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University instructors' reception of generative AI in academic research: Perceptions, practices, and challenges

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ABSTRACT

Universities have begun to use generative artificial intelligence (GenAI) in research well before agreeing on how its use ought to be governed. This study draws on reception theory and on technology acceptance research to ask how faculty members take up GenAI in their scholarship; reception is treated here as an active process in which the technology may be interpreted, negotiated, or resisted. Data came from 257 faculty members at public and private Jordanian universities, who completed a survey covering perceived usefulness, research practices, trust, ethical challenges, institutional support, and future adoption. GenAI was rated useful (M = 3.60), and respondents meant to keep using it (M = 3.50). Its actual use across research tasks, however, was moderate (M = 3.14), and trust in its outputs sat barely above the scale midpoint (M = 3.14). Of all the dimensions, ethical concern received the highest mean rating (M = 3.89), with 84.8% of respondents agreeing that outputs must be verified and 89.5% that GenAI use should be disclosed. Institutional support alone fell below the midpoint (M = 2.90), and it bore little relation to use. Future adoption was predicted by frequency of use, usefulness, trust, institutional support, and familiarity (R^2 = .53); ethical concern was not a significant predictor in the final model. Faculty aged 30–39 generally reported the most favourable reception, whereas discipline, experience, and publication record made little difference. A cluster analysis distinguished three reception positions, engaged-critical (37.4%), negotiated-pragmatic (34.6%), and guarded-sceptical (28.0%), which nevertheless showed similarly strong endorsement of verification and disclosure. Overall, the findings indicate a pattern of critical acceptance and support the development of explicit institutional guidance and training on responsible GenAI use in research.

KEYWORDS: generative AI, reception study, faculty members, academic research, research integrity, technology acceptance, higher education, Jordan

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1. Introduction

Since the public release of ChatGPT in November 2022, generative artificial intelligence (GenAI) has become increasingly prominent in academic work. Large language models can now suggest research questions, summarise literature, draft and revise text, propose analysis procedures, and help researchers prepare abstracts and presentations (Dwivedi et al., 2023). Such capabilities hold evident promise for university faculty members, whose professional advancement rests upon the production and publication of research. They nonetheless give rise to concerns that bear directly on the integrity of scholarly practice, among them fabricated references, plausible yet inaccurate explanations, ambiguous authorship, and the prospect that researchers may relinquish to the technology the analytical and critical reasoning on which research depends (Messeri & Crockett, 2024; Walters & Wilder, 2023).

Publishers moved first. Editors ruled within weeks that a language model cannot be named as an author and that its use has to be documented (Thorp, 2023); the Committee on Publication Ethics soon took the same line (Committee on Publication Ethics, 2023). By 2023 most large publishers had issued instructions on GenAI, according to a bibliometric analysis of their guidance, though the scope and detail of those instructions varied widely (Ganjavi et al., 2024). The universities have been slower, and less consistent. Their institutional statements have tended to address teaching and assessment in preference to research (Chan, 2023; Moorhouse, Yeo, & Wan, 2023), so that faculty members have largely been left to determine for themselves how GenAI might be incorporated responsibly into their research.

Previous corpus-assisted and critical discourse studies have demonstrated the value of systematic linguistic analysis in examining media representations, political discourse, and ideological bias, while highlighting the methodological challenges of ensuring objectivity in research, particularly the limitations of corpus-based approaches in eliminating researcher bias (Haider, 2019a, 2019b, 2019c). Most empirical research on GenAI in higher education has concentrated on students, examining their attitudes, their use of ChatGPT for assignments, and the threat such use poses to assessment (Abdaljaleel et al., 2024; Gwasmeh et al., 2026; Haider, 2026a; Strzelecki, 2024). Faculty members have received less attention, and existing studies have generally focused on teaching (Mah & Groß, 2024). Their role as researchers has drawn still less attention, even though it is faculty who determine how GenAI enters the scholarly record. When *Nature* surveyed researchers internationally, respondents anticipated that GenAI would become important to their work, while voicing unease about misinformation, plagiarism, and a decline in research quality (Van Noorden & Perkel, 2023). Evidence from Arab universities is particularly limited. What research exists in the region has dealt largely with students, whether in health disciplines (Abdaljaleel et al., 2024; Sallam et al., 2023) or in language and translation programmes (Gwasmeh et al., 2026; Haider, 2026a), or else with the broad implications of GenAI for researchers (Al-Zahrani, 2024); faculty across disciplines and institution types have seldom been examined. The present study addresses this gap by examining faculty engagement with GenAI as a matter of *reception*. According to reception theory, meaning is produced in the encounter between an object and those who interpret it, rather than being simply carried by a text or a technology (Jauss, 1982). More recently, reception research has been extended to AI-generated language, with studies of how Arabic speakers respond to AI-dubbed videos, to AI-translated idioms and proverbs, and to AI translation in professional settings (Ahmad, Haider, & Saed, 2025; Darwish et al., 2025; Haider, 2026b). Faculty members neither adopt nor reject GenAI in any straightforward fashion. How they read it depends on the norms of their discipline, on professional values and institutional conditions, and on what they have experienced for themselves; the resulting positions often hold perceived benefits and lingering reservations together. Combining this perspective with established models of technology acceptance (Davis, 1989; Venkatesh et al., 2003), the study examines six dimensions of reception. These concern how useful faculty consider GenAI, how they use it in research, how far they trust it, what ethical difficulties they see in it, what support their institutions give them, and whether they plan to continue using it.

Two questions are addressed:

> RQ1. In what ways do university faculty members receive GenAI in academic research, with respect to perceived usefulness, research practices, trust, ethical challenges, and institutional support, and does their reception vary with gender, age, academic rank, discipline, experience, and institution type?
>
> RQ2. Which dimensions of reception predict faculty members' intention to adopt GenAI in their future research, and what distinct reception positions can be identified among them?

2. Literature Review and Theoretical Framework

2.1 Reception theory and faculty as readers of GenAI

Reception theory emerged within literary studies as a corrective to approaches that placed meaning wholly in the text. For Jauss, each reader approaches a work with a "horizon of expectations" shaped by earlier experience, by the conventions of genre, and by social context, so that the meaning of the work arises where these horizons meet the work itself (Jauss, 1982). Fish extended the argument by locating interpretation within "interpretive communities", whose shared assumptions shape what is considered a reasonable interpretation (Fish, 1980). In media and cultural studies, Hall's encoding/decoding model proposed that audiences may take up a message in a dominant-hegemonic way, accepting its preferred meaning; in a negotiated way, accepting it in principle while adapting it to local conditions; or in an oppositional way, rejecting its framing (Hall, 1980).

