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The mediated message model: Understanding faculty GenAI adoption decision-making and guiding optimal faculty development

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ABSTRACT

This study highlights that understanding how faculty adopt technology requires integrated theoretical frameworks rather than the single-theory models often seen in current research. Faculty responses to disruptive technologies, such as generative AI (GenAI), involve complex psychological processes that are frequently overlooked by traditional models. To address this, we developed the Mediated Message Model (MMM) by combining communication theory, behavioral prediction, and motivational psychology, targeting four gaps: fragmented focus, lack of contextual sensitivity, limited process understanding, and constraints. We utilized this framework to design and evaluate a faculty development program featuring a book club format, involving fifty-six faculty members across two cohorts during the 2024–2025 academic year. Data from surveys (n = 30), interviews (n = 6), and action plans (n = 28) supported our predictions, demonstrating that faculty responses depend on interactions between perceived efficacy and value, rather than solely on individual psychological factors. Our analysis identified four distinct cognitive-behavioral outcomes—engaged adoption, impassive acceptance, discouraged hesitation, and aversive rejection—that stem from specific efficacy-value combinations. Faculty members needed multiple stimuli—such as personal experiences, peer demonstrations, and authoritative readings—to effectively adopt GenAI, as no single approach was sufficient. The study also revealed goal orientation patterns indicating that intrinsic versus extrinsic motivation influences technology integration, opening avenues for future research. The MMM advances both theory and practice by aiding faculty development leaders in designing comprehensive, evidence-based strategies that consider the psychological complexity involved in the adoption of GenAI.

Keywords: generative artificial intelligence, faculty development

INTRODUCTION

Generative artificial intelligence (GenAI) is changing workplaces everywhere. Unlike previous technological shifts that primarily impacted skilled manual labor or desk jobs, GenAI affects anyone working with text, images, and sound (Bowen & Watson, 2024), including college faculty members. Faculty already face challenges when adopting new technology, such as digital literacy, resistance to change, time constraints, competing responsibilities, and concerns about academic integrity (Gkrimpizi et al., 2023; Polly et al., 2021; Reid, 2017). GenAI intensifies these challenges due to its rapidly advancing abilities, uncertain institutional policies, and ethical issues related to teaching and assessment (Lamrabet et al., 2025; Michel-Villarreal et al., 2023).

New faculty development strategies are essential to help faculty adapt to paradigm-shifting technologies, such as GenAI. Traditional one-time professional development workshops often fall short for technologies that require significant mindset shifts and practice changes (Mercader & Gairín, 2020). Additionally, many faculty development initiatives tend to assume that skill acquisition will automatically lead to the adoption of technology. These approaches overlook the cognitive, behavioral, and other factors that influence faculty's decisions.

This study presents and validates the Mediated Message Model (MMM) as a framework that combines concepts from communication theory, behavioral prediction theory, and motivational psychology to understand technology adoption decisions in academic settings and to inform faculty development initiatives accordingly. To demonstrate the practical usefulness of the MMM, we applied it to the design, implementation, and assessment of a faculty development program focused on GenAI, which included a book club format. Our research questions were:

RQ1: How do the cognitive-behavioral processes in the MMM appear in faculty descriptions of their GenAI integration journey?

RQ2: How does using the MMM in faculty development design affect cognitive-behavioral outcomes?

LITERATURE REVIEW

To better support faculty in adopting GenAI and other paradigm-shifting technologies, we need to examine the challenges and identify frameworks that explain their decision-making processes. This information should then be used to guide faculty development. Although research has identified many barriers and facilitators to faculty technology adoption, most faculty development efforts lack a comprehensive conceptual model and rarely incorporate established psychological theories. Overall, the literature presented here suggests that faculty development leaders need a new framework. This review examines existing approaches to faculty technology adoption, identifies key theoretical gaps, and lays the groundwork for an integrated framework that addresses these limitations.

The Need for Theoretical Foundations in Faculty Development

Faculty technology adoption challenges remain consistent across various innovations, from early computer integration in the 1980s to newer ones, such as mobile apps, search engines, and GenAI. A recent survey reveals that two out of five faculty members are familiar with GenAI, yet only 14% express confidence in their ability to utilize it in teaching (Coffey, 2024). The main issues stem from how faculty respond to and approach technological change: initial skepticism about its educational value, concerns about time and training requirements, questions about maintaining quality, and inconsistent adoption despite institutional support (Gkrimpizi et al., 2023; Polly et al., 2021).

Institutions have addressed these challenges through similar efforts, including brief, one-time training sessions that focus on technical skills. These sessions often provide limited opportunities for practice and reflection, and can cognitively overwhelm participants (Mercader & Gairín, 2020; Olari et al., 2025). Additionally, such initiatives typically assume that simply acquiring new knowledge and skills will lead to the adoption of technology. This overlooks the cognitive, emotional, and environmental factors that influence faculty decisions (Elsakova & Markus', 2024). The gap between training and actual implementation highlights a need for a deeper understanding of faculty's technology adoption choices and more effective faculty development approaches. Given these persistent challenges in faculty development, examining existing theoretical frameworks reveals both their contributions and limitations in explaining faculty decisions regarding technology adoption.

Comparative Analysis of Theoretical Frameworks for Faculty Technology Adoption

The limited success of atheoretical or single-theory approaches to faculty development emphasizes the need for frameworks that account for the cognitive-behavioral processes behind technology adoption decisions. Analyzing existing conceptual models reveals both strengths and limitations in explaining faculty decisions about adopting technology.

Technology acceptance models and utility-focused frameworks

Traditional technology acceptance models, including the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), focus on utility calculations and ease of use as key drivers of technology adoption. A meta-analysis of 114 empirical studies confirmed that models like these explain technology acceptance quite well in educational settings but tend to be more effective when implementation is mandatory or highly incentivized (Scherer & Teo, 2019). They often fall short in academic environments where faculty have professional autonomy and face competing priorities (Xue et al., 2024). This is partly because these models emphasize rational decision-making and overlook the emotional factors and professional considerations that influence faculty's use of technology.

