This tension displays what Markovsky [8] recognizes as inherent incompatibilities within epistemic cultures when encountering disruptive technologies. While there is abundant theoretical discussion about the implications of AI [4, 9], empirical research into its real-world uptake is surprisingly scarce, especially when it comes to interdisciplinarity and professional life span considerations. Indeed, the current research literature on AI presents several important limitations in terms of methodology, such as limited samples, interdisciplinarity, Western bias, and longitudinal analysis [10, 11]. It fails to account for the distinct socio-technical imaginaries and institutional peculiarities that characterize non-Western environments like Libya. This gap is even wider among Arabic-speaking researchers and students. While large-scale polls have found that the

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global community of academics is quickly adopting AI tools into their workflows [9,10], there have been only a few surveys of Arabic-speaking academics.

Two recent surveys from Libyan academia report that awareness and usage of AI tools are quickly increasing amongst students and faculty [12,13]. However, both of these surveys focused on the classroom use of AI tools. One Libyan study further discovered that most AI users learn about these tools independently. These gaps have been filled by a comprehensive research methodology combining qualitative and quantitative approaches, paying particular attention to Arab speaking scholars based in Libya. The Libyan situation provides an interesting case study of the use of AI tools, taking into account the pressures exerted from having to operate in an environment characterized by English language dominance while communicating in Arabic, among others. The research questions that the current study attempts to address are the following: 1- To what extent does the adoption and usage of AI differ in terms of the disciplinary and demographic differences existing within academic circles? 2- Which epistemic and ethical approaches are characteristic of researchers using AI? 3- What kind of mediating role can be observed regarding the connection between AI adoption and the implementation of research ethics principles by institutional settings?

Theoretical Framework and Research Hypotheses

Adapting Technology Acceptance for Academic Knowledge Work.

Our analytical framework builds upon basic technology acceptance theories and adapts them to include factors unique to academic knowledge work. Standard theories (TAM, TPB) need to be extensively adapted to be used in AI implementation in research environments [14]. Recent studies have found that needs of a psychological nature, specifically relatedness, autonomy, and competence, are crucial for the implementation of AI in higher education institutions in Arabic-speaking countries. Such needs are implicit and explicit in the extended ATAM framework, where institutional legitimacy corresponds to relatedness to organizational culture and policies, disciplinary alignment pertains to competence and autonomy, and ethical compatibility supports an autonomous sense of competence. Based on the above framework, we propose four constructs relevant specifically for academics:

Epistemic Utility

The perception of the usefulness of AI as contributing to the creation of knowledge, as opposed to simply increasing the efficiency of the tasks performed. This construct takes into account that academics assess their tools not based solely on efficiency, but also on whether the tool helps advance the epistemology of the research conducted [15]. (Our operationalization measures this construct using perceived productivity utility items, since epistemic utility is measured through the efficiency achieved, and, therefore, facilitates cognition).

Disciplinary Fit

The perception of how well AI aligns with the particular epistemic traditions, research practices, and rhetoric characteristic of a given field of study. As it will be demonstrated, tools that are perfectly suited to be used within scientific processes could be completely inappropriate for the humanities [16]. (In the questionnaire, this construct is assessed using perceived discipline-specific practices related to AI).

Institutional Legitimacy

The perceived alignment of AI use with organisational policies, collegial norms, and reward structures. Research on AI governance demonstrates that institutional policy clarity is a critical determinant of responsible AI use [17]. (In the study, institutional legitimacy is operationalized through perceived clarity of institutional policies, which we treat as the primary indicator of this construct).

Ethical compatibility

The perceived consistency of AI use with research integrity principles and professional ethics. This acknowledges that academic technology adoption involves not merely instrumental calculations but moral judgments about appropriate scholarly conduct [18]. (Our survey measures this construct using items about ethical concerns, including worries about plagiarism, skill erosion, and appropriate use boundaries).

Hypothesized Relationships in the ATAM

Based on the four constructs defined above, the Academic Technology Acceptance Model (ATAM) makes the following predictions regarding the direction of relationships see (Figure 1):

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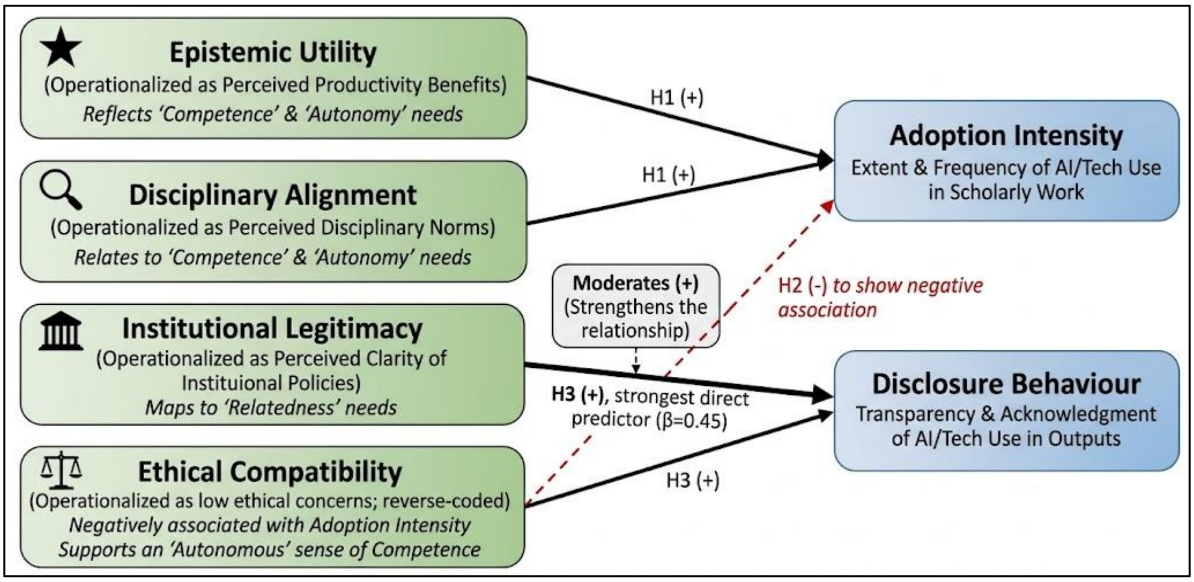

Figure 1. The Academic Technology Acceptance Model (ATAM). Epistemic Utility and Disciplinary Alignment are hypothesised to positively affect Adoption Intensity (H1). Ethical Compatibility is negatively associated with Adoption Intensity (H2). Both Institutional Legitimacy and Ethical Compatibility positively predict Disclosure Behaviour (H3). Institutional Legitimacy also moderates the effect of Ethical Compatibility on Disclosure Behaviour, strengthening this relationship (moderation). Standardised coefficient β = 0.45 indicates the direct effect of Institutional Legitimacy on Disclosure Behaviour

Epistemic Practices and Academic Identity
The use of AI in this regard not only transfers knowledge but also helps to create knowledge as well. Outsourcing tasks like reviewing the literature, formulating hypotheses, and constructing arguments by making use of AI brings into play nonhuman entities in the process of creating knowledge, creating many philosophical problems related to the role of scholars and the ethics of scholarship. The complexity is increased in Libya due to the linguistic issues that arise in this context, as AI performs many functions such as translation, learning new words, and understanding English language literature, though there are no formal avenues available for this purpose [19].

Institutional Logics and Ethical Governance
The Institutional Logics approach by Thornton et al. [20] is utilized to evaluate the different value systems in adopting artificial intelligence: the logic of profession, the logic of market efficiency and productivity, and the logic of technology innovation. The conflict between these logics results in the phenomenon referred to as institutional complexity by Greenwood et al. [21]. This demonstrates how institutional logics directly influence the challenges of ethical governance by creating environments of inconsistent policies and ambiguous ethical frameworks. Research Hypotheses. Using the constructs of the ATAM framework along with the proposed empirical measures outlined above, the following hypotheses will be tested:

H1 (Epistemic Utility and Adoption Intensity)
Perceived epistemic utility (as measured by productivity improvements) has a positive relationship with AI adoption intensity (AI frequency and breadth of adoption).