These concepts provide a basis for examining technology use in academic work. By the time GenAI reaches faculty members, it has already been framed for them, presented by its developers as a productivity tool, by publishers as a potential challenge to research integrity, and by universities, where guidance is available, in the language of policy. Faculty interpret these framings within their disciplinary contexts, and those disciplines function as interpretive communities, each with its own standards of evidence, originality, and authorship. A reception approach is accordingly concerned with how faculty make sense of GenAI, which of its uses they treat as legitimate, and where they set limits, alongside whether they use it. It also leaves room for mixed positions: a researcher may use GenAI routinely while remaining sceptical of its outputs, much as a negotiated reader accepts a message while qualifying it.

2.2 Technology acceptance perspectives

Research on the adoption of technology contributes measurable constructs that complement the interpretive orientation of reception theory. Within the Technology Acceptance Model, perceived usefulness and perceived ease of use were identified as the principal determinants of the intention to use a technology (Davis, 1989). The Unified Theory of Acceptance and Use of Technology extended this account to include performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Diffusion of innovations theory adds that adoption depends on the perceived relative advantage, compatibility, complexity, trialability, and observability of an innovation, and that adopters differ in how quickly they take it up (Rogers, 2003).

These frameworks have been widely applied to studies of ChatGPT adoption. Among students, performance expectancy and habit have been found to be strong predictors of behavioural intention (Strzelecki, 2024), and perceived usefulness, ease of use, perceived risk, and anxiety have been associated with attitudes and usage (Abdaljaleel et al., 2024; Sallam et al., 2023). In Jordan, reception and adoption have also been examined for AI translation among business professionals (Haider, 2026b) and for AI-generated feedback on university students' English (Haider, 2026a). Facilitating conditions, which correspond to institutional support in the present study, are of particular interest in the case of GenAI because the technology is freely available to individuals regardless of whether their institution provides it. The present study uses the acceptance tradition to structure measurement, while relying on reception theory to interpret the patterns that emerge.

2.3 GenAI in academic research: usefulness and practices

Commentators have identified many possible uses of GenAI across the research cycle. Language models can help generate and refine research ideas, summarise and compare studies, suggest methods and instruments, explain statistical procedures, and improve the clarity of writing (Dwivedi et al., 2023). For researchers who write in English as an additional language, help with language editing may be especially valuable, and AI tools are increasingly used to translate academic texts such as Arabic research titles into English, a use whose accuracy has been assessed in recent work (Al-Salman & Haider, 2024). Reviews of the early literature found that perceived benefits clustered around efficiency, writing support, and access to explanations, while concerns clustered around accuracy, bias, and integrity (Lo, 2023).

Use of GenAI has grown quickly, but not evenly. In the survey that *Nature* conducted among more than 1,600 researchers, many reported turning to GenAI to write code, to brainstorm, and to draft text, and a majority expected such tools to become very important or essential in their fields within a decade (Van Noorden & Perkel, 2023). At a German university, faculty members were grouped into distinct profiles according to

their use of AI and their self-efficacy, and their needs for professional development varied across profiles (Mah & Groß, 2024). Al-Zahrani's study in Saudi Arabia found researchers broadly favourable towards GenAI's contribution to research, while recognising the risks it posed to originality and quality (Al-Zahrani, 2024). Much less is known about which research tasks faculty actually entrust to GenAI and how such delegation relates to their perceptions of it.

2.4 Trust and verification

Trust is a central concern when users cannot readily verify a technology's outputs. Reviews of human trust in AI indicate that trust rests on the tangibility, transparency, reliability, and immediacy of a system, and that people may trust AI too much or too little depending on how it presents itself (Glikson & Woolley, 2020). GenAI poses a particular difficulty here, since its output is fluent and confident regardless of its accuracy. ChatGPT has been shown to fabricate references whose titles and authors appear entirely plausible (Walters & Wilder, 2023). Evaluations of ChatGPT, Gemini, and other AI tools applied to Arabic–English material, from idioms and proverbs and classical verse to culture-bound expressions, social media posts, and automatically generated subtitles, have likewise assessed the reliability of fluent output without human verification (Akasheh et al., 2024; Almahasees et al., 2026; Dweik, Haider, & Saed, 2026; Farghal & Haider, 2024; Obeidat et al., 2024; Tannous & Haider, 2025). Messeri and Crockett (2024) cautioned that dependence on AI may foster "illusions of understanding", in which researchers believe they know more than they actually do.

Verification is an essential response to potentially unreliable output. Guidance issued by publishers and international bodies assigns responsibility for the accuracy of AI-assisted work to its human authors (Committee on Publication Ethics, 2023; Hosseini, Rasmussen, & Resnik, 2024; Miao & Holmes, 2023). In Jordanian professional settings, too, trust has emerged as central to the reception and adoption of AI translation (Haider, 2026b). Whether faculty members accept this responsibility, and how trust in GenAI relates to their commitment to verification, remain empirical questions that the present study examines.

2.5 Ethical challenges: originality, authorship, and disclosure

Debate over the ethics of GenAI in research has revolved around originality, authorship, accountability, and disclosure. Editors and publishers concur that GenAI cannot satisfy the criteria for authorship, since it is incapable of taking responsibility for a work (Committee on Publication Ethics, 2023; Thorp, 2023). Scholars have cautioned that GenAI may make plagiarism easier and misconduct harder to detect (Cotton, Cotton, & Shipway, 2024), and that intellectual responsibility for AI-generated text remains an unsettled question (Hosseini et al., 2024). A study of academics found that integrity concerns and the perceived pressure to publish together shaped intentions to use ChatGPT (Bin-Nashwan, Sadallah, & Bouteraa, 2023). There is also concern that over-reliance may weaken researchers' independent critical thinking, particularly among early-career researchers who are still developing their scholarly judgement (Messeri & Crockett, 2024).

Disclosure has emerged as the most widely agreed response. Many publisher policies require authors to declare GenAI use, although they differ over what must be declared and where (Ganjavi et al., 2024). Less is known about the extent to which individual faculty members endorse these norms, and whether ethical concern actually discourages use or coexists with it.

2.6 Institutional support and policy

Faculty reception of a technology are shaped by their universities, through the guidance, training, infrastructure, and culture those institutions provide. Jordanian research on how university instructors and students experienced online testing and emergency online learning during COVID-19 (Al-Salman & Haider, 2021; Haider, Hussein, & Saed, 2022) has demonstrated the value of studying new technologies from the standpoint of the people expected to use them. When university guidelines on GenAI were analysed, most top-ranking institutions were found to have issued guidance by mid-2023, although that guidance dealt overwhelmingly with teaching and assessment (Moorhouse et al., 2023). Chan (2023) put forward a policy framework spanning pedagogical, governance, and operational dimensions and observed that staff training was a recurring gap. UNESCO's guidance urged institutions to validate GenAI tools, to build the capacity of researchers and teachers, and to develop ethical rules for the use of these tools in research (Miao & Holmes, 2023). Many of the researchers

surveyed by *Nature* reported receiving little or no guidance from their institutions (Van Noorden & Perkel, 2023). The literature reviewed provides limited systematic evidence on how faculty in the Arab region perceive institutional support, or of whether such support is associated with their use of GenAI.