While TAM and UTAUT effectively predict technology adoption in organizational settings with clear incentive structures, these models primarily focus on utility calculations, overlooking the emotional and professional identity factors that influence faculty decisions. Additionally, these frameworks lack context sensitivity because they were designed for business environments where employees have limited autonomy. They fail to address the unique aspects of academic settings, where faculty retain significant control over pedagogical choices. Adopting GenAI involves complex issues, such as maintaining academic integrity, preserving pedagogical authority, and managing professional reputation—elements that utility-focused models cannot adequately capture.

Social cognitive theory and self-efficacy approaches

Self-efficacy beliefs have been partially shown to help explain how faculty adopt technology, including GenAI (Nguyen et al., 2023; Wang & Chuang, 2024). Self-efficacy, a key concept within Bandura's (1977) social cognitive theory, refers to a person's belief in their ability to succeed in a specific situation. Williams et al. (2023) found that self-efficacy predicts successful technology integration. Similarly, Gomez et al. (2022) discovered that K-12 teachers with stronger self-efficacy beliefs integrate technology more effectively. However, many of them reported only "fair" confidence levels, with gaps between their beliefs and actual use. Nonetheless, self-efficacy alone does not guarantee adoption. Faculty may feel confident in using technology but still hesitate due to concerns about pedagogical value or lack of institutional support (Ertmer & Ottenbreit-Leftwich, 2010). Faculty development programs that focus solely on building confidence overlook other essential factors. A supportive institutional culture and approaches that address multiple factors in decision-making are equally important.

Although self-efficacy beliefs partly explain faculty confidence with technology, this single-construct approach offers a limited understanding by viewing adoption primarily as a confidence issue rather than recognizing the complex psychological processes involved in faculty decision-making. Self-efficacy theory also highlights limitations in how interventions are designed, as programs that focus solely on skill-building overlook the importance of perceptions of value, institutional constraints, and motivational factors that influence whether confident faculty members actually incorporate technology meaningfully into their practice. Faculty may feel technically capable of using GenAI while also questioning its pedagogical value or professional appropriateness—a complexity that self-efficacy alone cannot address.

Diffusion of innovations theory

Rogers' (1962) diffusion of innovations theory explains how, why, and at what rate new ideas and technologies spread. He argued that diffusion is the process by which an innovation is communicated over time among members of a social system (Rogers, 2003). Raman et al. (2024) employed the theory to explain the adoption of ChatGPT among university students. Cain et al. (2024) applied it to understand academic responses to crisis-driven technology adoption during the COVID-19 pandemic. However, the diffusion of innovations theory provides limited guidance for designing faculty development initiatives. Its focus on social influence does not fully account for cognitive-behavioral factors that influence faculty technology decisions.

Diffusion of innovations theory provides useful insights into social influence processes but has limitations in intervention design due to its narrow focus. It emphasizes social adoption patterns but offers limited guidance for understanding individual psychological mechanisms or creating targeted faculty development programs. The theory's broad sociological view cannot explain the specific cognitive-behavioral factors that cause some faculty members to progress from awareness to implementation, while others remain in earlier stages. It also lacks strategies for influencing personal decision-making processes that ultimately drive individual faculty choices regarding GenAI integration.

Gaps in Existing Theoretical Approaches

While each of these established frameworks offers valuable insights into aspects of technology adoption, their individual limitations highlight broader systematic gaps that necessitate a more comprehensive theoretical approach. Effective faculty development requires frameworks that address the intersection of cognitive-behavioral factors, social influences, institutional constraints, and technological features. However, our literature review reveals a significant gap in methods that effectively integrate these multiple dimensions. Among the existing approaches, Kimmons et al. (2020) argue they have been adopted "in anarchic ways," avoiding critical scrutiny. That said, there are at least four limitations in the current theoretical methodology.

1. Fragmented focus: Many theories fail to integrate the multiple dimensions of the decision-making process (Lu et al., 2019).

2. Context insensitivity: Many frameworks developed for organizational or consumer contexts may not address the unique characteristics of academic settings (Sadeck, 2022).

3. Limited process understanding: Existing theories often view adoption as a binary outcome rather than a dynamic process (Shachak et al., 2019).

4. Intervention design limitations: Most frameworks provide limited guidance for designing effective interventions (Xue et al., 2024).

These gaps are particularly concerning given what we already understand about faculty decision-making processes for technologies less disruptive than GenAI. These theoretical limitations collectively demonstrate why faculty technology adoption requires integrated approaches that address multiple psychological and contextual factors simultaneously. The fragmented focus of single-theory models means that interventions based solely on utility, self-efficacy, or social influence fail to capture the full complexity of faculty decision-making. Frameworks developed for business or consumer settings overlook the unique professional autonomy and pedagogical concerns that characterize academic environments. Limited process understanding results in interventions that treat adoption as a simple outcome rather than recognizing the dynamic psychological processes that develop over time. Additionally, limitations in intervention design often result in professional development lacking the necessary theoretical guidance to influence the factors that drive successful technology integration.

Theoretical Foundations Underlying Faculty Technology Adoption

While educational technology frameworks show significant gaps, theories from communication, behavioral science, and motivational psychology, when strategically combined, offer untapped potential for understanding faculty technology adoption. Additionally, we know that faculty respond better to opportunity-focused rather than deficit-focused messaging (Galimova et al., 2024; Saif et al., 2024), prefer learning from colleagues over external mandates (Belt & Lowenthal, 2020), and require clear evidence of the usefulness of technology (Wang & Xue, 2022).

Instead of relying solely on models developed within educational settings, we can draw from three well-established theoretical fields that have proven effective in related areas: communication theory, behavioral prediction theory, and motivational psychology. Although these approaches have seen limited application in faculty development contexts, their focus on cognitive-behavioral processes aligns well with the complex decision-making processes involved in GenAI and other technologies. The following analysis explores how these interdisciplinary approaches complement each other and provide a foundation for our MMM.