H2 (Ethical Compatibility and Adoption Intensity)
Ethical concerns (inverse of ethical compatibility) have a negative relationship with AI adoption intensity. Scholars with higher perceptions of ethical incompatibility will adopt AI less often and use fewer AI tools.

H3 (Institutional legitimacy and Disclosure behavior)
Perceived institutional legitimacy (measured by policy clarity) has a positive relationship with consistent AI assistance disclosure.

H4 (Strength of Predictors)
Institutional legitimacy has a stronger positive relationship with disclosure behavior than does ethical compatibility or epistemic utility. Specifically, policy clarity will be the dominant predictor of disclosure.

H5 (Disciplinary Alignment as Moderator/Mediator)
Disciplinary alignment (operationalized via perceived disciplinary norms) mediates the relationship between epistemic utility and adoption intensity. Furthermore, the strength of this mediation differs between STEM and humanities researchers.

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H6 (Experience Cluster Affiliation)
Years of professional research experience significantly predict researcher cluster affiliation (Enthusiastic Adopters, Cautious Integrators, or Skeptical Minimalists), with early career researchers more likely to be Enthusiastic Adopters and senior researchers more likely to be Skeptical Minimalists.

H7 (Mediation of Critical Verification)
Critical verification actions (e.g., fact checking, external verification of AI products) serve as mediators between ethical compatibility and the act of disclosure. In other words, higher ethical compatibility results in greater verification, which subsequently triggers disclosure. This effect is, however, attenuated by the lack of institutional guidelines.

Methodology

Research Design

This study employed a sequential explanatory mixed-methods design: quantitative survey data collection and analysis were followed by qualitative thematic analysis of open-ended responses to elaborate upon and contextualize statistical findings.

Instrument Development

Development of the survey tool took place via a structured three-step procedure. Firstly, we undertook a detailed review of the literature, searching in the Web of Science, Scopus, and Google Scholar databases (2015 – 2025) for the terms "artificial intelligence, academic research, technology adoption, research ethics," and related keywords. The output of this review formed a list of 94 possible items to include in the survey. Secondly, we performed expert validation by three academics working in the areas of artificial intelligence, educational technology, and computer science (from Libyan research institutions). Expert validation involved the examination of each item in terms of clarity, relevance, and representativeness. Any items with a content validity ratio of less than 0.70 underwent modification or exclusion. Finally, we performed pilot testing using 15 target respondents. The final instrument comprised 48 items across six domains: 1- demographic and professional background (7 items); 2- AI tool adoption and usage patterns (12 items); 3- motivations and perceived benefits (8 items); 4- ethical concerns and disclosure practices (9 items); 5- institutional context and policy awareness (6 items); and 6- epistemological orientations toward AI-mediated scholarship (6 items). All constructs used a five-point Likert scale (from strongly disagree = 1 to strongly agree = 5), except when frequency or nominal measurement was appropriate. (Table 1) below provides an overview of the six constructs, item numbers, and format of the final questionnaire.

Table 1. The six domains, number of items, and response formats of the final instrument

Domain	Constructs Measured	Number of Items	Response Format
Demographics	Position, experience, discipline, institution type	7	Categorical, continuous (where applicable)
AI Usage Patterns	Adoption, frequency, tools, applications	12	Multiple selection, frequency scales (e.g., Likert or ordinal)
Motivations and Perceived Benefits	Efficiency, quality, innovation, skill development	8	5-point Likert (1 = strongly disagree to 5 = strongly agree)
Ethical Considerations	Attribution, transparency, integrity, bias awareness	9	5-point Likert (1 = strongly disagree to 5 = strongly agree)
Institutional Context	Policies, support, norms, rewards	6	5-point Likert (1 = strongly disagree to 5 = strongly agree) and categorical (e.g., presence of policies)
Epistemological Orientations	Nature of knowledge, AI-mediated scholarship, trust in AI-generated outputs	6	5-point Likert (1 = strongly disagree to 5 =

Sampling Strategy and Data Collection

Employing purposive maximum variation sampling, we recruited participants from public universities and research institutes across Libya's major geographic regions. Recruitment occurred via institutional email lists, professional academic network groups on social media, and direct contact with department heads. We explicitly sought variation across three predefined strata: 1- type of institution (comprehensive university, specialised institute, faculty); 2- academic position (from Master's student to Full Professor); and 3- primary disciplinary area (categorised into seven groups based on Libyan institutional classification systems). Inclusion criteria were: 1- current engagement in academic research (active involvement in at least one

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research project within the preceding 12 months); 2- primary institutional affiliation with a Libyan research institution; and 3- work in any academic discipline. No exclusion criteria were applied regarding AI experience or familiarity.
Data collection occurred from October 4 to October 28, 2025; the survey was conducted using Google Forms survey software in Modern Standard Arabic. The median completion time was 18.7 minutes. Of 191 individuals who accessed the survey link, 130 provided complete responses meeting quality checks (attention check items, completion time greater than 5 minutes, no straight lining), yielding a response rate of 68.0%. Table 2 presents participant demographics.

Table 2. Demographic and Academic Characteristics of the Study Participants (N = 130)

Characteristic	Categories	Number	Percentage	95% Confidence Interval
Gender	Male	99	76.2	[68.2, 82.8]
	Female	31	23.8	[17.2, 31.8]
Academic position	Lecturer	40	30.8	[23.4, 39.2]
	PhD student	39	30.0	[22.7, 38.4]
	Assistant professor	25	19.2	[13.2, 27.0]
	Master's student	13	10.0	[5.7, 16.6]
	Associate professor	6	4.6	[1.9, 10.0]
	Full professor	1	0.8	[0.0, 4.6]
	Other (research assistant, visiting scholar, emeritus)	6	4.6	[1.9, 10.0]
Research experience	More than 10 years	74	56.9	[48.2, 65.3]
	6–10 years	30	23.1	[16.5, 31.1]
	3–5 years	15	11.5	[6.9, 18.4]
	Less than 3 years	11	8.5	[4.5, 14.8]
Primary discipline	Medical/health sciences	37	28.5	[21.3, 36.8]
	Natural/engineering sciences	29	22.3	[15.9, 30.3]
	Business/economics	18	13.8	[8.7, 21.0]
	Environmental sciences	17	13.1	[8.1, 20.2]
	Biotechnology	15	11.5	[6.9, 18.4]
	Humanities/social sciences	10	7.7	[4.0, 13.9]
	Other (mathematics, education, law)	4	3.1	[1.0, 7.9]

Participants identities have been fully anonymized, and all direct quotations presented in this research are provided solely to help explain different perspectives on the adoption of artificial intelligence, without any intention to harm or defame any participant."

Analytical Approach

Data analysis employed an integrative mixed methods framework across four sequential phases.

Phase 1: Quantitative descriptive and inferential analysis

Descriptive statistics were computed with 95% exact binomial confidence intervals for proportions. For means, we employed bootstrapping (1000 resamples) to obtain bias corrected and accelerated confidence intervals, as Shapiro-Wilk tests indicated non-normal distributions for several Likert scale items (Wringing from 0.82 to 0.94, all $p < 0.05$).

Phase 2: Factor analysis and cluster modelling

Exploratory factor analysis used principal axis factoring with ProMax rotation (kappa = 4). A kappa value of 4 was chosen to allow for moderate correlation between factors, reflecting the theoretical expectation that the four ATAM constructs (productivity enhancement, ethical concern, institutional support, critical skill preservation) are related but conceptually distinct. Factorability was confirmed with Kaiser Meyer Olkin measure = 0.84 and Bartlett's test of sphericity ($x^2 = 1124.7$, df = 276, $p < 0.001$). Hierarchical cluster analysis used squared Euclidean distance and Ward's minimum variance method, validated by silhouette analysis (average silhouette width = 0.71) and k means cross validation. For all factor analyses, we report percentages of common variance explained after oblique rotation, as is standard when factors are expected to correlate.

