Faculty Beliefs, Pedagogical Knowledge, and Adoption Intentions of Generative AI in Mathematics Education: Evidence from Saudi Higher Education

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Abstract

Generative artificial intelligence (AI) is increasingly reshaping higher education. In mathematics education, where abstraction, rigor, and proof are central, the pedagogical implications of generative AI are particularly consequential. Tools such as ChatGPT offer opportunities for personalized feedback and instructional scaffolding, yet they also raise concerns related to accuracy, academic integrity, and overreliance. In this context, faculty beliefs and instructional reasoning play a decisive role in determining whether AI is adopted or resisted. This study examined mathematics faculty perspectives on generative AI adoption across three public universities in Saudi Arabia's Eastern Province. It focused on teaching beliefs, pedagogical and technological knowledge, digital experience, and adoption intentions, drawing on Teachers' Beliefs Typology, the Technological Pedagogical Content Knowledge framework, and Diffusion of Innovation theory as an integrated analytical lens. A descriptive–correlational design enriched with qualitative insights was employed, with data collected from 144 faculty members and analyzed using statistical and thematic techniques. The findings indicate a pattern of cautious optimism. Connectionist teaching beliefs and pedagogical–technological knowledge strongly predicted adoption intentions, while transmission-oriented beliefs were negatively associated with adoption. Digital experience showed a smaller positive association. Qualitative findings highlighted perceived benefits such as efficiency and personalized support, alongside concerns regarding reliability and academic integrity. Differences by academic rank were observed, with lecturers and assistant professors reporting higher adoption intentions than full professors. Overall, the findings demonstrate how disciplinary beliefs and professional knowledge jointly shape faculty adoption intentions in mathematics education, offering actionable insights for institutional policy and professional development initiatives.

Keywords: generative artificial intelligence, mathematics education, teachers' beliefs, TPACK, diffusion of innovation, higher education adoption

1. Introduction

Generative artificial intelligence (AI) is rapidly reshaping higher education. Tools such as ChatGPT can generate explanations, provide feedback, and simulate human-like dialogue, creating new opportunities for teaching and learning. In mathematics education, this development is especially consequential. Mathematics relies on abstraction, proof, and structured reasoning, and the integration of AI introduces both opportunities and risks—enhancing visualization and engagement while simultaneously challenging traditional notions of rigor, authorship, and academic integrity.

International literature reflects this tension. Studies highlight improvements in efficiency and inclusiveness, yet concerns persist regarding critical thinking, accuracy, and ethical use (Grassini, 2023; Malik et al., 2025). Within mathematics education, generative AI can support visualization and adaptive learning (Mohamed et al., 2022), but it remains limited in handling complex abstraction and proof construction (Richard et al., 2022). Consequently, effective adoption depends not only on technological capacity but also on how faculty perceive the pedagogical and ethical alignment of AI.

Teachers' Beliefs Typology (Askew et al., 1997), the Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006), and Diffusion of Innovation theory (Rogers et al., 2014) together provide a coherent foundation for understanding how disciplinary orientations, professional knowledge, and perceived innovation attributes shape adoption intentions.

Despite growing international interest in generative AI in higher education, the perspectives of mathematics faculty in the Arab region—particularly in Saudi Arabia—remain insufficiently examined. Existing studies have focused primarily on students' acceptance or on general information and communication technology integration in school contexts, leaving university faculty, and mathematics educators in particular, comparatively understudied. This gap is notable given that Saudi Vision 2030 explicitly emphasizes digital transformation, innovation, and pedagogical modernization in universities. Addressing this gap requires an analytical approach that accounts for disciplinary beliefs, pedagogical–technological reasoning, and the ways in which educational innovations are evaluated and adopted within higher education contexts. Therefore, this study is guided by the following research questions:

1. What teaching beliefs are dominant among mathematics faculty in Saudi higher education?
2. What instructional practices do faculty report when integrating generative AI?
3. What benefits and challenges do they perceive in using AI tools?
4. How do beliefs, instructional practices, digital experience, and adoption intentions relate?
5. Do adoption intentions vary by rank, gender, course type, or digital experience?

By addressing these questions, the study contributes to global debates on AI in higher education while providing context-specific insights from the Saudi context and the wider Arab region. More broadly, it clarifies how mathematics faculty beliefs and professional knowledge shape the responsible and sustainable adoption of generative AI in teaching and learning.

2. Literature Review

Generative artificial intelligence (AI) has entered higher education at a transformative pace. Universities are increasingly adopting generative tools such as ChatGPT to support learning, feedback, and assessment, while simultaneously navigating ethical concerns, academic integrity, and curricular alignment. Global research views generative AI as both an opportunity, enhancing personalization, efficiency, and engagement, and a challenge for autonomy, originality, and critical thinking in academic contexts (Grassini, 2023; Malik et al., 2025). This duality is particularly evident in mathematics education, a field shaped by abstraction, rigor, and proof-based reasoning.

2.1 Faculty Beliefs and Openness to Innovation

Faculty beliefs constitute a foundational construct in explaining instructional change in higher education. Although Teachers' Beliefs Typology was originally developed in school-based mathematics contexts, Askew et al. (1997) distinguished transmission, discovery, and connectionist orientations that remain relevant for understanding epistemic stances and pedagogical reasoning among university faculty. Classic mathematics education literature demonstrates that these belief orientations shape how educators interpret instructional innovation, often determining whether new tools are perceived as intellectually valuable or pedagogically risky (Thompson, 1992; Philipp, 2007).

More recent evidence indicates that these orientations continue to influence faculty responses to digital tools in higher education, particularly in disciplines that emphasize conceptual rigor and methodological precision (Li et al., 2025; Faisal, 2024). In the context of generative artificial intelligence, they frame how mathematics faculty evaluate the pedagogical legitimacy of AI, shaping whether such tools support conceptual development or undermine mathematical reasoning and proof. These orientations are especially consequential because they directly shape perceived compatibility, one of the strongest predictors of adoption within Diffusion of Innovation theory (Rogers et al., 2014).

2.2 Generative AI in Mathematics Education

Research in mathematics education highlights substantial pedagogical benefits associated with generative AI, including scaffolding, visualization, adaptive learning, and differentiated instruction (Mohamed et al., 2022; Opesemowo, 2025). Adaptive systems allow learners to explore multiple solution pathways, strengthen procedural fluency, and develop conceptual insight. However, important limitations remain, as generative models tend to perform well at routine procedures but struggle with abstraction, proof validation, and complex reasoning. (Richard et al., 2022). Recent reviews in mathematics education emphasize that these tensions reflect discipline-specific challenges related to epistemic authority and mathematical rigor when integrating AI into instruction (Mavrikis & Margeti, 2025).