Three gaps emerge from this literature. Faculty members in their capacity as researchers have attracted less attention than students or teachers. Most studies also measure attitudes or intentions in isolation and do not consider how usefulness, trust, ethical concern, and institutional conditions combine to form faculty members' overall reception. Evidence from Arab universities also remains limited and is concentrated largely in health disciplines. Drawing on reception theory together with the acceptance tradition, the present study measures six dimensions of reception among faculty members in Jordan, across disciplines and institution types; it then examines how these dimensions relate to one another and identifies the distinct reception positions identified within the sample.

3. Method

3.1 Research design

The study used a cross-sectional survey design. A structured questionnaire translated the reception framework into measurable form, so that the overall pattern of reception could be described, groups compared, and predictors of future adoption modelled; it also made it possible to look for subgroups whose reception profiles differed.

3.2 Instrument

There were two sections to the questionnaire. In the first, respondents gave demographic and professional details (gender, age group, university type, academic rank, discipline, years of experience, and number of publications) and described their experience with GenAI. For the latter, they rated their familiarity with GenAI and how often they used it, each on a five-point scale, named the GenAI tool they relied on most, and indicated the research activities for which they used it; more than one activity could be selected.

The second section held 30 Likert items, five for each of the six dimensions, answered on a scale from 1 (strongly disagree) to 5 (strongly agree). Items Q01–Q05 dealt with perceived usefulness, that is, whether GenAI makes research more efficient and of higher quality; they were adapted from the usefulness construct of technology acceptance research (Davis, 1989; Venkatesh et al., 2003). Q06–Q10 asked how far GenAI was used at each stage of a project, from generating ideas through to revising manuscripts. Confidence in the reliability and accuracy of GenAI output was the subject of the trust items, Q11–Q15 (Glikson & Woolley, 2020). The ethical challenges items (Q16–Q20) were informed by publication ethics guidance (Committee on Publication Ethics, 2023; Hosseini et al., 2024) and asked about originality, fabricated references, critical thinking, authorship, and disclosure. Institutional support (Q21–Q25) corresponds to what acceptance models call facilitating conditions (Venkatesh et al., 2003) and covered guidance, training, policy, resources, and encouragement. The last five items, Q26–Q30, captured attitudes towards GenAI and the intention to keep using it and to use it more. Table 5 reproduces the full wording of every item.

3.3 Data analysis

Analyses were performed in Python with the pandas, SciPy, statsmodels, scikit-learn, and factor_analyzer libraries. The dataset contained no missing values. To examine construct validity, an exploratory factor analysis (minimum residual extraction with promax rotation) was carried out once sampling adequacy had been checked by means of the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity (Hair et al., 2019). Cronbach's alpha and composite reliability served as indices of internal consistency, and average variance extracted as an index of convergent validity (Hair et al., 2019). Because a single self-report survey was used, Harman's single-factor test was applied as a preliminary assessment of common method variance (Podsakoff et al., 2003).

Construct scores were calculated as item means. Descriptive statistics and one-sample t-tests against the scale midpoint (3) described the overall level of each dimension, and independent-samples t-tests and one-way ANOVAs, with Tukey HSD post hoc comparisons, examined group differences (RQ1); effect sizes are reported as Cohen's d and eta squared (Cohen, 1988). Pearson correlations and hierarchical multiple regression

examined predictors of future adoption, and a bootstrapped indirect effect (2,000 resamples) examined the indirect association between usefulness and adoption through trust (RQ2). Finally, k-means cluster analysis on standardised construct scores identified reception positions, and chi-square tests examined their composition.

3.4 Validity and reliability of the instrument

Sampling adequacy was good (KMO = .864), and Bartlett's test was significant, $\chi^2(378) = 1781.0$, $p < .001$. Item analysis showed that two items behaved differently from the rest of their scales. Q15 ("GenAI outputs require careful verification") had a corrected item–total correlation of –.11 with the trust scale, and Q20 ("Researchers should disclose GenAI use") had a correlation of –.09 with the ethical challenges scale. Nearly everyone agreed with both statements, so they seem to register norms that are widely shared, not differences between individuals. Dropping them lifted alpha from .45 to .58 for trust and from .46 to .58 for ethical challenges. Both were therefore left out of the construct scores and treated on their own, Q15 as a verification norm and Q20 as a disclosure norm.

Six factors with eigenvalues above 1 emerged from an exploratory factor analysis of the other 28 items (6.18, 2.23, 1.86, 1.50, 1.34, and 1.14; the seventh fell to 0.93. This matches the intended structure. No item loaded more highly on another factor than on its own. The loadings were .46–.72 for usefulness, .60–.71 for research practices, .41–.59 for ethical challenges, .44–.61 for institutional support, and .38–.67 for future adoption. Trust was less clean. Q12 (.66) and Q14 (.55) loaded well on it, but Q11 (.36) and Q13 (.25) did not, and Q13 loaded almost as strongly on future adoption (.24). The first unrotated factor accounted for only 22.1% of the variance, far short of the 50% benchmark, which suggests that responses were not dominated by a single factor; this test alone, however, cannot rule out common method bias (Podsakoff et al., 2003).

The reliability statistics appear in Table 1. Internal consistency was acceptable for research practices, future adoption, and usefulness (α = .75–.82), whereas institutional support fell below the conventional threshold (α = .65); trust (α = .58) and ethical challenges (α = .58), by contrast, fell short of it. Since thresholds for alpha are conventions rather than fixed rules, and short scales covering a broad construct commonly yield lower values (Hair et al., 2019), these values warrant cautious interpretation rather than dismissal of the scales. All AVE values were below .50, indicating limited convergent validity, and composite reliability was also low for trust, ethical challenges, and institutional support. Results involving these constructs should therefore be interpreted cautiously, as discussed in the limitations.

Table 1: *Reliability and Validity of the Reception Dimensions*

Dimension	Items retained	α (5 items)	α (retained)	CR	AVE	EFA loadings
Perceived usefulness	Q01–Q05	.75	.75	.75	.38	.46–.72
Research practices	Q06–Q10	.82	.82	.82	.48	.60–.71
Trust	Q11–Q14	.45	.58	.59	.27	.25–.66
Ethical challenges	Q16–Q19	.46	.58	.59	.27	.41–.59
Institutional support	Q21–Q25	.65	.65	.65	.27	.44–.61
Future adoption	Q26–Q30	.77	.77	.77	.41	.38–.67

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted, computed from single-factor solutions. The EFA loadings shown are the primary-factor pattern loadings obtained from a six-factor minimum residual solution with promax rotation (28 items). Q15 (verification) and Q20 (disclosure) were excluded from the trust and ethical challenges scores and analysed as single items. KMO = .864; Bartlett's $\chi^2(378) = 1781.0$, $p < .001$.