Communication theory

Communication theory offers valuable insights into how faculty respond to new technologies, recognizing that behavioral choices involve complex cognitive and emotional processes. One such framework is the Extended Parallel Process Model (EPPM) (Witte, 1992, 1994). Educational researchers have used this theory to study teacher intervention behaviors in bullying situations (Duong & Bradshaw, 2013), instructional design for online literacy skills (Banas, 2010), and student reactions to health and civic engagement messages (Roberto et al., 2023). However, few studies have applied this model—originally from health communication—to educational technology contexts. Because EPPM effectively addresses threat perceptions and efficacy beliefs, which are critical factors in faculty technology decisions, applying this model to educational technology adoption presents a valuable opportunity.

The EPPM explains how people process messages about threats and opportunities while evaluating their ability to respond through two pathways:

1) Danger control (focusing on problem-solving strategies to address the issue effectively) and
2) Fear control (managing emotional responses when feeling unable to cope with the challenge).

The model is based on the principle that people's decision-making relies on two key efficacy beliefs:

1) Response efficacy (belief that a recommended action will effectively resolve the issue) and
2) Self-efficacy (confidence in one's ability to successfully perform the recommended action).

When both efficacy beliefs are high, individuals engage in danger control and take constructive steps; when efficacy beliefs are low, they fall into fear control, focusing on managing anxiety rather than addressing the core problem.

The EPPM is particularly helpful for understanding how faculty adopt GenAI and other technologies because academic professionals often encounter information that presents both opportunities and challenges. Faculty need to interpret messages about the benefits of GenAI while evaluating their confidence in using these tools without affecting their professional effectiveness. The EPPM's dual processing mechanism directly relates to the perceived efficacy mediator in the MMM, providing a solid theoretical basis for understanding how faculty interpret information about technology and why some focus on strategic implementation, while others become preoccupied with concerns about professional competence and control.

Behavioral prediction theory

While communication theory provides crucial insights into message processing, understanding behavioral intentions requires complementary perspectives from behavioral prediction research. The Integrative Model of Behavior Prediction (IMBP) (Fishbein & Yzer, 2003) has proven applicable in educational technology settings. Research has used the IMBP to examine technology adoption choices among teachers and students, explaining teachers' willingness to adopt technology through attitudes, self-efficacy, and subjective norms (Kreijns et al., 2013; Prenger & Schildkamp, 2018; Wang et al., 2019). Zhou et al. (2023) extended the model to better understand how teachers continually learn TPACK (technological, pedagogical, and content knowledge).

The IMBP suggests that perceptions shape behavioral intentions through three cognitive-affective factors: attitudes toward the behavior (how positively or negatively someone evaluates performing the specific action), perceived behavioral control (beliefs about one's ability to perform the behavior successfully), and perceived norms (perceptions about what others expect or what others typically do) (Fishbein & Yzer, 2003). The model acknowledges that intentions alone do not guarantee action, recognizing that individual skills and environmental factors influence whether intentions translate into behavior. Its emphasis on perceived behavioral control is especially important in academic settings, where successful implementation depends on institutional support and faculty development of skills. However, the model's focus on social norms may have limited relevance in academic environments.

Motivational psychology

Although behavioral prediction models explain how intentions are formed, they need to be combined with motivational frameworks to fully understand how faculty assess the value of technology integration efforts, as faculty often prioritize professional autonomy and individual pedagogical judgments. Expectancy-value theory, a motivational psychology theory, has demonstrated relevance across various educational contexts, providing insights into student motivation and decision-making processes (Boström & Palm, 2020; Chan & Zhou, 2023; Wang & Xue, 2022). However, its specific application to faculty technology adoption remains unclear despite its strong theoretical alignment with faculty decision-making processes.

Expectancy-value theory (Eccles & Wigfield, 2002; Wigfield & Eccles, 2020) examines the expected benefits and perceived costs associated with a suggested behavior through four key components: utility value (how useful the behavior is for achieving personal or professional goals), intrinsic value (inherent enjoyment or interest in the behavior itself), attainment value (importance of performing well on the behavior for one's identity or self-concept), and cost factors (what must be sacrificed, invested, or risked to engage in the behavior). The theory suggests that people are most likely to engage in behaviors when they perceive high value and believe the costs are manageable or worthwhile.

Expectancy-value theory is particularly helpful for understanding how faculty adopt GenAI and other technologies, as academic professionals often conduct detailed value assessments of new practices. They weigh potential benefits against factors like time commitment, learning curves, and professional risks. Faculty evaluate whether technology helps them meet their teaching or research goals (utility), if it is engaging to use (intrinsic), whether adopting it aligns with their professional identity (attainment), and if the necessary time and effort are justified (cost). These value-based judgments directly influence the perceived value mediator in the MMM, supporting the theoretical foundation for understanding how faculty evaluate technology opportunities.

Evidence for Theory-Driven Approaches

The theoretical foundations of communication, behavioral, and motivational psychology provide a strong basis for integration, and recent faculty development initiatives demonstrate the practical benefits of multi-theoretical approaches. For example, Lee et al. (2022) created a book club model for AI faculty development that incorporates cognitive load theory, communities of practice, and design justice principles. Their approach promoted continuous learning, built peer networks, and addressed ethical concerns. Faculty could gradually shift their thinking into a supportive environment, rather than relying solely on intensive workshops. Nazaretsky et al. (2022) adopted a different approach, focusing on teacher trust in AI educational technology. Their program drew on trust theory, cognitive bias research, and decision-making studies to address psychological barriers, including algorithm aversion, confirmation bias, and misconceptions about AI. Faculty shifted from skepticism to willingness to try AI tools.