Consequently, successful implementation requires balancing efficiency with mathematical rigor, raising questions about how mathematics faculty perceive AI's role in instruction.

2.3 Technology Integration and TPACK

The Technological Pedagogical Content Knowledge (TPACK) framework conceptualizes teaching as the interplay between content knowledge, pedagogical strategy, and technological integration (Mishra & Koehler, 2006). In mathematics education, recent studies emphasize that TPACK development reflects ongoing professional reasoning rather than static competence (Priyanda et al., 2025). Evidence suggests that faculty in higher education often possess strong disciplinary expertise and broad pedagogical knowledge yet may encounter challenges in content-specific technology integration, particularly when emerging tools introduce epistemic uncertainty or higher levels of abstraction (Sridana et al., 2025; Li et al., 2025). These challenges are especially salient for mathematics faculty, given the centrality of abstraction, formal reasoning, and proof in the discipline. In this study, the TPACK framework therefore represents a key mechanism through which epistemic beliefs are translated into instructional decisions about integrating generative AI into mathematics teaching.

2.4 Diffusion of Innovation (DOI) and Adoption in Higher Education

Diffusion of Innovations theory explains how perceptions of relative advantage, compatibility, complexity, trialability, and observability shape adoption (Rogers et al., 2014). Empirical research in higher education confirms that faculty adopt AI when they perceive alignment with their professional values and observe meaningful instructional benefits (Frei-Landau et al., 2022; Almaiah & Al-Khasawneh, 2022). Barriers commonly arise from limited training, technical complexity, and institutional uncertainty. More recent studies adopt integrative perspectives on technology adoption, demonstrating that adoption reflects both individual factors, such as digital experience and pedagogical confidence, and institutional conditions, including policy, resources, and organizational culture (Li, 2025). In this study, DOI offers a useful framework for understanding how faculty evaluate the compatibility of generative AI with mathematical reasoning and disciplinary norms.

2.5 Generative AI in Saudi Higher Education

Saudi higher education is undergoing rapid digital transformation, guided by Vision 2030 priorities for innovation and global competitiveness. Local studies report that generative AI improves access, inclusivity, and learning support (Faisal, 2024; Sobaih et al., 2024). Faculty consistently highlight potential benefits for instruction but point to persistent barriers, including limited institutional guidance, insufficient training, and ethical concerns (Alammari, 2024; Aldossary et al., 2024; Abouammoh et al., 2025). At a broader regional level, empirical evidence suggests that perceived usefulness, ease of use, and social influence remain robust predictors of generative AI acceptance across higher education contexts (Abdaljaleel et al., 2024).

In mathematics education within higher education, empirical research remains limited. Existing work suggests that Saudi mathematics faculty generally demonstrate strong disciplinary and pedagogical knowledge yet continue to face challenges in content-specific technology integration (Bingimlas, 2018; Alqahtani & Alibraheim, 2025). These findings indicate that while mathematics faculty value digital innovation, adoption is often constrained by systemic and professional factors, particularly in the context of generative AI.

2.6 Summary and Research Gap

The literature presents a coherent yet complex picture: generative AI enhances personalization and engagement while also raising concerns related to academic integrity and cognitive rigor (Baig & Yadegaridehkordi, 2024; Grassini, 2023; Malik et al., 2025). In mathematics education, this duality persists, as AI supports procedural fluency but continues to struggle with abstraction and proof-based reasoning (Mohamed et al., 2022; Opesemowo, 2025; Richard et al., 2022). Faculty beliefs and professional reasoning emerge as crucial antecedents to technology integration, shaping whether instructional tools are perceived as pedagogically legitimate or epistemically disruptive (Thompson, 1992; Philipp, 2007; Li et al., 2025). Conceptual frameworks such as the Technological Pedagogical Content Knowledge (TPACK) framework and Diffusion of Innovations theory demonstrate that adoption depends on the interaction between beliefs, professional knowledge, and perceived innovation attributes within institutional ecosystems (Sridana et al., 2025; Li, 2025).

Yet within the Saudi context, empirical studies remain limited and have focused predominantly on students or school-based teachers rather than university faculty. Research examining mathematics faculty, who operate at the intersection of abstraction, pedagogy, and technological innovation, remains particularly scarce. Addressing this gap requires an integrative analytical approach capable of capturing how disciplinary beliefs, pedagogical–technological reasoning, and innovation appraisal jointly shape generative AI adoption in higher education.

3. Theoretical Framework

This study is grounded in three interrelated frameworks that collectively explain how mathematics faculty perceive and adopt generative AI. Together, they provide a coherent conceptual lens linking professional beliefs, pedagogical reasoning, and institutional adoption.

The first framework, Teachers' Beliefs Typology (Askew et al., 1997), distinguishes transmission, discovery, and connectionist orientations. These orientations shape how faculty evaluate the pedagogical value of AI. Transmission-oriented faculty tend to emphasize control, accuracy, and academic integrity; connectionist faculty are more inclined to consider AI as a resource for examples, modeling, and real-world applications, while discovery-oriented faculty may experiment with AI for inquiry-based exploration. Across the international literature, this typology has consistently shown that entrenched beliefs function as either drivers or barriers to educational innovation.

The second framework, Technological Pedagogical Content Knowledge (TPACK) (Mishra & Koehler, 2006), provides the pedagogical mechanism through which beliefs translate into instructional choices. Within mathematics education, TPACK informs how digital technologies can support scaffolding, visualization, and reasoning while preserving disciplinary rigor. Yet global evidence indicates that mathematics faculty often possess strong content and pedagogical expertise but struggle to position emerging technologies such as generative AI within the epistemic norms of mathematics (Li et al., 2025; Sridana et al., 2025). In this study, TPACK therefore operates as a mediating construct linking underlying beliefs to instructional decisions about AI-based teaching practices.