Phase 3: Structural equation modelling and machine learning

Confirmatory factor analysis validated the measurement model. Structural equation modelling tested the ATAM using maximum likelihood estimation with robust standard errors. Random forest classification

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(Python, Scikit-learn, with estimators = 500, max depth = 10, min samples leaf = 5) predicted consistent disclosure with 10-fold cross-validation. Social network analysis of tool co-usage used the igraph package in R; nodes represented individual AI tools, edges indicated co-usage by at least two respondents, and edge weights corresponded to co-occurrence counts.

Phase 4: Qualitative content analysis
Thematic analysis of open-ended responses followed Braun and Clarke's six-phase approach, using a hybrid deductive-inductive coding strategy. One researcher independently coded 30% of responses (142 discrete statements), achieving inter-rater reliability (κ = 0.82).

Results

Adoption Landscape: Near-Universality with Stratified Engagement
Of 130 participants, 125 (96.2%, 95% CI [92.1, 98.6]) reported using at least one AI tool for research purposes. Daily use was reported by 36.6% (n = 47, 95% CI [28.6, 45.3]), while 30.5% (n = 40, 95% CI [23.2, 38.9]) reported use several times weekly. Only 3.8% (n = 5, 95% CI [1.4, 8.9]) reported rare use (Figure 2).

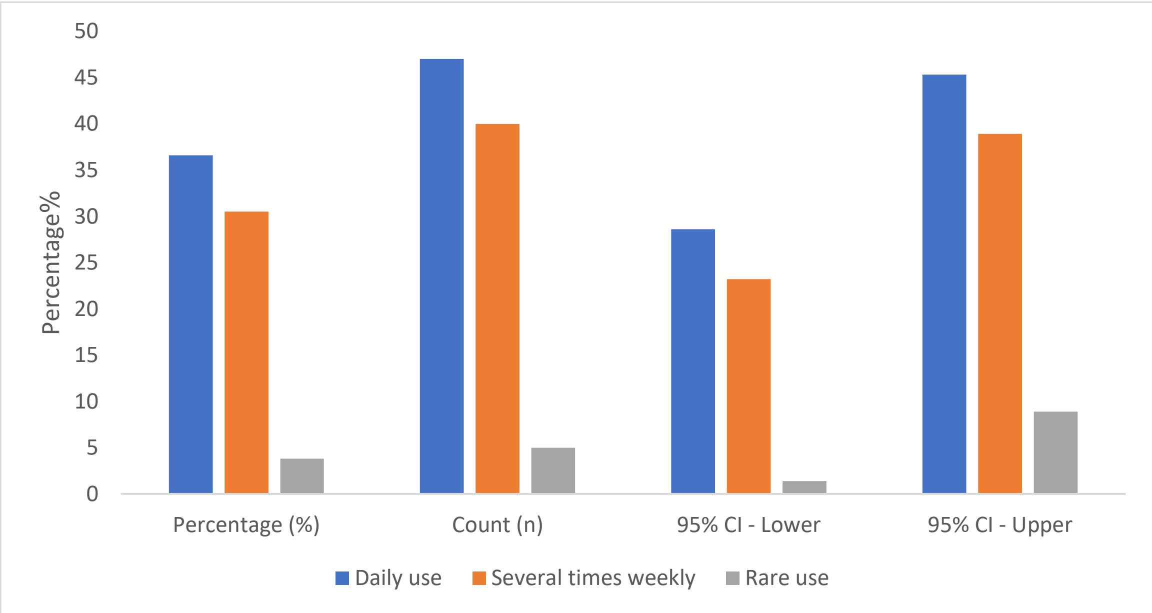

Figure 2. AI usage frequency among researchers (N = 130). Bars represent percentages with 95% confidence intervals. Daily use: 36.6% (n = 47); several times/weeks: 30.5% (n = 40); rare use: 3.8% (n = 5)

A clear hierarchical structure characterizes the AI tool ecosystem. ChatGPT dominates with 85.5% adoption (n = 111, 95% CI [78.6, 90.7]), followed by DeepSeek (45.8%, n = 59, 95% CI [37.3, 54.6]) and Google Bard or Gemini (32.6%, n = 42, 95% CI [25.0, 41.2]). Grammarly and related writing assistants (22.5%, n = 29, 95% CI [15.9, 30.7]), Microsoft Copilot (7.8%, n = 10, 95% CI [4.0, 14.2]), and Meta AI (9.3%, n = 12, 95% CI [5.1, 16.0]) constitute secondary tools. Notably, all dominant tools are commercial products developed in Anglophone contexts; no participant reported use of Arabic-developed AI tools for research (Figure 3).

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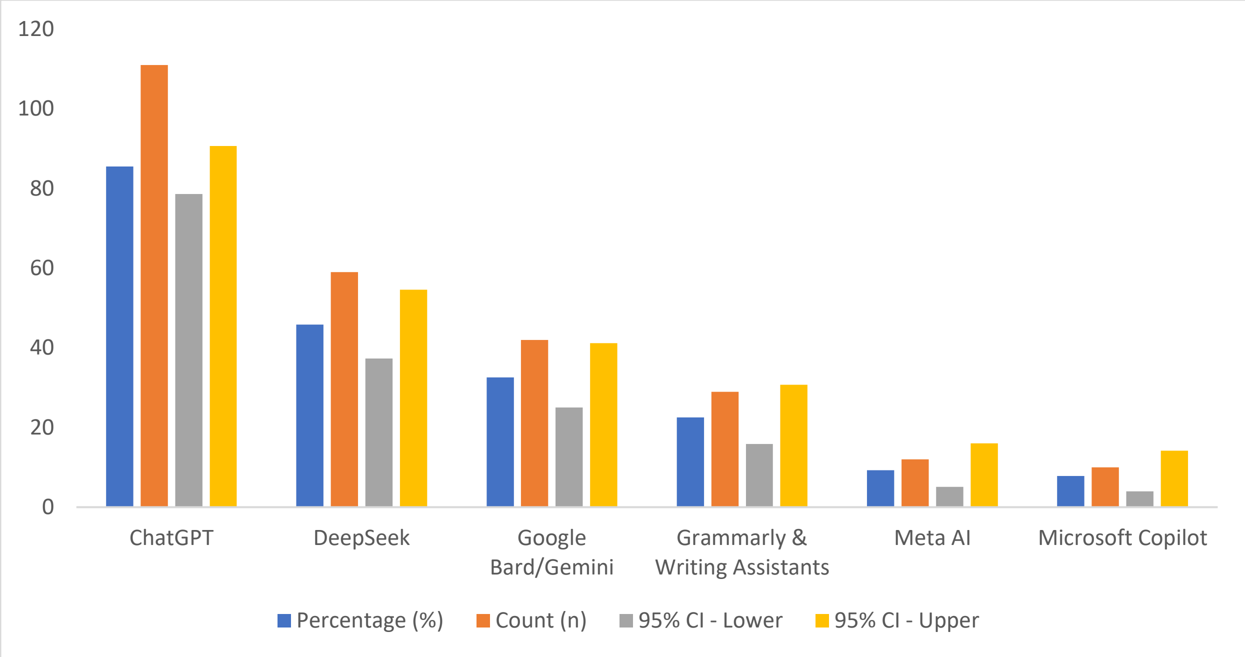

Figure 3. Usage rates of AI tools among researchers (N = 130). Bars show percentages with 95% confidence intervals. ChatGPT: 85.5% (n = 111); DeepSeek: 45.8% (n = 59); Google Bard/Gemini: 32.6% (n = 42); Grammar assistants: 22.5% (n = 29); Meta AI: 9.3% (n = 12); Microsoft Copilot: 7.8% (n = 10)

Application Domains: From Language Enhancement to Epistemic Functions

Language-related tasks dominate: 85.5% (n = 111) of users employ AI for text improvement and language polishing. However, substantive epistemic applications are also widespread: 61.1% (n = 79) use AI for drafting manuscripts and research proposals; 45.8% (n = 59) for literature review and synthesis; 42.7% (n = 55) for translation between Arabic and English; 33.6% (n = 44) for coding and software development; and 29.0% (n = 38) for data analysis and interpretation (Figure 4).

