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Undergraduate mathematics faculty attitudes and experiences with generative AI integration

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Abstract
Generative artificial intelligence (GenAI) is rapidly reshaping undergraduate mathematics instruction, posing challenges to teaching, assessment, and academic integrity amid limited institutional guidance. This mixed-methods study examined undergraduate mathematics faculty attitudes toward GenAI integration (N = 41) using the technology acceptance model (TAM) and will-skill-tool (WST) frameworks. Faculty showed moderate openness/curiosity (M = 3.46), low confidence (M = 2.85), strong institutional support needs (M = 3.86), and minimal teaching influence (M = 2.95). Student impact concerns correlated with openness/curiosity (r = .33, $p < .05$) and curriculum modification willingness (r = .45, $p < .01$). Multiple regression revealed openness/curiosity as the only significant predictor of professional practice influence (β = .50, p = .013, R^2 = .41), challenging TAM's emphasis on perceived ease of use. Despite low confidence, 73.9% modified their teaching. Findings reveal incomplete WST implementation, underscoring institutional needs for support systems enabling responsible GenAI integration.

Keywords: generative artificial intelligence, mathematics faculty attitudes, technology acceptance model, will-skill-tool framework

INTRODUCTION

Generative artificial intelligence (GenAI) has rapidly emerged as a transformative tool in higher education. GenAI offers the benefits of personalized instruction, instant feedback on mathematical problems, and support for mathematical communication through natural language interactions (Pardos & Bhandari, 2024; Rizos et al., 2024; Wardat et al., 2023). However, significant concerns have emerged, including content accuracy issues with error rates ranging from 15% to 40% in complex mathematical solutions, promotion of surface-level engagement over deep mathematical reasoning, and academic integrity challenges (Luo, 2024; Zhang et al., 2025).

Undergraduate mathematics education presents unique considerations for GenAI integration due to the emphasis on problem-solving processes and mathematical reasoning. This requires careful evaluation of how GenAI affects these core pedagogical approaches (Walter, 2024). As GenAI becomes increasingly sophisticated and accessible faculty must make deliberate decisions about how to incorporate it into their teaching.

Understanding faculty attitudes toward GenAI in mathematics education is essential because instructor perspectives directly influence adoption rates, implementation strategies, and curriculum modification decisions (Zhang et al., 2025). While studies have explored general faculty perceptions of GenAI (Baidoo-Anu & Owusu Ansah, 2023; Kim et al., 2025), research examining mathematics faculty specifically remains limited. Existing studies have not investigated how multiple attitude dimensions relate to one another within individual faculty members, nor have they examined how these attitudes predict changes in instructional methods, curriculum design, and academic policy participation. Moreover, no studies have examined undergraduate mathematics faculty attitudes toward GenAI integration using both the technology acceptance model (TAM) and will-skill-tool (WST) frameworks. A mixed-methods study is needed to

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Contribution to the literature

- It appears to be among the first studies to explicitly integrate the Technology Acceptance Model and the will-skill-tool framework to examine faculty attitudes toward GenAI, suggesting that successful integration may require simultaneous alignment of individual motivation (will), pedagogical competence (skill), and institutional support (tool).
- It extends TAM-based research by demonstrating that curiosity, rather than confidence or perceived ease of use, uniquely predicts GenAI integration among undergraduate mathematics faculty, a finding that contrasts with K-12 settings where self-efficacy has emerged as a key predictor.
- Unlike prior research that examined isolated faculty attitudes, this study systematically demonstrates that faculty hold multiple, sometimes contradictory attitudes simultaneously, revealing that those who express greater concerns about student impacts also show higher openness and willingness to modify curricula, positioning concern as a motivator rather than a barrier to engagement.

examine faculty attitudes and experiences with GenAI integration.

Purpose of the Study

This study investigates undergraduate mathematics faculty attitudes toward GenAI integration. Grounded in the TAM and WST framework, this research examines faculty attitudes across eight dimensions: openness/curiosity, student impact concerns, integration confidence, preference for traditional methods, curriculum modification willingness, equity/access concerns, institutional support needs, and professional practice influence. The research questions (RQs) are:

RQ1. What are faculty attitudes toward GenAI integration across the eight dimensions?

RQ2. How do the eight attitude dimensions correlate with each other?

RQ3. Which attitude dimensions predict professional practice influence?

RQ4. How do faculty describe their experiences and perspectives regarding GenAI integration?

LITERATURE REVIEW

Theoretical Framework: Technology Acceptance Model and Will-Skill-Tool Framework

The TAM (Davis, 1989) provides a theoretical framework for understanding technology adoption through two key cognitive beliefs: perceived usefulness (the degree to which a system will enhance job performance) and perceived ease of use (the extent to which using the system will be free of effort). These perceptions determine whether users will adopt and use the technology (Venkatesh & Bala, 2008). TAM has proven particularly relevant for understanding GenAI adoption in mathematics education. Research on Finnish high school students found that both perceived usefulness and ease of use predicted their intention to use GenAI in mathematics education (Daher et al., 2025). Additionally, Wang et al. (2024) found that pre-service teachers' technology self-efficacy positively influenced their perceptions of GenAI's usefulness and ease of use.

The WST framework (Knezek & Christensen, 2016; Petko, 2012) identifies three essential conditions for successful technology integration. The will component represents teachers' motivations, attitudes, and beliefs about technology integration. The skill component encompasses perceived confidence and competence in both technical and pedagogical technology use. The tool component addresses technology availability, infrastructure, and institutional support systems. The framework's core principle asserts that all three components must be present simultaneously; the absence of any single component will result in implementation failure. While research from the Philippines found that skill was the strongest predictor of successful technology integration in science and mathematics classrooms (Sasota et al., 2021), all three components remain essential for sustained adoption (Zhang et al., 2025).

Integrating TAM and WST provides a comprehensive framework for examining faculty attitudes (will), capabilities (skill), and institutional support (tool) necessary for GenAI integration in mathematics education. This study applies an extended TAM framework alongside the WST framework to examine faculty attitudes across eight dimensions, each aligned with specific components of both frameworks (**Table 1**). Some dimensions align with multiple framework components. For example, student impact concerns align with both perceived usefulness and attitude formation (TAM) and the will component (WST), while equity/access concerns align with attitude formation (TAM) and both will and tool components (WST).