4. Results

4.1 Demographic data

The sample comprised 257 faculty members in Jordan, primarily from public (52.5%) and private (45.9%) universities, with 1.6% reporting another institution type. Men and women were represented in roughly equal numbers (49.0% male, 47.9% female), and several academic ranks were represented, with assistant professors (37.0%) and associate professors (31.9%) forming the two largest groups. Of the eight disciplinary areas represented, humanities and languages (18.3%) and engineering and technology (15.6%) contributed the most respondents. The full demographic profile of the sample is reported in Table 2.

Table 2: *Profile of Participants (N = 257)*

Characteristic	Category	n	%
Gender	Female	123	47.9
	Male	126	49.0
	Prefer not to say	8	3.1
Age group (years)	Under 30	12	4.7
	30–39	73	28.4
	40–49	95	37.0
	50–59	64	24.9
	60 or above	13	5.1
University type	Public	135	52.5
	Private	118	45.9
	Other	4	1.6
Academic rank	Professor	34	13.2
	Associate Professor	82	31.9
	Assistant Professor	95	37.0
	Lecturer/Instructor	44	17.1
	Other	2	0.8
Discipline	Humanities and Languages	47	18.3
	Engineering and Technology	40	15.6
	Medicine and Health Sciences	38	14.8
	Natural and Applied Sciences	35	13.6
	Business and Economics	33	12.8
	Education	27	10.5
	Social Sciences	29	11.3
	Other	8	3.1
Academic experience (years)	Less than 5	30	11.7
	5–9	47	18.3
	10–14	63	24.5
	15–19	49	19.1
	20 or more	68	26.5
Number of publications	None	9	3.5
	1–5	47	18.3
	6–10	55	21.4
	11–20	75	29.2
	More than 20	71	27.6

Self-reported familiarity with GenAI was moderately high (M = 3.58, SD = 0.92), with more than half of the respondents (55.6%) selecting 4 or 5 on the scale. The mean frequency of use was 3.46 (SD = 1.03); approximately half of the sample (49.8%) selected 4 or 5, whereas only five respondents (1.9%) reported the lowest frequency of use and identified no primary tool. ChatGPT was the predominant primary tool (56.4%), followed by Gemini (16.3%), Microsoft Copilot (11.3%), Perplexity AI (7.8%), and Claude (5.1%), and the choice of tool was not significantly associated with discipline, $\chi^2(42) = 42.66$, $p = .443$.

Each of the 252 respondents who reported using GenAI identified between one and four research activities (M = 1.73, SD = 0.88), and these activities were distributed fairly evenly (Table 3). Methodology design (26.1%), research questions (23.0%), and abstracts and presentations (22.6%) were cited most often, yet no activity was selected by appreciably more than a quarter of the sample. The pattern points to a selective use of GenAI, generally confined to one or two tasks and not extended across the entire research cycle.

Table 3: *Primary GenAI Tool and Research Activities Supported by GenAI*

Item	n	%
Primary GenAI tool		
ChatGPT	145	56.4
Gemini	42	16.3
Microsoft Copilot	29	11.3
Perplexity AI	20	7.8
Claude	13	5.1
None reported	5	1.9
Other	3	1.2
Research activities supported by GenAI (multiple responses)		
Methodology design	67	26.1
Research questions	59	23.0
Abstracts/presentations	58	22.6
Language editing	56	21.8
Literature summaries	53	20.6
Data analysis	52	20.2
Manuscript drafting/editing	48	18.7
Research ideas	43	16.7

Note. Percentages are calculated on the basis of the full sample (N = 257). Multiple responses were permitted for research activities; on average, the 252 respondents who used GenAI selected 1.73 activities.

4.2 Perceptions, practices, and challenges (RQ1)

Descriptive statistics for the six dimensions are summarised in Table 4, and the item-level results are reported in Table 5. All six means differed significantly from the scale midpoint (all $p \leq .008$), though the differences varied in both direction and magnitude. Considered jointly, these results are indicative of qualified acceptance.

Table 4:*Descriptive Statistics for the Six Reception Dimensions*

Dimension	M	SD	t(256)	p	% above 3.5	% below 2.5
Perceived usefulness	3.60	0.64	15.09	< .001	54.1	5.4
Research practices	3.14	0.77	2.94	.004	34.6	21.8
Trust	3.14	0.60	3.64	< .001	21.8	10.9
Ethical challenges	3.89	0.56	25.39	< .001	70.4	1.2
Institutional support	2.90	0.58	–2.67	.008	14.8	24.1
Future adoption	3.50	0.70	11.48	< .001	50.2	7.8

Note. Scores could range from 1 to 5; each t-test compares the mean of a dimension with the scale midpoint of 3. The percentage columns report the proportion of respondents whose mean on a given dimension was above 3.5 (overall agreement) or below 2.5 (overall disagreement).

Usefulness. GenAI was perceived as useful (M = 3.60, SD = 0.64), and 54.1% of respondents obtained a usefulness score above 3.5. Ratings of the five usefulness items were closely comparable (M = 3.52–3.67), with agreement ranging between 51.8% and 57.2%. Respondents acknowledged its help in finding topics, organising information, and saving time, and rated none of these benefits much above the others.

Research practices. Use lagged behind perceived usefulness (M = 3.14, SD = 0.77). For individual practice items, agreement lay between 34.6% and 39.3% and disagreement between 21.8% and 26.8%. Methodology and instrument development (Q08) was the practice most often endorsed, at 39.3%; data analysis or interpretation (Q09) was the least, at 34.6%. In other words, faculty appear to see more in GenAI than they presently draw on.

Trust. Trust was positive, but only just (M = 3.14, SD = 0.60). About a third of respondents called

GenAI a reliable source of support (33.5%), said it explains research concepts accurately (35.8%), or expressed confidence in its handling of complex tasks (33.1%); between 19.5% and 26.1% disagreed with each of these statements. Verification was a different matter. Fully 84.8% agreed that GenAI outputs must be carefully verified before use (Q15, M = 4.23), and just 0.8% disagreed. Agreement with this item did not correlate significantly with the trust score ($r = -.11$, $p = .084$). One reading is that respondents see verification as a professional duty whatever their level of trust, although a non-significant correlation does not in itself prove that the two are unrelated.

Ethical challenges. No dimension had a higher mean than ethical concern (M = 3.89, SD = 0.56); 70.4% of respondents scored above 3.5 on it. Roughly seven in ten (68.9% to 70.8%, depending on the item) agreed that GenAI threatens originality, makes fabricated references more likely, may weaken critical thinking, and complicates authorship. Disclosure (Q20) drew more agreement than any other item, at 89.5% (M = 4.33), with only 0.4% dissenting. Here too, as with verification, the correlation with the ethical concern score was not significant ($r = -.09$, $p = .162$).

Institutional support. Institutional support was the only dimension rated below the midpoint (M = 2.90, SD = 0.58), $t(256) = -2.67$, $p = .008$. Asked whether their university offered adequate guidance, training, clear policies, technological resources, or encouragement, between 22.2% and 27.6% agreed, and about a third disagreed in each case. Guidance on responsible use (Q21) and encouragement of responsible exploration (Q25) were rated lowest, both at M = 2.87.