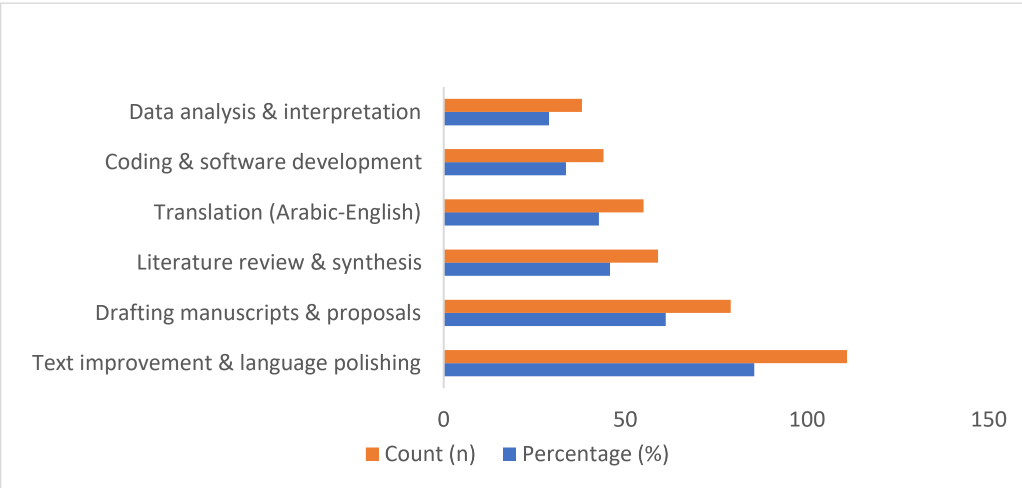

Figure 4. Research tasks supported by AI among respondents (N = 130). Task frequencies: text improvement (n = 111, 85.5%); drafting (n = 79, 61.1%); literature synthesis (n = 59, 45.8%); translation (n = 55, 42.7%); coding (n = 44, 33.6%); data analysis (n = 38, 29.0%). [Percentages are proportions of total respondents; not total task mentions

Significant disciplinary variations emerged (x^2 = 48.33, df = 24, p = 0.004, Cramér's V = 0.32). Researchers in STEM fields (medical/health sciences, natural sciences, engineering, biotechnology) were substantially more likely to use AI for coding (OR = 4.2, 95% CI [2.1, 8.5], p < 0.001) and data analysis (OR = 3.1, 95% CI [1.4, 6.8], p = 0.005) compared to humanities and social sciences researchers. Conversely, humanities scholars demonstrated significantly higher odds of using AI for translation (OR = 2.8, 95% CI [1.2, 6.7], p = 0.018) and literature synthesis (OR = 2.4, 95% CI [1.1, 5.3], p = 0.029) (Figure 5).

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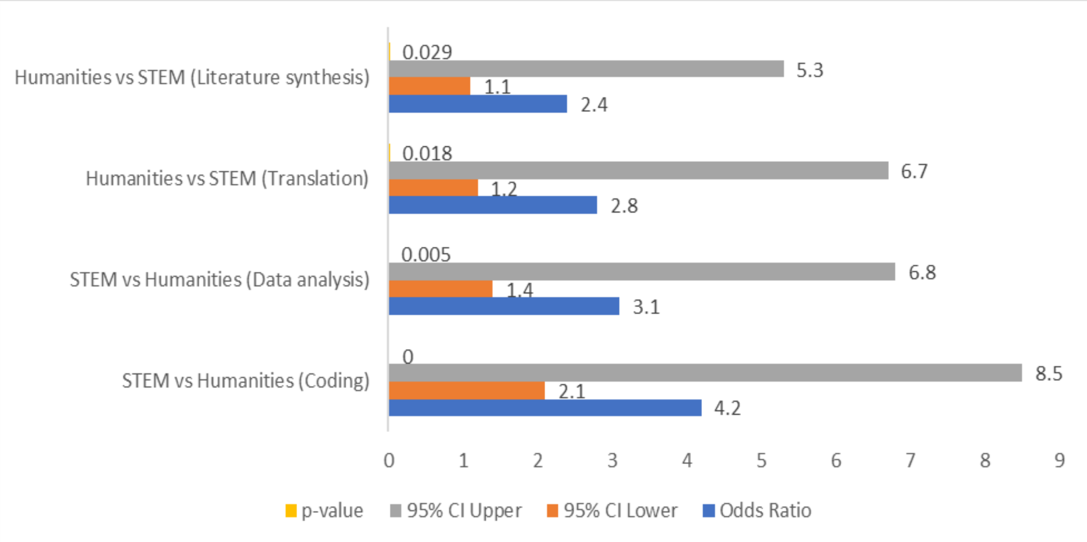

Figure 5. Odds ratios (95% CI) for AI task use by discipline. STEM fields had higher odds for coding (OR = 4.2, p < 0.001) and data analysis (OR = 3.1, p = 0.005); Humanities had higher odds for translation (OR = 2.8, p = 0.018) and literature synthesis (OR = 2.4, p = 0.029). Overall x^2 = 48.33, df = 24, p = 0.004, Cramér's V = 0.32

Factor Structure of AI Perceptions and Attitudes.

Exploratory factor analysis (principal axis factoring with Promax rotation, $\kappa = 4$) yielded a four-factor solution that accounted for 68.4% of the total common variance after rotation. The eigenvalues for the four unrotated factors were 4.12, 2.87, 2.15, and 1.76, which together explained 22.7% of the total variance in the 48 observed items (calculated as the sum of eigenvalues/number of items × 100). Following rotation, the percentage of common variance explained by each factor was: Factor 1 (Productivity Enhancement) 34.3%, Factor 2 (Ethical Concern) 23.9%, Factor 3 (Institutional Support) 17.9%, and Factor 4 (Critical Skill Preservation) 14.7%. These rotated percentages sum to 90.8% of the common variance (not total variance), which is typical for oblique rotations where factors are correlated. The four-factor measurement model was confirmed via confirmatory factor analysis with acceptable fit: $x^2(98) = 187.43$, $p < 0.001$; CFI = 0.93; TLI = 0.91; RMSEA = 0.06 (90% CI [0.05, 0.08]); SRMR = 0.05. Cronbach's α values were 0.89, 0.83, 0.81, and 0.78, respectively (Figure 6).

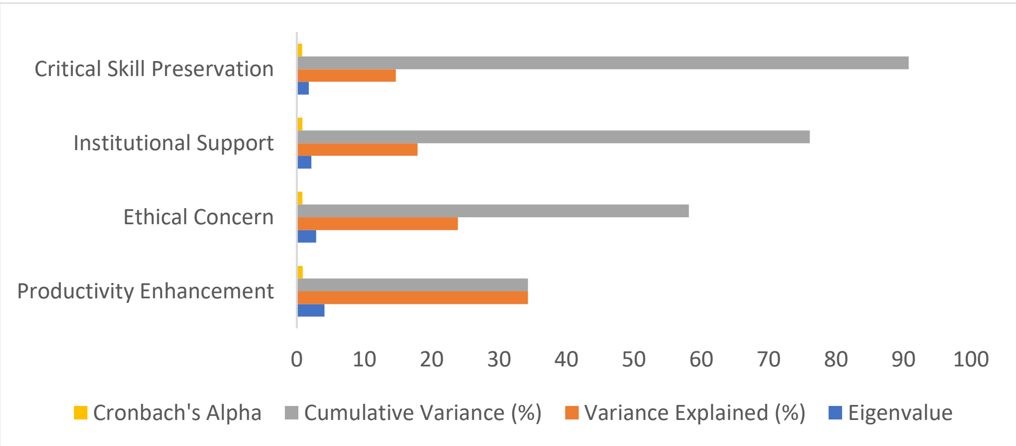

Figure 6. Percentage of common variance explained after rotation (four-factor solution). Factor analysis of AI attitudes: eigenvalues, variance explained (%), and Cronbach's α. Four factors emerged: Productivity Enhancement (λ = 4.12, 34.3%, α = 0.89); Ethical Concern (λ = 2.87, 23.9%, α = 0.83); Institutional Support (λ = 2.15, 17.9%, α = 0.81); Critical Skill Preservation (λ = 1.76, 14.7%, α = 0.78). Common variance explained = 68.4%

(Table 3) presents the fit indices of the four-factor measurement model, including CFI, TLI, RMSEA, SRMR, and the x^2/df ratio, alongside their respective values and acceptable thresholds. All values are within the recommended limits, indicating a good model fit. Confirmatory factor analysis confirmed the four-factor measurement model with acceptable fit: x^2 (98) = 187.43, $p < 0.001$; CFI = 0.93; TLI = 0.91; RMSEA = 0.06 (90% CI [0.05, 0.08]); SRMR = 0.05.