GenAI in Mathematics Education

As GenAI becomes more prevalent in mathematics education (Kasneci et al., 2023), it offers specific capabilities that can enhance learning while also introducing serious risks for students and teachers. For students, GenAI can generate worked solutions, step-by-

Table 1. Eight attitude dimensions aligned with TAM and WST frameworks

Study dimension	TAM alignment	WST alignment
1. Openness/curiosity: Interest in exploring GenAI potential for mathematics instruction	**Perceived usefulness:** Faculty interest indicates belief that GenAI could enhance teaching effectiveness	**Will component:** Faculty motivation and positive attitudes toward GenAI integration
2. Student impact concerns: Worries about GenAI effects on student learning and development	**Perceived usefulness & attitude formation:** Faculty concerns about whether GenAI enhances or hinders student learning outcomes, which influences overall attitude toward integration	**Will component:** Faculty beliefs and values about appropriate GenAI use
3. Integration confidence: Faculty confidence in effectively using GenAI tools	**Perceived ease of use:** Faculty belief that GenAI integration will be manageable and feasible	**Skill component:** Faculty perceived competence and confidence with GenAI
4. Traditional methods preference: Preference for established teaching approaches over GenAI	**Attitude formation:** Preference that negatively influences attitude toward new technology	**Will component:** Faculty values and resistance to GenAI integration over established practices
5. Curriculum modification willingness: Readiness to adapt courses and materials for GenAI integration	**Behavioral intention:** Faculty intention to actually implement GenAI in teaching	**Will component:** Faculty motivation to invest effort in GenAI integration
6. Equity/access concerns: Worries about fairness and accessibility issues with GenAI	**Attitude formation:** Ethical concerns that influence overall technology acceptance	**Will & tool components:** Faculty values (will) and concerns about equitable GenAI access for all students (tool)
7. Institutional support needs: Required training, resources, and policies for GenAI implementation	**External variables:** Contextual factors that influence technology acceptance process	**Tool component:** Essential infrastructure and support systems for successful GenAI integration
8. Professional practice influence: Actual impact of GenAI attitudes on teaching methods and curriculum	**Actual system use:** Real behavioral changes resulting from technology acceptance	**Integration success:** Outcome when will, skill, and tool components align for GenAI integration

step hints, personalized practice problems, and immediate feedback across various mathematical domains (Kasneci et al., 2023; Pardos & Bhandari, 2024). Pardos and Bhandari (2024) conducted a randomized controlled study (N = 274) comparing ChatGPT-generated hints to human tutor-authored hints across four mathematics subject areas. Their findings revealed that ChatGPT-generated hints produced statistically significant learning gains of 17% compared to a no-help control condition showing only 1.85% gains ($p < 0.001$ vs $p = 0.192$). Notably, while human tutor-authored hints showed 11.62% gains, this improvement was not statistically significantly different from the control condition ($p = 0.087$), making ChatGPT the only intervention to produce statistically significant learning gains compared to no help. Time-on-task was equivalent between ChatGPT and human tutor conditions. For teachers, GenAI offers possibilities for creating personalized learning materials, generating practice problems and quizzes, providing adaptive feedback, supporting lesson planning, and reducing grading workload (Kasneci et al., 2023). These mixed results help explain why faculty hold complex attitudes toward GenAI: while it can produce significant learning gains, the high error rates (32%) raise concerns about reliability and the need for instructor oversight.

However, significant challenges exist alongside these benefits. Bastani et al. (2025) conducted a large-scale field experiment with nearly 1,000 high school mathematics students, comparing three conditions: no AI access (control), a standard ChatGPT-like interface (GPT base), and GPT-4 with teacher-designed instructions to guide rather than provide answers (GPT tutor). While GPT-4 access significantly improved performance during assisted practice (48% for GPT base, 127% for GPT tutor), these benefits disappeared on independent assessments. Students who used GPT base performed 17% worse than control students on unassisted exams ($p < 0.05$) because they copied complete solutions rather than engaging substantively with problems, using GPT-4 as a respect "crutch" that prevented skill development. This finding directly informs faculty concerns about student impact, revealing that GenAI integration requires intentional pedagogical design. GPT tutor was programmed to provide teacher-designed hints rather than complete solutions, include correct answers to reduce errors, and offer guidance on common mistakes. Students using GPT tutor showed no performance decline on unassisted exams, demonstrating that careful design preserves skill development and may increase faculty willingness to integrate GenAI when properly supported

Additional concerns include error rates in AI-generated content. ChatGPT-generated hints contained incorrect work or answers in 32% of cases (Pardos & Bhandari, 2024), while GPT base provided correct answers only 51% of the time (Bastani et al., 2025). Although error-checking techniques can reduce these rates significantly (to nearly 0% for algebra and 13% for statistics), the high initial error rates demonstrate that AI-generated mathematical content requires systematic verification. Beyond accuracy, Kasneci et al. (2023) identify challenges including potential bias, copyright issues, privacy concerns, computational costs, and inequitable access across educational contexts and languages.

These findings point to essential strategies for responsible GenAI integration: developing teacher competencies, implementing data privacy measures, incorporating pedagogical guardrails (as demonstrated by GPT tutor), ensuring transparency about limitations, requiring ongoing human verification, and educating students about responsible use (Bastani et al., 2025; Kasneci et al., 2023). However, implementing these strategies depends fundamentally on faculty attitudes, whether faculty perceive GenAI as beneficial, feel confident integrating it, and receive adequate institutional support. We now turn to research examining these faculty attitudes.

Faculty Attitudes Toward GenAI

Faculty attitudes toward GenAI given GenAI's benefits and risks for mathematics learning, how do faculty perceive these tools? Research examining faculty attitudes reveals tension between perceived benefits and significant concerns, alongside calls for stronger institutional support. Regarding benefits, faculty recognize GenAI's potential for students including immediate responses to questions, language support, and personalized tutoring (Farrelly & Baker, 2023). Faculty also appreciate GenAI's capacity to assist with grading, generating feedback, and creating lesson plans or assessment prompts, potentially reducing workload and improving efficiency (Michel-Villarreal et al., 2023).

Despite potential benefits, faculty express significant concerns about GenAI integration, particularly regarding academic integrity and student outcomes (Lim et al., 2023; Michel-Villarreal et al., 2023; Smolansky et al., 2023; Yoon et al., 2024). In a survey of 36 educators and 389 students across two universities, both groups reported that GenAI availability substantially reduces assessments' capacity to ensure academic integrity (Smolansky et al., 2023). Faculty are concerned that students can use GenAI to submit work that is not their own, making it difficult to distinguish between student-generated and AI-generated content and challenging their ability to assess students' actual understanding (Lim et al., 2023). In addition to academic integrity concerns, faculty worry about GenAI's impact on student learning and cognitive development. Research examining GenAI capabilities identifies concerns about accuracy and quality control, with risks that students may accept incorrect information without verification (Michel-Villarreal et al., 2023). Studies raise additional concerns about student overreliance on GenAI, particularly in mathematics, where undergraduate students tend to rely on GenAI as an authority figure in mathematical proving rather than developing critical thinking skills and confidence in autonomous reasoning (Yoon et al., 2024). Faculty also identify the critical need for institutional support to address these challenges. Survey research shows that approximately 80% of both faculty and students agree universities should develop formal policies to guide GenAI use (Kim et al., 2025). With GenAI use for teaching still relatively rare and few clear university guidelines currently in place, faculty face challenges in rethinking assessment practices without adequate support (Baidoo-Anu & Owusu Ansah, 2023; Kim et al., 2025). The lack of clear institutional guidelines is particularly troubling for instructors who look to institutional guidance to inform their practices (Moorhouse et al., 2023). Successful integration depends not only on clear institutional policies but also on supportive social environments where faculty can access peer support and learn from colleagues' experiences (Shata & Hartley, 2025).