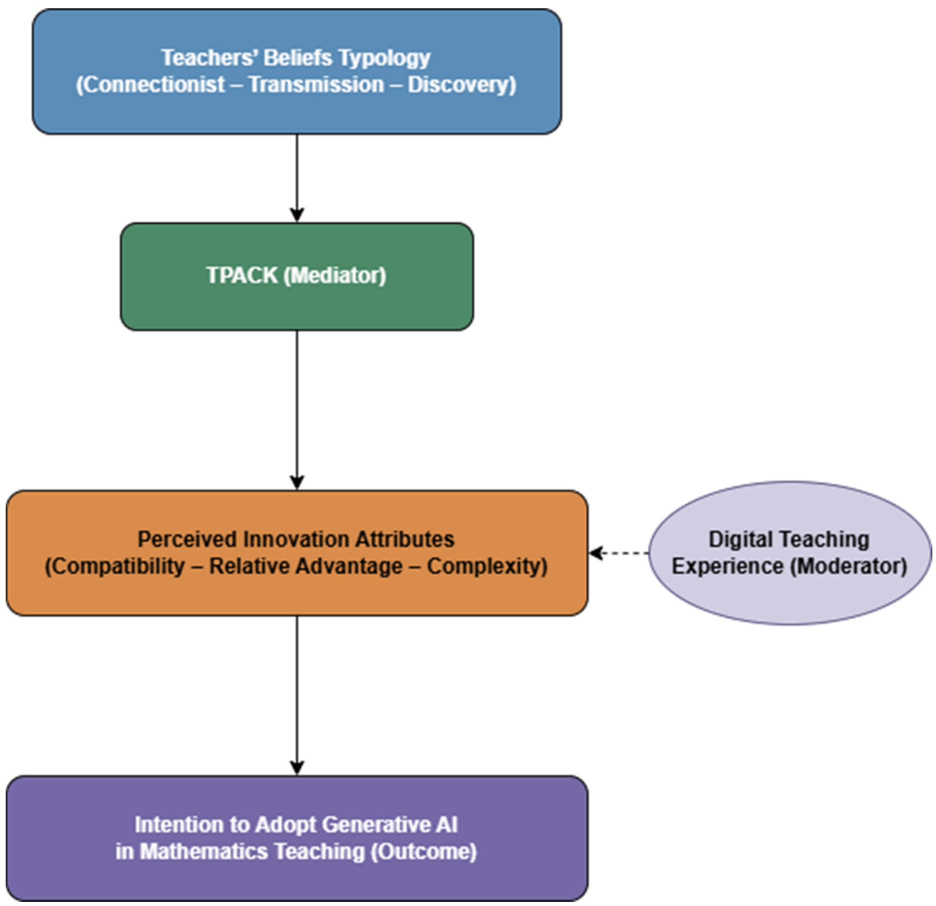

Figure 1. Conceptual Model of Generative AI Adoption in Mathematics Teaching

The third framework, Diffusion of Innovations (DOI) theory (Rogers et al., 2014), explains how adoption is shaped by the ways innovations are perceived within institutional and disciplinary contexts. DOI highlights attributes such as relative advantage, compatibility, and complexity, which are particularly relevant when evaluating generative AI's usefulness, alignment with mathematics instruction, and cognitive demands. The extent to which faculty perceive AI as compatible with mathematical reasoning, or as increasing complexity and uncertainty, reflects central DOI dynamics (Frei-Landau et al., 2022; Li, 2025).

Taken together, these three frameworks are proposed to operate sequentially in shaping generative AI adoption. Belief orientations influence TPACK development (Beliefs → TPACK), which in turn shapes the evaluation of key DOI attributes (TPACK → DOI attributes), ultimately predicting faculty adoption intentions (DOI attributes → Adoption intentions). This sequential pathway reflects the mediated nature of adoption proposed in this study, whereby epistemic orientations provide the foundation for pedagogical–technological reasoning, which then informs innovation appraisal and adoption decisions.

Furthermore, drawing on emerging technology adoption research, the model incorporates digital teaching experience as a potential moderating variable. Faculty with extensive technological exposure may demonstrate greater confidence in interpreting AI-generated outputs, a stronger ability to verify accuracy, and a higher readiness to integrate generative tools within mathematical instruction. Digital experience is therefore conceptualized not merely as a demographic descriptor but as an enabling contextual factor that can strengthen or weaken the pathway between pedagogical reasoning, DOI appraisal, and adoption intentions.

Accordingly, Figure 1 illustrates the mediated–moderated conceptual model proposed in this study, specifying how belief orientations shape TPACK reasoning, how TPACK informs perceived DOI attributes, and how these appraisals converge to influence adoption intentions, with digital experience moderating the strength of these relationships.

4. Methodology

4.1 Research Design

This study employed a descriptive–correlational design incorporating mixed-methods elements to explore how mathematics faculty in Saudi higher education perceive and adopt generative AI. The approach suited the study's purpose: to describe dominant teaching beliefs and practices, identify perceived benefits and challenges, and examine relationships among beliefs, professional knowledge (TPACK), digital experience, and adoption intentions. It also enabled comparisons across demographic variables such as academic rank, gender, and course type. The combination of quantitative surveys and open-ended responses provided measurable trends alongside contextual insights, aligning with recommendations for technology adoption studies (Creswell & Clark, 2018).

In addition, the study followed an explanatory sequential mixed-methods design, in which the quantitative phase was conducted first and served as the primary component for identifying numerical trends, followed by a qualitative phase designed to explain and enrich these findings (Creswell & Clark, 2018). This sequencing allowed statistical results to guide thematic interpretation, thereby increasing explanatory power.

4.2 Population and Sample

The population comprised all faculty members teaching mathematics-related courses in three public universities in Saudi Arabia's Eastern Province. Mathematics instruction in Saudi higher education extends beyond mathematics departments to preparatory, engineering, and applied colleges offering both foundational and advanced courses. The total estimated population was approximately 450 faculty members.

A purposive sampling approach was used to select the participating universities. The three universities were purposively selected to represent different institutional profiles within the Eastern Province—one large research-intensive university, one mid-sized comprehensive university, and one primarily teaching-oriented university.

From this population, 144 valid responses were obtained—approximately one-third of the estimated population. This sample size is considered appropriate for educational survey research and sufficient to detect medium-sized effects with 0.80 statistical power at $\alpha = 0.05$ (Cohen, 1988). The sample included faculty across genders, academic ranks, course types, and levels of digital experience, capturing the diversity of mathematics instruction in Saudi universities. Demographic details are presented in the Results section.

A priori power analysis using G*Power 3.1 (Faul et al., 2007) indicated that 138 participants were required to detect medium effect sizes ($f^2 = 0.15$) in multiple regression with $\alpha = .05$ and power = .80. The achieved sample of 144 exceeded this requirement. Invitations were sent to approximately 450 eligible faculty members, yielding 156 responses, of which 144 were complete and valid (response rate = 34.7%; completion rate = 92.3%).