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Table 3. Fit indices of the four-factor measurement model.

Fit index	Value	Threshold
CFI	0.93	≥ 0.90
TLI	0.91	≥ 0.90
RMSEA	0.06	≤ 0.08
SRMR	0.05	≤ 0.08
x^2/df	1.91	< 3.00

User Typology: Three Distinct Adopter Clusters

Hierarchical cluster analysis identified three distinct researcher segments, validated through silhouette analysis (average silhouette width = 0.71) and stability testing. (Figure 7) shows the distribution.

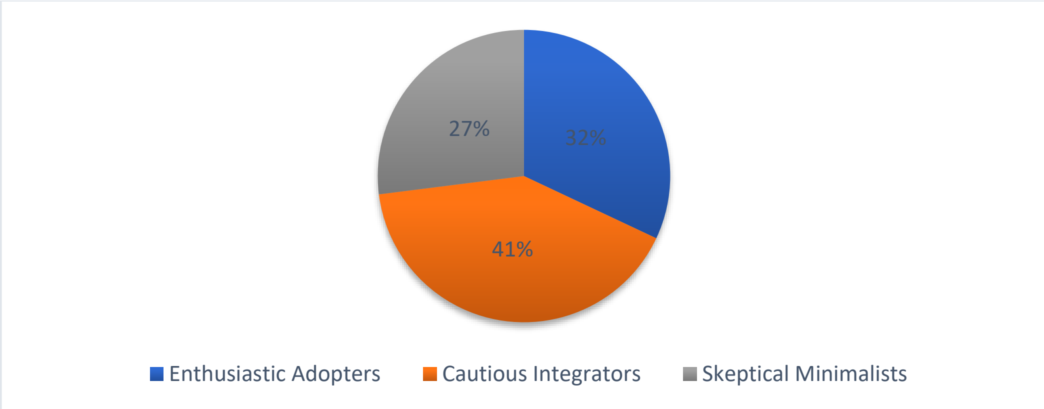

Figure 7. AI adopter cluster distribution. Cautious Integrators: 41%; Enthusiastic Adopters: 32%; Skeptical Minimalists: 27%. Average silhouette width = 0.71.

Cluster 1

Enthusiastic Adopters (32%, n = 42). This cluster consists predominantly of early-career researchers (mean experience = 4.2 years, SD = 2.1). Enthusiastic Adopters demonstrate the highest usage frequency (76.2% daily use), broadest tool repertoires (mean = 3.4 tools, SD = 0.9), and most positive productivity perceptions (mean = 4.5, SD = 0.6 on a five-point scale). They express the lowest ethical concern scores (mean = 2.3, SD = 0.7) but also the lowest rates of critical verification (47.6%). Qualitative responses from this cluster emphasise transformation: AI has fundamentally changed how I do research. I can explore ideas I never would have had time to pursue before” (P47, Biotechnology PhD candidate).

Cluster 2

Cautious Integrators (41%, n = 53). The second career stage cluster (mean experience = 8.7 years, SD = 3.4) is the largest. Cautious Integrators strategically use AI: 24.5% daily use, medium scope of tool usage (mean = 1.9, SD = 0.7), medium-high ethical concern (mean = 3.8, SD = 0.6), and strong verification behaviors (81.1%). The qualitative data shows the boundary management: "I utilize ChatGPT in polishing the English language and developing search terms for literature searches, but will never trust it for the development of theory and findings' interpretation" (P89, Associate Professor, Environmental Science).

Cluster 3

Skeptical Minimalists (27%, n = 35). This is a cluster of predominantly experienced researchers (mean experience = 14.3 years, SD = 4.8) who have only task-based AI involvement (8.6% daily use; mean = 1.2 tools, SD = 0.5). They show the highest ethical concerns (mean = 4.2, SD = 0.5) and the highest levels of verification behavior (85.7%). Many participants explain their resistance in terms of professional identity: "After 25 years of shaping my scholarly voice, I am certainly not going to give it to an algorithm" (P112, Professor, History). Post hoc comparisons (Tukey HSD) confirmed significant differences between all three clusters on research experience ($p < 0.001$ for all pairwise comparisons), usage frequency ($p < 0.001$), tool repertoire size ($p < 0.001$), productivity enhancement scores ($p < 0.001$), and ethical concern scores ($p < 0.001$). Disclosure rates, however, did not differ significantly across clusters ($x^2 = 1.87$, $p = 0.39$), suggesting that non-disclosure is a systemic phenomenon transcending individual attitudes.

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Table 4. Characteristics of AI adopter clusters

Characteristic	Enthusiastic Adopters (n = 42)	Cautious Integrators (n = 53)	Skeptical Minimalists (n = 35)	Test statistic	p-value	Effect size
Mean experience (years, ± SD)	4.2 ± 2.1	8.7 ± 3.4	14.3 ± 4.8	F (2,127) =58.34	<0.001	η^2 = 0.48
Daily usage (%)	76.2	24.5	8.6	x^2 (2) =48.17	<0.001	Cramér's V = 0.61
Mean number of tools used (± SD)	3.4 ± 0.9	1.9 ± 0.7	1.2 ± 0.5	F (2,127) =87.45	<0.001	η^2 = 0.58
Productivity enhancement score (1–5, mean ± SD)	4.5 ± 0.6	3.9 ± 0.7	3.1 ± 0.8	F (2,127) =42.18	<0.001	η^2 = 0.40
Ethical concern score (1–5, mean ± SD)	2.3 ± 0.7	3.8 ± 0.6	4.2 ± 0.5	F (2,127) =98.76	<0.001	η^2 = 0.61
Consistent disclosure (%)	9.5	15.1	8.6	x^2 (2) =1.87	0.39	Cramér's V = 0.12
Critical verification (%)	47.6	81.1	85.7	x^2 (2) =18.45	<0.001	Cramér's V = 0.38
Consistent disclosure (adjusted for policy awareness)	9.5%	15.1%	8.6%	x^2 (2) =1.87	p=0.39	Cramér's V=0.12

Motivational Structures: Beyond Efficiency

While time efficiency was the most frequently endorsed motivator (91.6%, n = 114), qualitative analysis revealed four distinct motivational frames. The efficiency imperative emphasises time savings and workload reduction. The quality enhancement frame, particularly prevalent among nonnative English speakers, emphasises AI's role in improving clarity and international competitiveness: “English is my third language. AI helps me express my ideas at the level expected by top journals” (P18, PhD candidate, Environmental Science). Cognitive Augmentation Frame AI extends my intellectual capacity. Competitive Pressure Frame: My peers are using it. If I do not, then I will lag behind” (P77, Associate Professor, Biotechnology).

Ethical Navigation: Between Innovation and Integrity

A profound disclosure deficit emerged. Only 11.5% (n = 15, 95% CI [6.9, 18.4]) of AI users consistently acknowledge AI assistance in their research outputs. Conversely, 47.3% (n = 62, 95% CI [38.6, 56.1]) never disclose AI use, while 29.0% (n = 38, 95% CI [21.6, 37.5]) disclose sometimes, and 10.7% (n = 14, 95% CI [6.2, 17.5]) are considering disclosure but have not yet implemented it. This disclosure deficit exists alongside widespread awareness of ethical concerns.

When asked directly, 73.8% (n = 96, 95% CI [65.4, 80.8]) reported always verifying AI-generated content. However, the gap between verification and disclosure suggests what researchers have termed ethical fading. As one participant explained: I know I should disclose, but it doesn't feel like I'm doing anything wrong. Everyone does it. They are so ambiguous that I have no idea what a disclosure entails (P41, Lecturer, Engineering). There were three different types of ethical paradigms associated with decision-making regarding disclosure identified through qualitative analysis. Consequentialism (38%) is concerned about the consequences.