While research has identified general benefits and concerns regarding GenAI in education, significant gaps remain in research on undergraduate mathematics faculty. First, while existing research has examined various faculty perceptions and concerns about GenAI in education (Baidoo-Anu & Owusu Ansah, 2023; Kim et al., 2025; Shata & Hartley, 2025), these studies have not systematically examined how faculty attitudes toward GenAI relate to one another. Specifically, it is unknown whether individual faculty hold multiple, potentially conflicting attitudes simultaneously, for instance, being both curious about GenAI's potential and concerned about its risks. Second, while factors influencing adoption have been identified (Harper, 2024; Shata & Hartley, 2025), the relationship between specific attitudes and actual changes in instructional methods, curriculum design, and policy participation remains unexplored. Finally, qualitative research examining undergraduate mathematics faculty's lived experiences with GenAI integration is limited. This study addresses these gaps by measuring undergraduate mathematics faculty attitudes across eight dimensions, examining correlations among dimensions, testing how attitudes predict professional practice influence, and exploring faculty experiences through qualitative methods.

METHODS

Research Design

This study employed a convergent mixed methods design (Creswell & Plano Clark, 2018) to examine undergraduate mathematics faculty attitudes toward GenAI integration. Data were collected through a single anonymous, self-administered online survey containing both Likert-scale items and open-ended questions. The study was conducted at a public state university in the western United States (USA) offering mathematics courses ranging from developmental through upper-division levels.

Participants

Sampling rationale: This study was conducted at a large public university in the western USA that serves over 48,000 students and offers undergraduate mathematics courses ranging from developmental through upper-division levels. The institution was purposefully selected for three reasons. First, the university houses a dedicated AI institute that actively supports faculty development and curriculum integration of GenAI, providing faculty with institutional resources and professional development opportunities relevant to GenAI integration. Second, as a teaching-focused institution, faculty engage regularly in pedagogical innovation and classroom-centered instructional practices directly impacted by emerging GenAI. Third, the mathematics faculty at this institution encompass diverse employment types (full-time, part-time, lecturers) teaching courses ranging from developmental through upper-division levels, enabling comprehensive examination of attitudes across diverse teaching environments. All 99 faculty members teaching undergraduate mathematics were invited to participate to maximize representation across employment types, course levels, and teaching experience.

The target population included all 99 faculty members teaching undergraduate mathematics courses in the mathematics department and mathematics and quantitative reasoning department at a public 4-year university in the western USA during Fall 2025. 41 faculty members participated, representing a 41.4% response rate.

The sample included 27 full-time faculty (65.9%), 12 part-time faculty (29.3%), and 2 (4.9%) indicating other employment status. Most participants were experienced educators: 23 (56.1%) had more than 15 years of teaching experience, 16 (39.0%) had 5-15 years, and 2 (4.9%) had less than 5 years.

Participants taught across diverse course levels: 24 (58.5%) primarily taught developmental and quantitative reasoning (MAT 0980-1035), 7 (17.1%) taught college algebra and statistics (MATH 1050-1090, STAT 1040), 3 (7.3%) taught calculus and differential equations (MATH 1210-2270, STAT 2040), 5 (12.2%) taught upper-division courses (3000 level and above), 1 (2.4%) taught mathematics education, and 1 (2.4%) indicated other.

Participants reported high comfort with general technology in teaching. Most (n = 26, 63.4%) were very comfortable, 11 (26.8%) were somewhat comfortable, 3 (7.3%) were neutral, and 1 (2.4%) was somewhat uncomfortable. No participants reported being very uncomfortable. Prior GenAI use varied. The most common response was sometimes (n = 18, 43.9%), followed by rarely (n = 9, 22.0%) and never (n = 7, 17.1%). Four participants (9.8%) reported using GenAI usually, and 3 (7.3%) always.

Procedure

After receiving Institutional Review Board approval, faculty were recruited through departmental email lists during a 3-week data collection period in Fall 2025. The survey was administered via Qualtrics. An initial invitation email was sent at the start of data collection, followed by two reminder emails sent during weeks 2 and 3. After reviewing an informed consent form detailing the study's purpose, procedures, confidentiality, and voluntary participation, participants indicated consent by selecting *I agree to participate* before accessing the survey. Those who declined were directed to exit. The survey took approximately 15-20 minutes to complete and could be accessed at participants' convenience. Participants could withdraw their responses after submission if desired.

Data Screening

All 41 participants completed the quantitative Likert-scale items measuring the eight attitude dimensions. Participants varied in their completion of open-ended qualitative questions, with response rates ranging from N = 21 to N = 34 across the five open-ended items. Data were screened for outliers and distributional assumptions prior to quantitative analysis. No responses were excluded based on data quality criteria.

Study Instrument

The survey consisted of 46 items in three sections: demographic information (6 items), attitude and influence scales (35 items), and open-ended questions (5 items). The instrument measured eight attitude dimensions: openness/curiosity (4 items), student impact concerns (5 items), integration confidence (6 items), preference for traditional methods (3 items), curriculum modification willingness (4 items), equity/access concerns (4 items), institutional support needs (2 items), and influence on professional practice (7 items).

Quantitative items utilized a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*). Example items included "I am interested in using GenAI in my mathematics courses" (openness/curiosity), "I worry that GenAI might hurt students' ability to solve math problems on their own" (student impact concerns), and "my attitudes toward GenAI have influenced how I teach" (influence on professional practice). Demographic items employed categorical response options (e.g., years of experience, employment status, and course levels taught).

Qualitative items comprised five open-ended questions that asked faculty to:

(1) describe their overall thoughts and feelings about using GenAI in mathematics classes,

(2) explain their comfort level with GenAI tools and factors affecting readiness,

(3) discuss potential curricular changes and concerns if required to integrate GenAI,

(4) identify needed institutional support (policies, guidelines, protocols) for implementation, and

(5) provide examples of how their attitudes have influenced or might influence their teaching practice.

The survey was developed based on the TAM and WST frameworks, with some items adapted from recent research on GenAI literacy and teacher attitudes in mathematics education (Pörn et al., 2024; Wijaya et al., 2024). Survey items measured the eight attitude dimensions. To establish content validity, the survey was reviewed by three undergraduate mathematics faculty with expertise in GenAI integration. Reviewers evaluated each item for clarity, alignment with the theoretical framework, and appropriateness for the target population. Based on their feedback, several items were revised for clarity, and redundant items were removed or simplified. The final instrument demonstrated acceptable to good internal consistency reliability across all eight dimensions (Cronbach's α = .65 to .94).

Data Collection and Analysis

The survey was administered online. Participants accessed the survey via email link. The survey gathered demographic information, attitudes toward GenAI in mathematics, current GenAI usage patterns, perceived benefits and barriers to GenAI integration, and influence on instructional methods and curriculum design.