4.3 Instruments

Data were gathered using a structured online survey adapted from established scales to ensure reliability and contextual validity. The instrument contained four components:

1. **Teaching Beliefs Questionnaire (TBQ)** (Askew et al., 1997): 18 items measuring transmission, discovery, and connectionist orientations. The items were adapted by aligning their descriptors with generative AI contexts through expert review.
2. **TPACK Scale** (Schmidt et al., 2009, adapted for mathematics/AI): 24 items across seven domains assessing the integration of pedagogy, content, and technology, with additional references to AI-supported instruction.
3. **Adoption Intentions Survey (AIS)** (based on Rogers et al., 2014; Davis, 1989): 20 items addressing perceived usefulness, ease of use, social influence, and innovation attributes such as compatibility and complexity, derived from a synthesis of DOI constructs.
4. **Open-Ended Items**: Three prompts invited participants to describe perceived benefits, challenges, and links between their teaching beliefs and AI perspectives.

All items were presented in English, with Arabic translation available upon request. Content validity was established through expert review by three mathematics education scholars. Pilot testing ($n = 15$) confirmed item clarity, relevance to AI practices, and reliability, with Cronbach's α values exceeding 0.80 across subscales.

The instrument was originally developed in English and underwent forward and back translation by two bilingual mathematics education experts to ensure linguistic and conceptual equivalence. The Arabic version was offered as an alternative, although 98% of respondents chose the English version. In the present sample, internal consistency was high across all measures: TBQ subscales $\alpha = .84–.91$; TPACK $\alpha = .89$; AIS $\alpha = .87$.

4.4 Demographic Data

A short demographic section captured gender, academic rank (lecturer, assistant professor, associate professor, and full professor), course type (foundational vs. advanced), and digital experience. These variables supported subgroup comparisons and correlation analyses. This section appeared at the beginning of the survey to facilitate participant profiling while maintaining anonymity and voluntary participation.

4.5 Procedures

Ethical approval was obtained from the Committee for Scientific Research Ethics at King Faisal University, Saudi Arabia. Data were collected online over a four-week period, from March 2025 to April 2025. Faculty invitations were sent via email and included information about the study objectives, confidentiality, and the estimated completion time (15–20 minutes). A reminder email was sent midway through the data collection period. Informed consent was obtained electronically before participation. Participants first viewed an online consent page outlining the study aims, voluntary participation, confidentiality, and the right to withdraw at any time without penalty. Consent was indicated by selecting an "I agree to participate" option before accessing the survey. Participation was voluntary and anonymous; no incentives were offered, and no identifying information was collected. All data were stored on encrypted servers in accordance with institutional research ethics policies.

4.6 Data Analysis

Quantitative data were analyzed using descriptive statistics (means, standard deviations, and frequencies) to profile teaching beliefs, instructional practices, and adoption intentions (Research Questions 1–3). Group differences across demographic variables (Research Question 5) were examined using independent-samples t-tests and one-way ANOVA. When the ANOVA results indicated statistically significant differences among groups, Tukey post-hoc comparisons were conducted to identify specific group differences ($p < 0.05$). Relationships among beliefs, TPACK, digital experience, and adoption intentions (Research Question 4) were examined using Pearson's correlations and multiple regression models, treating beliefs and TPACK as predictors and adoption intentions as the dependent variable. Assumptions of normality (Shapiro–Wilk), multicollinearity ($VIF < 5$), and homoscedasticity were examined prior to conducting the regression analyses. Preliminary checks confirmed normality (Shapiro–Wilk $p > .05$ for most variables), homoscedasticity, linearity, and the absence of multicollinearity (all $VIF < 2.1$).

Qualitative data were analyzed thematically using Braun and Clarke's (2006) six-phase framework. Both inductive and deductive coding were applied: themes such as personalized feedback and efficiency emerged inductively, whereas constructs such as compatibility with pedagogy reflected Diffusion of Innovation theory. Coding was conducted by the lead researcher, while a second coder independently reviewed 30% of responses, yielding an inter-coder reliability of $\kappa = 0.85$. Triangulation of quantitative and qualitative findings strengthened the interpretive validity of the results.

This section reports quantitative and qualitative findings addressing the five research questions. Statistical analyses present descriptive and inferential results, whereas qualitative findings summarize recurrent themes from open-ended responses. Interpretation is reserved for the Discussion section.

5. Results

5.1 Sample Characteristics

A total of 144 mathematics faculty members from three public universities in Saudi Arabia's Eastern Province participated in the study. The sample included 74 males (51.4%) and 70 females (48.6%). Academic ranks ranged from lecturers (25.0%) to assistant professors (33.3%), associate professors (27.8%), and full professors (13.9%). Course assignments were nearly evenly divided between foundational courses (51.4%) and advanced courses (48.6%). Participants reported an average of 6.5 years of digital experience (SD = 3.2, range = 0–15). Table 1 presents the demographic and professional characteristics of the participating mathematics faculty members.

Table 1. Sample Characteristics of Faculty Participants (N = 144)

Variable	Category	n	%
Gender	Male	74	51.4
	Female	70	48.6
Academic Rank	Lecturer	36	25.0
	Assistant Professor	48	33.3
	Associate Professor	40	27.8
	Full Professor	20	13.9
Course Type	Foundational	74	51.4
	Advanced	70	48.6
Digital Experience	Years (M = 6.5, SD = 3.2, range = 0–15)	—	—

5.2 RQ1. Dominant Teaching Beliefs

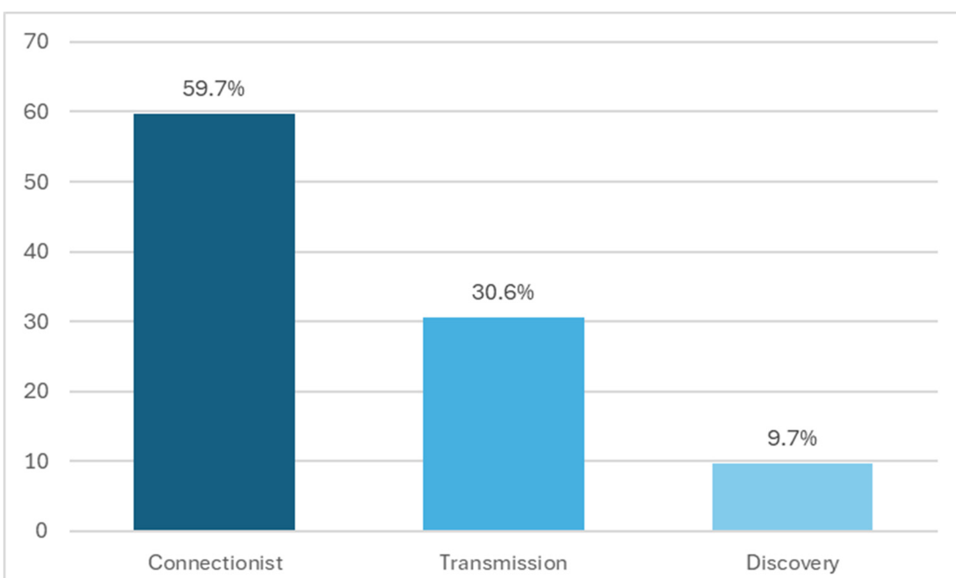

Figure 2. Distribution of Dominant Teaching Belief Orientations

Table 2. Descriptive Statistics for TBQ Subscales and Dominant Orientations (N = 144)