Future adoption. Respondents expressed a moderately positive intention to continue using GenAI (M = 3.50, SD = 0.70). Around half agreed that they had a positive attitude (47.9%), intended to increase their use (50.2%), were willing to try new applications (54.9%), would recommend responsible use to colleagues (54.1%), and expected GenAI to become integral to research (51.0%).

Table 5: *Item-Level Responses*

Item	Statement	M	SD	% agree	% disagree
Perceived usefulness					
Q01	Generative AI helps me complete research-related tasks more efficiently.	3.52	0.94	51.8	12.8
Q02	Generative AI facilitates the identification of relevant research topics and ideas.	3.67	0.88	57.2	8.9
Q03	Generative AI improves my ability to organize and synthesize academic information.	3.61	0.86	56.0	9.7
Q04	Generative AI contributes to improving the quality of my academic research.	3.61	0.89	53.3	9.7
Q05	Generative AI reduces the time and effort required to prepare academic manuscripts.	3.60	0.94	54.9	12.8
Research practices					
Q06	I use generative AI to explore research ideas and formulate research questions.	3.18	1.02	35.8	21.8
Q07	I use generative AI to summarize or critically examine academic literature.	3.14	1.02	35.4	25.3
Q08	I use generative AI to assist with research methodology or instrument development.	3.19	1.02	39.3	23.3
Q09	I use generative AI to support data analysis or the interpretation of research findings.	3.10	1.00	34.6	25.7
Q10	I use generative AI to revise academic writing, improve language, or organize manuscripts.	3.10	1.01	37.7	26.8
Trust					
Q11	I consider generative AI a reliable source of support for academic research.	3.14	0.90	33.5	23.3
Q12	I trust generative AI to provide accurate explanations of research-related concepts.	3.22	0.92	35.8	19.5
Q13	I believe generative AI can produce academically sound content when used appropriately.	3.11	0.88	33.1	22.2

Item	Statement	M	SD	% agree	% disagree
Q14	I am confident in the ability of generative AI to support complex research tasks.	3.07	0.90	33.1	26.1
Q15†	I believe generative AI outputs require careful verification before being incorporated into academic research.	4.23	0.72	84.8	0.8
Ethical challenges					
Q16	The use of generative AI in research raises concerns about academic originality.	3.91	0.86	69.3	5.4
Q17	Generative AI increases the risk of including inaccurate or fabricated references in academic publications.	3.88	0.82	70.8	5.1
Q18	Excessive reliance on generative AI may undermine researchers' independent critical thinking.	3.88	0.80	68.9	3.9
Q19	The use of generative AI in academic research raises concerns about authorship and intellectual responsibility.	3.88	0.88	69.6	7.0
Q20†	Researchers should disclose the use of generative AI in academic publications when required by relevant ethical or publishing guidelines.	4.33	0.67	89.5	0.4
Institutional support					
Q21	My university provides adequate guidance on the responsible use of generative AI in research.	2.87	0.88	22.6	33.1
Q22	My university offers sufficient training opportunities for integrating generative AI into academic research.	2.92	0.88	24.5	30.7
Q23	My university has clear policies regarding the ethical use of generative AI in research and publication.	2.95	0.96	27.6	32.3
Q24	I have access to the technological resources needed to use generative AI effectively in research.	2.91	0.90	24.1	31.1
Q25	My academic environment encourages the responsible exploration of generative AI in research activities.	2.87	0.87	22.2	33.5
Future adoption					
Q26	I have an overall positive attitude toward using generative AI in academic research.	3.49	0.96	47.9	14.0
Q27	I intend to increase my use of generative AI in future research projects.	3.44	1.01	50.2	17.9
Q28	I am willing to explore new generative AI applications to support my academic research.	3.57	0.95	54.9	13.2
Q29	I would recommend the responsible use of generative AI to other university faculty members.	3.51	0.95	54.1	16.0
Q30	I believe generative AI will become an integral component of academic research in the coming years.	3.48	0.94	51.0	15.6

Note. % agree = agree or strongly agree (4–5); % disagree = disagree or strongly disagree (1–2). † Item analysed separately (verification norm and disclosure norm) and not included in the dimension score.

4.3 Group differences (RQ1)

Most background characteristics showed limited associations with reception (Table 6). No statistically significant differences across disciplines were found for any dimension (all $p \geq .28$), and none were found across academic experience groups (all $p \geq .24$). Publication record was related only to institutional support, $F(4, 252) = 2.68$, $p = .032$, $\eta^2 = .041$, and no pairwise comparison reached significance. Female and male faculty did not differ significantly on any dimension; the largest gap was in ethical concern ($M = 3.96$ vs. 3.83), $t(247) = 1.85$, $p = .066$. Faculty at public universities reported slightly stronger ethical concern than those at private universities ($M = 3.96$ vs. 3.82), $t(251) = 2.04$, $p = .043$, $d = 0.26$, but the two groups did not differ on any other dimension, including institutional support.

Age showed the most consistent group differences. Age group was associated with usefulness, $F(4, 252) = 2.63$, $p = .035$, $\eta^2 = .040$; research practices, $F(4, 252) = 4.42$, $p = .002$, $\eta^2 = .066$; trust, $F(4, 252) = 2.79$, $p = .027$, $\eta^2 = .042$; ethical concern, $F(4, 252) = 3.98$, $p = .004$, $\eta^2 = .059$; and future adoption, $F(4, 252) = 4.15$, $p = .003$, $\eta^2 = .062$. Post hoc tests showed that faculty aged 30–39 rated usefulness higher than those aged

40–49 and 50–59, and reported more use, more trust, and stronger adoption intentions than those aged 50–59; faculty aged 40–49 also expressed stronger adoption intentions than those aged 50–59. The age effect on ethical concern reflected lower concern among the small group of faculty under 30 (M = 3.31) than among those aged 30–59 (M = 3.86–3.98). Academic rank had small effects on usefulness, $F(4, 252) = 2.68$, $p = .032$, $\eta^2 = .041$; research practices, $F(4, 252) = 2.98$, $p = .020$, $\eta^2 = .045$; and trust, $F(4, 252) = 2.92$, $p = .022$, $\eta^2 = .044$. Only the trust difference survived post hoc correction, with associate professors more trusting than lecturers (M = 3.26 vs. 2.94). These effects were generally small, although the age effects on research practices and future adoption approached or reached the conventional threshold for a medium effect (Cohen, 1988).