Data analysis was conducted using a mixed-methods approach to address each RQ through corresponding analytical strategies. For **RQ1**, dimension scores were calculated by averaging items within each of the eight attitude dimensions. Negatively worded items within three dimensions (student impact concerns, preference for traditional methods, and equity/access concerns) were reverse-coded (6 minus original response) to ensure directional consistency within each dimension. Descriptive statistics (means and standard deviations) were calculated for each dimension based on participants' Likert-scale responses (1 = *strongly disagree* to 5 = *strongly agree*). Additionally, effect sizes (Cohen's *d*) were calculated for each dimension to assess practical significance.

Internal consistency reliability was assessed for each of the eight attitude dimensions. All dimensions demonstrated acceptable to good reliability: openness/curiosity (α = 0.88), student impact concerns (α = 0.74), integration confidence (α = 0.88), preference for traditional methods (α = 0.80), curriculum modification willingness (α = 0.92), equity/access concerns (α = 0.85), institutional support needs (α = 0.65), and influence on professional practice (α = 0.94). All values, except institutional support needs, exceeded .70, meeting acceptable standards for exploratory research (Nunnally & Bernstein, 1994).

For **RQ2**, Pearson correlation coefficients were calculated among all eight attitude dimensions, yielding 28 unique bivariate correlations. Effect sizes were interpreted using Cohen's (1988) guidelines.

For **RQ3**, a multiple regression analysis was conducted to examine how seven attitude dimensions predicted faculty's perceived influence of GenAI on their professional practice. Openness/curiosity, student impact concerns, integration confidence, preference for traditional methods, curriculum modification willingness, equity/access concerns, and institutional support needs were entered simultaneously as predictors, with influence on professional practice as the dependent variable.

For **RQ4**, qualitative data from five open-ended survey questions were analyzed using a combined inductive-deductive approach to content analysis (Schreier, 2012). Responses were first coded inductively to identify emergent themes from participant responses. Similar codes were then categorized and thematically organized. These themes were subsequently mapped onto the eight attitude dimensions to determine whether qualitative findings supported and elaborated on quantitative patterns. Themes that did not align with the existing framework were retained as emergent themes.

The first author trained four faculty coders who independently coded all responses. Open-ended **RQ3** contained two parts coded separately, resulting in six coding sets. Inter-rater reliability was assessed using Fleiss' (1971) kappa: question 1 (κ = 0.783), question 2 (κ = 0.424), question 3 part 1 (κ = 0.722), question 3 part 2 (κ = 0.904), question 4 (κ = 0.805), and question 5 (κ = 0.821). Five coding sets achieved substantial to strong agreement, with a mean κ = 0.743. Discrepancies in question 2 (κ = 0.424, moderate agreement) were resolved through consensus discussion.

Table 2. Descriptive statistics and internal consistency reliability for attitude dimensions

Dimension	*M*	*SD*	*α*	*d*	Number of items
Openness/curiosity	3.46	1.16	0.88	0.40	4
Student impact concerns*	2.29	1.16	0.74	0.61	5
Integration confidence	2.85	1.11	0.88	0.14	6
Preference for traditional methods*	2.27	0.92	0.80	0.79	3
Curriculum modification willingness	3.10	1.15	0.92	0.09	4
Equity/access concerns*	2.69	1.11	0.85	0.28	4
Institutional support needs	3.86	0.96	0.65	0.90	4
Influence on professional practice	2.95	1.13	0.94	0.04	7

Note. N = 40 participants with complete data; α = Cronbach's alpha; & *Reverse-coded dimensions

Table 3. Correlations among faculty attitude dimensions toward GenAI integration

Dimension	1	2	3	4	5	6	7	8
1. Openness/curiosity	-							
2. Student impact concerns*	0.33*	-						
3. Integration confidence	0.29	-0.01	-					
4. Preference for traditional methods*	0.64**	0.34*	0.41*	-				
5. Curriculum modification willingness	0.65**	0.45**	0.36*	0.62**	-			
6. Equity/access concerns*	0.10	0.48**	-0.04	0.30	0.13	-		
7. Institutional support needs	0.13	-0.20	0.00	-0.02	0.22	-0.35*	-	
8. Influence on professional practice	0.58**	0.16	0.37*	0.45**	0.39*	0.17	0.10	-

Note. N = 39; Three dimensions (student impact concerns, preference for traditional methods, equity/access concerns) were reverse-coded; Higher scores on these dimensions indicate lower levels of concern/preference; *p < .05; & **p < .01

RESULTS

RQ1 examined mathematics faculty attitudes toward GenAI integration across eight dimensions. **Table 2** presents descriptive statistics, internal consistency reliability coefficients, and effect sizes for each dimension. Faculty expressed strongest positive attitudes toward institutional support needs (mean [*M*] = 3.86, standard deviation [*SD*] = 0.96, α = .65, *d* = 0.90) and openness/curiosity (*M* = 3.46, *SD* = 1.16, α = .88, *d* = 0.40), indicating strong need for institutional guidance and moderate interest in exploring GenAI applications.

Three dimensions showed means close to the scale midpoint with negligible effect sizes: curriculum modification willingness (*M* = 3.10, *SD* = 1.15, α = .92, *d* = 0.09), influence on professional practice (*M* = 2.95, *SD* = 1.13, α = .94, *d* = 0.04), and integration confidence (*M* = 2.85, *SD* = 1.11, α = .88, *d* = 0.14). These means close to the scale midpoint (ranging from 2.85 to 3.10, *d* = 0.04-0.14) indicate faculty responses were evenly distributed around neutral, showing no clear positive or negative trend toward curriculum modification, integration confidence, or perceived professional practice influence. Three reverse-coded dimensions showed below-midpoint scores: preference for traditional methods (*M* = 2.27, *SD* = 0.92, α = .80, *d* = 0.79), student impact concerns (*M* = 2.29, *SD* = 1.16, α = .74, *d* = 0.61), and equity/access concerns (*M* = 2.69, *SD* = 1.11, α = .85, *d* = 0.28). When reverse-coded, these low scores indicated that faculty demonstrated a strong preference for traditional teaching approaches (*d* = 0.79), moderate concerns about GenAI's student impacts (*d* = 0.61), and small equity/access concerns (*d* = 0.28). These scores indicate faculty lean toward traditional teaching methods and hold moderate concerns about GenAI's effects on students.

To examine **RQ2** regarding relationships among faculty attitude dimensions, Pearson correlation coefficients were calculated for all eight dimensions (see **Table 3**). The analysis revealed four strongly interconnected dimensions: openness/curiosity, curriculum modification willingness, (reverse-coded) preference for traditional methods, and influence on professional practice, with correlations ranging from r = .39 to .65 (p < .05), indicating these dimensions are strongly related. In other words, faculty who are open to GenAI is likely to also show willingness to update their curriculum, reduce reliance on traditional methods, and report greater influence on their professional practice.