Subscale	M	SD	Range	Dominant Orientation n (%)
Connectionist	4.2	0.6	2.8–5.0	86 (59.7%)
Transmission	3.8	0.7	2.5–4.9	44 (30.6%)
Discovery	3.5	0.8	2.0–4.7	14 (9.7%)

The analysis of the TBQ indicated higher mean scores for connectionist orientations (M = 4.2, SD = 0.6) than for transmission (M = 3.8, SD = 0.7) or discovery orientations (M = 3.5, SD = 0.8). The distribution of dominant belief profiles reflected this pattern: connectionist (59.7%), transmission (30.6%), and discovery (9.7%). Table 2 presents the descriptive statistics for the TBQ subscales and the distribution of dominant belief profiles. Figure 2 illustrates the distribution of teaching beliefs.

5.3 RQ2. Instructional Practices (TPACK)

Table 3. Descriptive Statistics for TPACK Subdomains (N = 144)

Subdomain	M	SD	Range
Technological Knowledge (TK)	3.4	0.7	1.5–4.8
Pedagogical Knowledge (PK)	3.8	0.6	2.0–4.9
Content Knowledge (CK)	3.9	0.6	2.5–5.0
Technological Pedagogical Knowledge (TPK)	3.5	0.7	1.8–4.7
Technological Content Knowledge (TCK)	3.6	0.6	2.2–4.8
Pedagogical Content Knowledge (PCK)	4.0	0.5	3.0–5.0
Overall (TPACK)	3.7	0.6	2.0–4.9

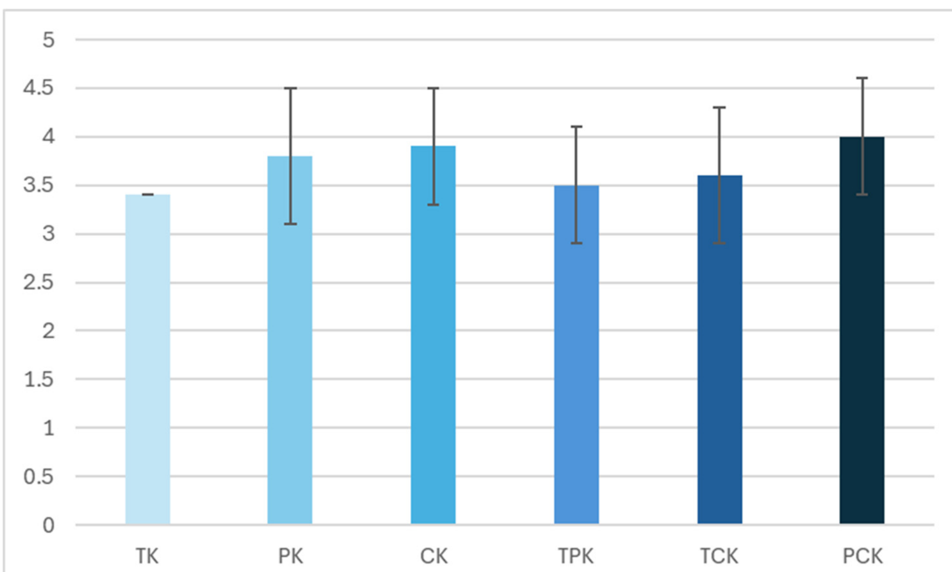

Figure 3. Mean Scores of TPACK Subdomains with Standard Deviation Error Bars

Overall TPACK proficiency was moderate (M = 3.7, SD = 0.6). Highest subscale means were found for PCK (M = 4.0, SD = 0.5) and CK (M = 3.9, SD = 0.6). Lower values were observed for TK (M = 3.4, SD = 0.7) and TPK (M = 3.5, SD = 0.7). Table 3 presents the descriptive statistics for the TPACK subdomains. Figure 3 illustrates the comparative distribution of TPACK subdomains. As shown in Figure 3, Pedagogical Content Knowledge (PCK) and Content Knowledge (CK) recorded the highest mean scores, whereas Technological Knowledge (TK) and Technological Pedagogical Knowledge (TPK) showed comparatively lower levels.

5.4 RQ3. Perceived Benefits and Challenges (AIS)

AIS subscales indicated relatively high perceived usefulness (M = 4.1, SD = 0.5), moderate ease of use (M = 3.6, SD = 0.7), moderately high social influence (M = 3.8, SD = 0.6), and relatively high perceived challenges (M = 3.9, SD = 0.6). Table 4 presents the descriptive statistics for the AIS subscales.

Table 4. Descriptive Statistics for AIS Subscales (N = 144)

Subscale	M	SD	Range	Cronbach's α
Perceived Usefulness	4.1	0.5	3.0–5.0	.88
Ease of Use	3.6	0.7	2.2–4.8	.85
Social Influence	3.8	0.6	2.5–4.9	.82
Challenges	3.9	0.6	2.8–5.0	.87

5.5 Qualitative Themes

Three recurrent qualitative themes were identified. Table 5 summarizes the themes derived from faculty members' open-ended responses and provides illustrative quotations, while Figure 4 presents their relative prevalence.

Table 5. Themes Derived from Open-Ended Responses

Theme	Representative code	Illustrative quote
Scaffolding and feedback	"student support"	"Provides instant feedback"
Efficiency in problem generation	"problem examples"	"Generates exercises quickly"
Integrity and accuracy concerns	"incorrect answers"	"Sometimes incorrect solutions"

Building on the qualitative responses, nearly 72% of faculty highlighted efficiency and automated problem generation as a key benefit, noting improvements in the speed of producing examples and formative tasks. Many respondents emphasized that generative AI tools can rapidly produce multiple variations of mathematical exercises, enabling instructors to diversify classroom tasks and formative assessments. This perception suggests that many faculty view generative AI primarily as a productivity-support tool that can assist in instructional preparation and task design rather than as a substitute for mathematical reasoning or proof construction.

Approximately 60% mentioned scaffolding and personalized feedback, especially with students who require conceptual reinforcement. Faculty indicated that AI-generated explanations and step-by-step prompts may help students visualize mathematical processes and support learners who struggle with abstract reasoning. These responses indicate that instructors perceive generative AI as a supplementary pedagogical resource capable of supporting conceptual clarification and differentiated instruction in mathematics learning environments.