As shown by Nazaretsky et al. (2022) and Lee et al. (2022), theory-driven professional development can lead to changes in efficacy beliefs, value perceptions, and locus of control—key factors that predict behavioral intentions. Building on this evidence, we propose the MMM, which systematically combines insights from message processing in communication theory, behavioral prediction theory, and motivational psychology. The preceding analysis reveals that faculty technology adoption requires a framework that combines insights from communication theory, behavioral prediction, and motivational psychology. The Mediated Message Model (MMM) addresses this need by offering a comprehensive framework for understanding and influencing the cognitive-behavioral processes underlying faculty technology adoption, addressing the limitations of traditional skill-focused training.

The Mediated Message Model: A New Theoretical Framework

Faculty encounter many competing factors when adopting new technologies. They have significant professional autonomy and manage multiple demands as they try to incorporate new tools into their existing teaching practices. The MMM recognizes these realities by focusing on how faculty interpret and respond to information about technology opportunities (see **Figure 1**). Building on the theoretical foundations discussed in the Literature Review, the MMM combines insights from communication theory, behavioral prediction theory, and motivational psychology into interconnected components that lead to four cognitive-behavioral outcomes. These outcomes ultimately influence whether and how faculty integrate GenAI and other emerging technologies into their teaching.

External Stimuli

External stimuli represent different ways in which faculty encounter information about technology opportunities. The MMM identifies three types of stimuli that influence faculty message processing:

Personal experiences

Personal experience involves direct engagement with technology, such as previous use of similar tools, opportunities for practice during training, or independent exploration. When faculty have firsthand evidence of

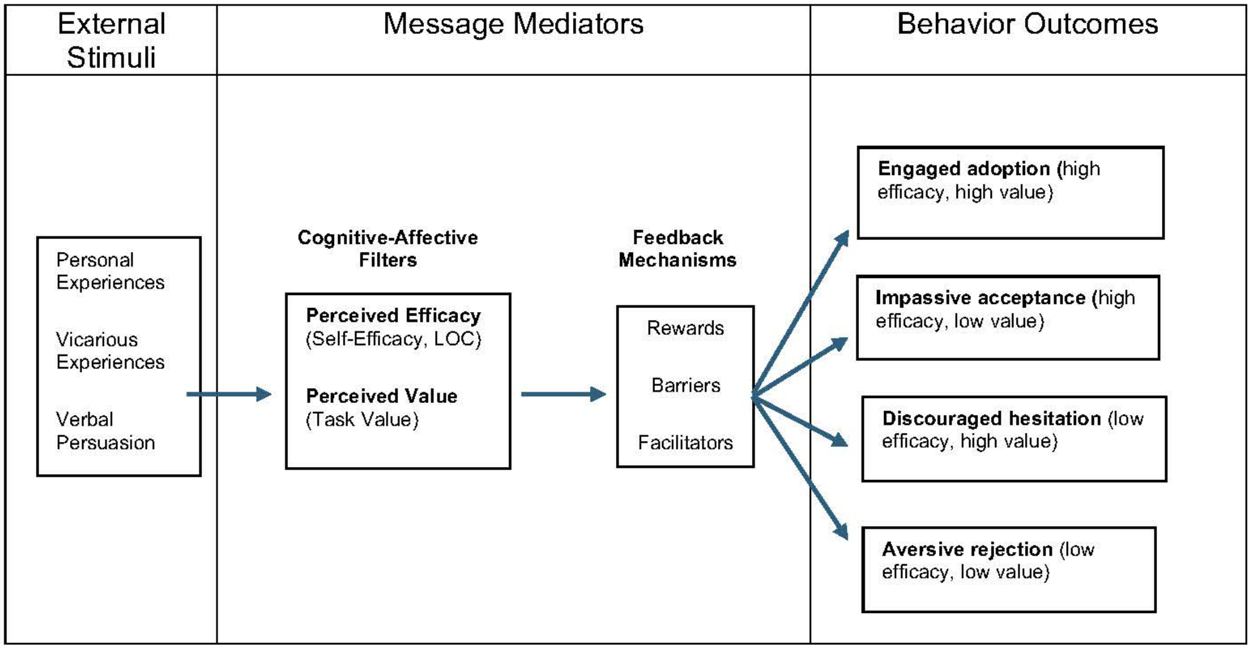

Figure 1. Mediated message model original

GenAI's capabilities and limitations, they can evaluate a technology's potential benefits and challenges within their professional context.

Vicarious experiences

Vicarious experiences involve observing colleagues' technology implementations, exposure to success stories, and demonstrations in similar work environments. These experiences provide credible evidence from comparable contexts without requiring personal investment, making them valuable for initially skeptical faculty.

Verbal persuasion

Verbal persuasion encompasses recommendations from trusted sources, institutional leadership requests, research findings on the effectiveness of technology, and policy messages regarding technology priorities. This stimulus type provides interpretive frameworks that help faculty understand the broader significance of their personal and vicarious experiences.

Message Processing Mediators

Message processing mediators are the cognitive-affective filters through which faculty interpret external stimuli and the feedback mechanisms that either reinforce or change those filters. Our initial framework identified two cognitive-affective filters and three feedback mechanisms that determine whether faculty process stimuli in ways that promote or hinder adoption.

Cognitive-affective filters

The cognitive-affective filters included perceived efficacy and perceived value.

Perceived efficacy includes both locus of control and self-efficacy. Locus of control refers to an individual's beliefs about their control over actions, despite external influences (Rotter, 1966). This component aligns with research indicating that faculty who perceive greater control over technology tend to view AI integration more favorably (Lamrabet et al., 2025). Self-efficacy represents faculty confidence in both their technical skills and their ability to handle integration challenges within their professional practice.

Perceived value captures faculty assessments of technology's benefits relative to its costs. Drawing on Wigfield and Eccles' expectancy-value theory (Eccles, 2005; Eccles & Wigfield, 2002), this evaluation encompasses faculty judgments about how effectively technology supports their professional goals (utility value) and their assessment of the resources, time, and effort required for successful implementation (cost considerations). Research indicates that faculty utility judgments significantly influence their willingness to adopt emerging technologies (Wang & Xue, 2022).