Student impact concerns correlated positively with equity/access concerns (r = .48, p < .01), curriculum modification willingness (r = .45, p < .01), preference for traditional methods (r = .34, p < .05), and openness/curiosity (r = .33, p < .05). Because student impact concerns was reverse-coded, positive correlations with openness/curiosity and curriculum modification willingness indicate that faculty with fewer student impact concerns demonstrated greater openness and willingness to adapt their curriculum. This suggests that faculty who have fewer concerns about student learning are more ready to integrate GenAI into their teaching.

Positive correlations with preference for traditional methods and equity/access concerns (both also reverse-coded) indicate these concerns aligned with each other and with traditional teaching preferences. This pattern suggests that faculty who prefer traditional teaching

Table 4. Summary of significant correlations among attitude dimensions

Relationship	r	p
Openness/curiosity ↔ student impact concerns	.33	.039
Openness/curiosity ↔ traditional methods	.64	< 0.001
Openness/curiosity ↔ curriculum modification willingness	.65	< 0.001
Openness/curiosity ↔ influence on practice	.58	< 0.001
Student impact concerns ↔ traditional methods	.34	.036
Student impact concerns ↔ curriculum modification willingness	.45	.004
Student impact concerns ↔ equity concerns	.48	.002
Integration confidence ↔ traditional methods	.41	.011
Integration confidence ↔ curriculum modification willingness	.36	.024
Integration confidence ↔ influence on practice	.37	.020
Traditional methods ↔ curriculum modification willingness	.62	< 0.001
Traditional methods ↔ influence on practice	.45	.004
Curriculum modification willingness ↔ influence on practice	.39	.015
Equity concerns ↔ institution support	-.35	.029

Note. $N = 39$ & All correlations shown are statistically significant at $p < .05$

Table 5. Multiple regression analysis predicting influence on professional practice

Predictor	B	SE	β	t	p
(Constant)	1.17	1.59		0.73	.469
Openness/curiosity	0.43	0.17	0.50	2.63	.013*
Student impact concerns	0.06	0.22	0.05	0.27	.786
Integration confidence	0.22	0.16	0.21	1.35	.185
Preference for traditional methods	0.11	0.20	-0.11	-0.58	.566
Curriculum modification willingness	-0.08	0.17	-0.11	-0.49	.631
Equity/access concerns	-0.20	0.15	-0.22	-1.32	.196
Institutional support needs	0.21	0.20	0.16	1.03	.311

Note. $R^2 = .41$; Adjusted $R^2 = .29$; $F\,(7, 32) = 3.23$; $p = .011$; & *p < .05

methods are also more likely to question whether GenAI can be accessed and used equitably by all students. Notably, institutional support needs negatively correlated with equity/access concerns ($r = -.35$, $p < .05$). Given that equity/access concerns was reverse-coded, faculty with greater equity concerns reported higher institutional support needs. This suggests that faculty who recognize equity concerns in GenAI integration actively seek institutional guidance to address them.

To facilitate interpretation and assess practical significance, **Table 4** presents the 14 statistically significant correlations with their effect size classifications. Openness/curiosity emerged as a hub dimension, demonstrating large positive correlations with curriculum modification willingness ($r = .65$, $p < .001$), (reverse-coded) preference for traditional methods ($r = .64$, $p < .001$), and professional practice influence ($r = .58$, $p < .001$). This suggests that openness to GenAI is the most influential attitude dimension, meaning faculty who are curious about GenAI are more open to changing how they teach, design courses, and engage with their professional practice.

Traditional methods preference also correlated strongly with curriculum modification willingness ($r = .62$, $p < .001$), indicating that faculty who are less attached to traditional teaching are also more willing to modify their curricula. Student impact concerns showed moderate positive correlations with equity concerns ($r = .48$, $p = .002$) and curriculum willingness ($r = .45$, $p = .004$), indicating that faculty who worry about student learning impacts also tend to have greater equity concerns. Institutional support needs showed a moderate negative correlation with equity/access concerns ($r = -.35$, $p = .029$), indicating that faculty with stronger equity concerns report greater needs for institutional support.

RQ3 examined how faculty attitudes toward GenAI predicted their self-reported influence on instructional methods, curriculum design, and academic policy participation. A multiple regression analysis was conducted with the seven attitude dimensions entered simultaneously as predictors of influence on professional practice. The overall regression model was statistically significant, $F(7, 32) = 3.23$, $p = .011$, and explained 41% of the variance in perceived influence on professional practice ($R^2 = .41$, Adjusted $R^2 = .29$), suggesting that faculty attitudes toward GenAI are meaningful but not the only factors shaping their professional practice.

Table 5 presents the standardized and unstandardized regression coefficients. Openness/curiosity emerged as the only significant predictor of influence on professional practice ($\beta = 0.50$, $p = .013$), indicating that faculty who are more open and curious about GenAI applications reported significantly greater perceived influence on their professional practice. This represents a moderate to large, standardized effect, suggesting that openness to GenAI

Table 6. Faculty responses about feelings toward GenAI integration

Themes	Sub-theme	*n* (%)	Example
Concerned (*n* = 13, 38.3%)	Dependency	4 (11.8)	"… I do worry some about them becoming too dependent on AI. Of course, I have the exams as leverage, in which exams are worth 40% of the course grade, and if students use too much AI as a crutch it will hurt them on exams ..."
	Academic integrity	4 (11.8)	"I believe that AI can greatly enhance human cognition, understanding, and speed up the learning process. My mean [main] concern is not knowing if a student used it to cheat on an exam and that it make cheating easier and harder to detect. But I believe it is still the responsibility of the professors to set appropriate boundaries, not permit AI on certain assessments, and design problems that might be difficult for AI to answer."
	Accuracy	3 (8.8)	"…Its capabilities will probably quickly improve, but at the moment Chat or similar may not always be a useful tool, because it may make mistakes and other problems ..."
	Critical thinking	2 (5.9)	"I'm pretty worried about it. Studies already show that AI use reduces critical thinking. I'm not sure that first-year math courses are the best place to use AI with students."
Mixed feelings		9 (26.5)	"Excited because it could revolutionize teaching pedagogy. Worried about students using it inappropriately and not learning."
Excited		6 (17.6)	"…Using AI makes work faster, sharper, and more effective. Ignoring it is like choosing long division by hand when a calculator is sitting right there. One of the hidden strengths of AI chatbots in education is that they create a low-pressure space for learning. Students can re-ask a question as many times as they need, in different ways, without fear of judgment or embarrassment."
Undecided		6 (17.6)	"Neutral. I'm not sure how it would be used in the classroom. I do use it often for random help on personal items and for creating print ready math problems."

Note. *N* = 34 respondents & Percentages based on total responses

exploration was the strongest predictor of perceived professional impact among the seven attitude dimensions.