However, about 44% pointed explicitly to concerns over incorrect outputs, hallucinations, and the lack of reliable mathematical reasoning. These concerns were particularly pronounced in relation to proof-based topics and advanced problem solving, where faculty stressed the importance of verification and disciplinary rigor. Instructors frequently emphasized that AI-generated solutions must be carefully checked, particularly when mathematical proofs or complex reasoning are involved.

These qualitative patterns provide additional insight into the quantitative findings of the study. The emphasis on efficiency and instructional support reflects the perceived relative advantage of generative AI, whereas concerns about reliability and correctness highlight tensions regarding its compatibility with the epistemic norms of mathematics education. In particular, the need to verify AI-generated outputs underscores the role of pedagogical–technological reasoning, suggesting that faculty rely on their TPACK when determining how and when generative AI can be integrated responsibly into mathematics instruction.

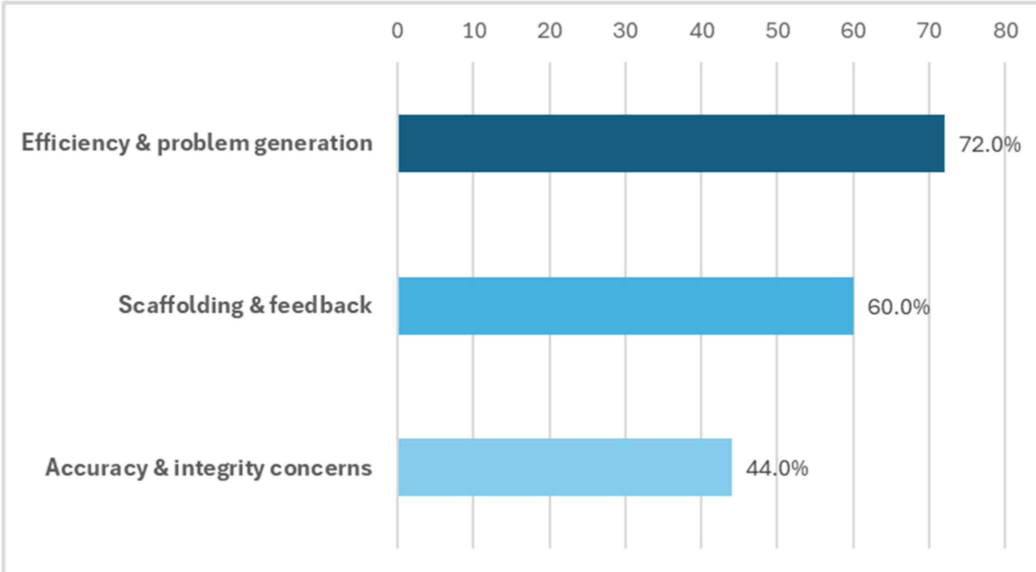

Figure 4. Prevalence of Qualitative Themes Identified in Faculty Responses

A representative participant remarked, "AI offers efficient generation of multiple examples, but I sometimes find myself checking every step carefully." Another respondent noted, "The tool helps weak students visualize problems, yet it is not fully reliable with proofs." These comments illustrate both enthusiasm and caution among faculty members regarding the use of generative AI in mathematics instruction.

Taken together, the qualitative findings suggest a pattern of cautious optimism: faculty recognize the pedagogical opportunities offered by generative AI while remaining attentive to issues of accuracy, verification, and academic integrity—particularly in mathematics, where proof and logical validation are central disciplinary practices.

5.6 RQ4. Relationships and Predictors of Adoption Intentions

Bivariate correlations indicated significant positive associations between adoption intentions and connectionist orientations ($r = .65$, $p < .01$), discovery orientations ($r = .45$, $p < .01$), and overall TPACK ($r = .55$, $p < .01$). Transmission orientations showed a significant negative association ($r = –.30$, $p < .01$). Digital experience exhibited a smaller positive correlation ($r = .28$, $p < .001$). Additional correlations among the predictor variables are presented in Table 6.

Table 6. Correlation Matrix for Main Study Variables (N = 144)

Variable	1	2	3	4	5
1. Connectionist Beliefs	—	–.25**	.35**	.50**	.65**
2. Transmission Beliefs		—	–.15	–.20*	–.30**
3. Discovery Beliefs			—	.40**	.45**
4. Overall TPACK				—	.55**
5. Adoption Intentions					—

*Note. *p < .05, ***p < .01 (two-tailed).*

5.7 Regression Model

Hierarchical multiple regression analysis including belief orientations in Block 1, TPACK in Block 2, and demographic controls in Block 3 explained 52% of the variance in adoption intentions ($R = .72$, $R^2 = .52$, adjusted $R^2 = .49$, $F(8, 135) = 18.31$, $p < .001$, Cohen's $f^2 = 1.08$). Multicollinearity was not a concern (tolerance > .75, VIF < 1.40), and the Durbin–Watson statistic was 1.94. Table 7 presents the results of the hierarchical multiple regression predicting adoption intentions.

Table 7. Multiple Regression Predicting Adoption Intentions (N = 144)

Predictor	B	SE	β	t	p	95% CI for B	Tolerance	VIF
(Constant)	1.12	0.34		3.29	.001	[0.45, 1.79]		
Connectionist Beliefs	0.52	0.11	.40	4.72	<.001	[0.30, 0.74]	.78	1.28
Transmission Beliefs	–0.18	0.09	–.14	–1.99	.048	[–0.36, –0.00]	.84	1.19
Discovery Beliefs	0.16	0.08	.12	1.92	.057	[–0.01, 0.33]	.81	1.23
Overall TPACK	0.48	0.10	.35	4.80	<.001	[0.28, 0.68]	.75	1.33
Digital Experience	0.04	0.02	.11	1.87	.064	[–0.00, 0.08]	.89	1.12
Lecturer	0.31	0.14	.17	2.21	.029	[0.03, 0.59]	.82	1.22
Assistant Professor	0.28	0.12	.16	2.33	.021	[0.04, 0.52]	.79	1.27
Associate Professor	0.15	0.11	.09	1.36	.176	[–0.07, 0.37]	.85	1.18

Model summary: $R = .72$, $R^2 = .52$, adjusted $R^2 = .49$, $F(8, 135) = 18.31$, $p < .001$, Cohen's $f^2 = 1.08$, Durbin–Watson = 1.94.