These filters function interdependently rather than independently. Faculty with high perceived efficacy but low perceived value might develop technical skills without meaningful integration. Conversely, faculty with high perceived value but low perceived efficacy might see the benefits of technology but not feel capable of implementing them. The MMM predicts that the best results require positive development across both cognitive and affective filters.

Feedback mechanisms

Feedback mechanisms continually shape faculty perceptions throughout the adoption process, highlighting that technology adoption decisions evolve rather than remain fixed. We identified three feedback mechanisms: rewards, barriers, and facilitators.

Rewards include external incentives such as institutional recognition, financial support, release time, and professional development opportunities. These rewards can boost faculty motivation to continue integrating technology and shape their perspective on future technological opportunities.

Barriers include resource shortages, time constraints, technical difficulties, inadequate institutional support, and policies that hinder implementation. Common barriers are insufficient training opportunities, lack of technical support, competing professional demands, and concerns about technology reliability. These obstacles can weaken faculty effectiveness and diminish their perceived value of technology integration.

Facilitators consist of supportive colleagues, accessible training resources, institutional encouragement, technical infrastructure, and environmental factors that promote implementation. Examples include peer mentoring programs, readily available technical support, leadership endorsement, and institutional policies supporting innovation.

The dynamic interaction among rewards, barriers, and facilitators forms feedback loops that constantly influence faculty perceptions and behaviors during the adoption process.

Cognitive-Behavioral Outcomes

The MMM model predicts four distinct cognitive-behavioral outcomes that explain and predict faculty responses to opportunities for technology integration opportunities.

Engaged adoption

Engaged adoption occurs when faculty recognize the high value of technology and believe they can use it effectively, leading to enthusiastic and strategic application. Faculty members who achieve this stage proactively seek ways to incorporate technology, experiment with innovative tools, and persist despite obstacles. They develop a deep understanding of what technology can accomplish and create meaningful connections between their use of technology and their professional goals.

Impassive acceptance

Impassive acceptance happens when faculty have high efficacy but perceive low value in technology for their work, resulting in competent but unenthusiastic use. These faculties can use technology effectively when required, but do not see it as central to their professional identity or goals. They may comply with institutional expectations without developing a personal commitment to using the technology.

Discouraged hesitation

Discouraged hesitation arises when faculty recognize the value of technology but lack the efficacy beliefs to implement it successfully, leading to interest without action. These faculty members have positive attitudes towards technology and see its potential benefits, but they feel overwhelmed by challenges in implementation. They may keep delaying adoption even though they understand its importance.

Aversive rejection occurs

Aversive rejection occurs when faculty perceive little value in technology and lack confidence in its effectiveness, resulting in active resistance or avoidance. Faculty in this group may view technology as a threat to their professional identity, unnecessary for their work, or too difficult to implement successfully. They deliberately avoid integration opportunities and might resist institutional technology initiatives.

These four behavioral outcomes help explain the range of faculty responses to technology integration initiatives and predict which interventions can encourage engaged adoption while addressing specific barriers associated with each pattern.

From Initial Framework to Enhanced Model

The framework outlined above represents our initial MMM (**Figure 1**), developed through a systematic integration of communication theory, behavioral prediction models, and motivational psychology. This initial framework guided our research design and data collection as we aimed to test its theoretical relationships in practice. However, our empirical investigation revealed that faculty technology adoption involves additional psychological processes not included in our original model. Specifically, we identified goal orientation as a key cognitive-affective filter that influences how faculty interpret and respond to opportunities for technology integration. These findings led to the improved MMM (**Figure 2**), which incorporates goal orientation alongside perceived efficacy and perceived value as the three main mediators of message processing. In our Findings and Discussion sections, we present empirical evidence for this theoretical update, demonstrating how faculty motivational orientations systematically shape their technology adoption behaviors.

Framework Application to Design

We used the MMM to design a comprehensive GenAI faculty development program, demonstrating its practical value and testing its theoretical concepts. Instead of creating generic technology training, we developed an intervention that focuses on the cognitive-behavioral processes outlined in our framework. This connected theory to practice by translating insights from communication, behavior, and motivational psychology into design choices. Our process began with the understanding that faculty technology adoption involves complex message processes that are often overlooked by traditional training methods. The MMM's focus on external stimuli led us to systematically include all three stimulus types: personal experiences through hands-on sessions, vicarious experiences via peer demonstrations and sharing, and verbal persuasion through readings and discussions that framed GenAI as a growth opportunity rather than a threat. We also integrated message processing mediators as cognitive-affective filters and embedded feedback mechanisms to produce the dynamic influences on adoption predicted by our framework.