The remaining six attitude dimensions did not significantly predict influence on professional practice: student impact concerns (β = 0.05, p = .786), integration confidence (β = 0.21, p = .185), preference for traditional methods (β = -0.11, p = .566), curriculum modification willingness (β = -0.11, p = .631), equity/access concerns (β = -0.22, p = .196), and institutional support needs (β = 0.16, p = .311). These findings suggest that while faculty express varying attitudes across multiple dimensions, openness and curiosity about GenAI is the primary driver of perceived influence on professional practice.

RQ4 examined how mathematics faculty describe their experiences with and perspectives on GenAI integration.

The first open-ended question asked faculty whether they felt excited, worried, or somewhere in between about GenAI (**Table 6**, *N* = 34), four main themes emerged: concerned (*n* = 13, 38.3%), mixed feelings (*n* = 9, 26.5%), excited (*n* = 6, 17.6%), and undecided (*n* = 6, 17.6%). Faculty who expressed concerned (*n* = 13) identified four specific worries: student dependency (*n* = 4), academic integrity (*n* = 4), accuracy of GenAI outputs (*n* = 3), and reduced critical thinking (*n* = 2). Faculty with mixed feelings (*n* = 9) simultaneously recognized GenAI's benefits for teaching while worrying about inappropriate student use and negative learning impacts.

Excited faculty (*n* = 6) viewed GenAI as enhancing teaching efficiency and learning, while undecided faculty (*n* = 6) were unsure how GenAI could be integrated into classroom instruction.

The second open-ended question asked faculty about their comfort level using GenAI in teaching (**Table 7**, *N* = 29). The largest group expressed uncomfortable (*n* = 12, 41.4%), with accuracy concerns being the most

Table 7. Faculty responses about comfort levels for GenAI use

Themes	Sub-theme	*n* (%)	Example
Uncomfortable (*n* = 12, 41.1%)	Accuracy concerns	4 (13.8)	"My concern is mostly on the accuracy front. I have done some freelancing as an AI reviewer and editor and know that most AI platforms have lots of inaccuracies or make simple things incredibly complicated at times. I hesitate to incorporate a lot of AI use due to inaccuracies that the platforms have, specifically with mathematics."
	Past negative experience	1 (3.4)	"From past experience, I have realized that the more moving parts and tech implemented, the more things there are to go wrong"
	No experience	1 (3.4)	"I have never tried to use GenAI in a live classroom setting. I am not comfortable. Not sure what the benefit of GenAI would be if I was there to teach what GenAI was being used for."
	Unpredictability	1 (3.4)	"GenAI can take you in directions you don't plan on going."

Note. *N* = 29 respondents & Faculty could express multiple themes; percentages do not sum to 100%

Table 7 (Continued). Faculty responses about comfort levels for GenAI use

Themes	Sub-theme	*n* (%)	Example
Uncomfortable (*n* = 12, 41.1%)	Harmful to critical thinking	1 (3.4)	"I'm not yet convinced I can use AI in a way that will enhance critical thinking and learning. I think it's more likely to have the opposite effect."
	Time constraints	1(3.4)	"I feel that our class time is so limited, that I don't want to use AI to take away from our time together."
	Unspecified	3 (10.3)	"Not comfortable. Not sure."
Comfortable (*n* = 11, 37.7%)	Personal use only	3 (10.3)	"I don't use AI for teaching, only for problem preparation. I've researched things with AI before. It doesn't explain things as well or as accurately as instructors do, nor does it understand the implications of what it is teaching. I can't think of many good reasons to use AI for instruction."
	Effective tool	2 (6.9)	"I like using GenAI when I teach. It's a very effective tool, and if used correctly it can provide useful information that I can use to enhance my teaching."
	Willing	1 (3.4)	"I am already using GenAI through the math programs that I use with the students. I do think it needs to be used in conjunction with traditional classroom learning so the teacher can access for mistakes or holes in the GenAI teachings."
	Unwilling	1 (3.4)	"Comfortable but unwilling."
	One to one instruction	1 (3.4)	"I feel like I can work with students one on one with it. I like to assess what each of their relationship is to AI to individualize it."
	Group work	1 (3.4)	"I feel comfortable using it in group work, especially for extra credit assignments…"
	But needs training	2 (6.9)	"I am comfortable, but we need to be trained first."
Developing comfort		2 (6.9)	"I have used it for one assignment and I felt like it went well, but I could definitely learn more on how to develop effective assignments. I have been using it more to make my assignments better and more difficult for students to cheat, which I feel more comfortable doing."
Neutral		2 (6.9)	"I haven't really considered how to use it when I teach. I have developed a few class activities that include it. But not really used it during lecture."
No use		3 (10.3)	"Not sure, I don't use GenAI."

Note. *N* = 29 respondents & Faculty could express multiple themes; percentages do not sum to 100%

Table 8. Faculty responses about curricular changes for GenAI integration

Themes	*n* (%)	Example from faculty response
Teaching materials	8 (29.6)	"I'd probably try first to implement it during in-class activities where I could be more directly involved."
Assessment method	6 (22.2)	"No more take-home exams." "Proper AI use would be best in mathematical discussions or even anything that involves writing about mathematical processes/explanations. This would likely be best for more essay type of assignments or assessments."
Teaching AI literacy	4 (14.8)	"I would add assignments to have students ask AI questions about topics for them to assess. Maybe a discussion board because I know how you ask a question and which AI engine you ask may produce different outcomes. This might be a good opportunity for the class to explore the difference."
No change needed	1 (3.7)	"GenAI is just a tool … I do believe it takes skills and experience to fully understand how to interact with GenAI."
Need information	8 (29.6)	"I would need more training and ideas to feel confident doing this and doing it in a way I feel is beneficial to the students …"

frequently mentioned barrier (*n* = 4, 13.8%). Other barriers included unpredictability, potential harm to critical thinking, time constraints, lack of experience, and past negative technology experiences. The second largest group indicated comfortable (*n* = 11, 37.9%), though comfort manifested in different ways: three faculty (*n* = 3, 10.3%) used GenAI for personal purposes only, two (*n* = 2, 6.9%) viewed it as an effective tool, and two (*n* = 2, 6.9%) emphasized needing training before full implementation. Smaller groups included developing comfort (*n* = 2, 6.9%), neutral (*n* = 2, 6.9%), and no use (*n* = 3, 10.3%).

The third open-ended question asked faculty about potential curricular changes if required to integrate GenAI (**Table 8**, *N* = 27), faculty identified three main areas: Teaching materials (*n* = 8, 29.6%), assessment method (*n* = 6, 22.2%), and teaching AI literacy (*n* = 4, 14.8%). An equal proportion (*n* = 8, 29.6%) indicated need information before making decisions, while one

Table 9. Faculty responses about institutional support needs for GenAI

Themes	*n* (%)	Example from faculty response
Need clear policies and guidelines	11 (52.4)	"I would like clear, university policy clarifying ethical and unethical uses of GenAI. I worry about getting caught between vague policies and student use of AI."
No institutional policies or guidelines needed	2 (9.5)	"I'm not sure institutional guidelines are needed. It is like most other things, you do your best to guess what will help your class learn the topics and set the guidelines for AI use on a class by class or project by project basis."
Need flexible policies and guidelines	3 (14.3)	"General and clear guidelines for GenAI would be nice to have on part of students and faculty, but I don't know about having strong and rigid rules on them. It depends on the course, I guess."
Need training to determine	2 (9.5)	"More of training how to implement the use of GenAI in the classroom then policies, guidelines, and protocols can follow."
No information given in the comment	3 (14.3)	"None."