The combined evidence suggests that mathematics faculty may currently occupy what Diffusion of Innovations theory describes as the persuasion stage, in which individuals develop favorable or unfavorable attitudes before making adoption decisions. The relatively strong association between connectionist beliefs and TPACK proficiency, together with the modest effect of digital experience, indicates that faculty are still negotiating the perceived compatibility and reliability of generative AI in mathematical reasoning rather than fully incorporating it into instructional routines.

5.8 RQ5. Group Differences

A one-way ANOVA revealed statistically significant differences in adoption intentions across academic ranks ($F(3, 140) = 3.90$, $p = .010$, $\eta^2 = .08$, indicating a small to medium effect). Tukey post hoc comparisons indicated that lecturers ($M = 4.0$, $SD = 0.5$) and assistant professors ($M = 3.9$, $SD = 0.6$) reported significantly higher adoption intentions than full professors ($M = 3.5$, $SD = 0.7$). No significant differences were found for digital experience ($F(2, 141) = 1.38$, $p = .26$) or course type ($t(142) = 1.12$, $p = .27$), while gender differences approached statistical significance ($t(142) = 1.98$, $p = .052$). Table 8 presents the ANOVA results for adoption intentions across academic ranks.

Table 8. ANOVA Results for Adoption Intentions by Academic Rank (N = 144)

Academic Rank	n	M	SD	F	p	η²
Lecturer	36	4.0	0.5			
Assistant Professor	48	3.9	0.6			
Associate Professor	40	3.7	0.6			
Full Professor	20	3.5	0.7			
Overall ANOVA				3.90	.010	.08

6. Discussion

The findings of this study provide a multidimensional picture of generative AI adoption among mathematics faculty in Saudi higher education. Combined quantitative and qualitative evidence indicates that adoption is shaped not only by technological familiarity but also by the interaction between educators' belief orientations, professional knowledge, and institutional context when evaluating innovation. Across the analyses, the strongest antecedents of adoption were epistemic orientations and TPACK proficiency, suggesting that conceptual views of mathematics teaching fundamentally shape how generative AI is interpreted pedagogically. These findings correspond with the pathways proposed in Figure 1, confirming that beliefs and pedagogical knowledge precede adoption decisions.

6.1 Dominant Teaching Beliefs

Beliefs emerged as a central foundation for adoption intentions among university mathematics faculty. Most participants demonstrated a connectionist orientation (59.7%), reflecting an emphasis on linking abstract mathematical ideas with real-world contexts and applied reasoning. This pattern aligns with contemporary reform-oriented perspectives in mathematics education and is consistent with the epistemic and pedagogical norms of higher education.

At the same time, transmission-oriented beliefs remained salient for approximately one-third of participants, indicating a continued commitment to procedural rigor and formal accuracy within university mathematics instruction.

Qualitative reflections reinforced these numerical patterns. Faculty frequently described teaching as linking mathematical structures to real-world reasoning, an approach that resonates with constructivist and sociocultural perspectives. Within the proposed framework, such perspectives function as the first step in the theoretical pathway, providing the epistemic stance through which technologically mediated instruction is evaluated. As illustrated in Figure 1, the findings confirm that beliefs act as a primary filter through which the pedagogical legitimacy of generative AI is judged.

6.2 Linking Beliefs to Diffusion of Innovation (DOI)

These belief orientations are particularly consequential because they directly shape perceived compatibility, which is one of the strongest predictors in Rogers's Diffusion of Innovations theory. Faculty who endorsed connectionist orientations tended to perceive AI as compatible with problem-based learning and the generation of instructional examples, whereas transmission-oriented faculty expressed concerns about accuracy, overreliance, and the erosion of mathematical rigor. This pattern supports the hypothesized pathway presented in Figure 1, where beliefs influence the evaluation of innovation attributes prior to the formation of adoption intentions.

6.3 Instructional Practices (TPACK)

Faculty reported moderate TPACK proficiency (M = 3.7), with strong scores in PCK and CK and relatively lower scores in TK and TPK. This imbalance has been observed internationally (Sridana et al., 2025; Li et al., 2025), but the difference here appears more pronounced, with TK (M = 3.4) and TPK (M = 3.5) remaining noticeably lower than CK (M = 3.9) and PCK (M = 4.0), suggesting that technology-specific professional knowledge remains comparatively underdeveloped. These results extend prior studies by demonstrating that TPACK mediates the relationship between belief orientations and adoption intentions rather than functioning as a parallel predictor.

Qualitative reflections further confirmed that faculty were not resistant to AI, but rather cautious in its practical application. Participants emphasized the need for experimentation, verification, and alignment with mathematical reasoning. In this regard, the findings provide empirical support for the mediating role of TPACK proposed in Figure 1, indicating that beliefs translate into instructional decision-making only when pedagogical–technological knowledge is sufficiently developed.

6.4 Perceived Benefits and Challenges

Quantitative results indicated high perceived usefulness and moderate ease of use, accompanied by notable concerns regarding academic integrity, reliability, and overreliance. These patterns mirror global debates in which AI is viewed as pedagogically promising but epistemically uncertain (Grassini, 2023; Malik et al., 2025). Qualitative findings likewise reflected cautious optimism: faculty valued personalized feedback and the generation of instructional examples but remained attentive to limitations related to accuracy and ethical risks.

From the perspective of Diffusion of Innovations (DOI) theory, adoption appears to remain in the persuasion stage, where perceived relative advantage is acknowledged but concerns about complexity and uncertainty persist. These findings reinforce the conceptual sequence proposed in Figure 1, in which beliefs shape compatibility assessments that are subsequently moderated by perceived complexity and institutional factors. The outcome is not uncritical adoption but a more reflective and informed acceptance of generative AI in mathematics instruction.

6.5 Relationships Between Beliefs, TPACK, and Adoption

The statistical analyses indicated strong correlations between connectionist beliefs and adoption ($r = .65$) and between TPACK and adoption ($r = .55$), values that exceed the moderate coefficients typically reported in technology adoption studies (often $r = .30$–$.45$). This pattern suggests that in mathematics education, epistemological orientations play a particularly pronounced role. Conversely, transmission beliefs were negatively associated with adoption, consistent with prior work linking rule-based instruction to resistance to innovation.

Hierarchical regression further confirmed these patterns. Beliefs and TPACK remained dominant predictors even after controlling for demographic variables, and connectionist beliefs emerged as the primary driver of perceived compatibility, one of the most consequential attributes in Diffusion of Innovations (DOI) theory. These findings provide direct empirical support for the hypothesized pathway presented in Figure 1, in which adoption intentions arise from the combined influence of belief orientations and mediated pedagogical expertise.