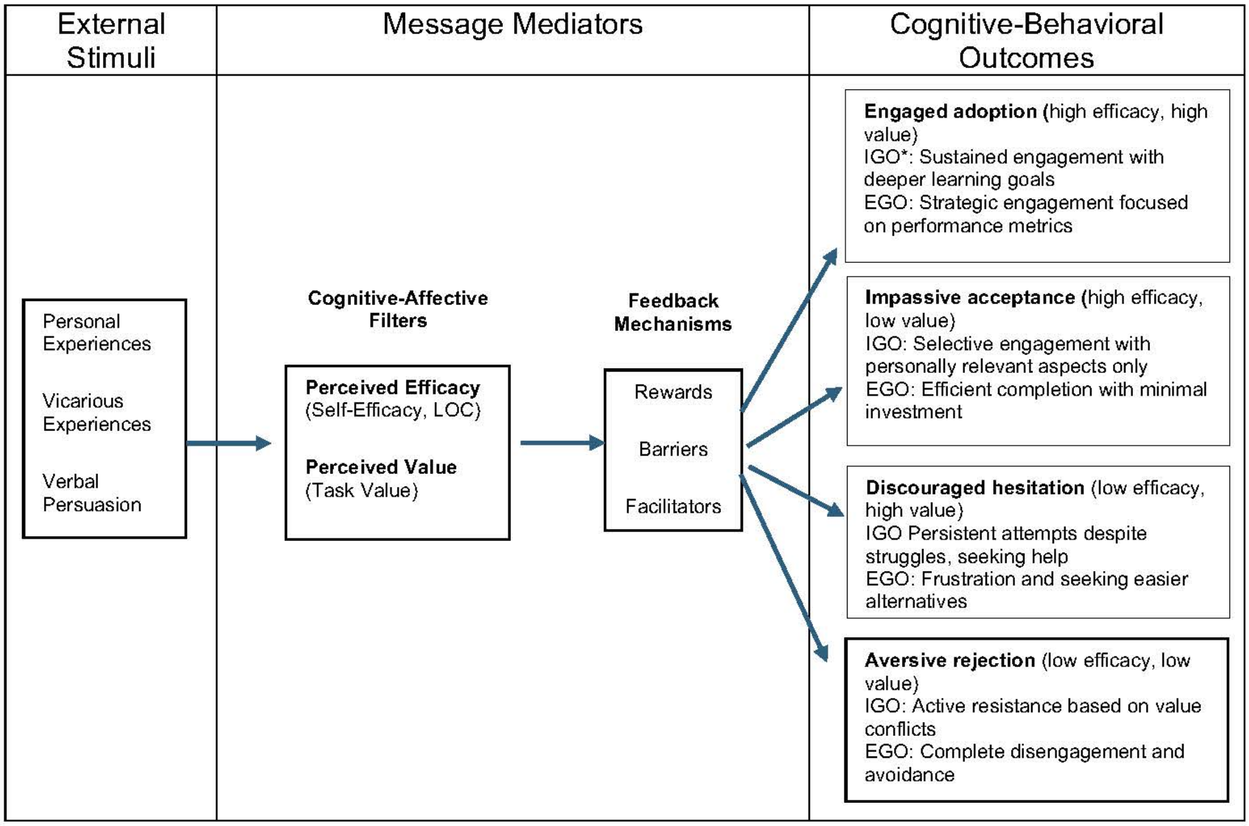

Figure 2. Mediated message model revised
*IGO = intrinsic goal orientation; EGO = extrinsic goal orientation

These theoretical principles led to the development of a five-session book club format, rather than traditional single-session workshops that focused solely on technical skills. See **Appendix A** - Book Club Outline and Description. We chose this extended format because the MMM requires ongoing exposure to external stimuli and multiple opportunities for peer modeling through vicarious experiences. The book club structure also provides time for message processing and creates a social learning environment that communication and behavioral prediction theories identify as essential for changing attitudes and behaviors.

Each session focused on specific MMM components to promote *engaged adoption*. Session 1 established perceived value by highlighting GenAI's benefits for teaching and research before covering technical details, applying expectancy-value theory's emphasis on recognizing utility to motivate. Sessions 2 and 3 aimed to boost efficacy through gradual skill development while emphasizing faculty control and agency, drawing from the EPPM's response efficacy concepts and the IMBP's focus on perceived behavioral control. Session 4 explored GenAI as a teaching assistant through practical applications, including developing discussion questions and rubrics, designing and customizing assignments, enhancing courses, and creating GenAI student tutors. This session offered tangible personal experiences, which communication theory identifies as influential message sources, while also supporting skill development that behavioral prediction models suggest influences implementation intentions.

Session 5 focused on transforming professional practice with GenAI, addressing concerns related to academic integrity, and assisting faculty in redesigning their approaches for the GenAI era. This final session integrated insights from all three theoretical areas by helping faculty evolve their professional identity, develop ethical use strategies, and see the long-term advantages of proactively adjusting their practices. The sequence intentionally transitioned from broad capabilities to specific professional applications, culminating in faculty members creating detailed action plans that incorporated concepts and skills from the series. Faculty could choose to concentrate their action plans on either teaching or research, aligning these choices with their personal goals and professional priorities.

Several months after the book club concluded, we organized a showcase where faculty members could present their action plans, share ideas across disciplines, and be recognized for their innovative approaches. This showcase served multiple theoretical purposes: it provided vicarious experiences for ongoing social learning, offered verbal encouragement through peer success stories, and established ongoing feedback through community recognition and support. The showcase also helped create a lasting community of practice to support continuous GenAI integration efforts, fostering the social environment that communication theory and behavioral prediction models identify as essential for maintaining behavior changes.

Throughout the entire program, we incorporated multiple feedback mechanisms, recognizing that technology adoption is an iterative process influenced by ongoing rewards, barriers, and facilitators. We provided external rewards through financial incentives: $400 for attending book club sessions and completing an action plan, plus an additional $200 for participating in the showcase. These incentives served two purposes: to reduce participation barriers and to offer positive reinforcement that, based on behavioral prediction models, encourages continued engagement with new behaviors.

Our barrier reduction strategies involved practical adjustments to minimize obstacles for faculty participation and skill development. We offered independent work time during and after sessions for practicing new skills, recorded all sessions for those who missed meetings, gradually increased the complexity of technical activities to prevent cognitive overload, and scheduled the book club sessions for both academic semesters at different times and on various weekdays to accommodate the varied faculty schedules. These strategies reflected IMBP insights about how environmental factors influence the translation of behavioral intentions into real actions.

This structured translation of MMM principles created a faculty development experience that addressed the full complexity of faculty technology adoption decisions by incorporating communication methods, behavioral prediction processes, and motivational evaluations. Instead of focusing on isolated factors like skills or attitudes alone, our design influenced the interconnected cognitive-behavioral processes that our cross-disciplinary framework identifies as shaping technology adoption outcomes.