Table 10. Faculty responses about GenAI influence on teaching practice

Themes	*n* (%)	Example from faculty response
Modified assessments	7 (31.8)	"It has helped me reshape my assignments as well as give me more ideas on how to assess students using more creative projects. I haven't used all the suggestions yet but I am excited to try."
Guide students' AI use	5 (22.7)	"I discuss the use of AI, particularly in homework. I don't discourage students from using it, but I stress that their exams will not have access, and they need to be able to complete the work on their own."
Use AI for instruction	5 (22.7)	"I use GenAI to check my work and to show students mistakes it makes, which helps them learn how to reason through problems."
No changes	6 (27.3)	"GenAI has not really changed my teaching. I see it as similar to tools like PhotoMath or the tutoring center."

Note. N = 23 coded responses from 22 faculty & One response addressed both modified assessments and guiding students' AI use

faculty member (n = 1, 3.7%) indicated no change needed. When these same faculty (N = 27) were asked about concerns regarding potential changes, more than half (n = 15, 55.6%) expressed no specific concerns. The remaining faculty (n = 12, 44.4%) identified concerns primarily related to guiding students to use GenAI responsibly (n = 4, 14.8%), with one faculty warning, "if we don't help students use it appropriately, then they'll use it on their own and likely not appropriately," and the need for faculty training (n = 3, 11.1%), as faculty felt they were "not tech savvy enough to know how to accomplish this." Smaller numbers cited time constraints (n = 2, 7.4%), concerns about current materials becoming unusable (n = 1, 3.7%), GenAI's unreliability (n = 1, 3.7%), and uncertainty about implementation options (n = 1, 3.7%).

The fourth open-ended question asked faculty to describe what institutional support they would need for GenAI implementation (**Table 9**, N = 21). The largest group of faculty (n = 11, 52.4%) expressed need clear policies and guidelines that distinguish ethical versus unethical uses of GenAI. A smaller group (n = 3, 14.3%) advocated for need flexible policies and guidelines that are adaptable to different departments and emphases. Two faculty (n = 2, 9.5%) indicated no institutional policies or guidelines needed, while another two (n = 2, 9.5%) indicated need training to determine what policies would be appropriate. Finally, three faculty members (n = 3, 14.3%) provided no information given in the comment.

The fifth open-ended question asked faculty how GenAI have changed their teaching practices (**Table 10**). Twenty-two faculty provided 23 coded responses, as one faculty member's response addressed two themes. The majority of faculty (n = 16, 72.7%) reported that GenAI had changed their teaching practices. Among the changes, the largest group (n = 7, 31.8%) indicated modified assessments, while two groups of equal size (n = 5, 22.7% each) described guiding students in appropriate uses of GenAI and using GenAI for instruction. Six faculty (n = 6, 27.3%) reported no changes to their teaching practices.

DISCUSSION

Undergraduate mathematics faculty demonstrated moderate openness toward GenAI but low integration confidence, strong traditional method preferences, moderate student impact concerns, and minimal perceived professional influence. This pattern aligns with recent research documenting widespread faculty skepticism despite acknowledged benefits (Watson & Raine, 2026) and attitude-implementation gaps among pre-service and K-12 teachers (Cheah et al., 2025; Yadav et al., 2025). However, mathematics faculty's pronounced traditionalism suggests unique disciplinary tensions not fully captured in general teacher education research. Specifically, mathematics faculty appear concerned with preserving procedural mastery and conceptual understanding that GenAI may undermine (Walter, 2024).

These findings illuminate incomplete WST framework: faculty possessed will (openness/curiosity) and recognized tool needs (institutional support) yet lacked skill (integration confidence). Moreover, their strong traditional teaching preferences reveal that the challenge was not merely technical but pedagogical, requiring faculty to reconcile GenAI with deeply held teaching values about mathematical reasoning and problem-solving.

Faculty with greater equity concerns recognized higher institutional support needs, indicating awareness that equitable GenAI integration requires institutional resources. This extends AI education ethics frameworks (Holmes et al., 2022; Su & Yang, 2023), which identified access disparities and algorithmic bias but did not examine how faculty perceive their support needs. Our results reveal that concerned faculty understand equity challenges require systemic institutional infrastructure, not merely individual awareness or action. This pattern also aligns with teacher education research documenting gaps between interest and implementation. Studies (Cheah et al., 2025; Yadav et al., 2025) found that pre-service and K-12 teachers held positive views about GenAI but faced implementation barriers due to inadequate training, confining use to lesson preparation rather than classroom instruction. This demonstrates that faculty motivation is necessary but insufficient for successful GenAI integration. Across K-12, teacher preparation, and undergraduate mathematics education, effective implementation requires institutions to provide professional development, ethical guidelines, and technical resources that enable faculty to translate attitudes into practice.

Regression analysis revealed that curiosity, rather than confidence, uniquely predicted GenAI's influence on professional practice. This finding directly challenges the TAM's emphasis on perceived ease of use (Davis, 1989; Venkatesh & Davis, 2000), which posits that users' confidence in their ability to use technology determines adoption. Our results also contrast with Kong et al.'s (2024) finding that K-12 teachers' self-efficacy (confidence) was essential for GenAI adoption. This discrepancy may reflect differences between K-12 and higher education contexts: university faculty have greater pedagogical autonomy and may experiment with technologies they don't yet feel confident using, whereas K-12 teachers face more standardized curricula and administrative oversight that require confidence before implementation. This interpretation is supported by our qualitative findings: the majority of faculty reported making teaching changes despite low confidence, suggesting they learned through experimentation rather than waiting for confidence to develop first.

For faculty GenAI use in undergraduate mathematics, curiosity appears more critical than confidence for driving adoption. Within the WST framework, this study shows that will (motivation) may serve as a prerequisite for developing skill (confidence), rather than vice versa. Qualitative evidence supports this interpretation: 73.9% of faculty reported making teaching changes despite low confidence, including modifying assessments (30.4%), guiding students in appropriate use (21.7%), and leveraging GenAI instructionally through AI-generated error analysis (21.7%). These changes demonstrate that faculty learn by doing openness/curiosity motivates initial experimentation with GenAI, and through this hands-on practice, faculty gradually develop the competence and confidence they initially lacked.