6.6 Demographic Differences

Academic rank was the only demographic variable to show statistically significant effects on adoption intentions ($\eta^2 = .08$, indicating a small to medium effect), with lecturers and assistant professors reporting higher intentions than full professors. This modest difference is consistent with Diffusion of Innovations research, which suggests that faculty at earlier or less institutionally entrenched career stages may be more open to pedagogical change, whereas senior academics often approach instructional innovations with greater caution. In contrast, digital experience, gender, and course type showed weak or non-significant effects, indicating that demographic and technological exposure variables play a limited role. Instead, these findings suggest that disciplinary beliefs and professional knowledge exert a stronger influence on adoption intentions, reinforcing the theoretical expectation that epistemic alignment, rather than exposure alone, underpins instructional innovation, as reflected in Figure 1.

6.7 Positioning within International Scholarship

By integrating Teachers' Beliefs Typology, the Technological Pedagogical Content Knowledge framework, and Diffusion of Innovations theory within a unified conceptual model, this study contributes to global scholarship by demonstrating that generative AI adoption in mathematics education is best understood as a staged process linking epistemic orientations, mediated pedagogical reasoning, and innovation appraisal. Empirically, the study extends existing research by highlighting the perspectives of university mathematics faculty within a context that has received limited attention in prior studies of generative AI adoption. Conceptually, the findings offer a transferable framework for understanding how disciplinary beliefs and pedagogical knowledge interact with innovation attributes to shape adoption decisions across higher education settings.

7. Implications and Contributions

The implications presented in this section are derived directly from the empirical findings of the study. In particular, the quantitative results demonstrated the mediating role of TPACK in shaping adoption intentions, while the qualitative findings revealed both the perceived pedagogical benefits of generative AI and faculty concerns regarding accuracy and disciplinary rigor. Together, these findings inform the practical, theoretical, and methodological implications outlined below**.**

7.1 Practical and Policy Implications

The empirical findings of this study provide several actionable implications for higher education policy and professional development. First, faculty development programs should prioritize training that integrates AI and TPACK, particularly for senior faculty who reported lower adoption intentions. Such programs may focus on AI-assisted reasoning, verification strategies, and the pedagogical integration of generative tools, ensuring that innovation strengthens rather than replaces mathematical rigor. Second, institutions should establish clear ethical and assessment policies outlining acceptable use, authorship boundaries, and verification protocols. The strong concerns about accuracy and integrity observed among transmission-oriented faculty emphasize the need for institutionally endorsed guidelines rather than individual discretion. Third, universities can support instructional experimentation by creating internal advisory units that help design AI enhanced tasks, curate reliable resources, and provide professional mentoring. Collectively, these steps would enable responsible and confident adoption of generative AI within mathematics teaching.

7.2 Theoretical, Methodological, and Practical Contributions

Theoretically, this study advances adoption scholarship by integrating Teachers' Beliefs Typology, the Technological Pedagogical Content Knowledge framework, and Diffusion of Innovations theory into a single explanatory pathway. Whereas previous research has typically examined these frameworks in isolation, the present study demonstrates how epistemic orientations shape perceptions of compatibility and, in turn, influence adoption intentions. By articulating these relationships within a unified model, the study offers a coherent perspective on how disciplinary beliefs and pedagogical–technological reasoning interact to inform generative AI adoption in mathematics education.

Methodologically, the mixed methods design enabled triangulation between quantitative trends and qualitative insights, clarifying how AI is negotiated in practice rather than assumed to be technically or pedagogically neutral. By measuring beliefs, professional knowledge, digital experience, and adoption intentions within a unified model, the study advances empirical understanding of how innovation diffuses in disciplines grounded in abstraction and proof.

Practically, the results highlight faculty, rather than students, as the primary agents of technological transformation. Adoption depends less on access or digital exposure and more on how instructors evaluate AI in relation to their disciplinary convictions, pedagogical standards, and professional identity. These insights inform institutional strategies for AI integration, suggesting that sustainable adoption requires attention to belief systems and professional reasoning, not merely the provision of technology.

8. Limitations and Future Directions

Several limitations should be acknowledged. The sample, while diverse across academic rank and course type, was confined to three public universities in one region, which may limit generalizability. The cross-sectional design also captures faculty perceptions at a specific moment in time, although attitudes toward AI are likely to evolve as institutional policies, infrastructures, and AI capabilities advance. Self-reported measures pose an additional limitation, particularly given the association between AI and innovation; social desirability bias cannot be ruled out.

Future studies should employ longitudinal or experimental designs to track changes in adoption behavior and test causal pathways among beliefs, TPACK proficiency, and classroom practices. Comparative studies across STEM disciplines would also help determine whether the observed relationships reflect dynamics unique to mathematics or broader trends in higher education. Finally, research on AI-assisted reasoning, verification strategies, and ethical evaluation may clarify how generative technologies reshape mathematical thinking rather than simply supporting procedural fluency.

9. Conclusion

This study examined how mathematics faculty in Saudi higher education perceive and integrate generative artificial intelligence by analyzing the interplay between teaching beliefs, pedagogical knowledge, digital experience, and adoption intentions. Guided by Teachers' Beliefs Typology, the Technological Pedagogical Content Knowledge framework, and Diffusion of Innovations theory, the findings indicate that adoption depends less on structural factors such as academic seniority and more on the alignment between epistemic beliefs, pedagogical–technological reasoning, and perceived compatibility. Faculty with connectionist orientations and stronger pedagogical–technological knowledge reported greater readiness to adopt generative AI, whereas transmission-oriented faculty expressed more cautious attitudes, largely driven by concerns related to accuracy, overreliance, and academic integrity.

Beyond the national context, the findings contribute a situated yet transferable perspective to international scholarship by illustrating that the educational integration of generative AI is shaped by how higher education systems negotiate meaning, authority, and disciplinary standards within technology-enhanced teaching environments. By clarifying how belief orientations and professional knowledge converge to shape adoption intentions, the study provides a conceptual and empirical foundation for guiding the responsible and sustainable integration of generative AI in mathematics education across diverse higher education systems.

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Authors contributions

Dr. Ben-Motreb conceived the study, designed the methodology, collected and analyzed the data, and wrote and revised the manuscript. The author approved the final version.

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Competing interests

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Use of AI

ChatGPT was used solely for language refinement to improve clarity, coherence, and academic style. All data, analyses, results, and interpretations were produced and verified by the author, who assumes full responsibility for the accuracy and integrity of the manuscript.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Sciedu Press.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

The study was conducted in accordance with the Committee for Scientific Research Ethics at King Faisal University. All datasets were collected and stored in compliance with the university's research ethics policies and privacy guidelines.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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