METHODOLOGY

This study assessed the validity and usefulness of the MMM in understanding faculty members' adoption of GenAI. Instead of focusing only on intervention effectiveness, and with Institutional Review Board approval, we examined whether the MMM's theoretical relationships were reflected in faculty responses.

Research Design for Theory Testing

Our research design addressed a key challenge: verifying whether the theoretical framework accurately explains real-world phenomena and demonstrates practical value. The MMM makes specific predictions about how faculty process messages about GenAI and other technologies, and how these processing patterns influence subsequent behaviors. Our data collection approach included multiple measurement points to track evolving decision-making processes and to evaluate how the model functions in practice.

Participants and Implementation Context

From a pool of fifty-six faculty members who participated in the two book club implementations during the 2024–2025 academic year, we recruited 30 members for the study. Faculty represented diverse disciplines at our public Midwest university: business, education, STEM, humanities, and health sciences. This disciplinary diversity was essential because the MMM predicts that message mediators operate similarly across different fields, even when implementation strategies vary by discipline. The two-cohort design enabled us to test the theory's consistency across different academic calendar periods.

Data Collection Instruments for Measuring Theoretical Constructs

We designed our data collection method to examine MMM's theoretical constructs. A survey administered before the initial book club meeting captured the two cognitive-affective filters, *perceived efficacy* and *perceived value*. See **Appendix B** – Survey & Interview Questions. We assessed perceived efficacy using four items that measured overall confidence in learning technology, specific beliefs about AI integration, confidence in solving technological problems, and locus of control over the success of AI tools. Perceived value was measured using four items that evaluated teaching quality improvements, time-saving benefits, student feedback, and the worthiness of learning investment. All items used a 5-point Likert rating scale. The Cronbach's alpha reliability coefficients for each subscale were: efficacy ($\alpha = 0.69$) and value ($\alpha = 0.83$). These values were near or above 0.70, indicating high internal consistency (Hair et al., 2006).

In addition to the cognitive-affective filters, we also asked participants to identify their college (Education, Arts & Sciences, Business & Technology) and whether they had previously used GenAi for teaching, research, or professional duties. The latter was asked as three binary (yes/no) questions. Finally, three open-ended questions explored faculty concerns about AI use, their desired AI applications in their work, and the motivations for integrating AI, providing deeper insight into value perceptions, potential barriers, and underlying motivations.

After the final book club meeting, faculty completed a post-survey. Three items (also on a 5-point Likert scale) captured faculty's evaluation of the series, and three open-ended questions aimed to capture the cognitive-behavioral outcomes, as well as ongoing barriers and strategies to overcome them, and desired resources to elevate their confidence.

Action plans served as a key tool for collecting data on faculty's cognitive-behavioral outcomes following the book club intervention. Faculty translated their GenAI learning into specific implementation strategies, choosing between teaching-focused or research-focused formats. Each format included selecting appropriate GenAI tools, setting timelines for implementation, and identifying strategies to overcome barriers. These structured documents provided rich qualitative data, showing how faculty processed the MMM's external stimuli through their perceived efficacy and value filters. This process helped us identify the four predicted cognitive-behavioral outcomes—engaged adoption, impassive acceptance, discouraged hesitation, and aversive rejection—based on the complexity, ambition, and scope of their plans. The action plans provided concrete evidence of faculty decision-making and linked survey responses to actual behavioral intentions, offering a comprehensive view of how theoretical ideas were translated into practical applications.

We conducted semi-structured interviews with six participants to explore their experiences with the MMM framework constructs. See **Appendix B** – Survey & Interview Questions. We recruited these participants through a question in the post-survey asking whether they would be willing to participate in a 30-minute interview. There were no other selection criteria besides having participated in the book club; thus, this was purposive sampling. These members represented the following academic programs: marketing and management, biology, human resource development, communications, and TESOL (Teaching English to Speakers of Other Languages; $n = 2$). We began by collecting their initial attitudes and beliefs about AI in higher education, focusing on views regarding AI's role in student learning and its applications in teaching, research, and professional practice. Then, we explored cognitive-behavioral outcomes by asking participants to describe specific changes they planned to make in their teaching, research, and other professional duties as a result of the book club experience. Finally, we evaluated feedback mechanisms by identifying anticipated implementation barriers, possible solutions, and additional support or resources participants needed to feel confident in AI integration.

Analytical Strategy for Testing Theoretical Relationships

Our data included both quantitative and qualitative sources, requiring different analytical strategies. Additionally, results were combined to triangulate the MMM's theoretical concepts, verifying whether different data sources showed consistent evidence of how MMM components function and identifying patterns that might suggest areas for theoretical refinement. SPSS statistical software was used to analyze the quantitative data. For qualitative data, framework analysis was employed, using the MMM's components as the initial coding structure, to examine whether the decision-making processes proposed by the framework appeared in faculty descriptions of their GenAI integration experiences. To ensure the integrity and accuracy of qualitative findings, multiple verification strategies were implemented throughout the analytical process.

Ensuring trustworthiness of qualitative data

Several strategies were employed to enhance the trustworthiness of the qualitative findings, with an emphasis on credibility, confirmability, and methodological rigor throughout the analysis. The approach combined a structured framework with multiple verification methods to reduce researcher bias and ensure accurate interpretation of faculty experiences.

Framework-guided coding for theoretical consistency

The MMM framework served as the analytical guide, with survey responses, interview transcripts, and action plans systematically reviewed for evidence of the identified theoretical constructs. This deductive approach ensured theoretical consistency while allowing inductive insights to surface from participant responses. The lead author initially conducted coding by pinpointing specific instances where participant language matched MMM components, and detailed analytical memos were created to document the reasoning behind each coding decision.