Faculty expressing greater student impact concerns also demonstrated higher openness/curiosity and curriculum modification willingness. This nuanced pattern challenges the simple concern-versus-enthusiasm dichotomy assumed in technology adoption literature (Baidoo-Anu & Owusu Ansah, 2023; Venkatesh & Davis, 2000). Qualitative findings revealed faculty simultaneously recognizing GenAI's potential alongside documented risks of academic integrity, dependency, and accuracy concerns (Cotton et al., 2023; Wardat et al., 2023), positioning concern as a complex motivator rather than engagement barrier in mathematics contexts.

When asked what changes they would make if required to integrate GenAI, faculty responses demonstrated thoughtful pedagogical planning. Faculty described redesigning course structure (29.6%), such as integrating AI chatbots, creating individualized assignments, and modifying exams; preventing academic integrity issues through assessment modifications (22.2%); and teaching students how to use GenAI appropriately (14.8%). These varied responses demonstrate that faculty recognize GenAI requires thoughtful integration with modified assessments, clear policies, and student training rather than unrestricted use.

Faculty's repeated emphasis on accuracy concerns reflects legitimate pedagogical judgment. Students who struggle with mathematics and need GenAI help most are also least able to identify when GenAI produces incorrect solutions (Bastani et al., 2025), potentially widening achievement gaps between stronger and weaker students. Addressing these concerns requires structured pedagogical approaches, such as having students verify AI-generated solutions, compare GenAI outputs to their own work, or identify and correct intentional errors in AI responses. This aligns with Joung and Kim's (2025) finding that when students analyzed

ChatGPT-generated responses rather than passively accepting outputs, they demonstrated improved performance, suggesting how assignments are designed determines whether GenAI supports or undermines learning.

Institutional support needs operated independently of faculty's personal attitudes toward GenAI. Even curious, confident, and willing faculty recognized the necessity of organizational infrastructure, validating the WST framework's principle that all three components must align simultaneously (Knezek & Christensen, 2016; Petko, 2012). While prior research emphasized individual teacher readiness (Sasota et al., 2021), our findings demonstrate that personal preparedness cannot substitute for institutional support. This gap between individual and institutional readiness has practical implications: even with 94% of top U.S. universities providing GenAI guidelines (An et al., 2025), faculty's persistent low confidence reveals that guidelines alone are insufficient without accompanying pedagogical training and implementation support. In practical terms, this means that even faculty who are curious about GenAI, confident in using it, or willing to modify curriculum still recognize they need institutional policies, guidelines, and resources. The single significant correlation was a negative relationship with equity/access concerns (r = -.35, p < .05), indicating that faculty who expressed greater equity concerns recognized higher institutional support needs. Research on AI in education has identified equity concerns including unequal access to AI tools across socioeconomic groups (Su & Yang, 2023) and bias in AI systems that may disadvantage students from certain demographic or cultural backgrounds (Holmes et al., 2022).

When asked about institutional support needs, faculty responses varied widely: 52.4% sought clear policies, 14.3% preferred flexible guidelines, 9.5% indicated no policies needed, and 9.5% needed training before determining policies. This reveals faculty lack two distinct knowledge types: technical competence and pedagogical frameworks for mathematics teaching (Çam & Koç, 2024; Mishra & Koehler, 2006). Moreover, while 94% of top U.S. universities provided GenAI guidelines (An et al., 2025), faculty reported low confidence (M = 2.85) and limited practice influence (M = 2.95), revealing that even when institutions provide GenAI resources, faculty still lack the confidence and knowledge to implement them effectively. This validates the WST framework: faculty need institutional support regardless of their personal motivation or confidence. Individual readiness cannot replace organizational infrastructure (Knezek & Christensen, 2016; Petko, 2012). Professional development must address both how to use GenAI (technical skills) and how to use it effectively within mathematics teaching (pedagogical knowledge), while balancing clear ethical guidelines with flexibility.

Four attitude dimensions formed a strongly interconnected cluster, suggesting these attitudes co-develop rather than operating independently. Specifically, openness/curiosity, curriculum modification, willingness, preference for traditional methods, and professional practice influence showed strong interrelationships. This pattern has not been documented in prior GenAI research, which typically examines isolated attitudes (Baidoo-Anu & Owusu Ansah, 2023; Kim et al., 2025). The paradoxical co-occurrence of curiosity and traditional teaching preferences likely reflects faculty's desire to integrate GenAI selectively, preserving mathematics' core values of procedural fluency and conceptual reasoning rather than wholesale instructional replacement.

Limitations and Implications

This study has several limitations. First, the small sample size (N = 41) limits statistical power and generalizability. Second, high correlations among attitude dimensions (r = .58 to .65) indicate conceptual overlap, suggesting openness/curiosity may represent the primary attitude influencing faculty GenAI use rather than eight distinct dimensions. Third, cross-sectional design prevents causal inference; longitudinal research is needed to determine whether curiosity drives practice changes or GenAI experience fosters curiosity. Fourth, self-report data may introduce social desirability bias.

Despite these limitations, findings offer important implications for mathematics education. Professional development programs should leverage faculty openness to GenAI (M = 3.46) through hands-on exploratory experiences rather than focusing solely on technical training. However, strong institutional support needs (M = 3.86) indicate that curiosity alone is insufficient; institutions must provide clear policies, technical infrastructure, and curriculum redesign support regardless of individual faculty attitudes. Faculty concerns about student impacts require direct attention, as greater concerns correlate with lower openness (r = .33, p < .05) and reduced willingness to modify curricula (r = .45, p < .01). Addressing these concerns requires clear ethical guidelines, evidence about GenAI's educational impacts, and pedagogical frameworks for responsible integration. Although findings emerge from one U.S. institution, mathematics educators globally may face similar challenges: faculty interest in GenAI but insufficient institutional support, alongside concerns about maintaining academic integrity and assessment validity.

CONCLUSION

This study investigated undergraduate mathematics faculty attitudes toward GenAI integration across eight dimensions and their relationships to professional practice. Faculty demonstrated moderate openness toward GenAI alongside low GenAI integration confidence, strong traditional method preferences, and high institutional support needs. These eight attitude dimensions were highly intercorrelated rather than independent, with openness/curiosity serving as a central hub connecting to curriculum modification willingness, traditional teaching preferences, and professional practice influence. Among the eight attitude dimensions examined, only openness/curiosity significantly predicted GenAI's influence on professional practice. This finding challenges the TAM's emphasis on perceived ease of use. Qualitative findings revealed that faculty hold nuanced perspectives, meaning they do not view GenAI simplistically; they simultaneously recognize GenAI's potential while expressing concerns about academic integrity, student dependency, and accuracy. Faculty view GenAI as requiring thoughtful integration with modified assessments and clear policies rather than unrestricted adoption.

Theoretically, these findings reveal incomplete WST implementation: while motivation (will) enabled engagement despite limited confidence (skill), inadequate institutional support (tool) prevents effective integration. Practically, institutions must develop comprehensive support systems, including clear policies, pedagogical training, and technical resources that complement faculty motivation and enable responsible GenAI integration in undergraduate mathematics education.

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