Table 6: *Differences in Reception by Background Characteristics*

Background variable	Usefulness	Practices	Trust	Ethical challenges	Institutional support	Future adoption
Gender, t(247) (d)	0.00 (0.00)	0.93 (0.12)	0.20 (0.03)	1.85 (0.23)	0.58 (0.07)	0.29 (0.04)
University type, t(251) (d)	0.71 (0.09)	0.38 (0.05)	1.80 (0.23)	2.04* (0.26)	0.04 (0.00)	1.33 (0.17)
Age group, F(4, 252) (η^2)	2.63* (.040)	4.42** (.066)	2.79* (.042)	3.98** (.059)	0.74 (.012)	4.15** (.062)
Academic rank, F(4, 252) (η^2)	2.68* (.041)	2.98* (.045)	2.92* (.044)	2.02 (.031)	1.06 (.017)	2.09 (.032)
Discipline, F(7, 249) (η^2)	0.68 (.019)	1.06 (.029)	1.05 (.029)	0.87 (.024)	1.25 (.034)	1.23 (.033)
Experience, F(4, 252) (η^2)	0.94 (.015)	1.37 (.021)	0.40 (.006)	0.97 (.015)	1.27 (.020)	0.95 (.015)
Publications, F(4, 252) (η^2)	0.18 (.003)	1.00 (.016)	0.45 (.007)	0.16 (.003)	2.68* (.041)	0.10 (.002)

Note. Gender compares female (n = 123) and male (n = 126) respondents; university type compares public (n = 135) and private (n = 118) universities. Absolute t and d values are shown; directions are reported in the text. *p < .05. **p < .01. ***p < .001.

4.4 Relationships among dimensions

The intercorrelations among the six dimensions and the two background measures are presented in Table 7. Future adoption correlated strongly with frequency of use (r = .65), usefulness (r = .58), and familiarity (r = .54), and positively with research practices (r = .51) and trust (r = .45). Frequency of use and research practices were very closely related (r = .83), as would be expected given that both measure use. Two patterns are particularly relevant. First, ethical concern was only weakly and negatively related to usefulness (r = –.17), trust (r = –.16), adoption (r = –.17), and frequency of use (r = –.13). These weak associations suggest that ethical concern was not strongly associated with lower use or adoption intentions. Second, institutional support was essentially unrelated to usefulness (r = .07), research practices (r = –.01), trust (r = .03), and frequency of use (r = –.03), and only weakly related to adoption (r = .14). Reported GenAI use therefore showed little association with perceived institutional support.

Table 7: *Correlations Among Reception Dimensions and GenAI Background*

Variable	1	2	3	4	5	6	7
1. Perceived usefulness	—						
2. Research practices	.49***	—					
3. Trust	.35***	.39***	—				
4. Ethical challenges	–.17**	–.09	–.16*	—			
5. Institutional support	.07	–.01	.03	.05	—		
6. Future adoption	.58***	.51***	.45***	–.17**	.14*	—	
7. GenAI familiarity	.50***	.48***	.48***	–.14*	.13*	.54***	—
8. GenAI use frequency	.61***	.83***	.45***	–.13*	–.03	.65***	.59***

Note. N = 257. *p < .05. **p < .01. ***p < .001.

4.5 Predictors of future adoption (RQ2)

In a hierarchical regression, familiarity and frequency of use entered in the first step explained 45.9% of the variance in future adoption, $F(2, 254) = 107.90$, $p < .001$. Adding the five reception dimensions in the second step explained a further 6.9%, $\Delta F(5, 249) = 7.27$, $p < .001$, giving a final R^2 of .528 (adjusted $R^2 = .515$), $F(7, 249) = 39.82$, $p < .001$ (Table 8). Variance inflation factors ranged from 1.05 to 4.40, indicating no severe multicollinearity, although the overlap between use frequency and research practices warrants attention.

In the final model, frequency of use was the strongest predictor ($\beta = .46$, $p < .001$), followed by perceived usefulness ($\beta = .22$, $p < .001$), trust ($\beta = .13$, $p = .012$), institutional support ($\beta = .12$, $p = .007$), and familiarity ($\beta = .12$, $p = .041$). Research practices did not add to the prediction once frequency of use was controlled ($\beta = -.10$, $p = .218$), which is consistent with the overlap between the two measures. Ethical concern was not a statistically significant predictor of adoption ($\beta = -.05$, $p = .243$). After adjustment for the other variables, ethical concern showed no statistically significant association with future adoption intentions.

Table 8: *Hierarchical Regression Predicting Future Adoption (Final Model)*

Predictor	B	SE	β	t	p	VIF
GenAI use frequency	0.310	0.062	.46	5.02	< .001	4.40
Perceived usefulness	0.245	0.062	.22	3.95	< .001	1.71
Trust	0.151	0.059	.13	2.54	.012	1.39
GenAI familiarity	0.091	0.044	.12	2.05	.041	1.80
Institutional support	0.147	0.054	.12	2.74	.007	1.05
Research practices	–0.087	0.071	–.10	–1.23	.218	3.25
Ethical challenges	–0.065	0.055	–.05	–1.17	.243	1.05
Constant	0.844	0.355		2.38	.018	

Note. Step 1 (familiarity and use frequency): $R^2 = .459$, $F(2, 254) = 107.90$, $p < .001$. Step 2 (adding the five reception dimensions): $\Delta R^2 = .069$, $\Delta F(5, 249) = 7.27$, $p < .001$. Final model: $R^2 = .528$, adjusted $R^2 = .515$, $F(7, 249) = 39.82$, $p < .001$.

The estimated indirect association between usefulness and future adoption through trust was significant (ab = .107, 95% bootstrap CI [.058, .162]). In a separate model, trust was predicted by familiarity ($\beta = .31$, $p < .001$) and frequency of use ($\beta = .24$, $p = .002$), but not by usefulness ($\beta = .04$, $p = .554$), ethical concern ($\beta = -.08$, $p = .167$), or institutional support ($\beta = -.01$, $p = .907$); together these explained 27.9% of its variance. Trust, then, went with familiarity and frequent use, not with perceived institutional support. Whether trust builds up through use cannot be settled with cross-sectional data.

4.6 Reception positions (RQ2)

Because reception theory anticipates qualitatively different readings, k-means cluster analysis was applied to standardised scores on the six dimensions. A three-cluster solution was retained because it corresponds to Hall's distinction between dominant, negotiated, and oppositional readings (Hall, 1980) and produced interpretable profiles. With an average silhouette coefficient of only .16 (against .23 for the two-cluster solution), the positions are better understood as points along a continuum than as sharply separated groups. Descriptive comparisons showed that the clusters differed on all six dimensions (all $p \leq .002$) but not on the verification norm, $F(2, 254) = 1.00$, $p = .368$, or the disclosure norm, $F(2, 254) = 0.29$, $p = .751$ (Table 9).