Deontological reasoning (29%) emphasizes duty and rule following. Virtue ethics (33%) focuses on scholarly character. Critically, these frameworks do not map neatly onto adopter clusters, but the absence of clear institutional guidance creates moral confusion and uncertainty about appropriate action despite ethical awareness (Figure 8).

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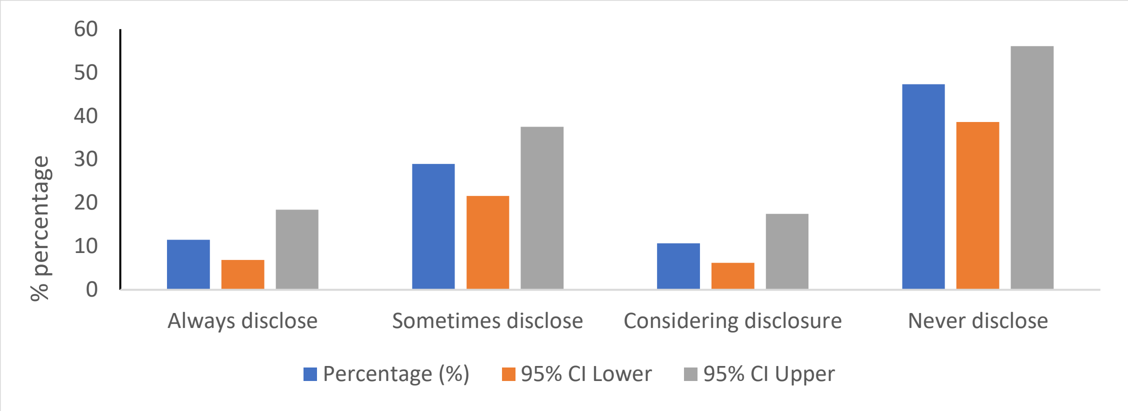

Figure 8. AI disclosure practices. Always: 11.5% (n = 15); Sometimes: 29.0% (n = 38); Considering: 10.7% (n = 14); Never: 47.3% (n = 62). Error bars = 95% CI. Over half of researchers never disclose AI use

Institutional Context: The Primary Mediator

The institutional environment emerged as the critical moderating factor. Strikingly, 45.0% (n = 58, 95% CI [36.5, 53.8]) of participants reported being unaware of any institutional policies regarding AI use in research. Only 23.3% (n = 30, 95% CI [16.7, 31.4]) characterised their institution's guidelines as clear and supportive. An additional 17.1% (n = 22, 95% CI [11.3, 24.8]) reported conditional allowance policies, while 13.2% (n = 17, 95% CI [8.1, 20.2]) indicated no clear policy yet exists, and 1.6% (n = 2, 95% CI [0.3, 5.8]) reported complete prohibition (N = 130 for policy related items (Table 5).

Table 5. Institutional AI policies reported by Libyan researchers (N = 130). Percentages and 95% confidence intervals (exact binomial) are presented

Institutional AI Policy	n	%	95% CI
Unaware of policies	58	45.0%	[36.5, 53.8]
Clear supportive guidelines	30	23.3%	[16.7, 31.4]
Conditional allowance	22	17.1%	[11.3, 24.8]
No clear policy yet	17	13.2%	[8.1, 20.2]
Complete prohibition	3	1.6%	[0.3, 5.8]

Structural Equation Modelling: Testing the ATAM

Structural equation modelling testing the proposed Academic Technology Acceptance Model (ATAM) demonstrated excellent fit: x^2 (112) = 145.32, p = 0.017; CFI = 0.94; TLI = 0.92; RMSEA = 0.05 (90% CI [0.03, 0.07]); SRMR = 0.04 (Figure 9).

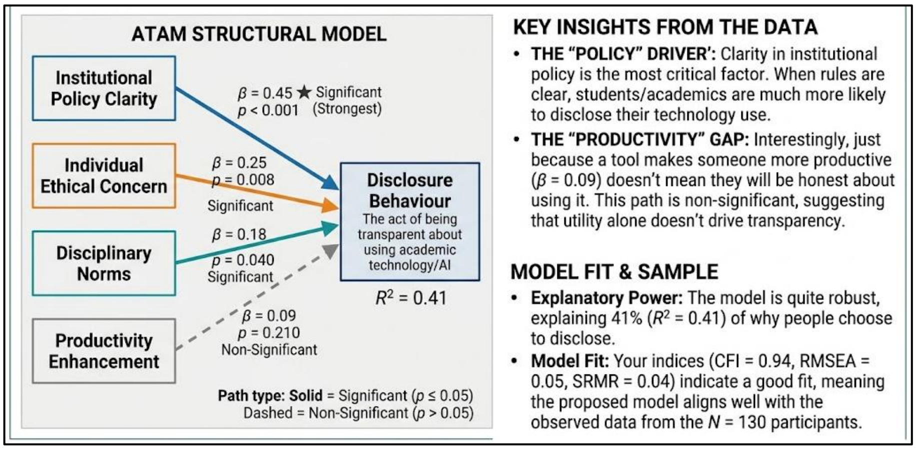

Figure 9. SEM path coefficients (ATAM). Significant paths: Institutional Policy Clarity → Disclosure (β = 0.45, p < 0.001); Ethical Concern → Disclosure (β = 0.25, p = 0.008); Disciplinary Norms → Disclosure (β = 0.18, p = 0.040). Non-significant: Productivity Enhancement → Disclosure (β = 0.09, p = 0.210, dashed). Fit: x^2(112) = 145.32, p = 0.017; CFI = 0.94; RMSEA = 0.05; SRMR = 0.04. R^2 = 0.41. N = 130

Consistent with the ATAM framework, Institutional Legitimacy (measured through policy clarity) was the strongest direct predictor of consistent disclosure (β = 0.45, p < 0.001, 95% CI [0.32, 0.58]), substantially exceeding the predictive power of individual Ethical Compatibility (β = 0.25, p = 0.008, 95% CI [0.09, 0.41]), Disciplinary Alignment (β = 0.18, p = 0.04, 95% CI [0.02, 0.34]), or Epistemic Utility (β = 0.09, p = 0.21, 95% CI [-0.05, 0.23]). The model explained 41% of the variance in disclosure behavior (R^2 = 0.41). (Figure 10) presents the standardized coefficients with 95% confidence intervals.

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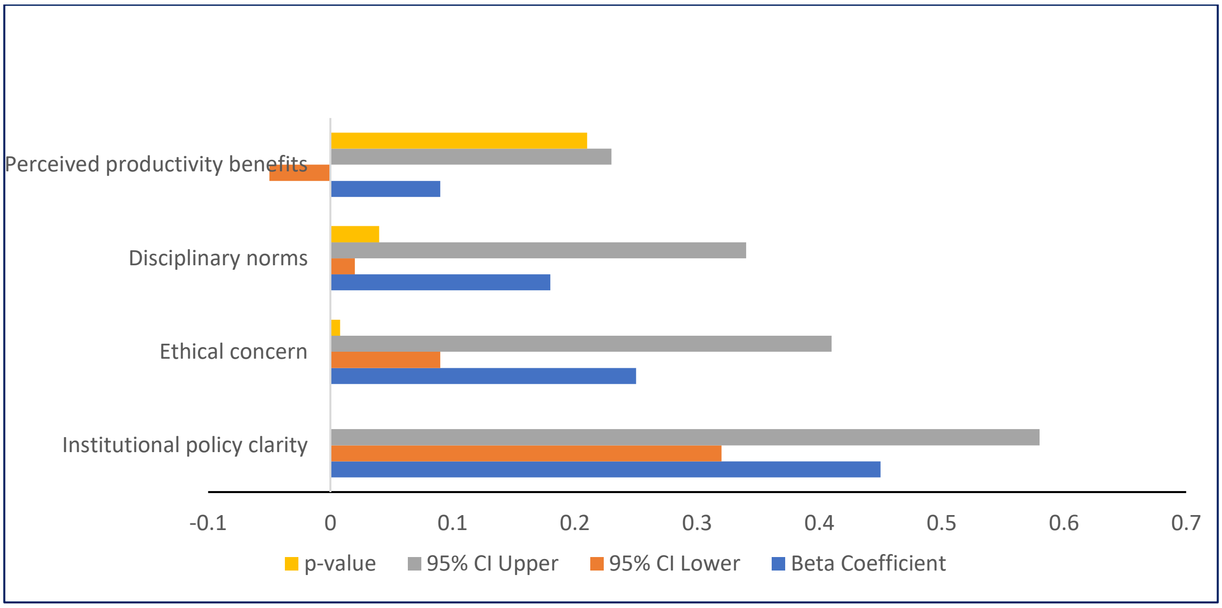