Table 9: *Profiles of the Three Reception Positions: Means (SD)*

Variable	Engaged-critical (n = 96, 37.4%)	Negotiated-pragmatic (n = 89, 34.6%)	Guarded-sceptical (n = 72, 28.0%)	F(2, 254)
Perceived usefulness	4.15 (0.44)	3.34 (0.47)	3.19 (0.51)	106.96***
Research practices	3.78 (0.47)	2.75 (0.57)	2.78 (0.76)	86.95***
Trust	3.51 (0.47)	3.13 (0.48)	2.65 (0.54)	63.09***
Ethical challenges	3.76 (0.58)	3.88 (0.53)	4.06 (0.53)	6.23**
Institutional support	2.91 (0.53)	3.27 (0.47)	2.45 (0.41)	58.03***

Variable	Engaged-critical (n = 96, 37.4%)	Negotiated-pragmatic (n = 89, 34.6%)	Guarded-sceptical (n = 72, 28.0%)	F(2, 254)
Future adoption	4.10 (0.48)	3.37 (0.44)	2.86 (0.53)	140.12***
Verification norm (Q15)	4.21 (0.74)	4.18 (0.67)	4.33 (0.75)	1.00
Disclosure norm (Q20)	4.32 (0.67)	4.37 (0.63)	4.29 (0.72)	0.29
GenAI use frequency	4.39 (0.57)	2.97 (0.73)	2.83 (0.92)	121.97***
GenAI familiarity	4.23 (0.64)	3.46 (0.75)	2.86 (0.83)	72.81***

Note. Positions were identified by k-means clustering of standardised scores on the six dimensions (average silhouette = .16). Verification and disclosure norms, use frequency and familiarity were not used for clustering. **p < .01. ***p < .001.

The **engaged-critical** position (n = 96, 37.4%) combined high usefulness (M = 4.15), the highest use of GenAI in research (M = 3.78), relatively high trust (M = 3.51), and strong adoption intentions (M = 4.10), with frequent use (M = 4.39). These faculty nevertheless reported considerable ethical concern (M = 3.76) and reported institutional support close to the sample mean (M = 2.91). In Hall's terms this comes close to a dominant reading of GenAI as a research tool, held in check by a clear sense of its risks.

Scores in the negotiated-pragmatic position (n = 89, 34.6%) were moderate for usefulness (M = 3.34), trust (M = 3.13), and adoption (M = 3.37), and research use was limited (M = 2.75). This was the only cluster to rate institutional support above the midpoint (M = 3.27), the highest of the three. What the profile suggests is conditional acceptance combined with a relatively positive view of institutional support; whether those institutional conditions actually shaped use, the data cannot say.

Faculty in the guarded-sceptical position (n = 72, 28.0%) trusted GenAI least (M = 2.65) and used it least often (M = 2.83). They also voiced the strongest ethical concern (M = 4.06) and saw the least institutional support (M = 2.45). In research use (M = 2.78) they were much like the negotiated-pragmatic group. Their adoption intention fell just under the midpoint (M = 2.86), yet they still judged GenAI slightly useful (M = 3.19), a stance that edges towards an oppositional reading but stops short of rejecting the technology.

Cluster membership was related to age, $\chi^2(8) = 19.26$, $p = .014$, Cramér's $V = .19$. The engaged-critical position accounted for 53.4% of faculty aged 30–39 but for only 20.3% of those aged 50–59 and 23.1% of those aged 60 and above. Membership was not related to academic rank, $\chi^2(8) = 12.63$, $p = .125$; discipline, $\chi^2(14) = 18.60$, $p = .181$; experience, $\chi^2(8) = 4.42$, $p = .818$; university type, $\chi^2(4) = 1.27$, $p = .866$; or gender, $\chi^2(4) = 5.74$, $p = .219$.

5. Discussion

The aim of this study was to understand how university faculty receive GenAI as a tool for research. The answer, broadly, is critical acceptance. Faculty find GenAI useful and expect to go on using it. Yet they trust it only moderately, apply it to few tasks, hold marked ethical concerns, and feel their institutions have not given them enough support. The discussion that follows examines the principal findings in light of the research questions and the existing literature.

5.1 Usefulness exceeds practice

Faculty rated GenAI's usefulness more favourably than their reported research practices (RQ1). Whereas usefulness stood well above the midpoint, research practices exceeded it only slightly, and most users confined GenAI to one or two activities. The same gap appears in the *Nature* survey, whose respondents anticipated substantial future benefits while reporting more limited current use (Van Noorden & Perkel, 2023), and it accords with the observation that early adoption tends to be exploratory and partial (Rogers, 2003). Seen from the standpoint of reception, faculty seem to acknowledge the relative advantage of GenAI while still testing how well it fits the norms of their own research. The fairly even distribution of activities is informative as well. In a region where many researchers publish in a second language (Al-Salman & Haider, 2024), it might be expected that GenAI to be confined to language editing, yet methodology design and the formulation of research questions were reported at least as often. These findings suggest that GenAI is used for substantive research tasks as well as presentation, reinforcing the need for verification and accountability.

5.2 Trust is conditional, and verification is a shared norm

Trust was among the lowest-rated dimensions above the midpoint, and only about a third of respondents agreed that GenAI is reliable or accurate. More than eight in ten, however, agreed that its outputs must be verified, with no significant association between verification endorsement and trust. This pattern suggests that support for verification may reflect a professional norm rather than simply distrust of GenAI; this is in keeping with the position of publishers and ethics bodies, who hold human authors responsible for AI-assisted content (Committee on Publication Ethics, 2023; Hosseini et al., 2024). Expressed in the terms of reception theory, verification operates as a rule of the scholarly interpretive community (Fish, 1980), one endorsed across the positions identified by the cluster analysis.

The regression results further indicate that trust is associated with use and familiarity, while the indirect-effect analysis links usefulness to adoption through trust. This is consistent with research showing that trust in AI is built through experience of its reliability (Glikson & Woolley, 2020), and similar questions of trust run through recent Jordanian work on AI translation in professional settings (Haider, 2026b). It also carries a risk. If trust increases with use, frequent users may come to rely on outputs that remain unreliable in specific ways, such as fabricated references (Walters & Wilder, 2023) or mistranslated idioms and culture-bound expressions (Dweik et al., 2026; Tannous & Haider, 2025), and fluent text may encourage the illusions of understanding described by Messeri and Crockett (2024). Although verification was strongly endorsed, endorsement does not necessarily indicate adherence, and this study did not observe actual verification behaviour.

5.3 Ethical concern coexists with use

Ethical challenges were the most strongly endorsed dimension (RQ1), in line with the prominence of originality, authorship, and fabricated citations in the literature (Cotton et al., 2024; Thorp, 2023). However, ethical concern was only weakly related to use and was not a significant predictor of adoption after adjustment for the other factors. Greater ethical concern was associated with only slightly lower reported use. A similar decoupling has been noted in studies of academics, where integrity concerns coexisted with intentions to use ChatGPT (Bin-Nashwan et al., 2023). A reception perspective helps explain this. Ethical concern may coexist with acceptance and influence the conditions under which GenAI is considered legitimate. This interpretation is consistent with the substantial concern reported by the most engaged group. The strong support for disclosure points in the same direction: faculty appear to accept GenAI on the condition that its use is made visible, which matches the direction of publisher policy (Ganjavi et al., 2024).