Figure 10. Standardized beta coefficients (β) with 95% confidence intervals from structural equation modelling predicting consistent disclosure of AI use ($N = 130$, $R^2 = 0.41$). Institutional legitimacy (policy clarity) was the strongest predictor ($β = 0.45$, $p < 0.001$), followed by ethical compatibility ($β = 0.25$, $p = 0.008$) and disciplinary alignment ($β = 0.18$, $p = 0.04$). Epistemic utility ($β = 0.09$, $p = 0.21$) was not significant. Error bars represent 95% confidence intervals

Additional Regression Analysis: Predictors of Positive AI Perception

Multiple regression analysis examining predictors of positive AI perception (composite score, α = 0.84, mean = 3.62, SD = 0.71) yielded a significant model ($R^2 = 0.42$, adjusted $R^2 = 0.40$, $F[5,124] = 18.93$, $p < 0.001$). Usage frequency was the strongest predictor ($β = 0.38$, $p < 0.001$), supporting a "mere exposure" effect. Research experience ($β = –0.29$, $p < 0.001$), disciplinary area ($β = 0.21$, $p = 0.004$), perceived institutional support ($β = 0.18$, $p = 0.01$), and ethical concern ($β = –0.15$, $p = 0.03$) also contributed significantly.

Machine Learning Classification: Random Forest

Accuracy for the random forest classification model for identifying disclosure consistency was 78.4% (10-fold cross validation; precision = 0.76, recall = 0.72, F1 score = 0.74). Feature selection indicated that institutional policy (0.32) was the most important variable, followed by ethical issue (0.25), frequency of use (0.18), academic position (0.15), and discipline (0.10). With respect to demographic variables, only academic position (0.15) was found moderately important, while gender, years of service, and age were found to be not so important (<0.05). This verifies that role-based variables are more significant than demographic characteristics (Figure 11).

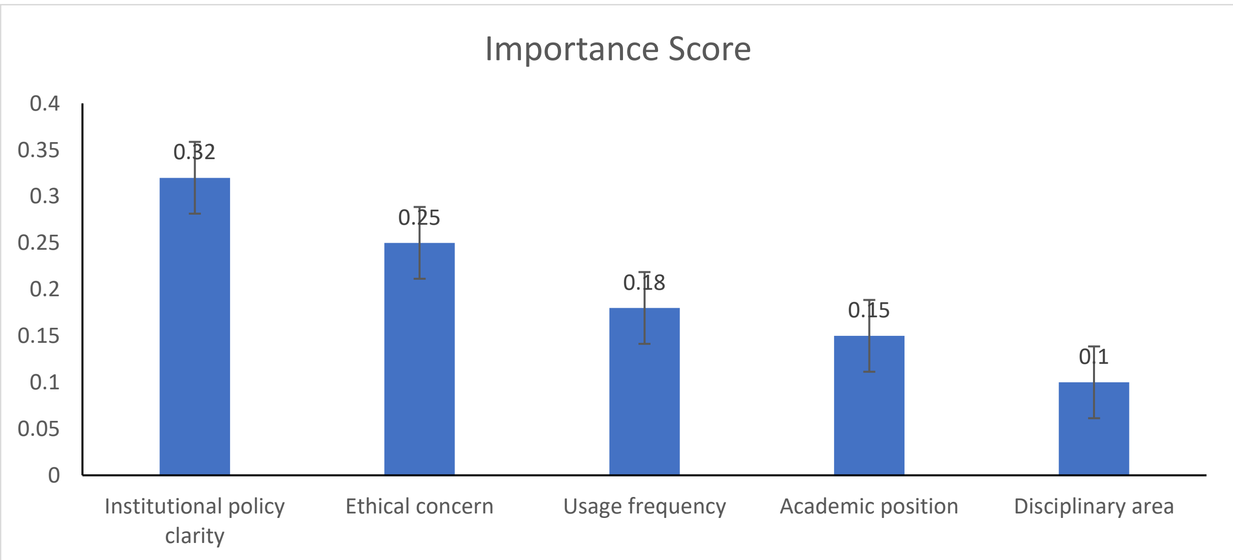

Figure 11. Feature importance from Random Forest classification predicting consistent AI disclosure. Model accuracy: 78.4% (10-fold cross-validation; precision = 0.76, recall = 0.72, F1 = 0.74). Institutional policy clarity was the dominant predictor (importance = 0.32), followed by ethical concern (0.25), usage frequency (0.18), academic position (0.15), and disciplinary area (0.10)

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Social Network Analysis of AI Tool Co-Usage
Social network analysis of tool co-usage revealed a pronounced core-periphery structure. ChatGPT functions as the central hub (degree centrality = 1.00, betweenness centrality = 0.68, eigenvector centrality = 1.00), connected to DeepSeek (degree = 0.83) and Google Bard or Gemini (degree = 0.67). The network exhibits high clustering (transitivity = 0.72) and low average path length (1.8), indicating a tightly interconnected ecosystem (Figure 12).

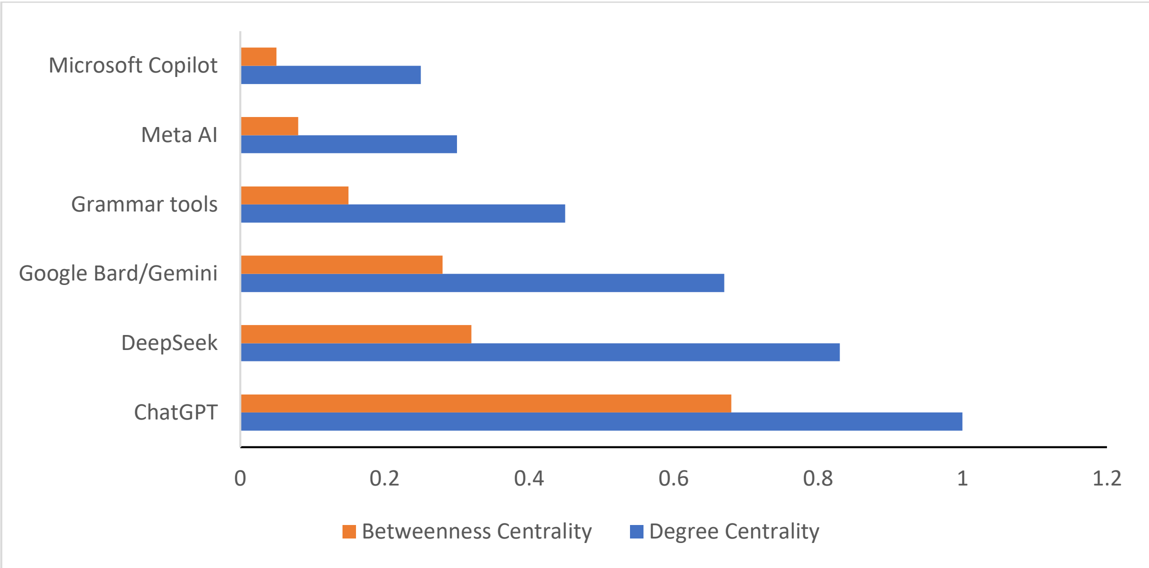

Figure 12. (A) Network graph of AI tool co-usage showing a core-periphery structure with ChatGPT as the central hub. (B) Centrality measures. The network exhibits high clustering (transitivity = 0.72) and low average path length (1.8), indicating a tightly interconnected ecosystem. Degree centrality: ChatGPT (1.00), DeepSeek (0.83), Google Bard/Gemini (0.67)

Discussion

Main Findings and Interpretation
Our findings lead to two paramount conclusions. First, AI has become near ubiquitous in Libyan academic research (96.2% adoption), but adoption is stratified by career stage, discipline, and attitude. The three adopter clusters, Enthusiastic, Cautious, and Skeptical, reflect different generational and epistemological positions. Second, the profound disclosure deficit (only 11.5% consistent acknowledgment) is driven primarily by institutional policy ambiguity, not by individual moral failure. The clarity of institutional policies had the most significant impact on ethical reporting (β = 0.45), even when compared to individual ethical concerns (β = 0.25). From this perspective, the whole problem of integrating responsible AI becomes redefined, since any action aimed at individual researchers' ethics works only partially, while the institutional level proves to be much more powerful. In particular, by minimizing moral ambiguity and encouraging transparency regarding the application of AI technologies, it will become possible to avoid ethical scandals in the future, thus achieving societal development through scientifically verified results.

Comparison with Prior Work
The disclosure rates we found are consistent with international studies. Bobier and colleagues [22], examining 1,808 publications across 20 bioethics journals, found that less than 1% contained any reference to generative AI use despite evidence suggesting actual utilization rates of at least 10%. The policy vacuum found in this study reflects difficulties experienced at other leading international universities, like Stanford University's 2026 governance assessment of its policies [23, 24, 25], indicating that the current frameworks used by such institutions are very reliant on course level discretion and unofficial advice, creating confusion. Although Stanford's policy challenges exist in a well resourced setting in the Western world, the policy void identified here in Libya is deeper still, compounded by specific linguistic problems (the Anglophone dominance in scientific publishing), cultural factors, and resource limitations. This illustrates the universal but highly context specific nature of issues related to AI governance, providing new perspectives on the matter from a developing country standpoint. This study findings about generational divisions (young Enthusiastic Adopters compared to older Skeptical Minimalists) correlate with literature on AI training at higher education institutions around the world and particularly in Libya [13, 26, 27], showing that professional development programs for learning AI are rare and most academics acquire knowledge about it through self learning [28, 29, 30].

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Theory Contributions: The Academic Technology Acceptance Model (ATAM)

The key theoretical contribution is an extension to the body of technology acceptance models, which is informed by and tested empirically using the specific case of knowledge creation within academic contexts. The model proposed in this thesis is called the Academic Technology Acceptance Model (ATAM), and it involves four different variables: epistemic usefulness, disciplinary fit, institutional legitimacy, and ethical compatibility. The evidence from this research that institutional legitimacy (policy clarity) outweighs disclosure behavior raises questions about the predominant approach to ethics training.

Practical Recommendations

For administrators at the university level: Adopt clearly defined and easily understandable policies regarding the use of AI that involve all relevant stakeholders, including faculty members and students. Such policies need to outline differences between the roles of AI being used as a resource and an aid, develop procedures for mandatory disclosures, prohibit AI from authorship, and create processes for ongoing reviews. Mandatory ethics and literacy training regarding the use of AI must be conducted as part of research integrity programs. For journal editors and publishers: Implement standardised, mandatory AI disclosure requirements in submission systems. Use a required field asking “Was AI used in the preparation of this manuscript? (Yes/No) with conditional follow-up items specifying tool(s) and nature of contribution (substantive versus formative).

Develop clear authorship policies stating that AI tools cannot be listed as authors and that all human authors remain fully responsible. Establish cross publisher harmonisation through a global task force. These protocols, mirroring successful implementations by leading publishers (e.g., the ICMJE disclosure framework), have demonstrably increased transparency and reduced instances of undisclosed AI use in pilot studies, thereby solidifying research integrity and enhancing the professional relevance of published work. For researchers: Adopt a critical verification routine for all AI generated content, including independent verification of factual claims and citations. Engage in departmental and disciplinary conversations about appropriate AI use. For Skeptical Minimalists, we recommend focused exploration of AI applications that complement rather than replace core expertise (e.g., generating initial literature search strings, formatting citations, creating visual abstracts). For example, using AI for citation formatting and generating initial literature search strings can reduce administrative research time by an estimated 15-20%, freeing up more time for critical intellectual work.

AI applications that are complementary to research can add greatly to the quality and accessibility of publications without necessitating a paradigmatic change in the research process. To research funding agencies and policymakers: Make provisions for investing in an open-source AI infrastructure that is suited to linguistic and cultural environments, such as language models optimized for the Arabic language. Fund research into cross cultural AI usage, ethics, and governance. Economic considerations in the implementation of AI technologies need to be addressed by resource strapped institutions. This will go a long way in democratising access to cutting edge research tools among many Arabic-speaking researchers while also relieving the economic burden caused by using foreign tools. Apart from democratizing access, localized AI technologies can help boost the production of research in vital fields (e.g., public health, environmental studies) in the region, which can lead to economic growth.

Limitations and Future Research

This study has several limitations. The cross sectional design captures a single time point; causal inference is tentative. The cross-sectional nature precludes definitive causal claims, particularly regarding the observed relationships between institutional policy clarity and disclosure behaviour, despite the use of structural equation modelling. While SEM identifies significant associations, it cannot establish cause and effect without temporal data. For instance, the strong association could be subject to reverse causality; institutions with higher disclosure rates might be more prone to developing clearer policies. Self selection and self-report bias may affect estimates; social desirability likely led to over reporting of verification and under-reporting of non-disclosure.

To mitigate social desirability bias, the survey emphasised anonymity and used neutral phrasing. A post hoc Harman’s single-factor test indicated that a single factor explained only 16.4% of total variance, suggesting that common method variance is unlikely to be a major threat. Beyond general self selection bias, the recruitment strategy itself (institutional email lists, social media groups, direct contact) might have introduced selection bias, potentially over representing researchers who are more technologically engaged, professionally connected, or motivated to participate. The context specificity to Libya limits direct generalisation to other Arabic-speaking countries or Global South institutions. The specificity of the context of Libya makes it impossible to make a direct generalization to other Arab-speaking nations or organizations in the developing world. The unique socio political climate, the disunited governance systems, and the different levels of technological development at Libyan universities could yield different responses in terms of the use of AI ethics in Libya. However, the proposed ATAM offers a theoretically transferable framework, and the identified types of issues (policy vacuum, generational divides) likely resonate in other contexts

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facing similar infrastructural gaps. The study does not provide any systematic assessment of the bias within algorithms used in Arabic language AI tools.
The intrinsic specificity of the Arabic language, together with the possible unrepresentative nature of the data used in training Arabic NLP systems, can cause a substantial bias in the output of the algorithms. This can affect the results of scientific research and perpetuate prejudices against particular dialects of the Arabic language. Economic aspects related to AI adoption were not considered in the study either. The economic challenges posed by commercial AI software subscriptions, computing power requirements, and training costs can prove to be a challenge for both financially constrained institutions and individuals alike within Libya. Future research should employ longitudinal cohort studies tracking AI adoption and attitudes over time; experimental designs isolating AI's causal effects on research tasks, cross cultural comparative research across multiple Arabic-speaking countries; policy implementation studies evaluating the effectiveness of various institutional governance models and specific policy interventions in addressing the identified disclosure deficit and moral confusion; ethnographic investigations of daily human-AI collaboration; algorithmic audit studies of Arabic-language AI tools; and research on economic sustainability and equity, including cost-effectiveness of providing licensed AI tools and equity of access across institutions.

Conclusion

Artificial intelligence is fundamentally reshaping academic knowledge production. In Libyan research institutions, adoption is nearly universal, yet ethical disclosure remains rare because institutional policies are absent or unclear. The primary remedy is not more ethics training for individuals but clear, accessible, and consistently enforced institutional guidelines. The Academic Technology Acceptance Model provides a diagnostic framework for understanding adoption patterns and designing interventions. The global academic community must act collectively, with university administrators, journal editors, researchers, and funders, to shape AI's trajectory towards transparency, equity, and respect for scholarly values. The window for shaping AI's trajectory in academia is open but narrowing.

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