Faculty at public universities expressed somewhat stronger ethical concern than their counterparts at private universities, but the difference was small and should not be overinterpreted. Differences in institutional culture, or in exposure to cases of research misconduct, might account for it, although the present data cannot test either explanation.

5.4 The institutional gap

Of the six dimensions, only institutional support was rated below the midpoint; about a third of respondents did not accept that their university gave them guidance, training, or clear policy on GenAI in research. This echoes international findings that institutional guidance has concentrated on teaching and assessment (Moorhouse et al., 2023) and that researchers often report receiving little guidance (Van Noorden & Perkel, 2023). The findings also show that perceived support was almost unrelated to how useful faculty found GenAI, how much they used it, or the extent to which they trusted it. This pattern is consistent with faculty adopting publicly accessible GenAI tools without relying heavily on institutional provision. This differs from the role usually given to facilitating conditions in acceptance models (Venkatesh et al., 2003), and may reflect the availability of GenAI tools outside institutional procurement processes.

This does not mean that institutional support is unimportant. It made a small independent contribution to adoption intentions, while the negotiated-pragmatic group combined the highest perceived support with moderate acceptance and limited research use. Support may therefore matter less for whether faculty use GenAI than for how they use it. Without explicit guidance, faculty may continue to rely on personal judgement rather than shared institutional standards. The calls by UNESCO and policy researchers for structured training and research-specific guidance (Chan, 2023; Miao & Holmes, 2023) are therefore well founded.

5.5 Age-related variation in reception

Contrary to what might be expected, discipline, experience, and publication record made little difference to reception (RQ1). Faculty across disciplines and university types held broadly similar views, apart from the small difference in ethical concern between public and private universities. Age was the most consistent source of variation: faculty aged 30–39 found GenAI more useful, reported greater trust, use, and adoption intentions than older colleagues, particularly those in their fifties, and more than half of them held the engaged-critical position. Promotion demands and efforts to develop a publication record may increase the appeal of time-saving tools for faculty in this age group, although these motivations were not measured. The pattern is consistent with diffusion research, in which earlier adopters tend to differ from later adopters in age and career stage (Rogers, 2003), and with evidence that faculty form distinct profiles of AI use with different development needs (Mah & Groß, 2024). The small group of faculty under 30 reported lower ethical concern than colleagues aged 30 to 59, which deserves attention as AI use becomes routine in university study, including in Jordanian and Iraqi translation classrooms (Gwasmeh et al., 2026).

5.6 Three reception positions

The cluster analysis offers a reception-based reading of the data (RQ2). Hall's model distinguishes dominant, negotiated, and oppositional decodings (Hall, 1980). The engaged-critical position resembles a dominant reading in its acceptance of GenAI as a research tool, but its high ethical concern shows that faculty in this position do not simply accept the framing offered by developers. The negotiated-pragmatic position accepts GenAI in principle while adapting it to perceived institutional conditions. The guarded-sceptical position leans towards opposition. Even so, an adoption intention close to neutral and a slightly favourable view of usefulness show that outright rejection was rare. That no clearly oppositional profile appeared suggests that, in this sample, doubts about GenAI and recognition of its usefulness tend to go together. Because the clusters were not sharply separated, these profiles are best treated as exploratory.

Support for verification and disclosure was similarly high in all three positions. Faculty may differ in how much they trust and use GenAI, but they appear to share a normative baseline, and because that baseline consists of norms they already accept, it gives institutional policy somewhere realistic to start.

6. Conclusion

The faculty in this study neither embraced GenAI uncritically nor turned it away. They found it useful and used it selectively. Their trust was cautious, their ethical concerns persistent, and the institutional support they received, in their view, inadequate. Critical acceptance is the most fitting description of this reception, and strong endorsement of verification and disclosure is what holds it together across the three positions. The principal division in how faculty receive the technology follows age more closely than discipline or rank. Many faculty already use GenAI in their research, so the task before universities is to provide guidance, training, and policies that support shared, accountable research practices.

For universities, the findings call for explicit institutional guidance on responsible GenAI use. Policies written specifically for research should set out which uses of GenAI are acceptable at each stage of the research process, specify expectations for verification and disclosure, and remain consistent with the requirements of publishers (Committee on Publication Ethics, 2023; Ganjavi et al., 2024). As faculty are already using GenAI, training should extend beyond introductory tool demonstrations to critical use, which includes checking references and claims, recognising the limitations of AI-generated analysis, and documenting the assistance AI has provided. Such training could also be tailored to reception position, with advanced, integrity-focused development offered to engaged-critical users and practical, low-risk starting points offered to guarded-sceptical colleagues (Mah & Groß, 2024). Recent Jordanian research on AI in university teaching and learning (Gwasmeh et al., 2026; Haider, 2026a) provides a foundation on which such training could build.

Research leaders and supervisors should note that faculty in their thirties were the most engaged and that the youngest faculty expressed the least ethical concern; together, these findings argue for building mentoring on the responsible use of GenAI into early-career development. Journals and research offices in Jordan may take the strong support for disclosure as an indication that clear disclosure requirements may be acceptable to faculty. Researchers should translate their endorsement of verification into concrete practices, such as checking every

AI-suggested reference against its original source; actual adherence to these norms remains to be established. On the theoretical side, the study demonstrates what is gained by combining reception theory with models of acceptance. Whereas the acceptance constructs accounted for about half of the variance in future adoption, the reception perspective brought to light patterns that a purely predictive model would have missed, among them the separation of trust from verification, the coexistence of concern and use, and exploratory reception profiles sharing a common normative basis.

The study has several limitations. Its cross-sectional design rules out causal conclusions, and the relationships among use, trust, and adoption may well run in both directions. Because the data are self-reported, they may also be influenced by social desirability, above all on normative items such as verification and disclosure, where the very high agreement may in part reflect socially expected responses. The reliability of the trust, ethical challenges, and institutional support scales fell below conventional thresholds, and AVE values indicated limited convergent validity, and two of the trust items loaded weakly on their factor; future work should refine these scales, perhaps by distinguishing trust in accuracy from confidence in capability and by measuring the various ethical concerns separately. The sample was not randomly drawn and came only from Jordanian universities, so generalising to other countries, or even to Jordanian faculty as a whole, would be unwarranted; some subgroups, faculty under 30 for example, were also small. Finally, since the clusters overlapped considerably, the reception positions should be read as tendencies along a continuum and not as discrete types.

Future work could take several directions from here. A longitudinal design would show how reception shifts as institutional policies mature and the tools improve. Interviews with faculty in each position would add depth, revealing how they interpret GenAI and negotiate its use day to day; audience-based reception studies of AI output in Arabic, among them work on AI dubbing and AI-translated idioms (Ahmad et al., 2025; Darwish et al., 2025), offer useful methodological models here. It would also be valuable to observe research behaviour directly, for instance how faculty check references produced by AI, to see whether the strong endorsement of verification is matched in practice. Comparative studies in other regions could then test whether the weak link between institutional support and GenAI use found in Jordan holds elsewhere.

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