Multiple verification strategies for improved credibility

Multiple verification methods were employed to enhance interpretive accuracy and address potential blind spots in individual researchers' interpretations. After initial coding, Claude.ai served as an independent analytical tool to review the same data sources using identical MMM framework criteria. This technological check provided an external validation of pattern recognition and helped uncover instances of theoretical constructs that might have been missed or misinterpreted during manual coding. Human and AI-assisted coding results were then systematically compared, with discrepancies resolved through careful reexamination of the original data and the alignment of the theoretical framework.

Collaborative review for confirmability

A co-author verification process was implemented to ensure that findings were based on participant data rather than individual researcher assumptions. After integrating insights from multiple coding approaches, all analytical notes, coding decisions, and initial interpretations were independently checked by the second author. This collaborative review involved examining the evidence supporting each identification of a theoretical construct, questioning interpretive assumptions, and proposing alternative explanations where participant responses might suggest different conclusions. The second author provided detailed feedback on both specific coding decisions and broader pattern interpretations, creating an audit trail that documented how conclusions developed through collaborative analysis.

Iterative refinement and accuracy verification

After collaborative review, analytical interpretations were refined based on feedback from the second author, and comprehensive results were documented to reflect the systematic analytical process. A final accuracy check of the written results was performed by the second author to ensure that reported findings accurately represented both the original participant data and the collaborative analysis conclusions. This iterative process established multiple checkpoints for identifying and correcting potential misinterpretations, thereby enhancing the overall reliability of the qualitative findings.

FINDINGS

Faculty responses to the AI Book Club provide strong evidence that understanding technology adoption requires the theoretical integration we proposed in our literature review. Rather than following a straightforward linear process from training to adoption, as single-theory frameworks suggest, faculty experiences revealed complex message processing. Our findings indicate that the MMM's integration of communication theory, behavioral prediction theory, and motivational psychology exposed the mechanisms behind faculty GenAI adoption decisions. These mechanisms would have remained hidden if we had relied solely on one theoretical approach.

Baseline Use of GenAI and Cognitive-Affective Filters

Of the 30 faculty who consented to participate in our study, some had experimented with GenAI. They used it for teaching (N = 21, 70%), research-related activities (N = 13, 43%), and other professional duties (N = 9, 30%). Pre-survey quantitative data (N = 30) revealed that participants had moderate levels of perceived efficacy (M = 3.98, SD = .72) and perceived value (M = 3.97, SD = .86), indicating neither strong confidence nor deep skepticism about GenAI integration initially. This moderate baseline created ideal conditions to observe theoretical processes, as faculty had room to shift in either direction.

Program Evaluations

Post-survey, quantitative data indicated that the faculty appreciated the book club series, showing that it effectively addressed their concerns about AI in higher education (M = 4.00, SD = 1.12) and that they would recommend the series to colleagues (M = 4.35, SD = 1.10). The rating regarding the content presentation methodology as a match to their learning style and needs was moderate (M = 3.90, SD = 1.32), suggesting opportunities for ongoing improvement.

Qualitative Findings Supporting Theoretical Predictions

Our qualitative findings support MMM's integrated approach to predicting faculty responses. Our framework predicted that faculty would cluster into four distinct behavioral outcome patterns based on the interaction between efficacy and value perceptions. Language supporting *engaged adoption* was the most common cognitive-behavioral outcome, with faculty demonstrating detailed strategic thinking and comprehensive implementation plans that reflected higher behavioral control and value recognition. The distribution of other outcomes, including *impassive acceptance*, *discouraged hesitation*, and *aversive rejection*, closely matched theoretical expectations. More importantly, the complexity of each outcome pattern confirmed our argument that understanding faculty technology adoption requires integrated theoretical models.

Faculty responses demonstrating *engaged adoption* combined high perceived value with strong efficacy, precisely as the MMM predicts. These faculty members developed the most advanced and innovative implementation strategies, providing strong evidence of the theoretical framework's validity. One faculty member's research action plan exemplifies *engaged* adoption through its detailed, twelve-month timeline, which includes specific AI integration phases, distinct applications for different research stages, and sophisticated quality control mechanisms. The plan's complexity and ambition reflect the high value perception and strong efficacy that the MMM identifies as *engaged adoption*.

The presence of all four predicted outcome types, even in our relatively small sample, provides strong support for the MMM's theoretical validity. Impassive acceptance, which combines high efficacy with low value, was less common but appeared in faculty who showed technical competence yet still had doubts about GenAI's educational value. Discouraged hesitation, which combines low efficacy with high value, was observed among faculty members who recognized GenAI's importance but felt uncertain about their ability to implement it. Aversive rejection, characterized by low efficacy and low value, was the least frequent and primarily occurred among faculty members concerned about AI replacing human judgment.

Faculty Transformation Requiring Multi-Theoretical Explanations

Faculty members' psychological shifts revealed interconnected processes that required our integrated MMM for full understanding. Initially, faculty members approached GenAI integration with skepticism, based on concerns about academic integrity and professional identity. The pre-survey open-ended data showed anxiety about "being caught using AI," "falling behind," and feeling "unprepared." These responses reflected a low locus of control and self-efficacy, as predicted by behavioral prediction theory, as well as uncertainty about the technology's value, consistent with motivational psychology. The transformation resulting from our intervention demonstrates how combining theoretical frameworks enhances the understanding of faculty technology adoption. Faculty eventually described AI using collaborative language, such as "second brain," "thinking partner," and "complementary tool." Post-survey responses and interviews revealed shifts from external attribution language, such as "being overtaken" and "replaced by AI," to internal attribution patterns, including "I will implement," "I plan to control," and "I intend to integrate." This change showed concurrent shifts in both perceived efficacy and value.

Theoretical Mechanisms Working in Concert

The book club intervention delivered three types of external stimuli designed to influence faculty message processing. Our findings indicate that these stimuli combined to promote the desired cognitive-behavioral outcome of engaged adoption. These findings support our argument that faculty adoption of GenAI requires an integrated theoretical approach and explanation, especially one that addresses the complex aspects of behavioral decisions.

Personal experiences

Personal experiences with GenAI tools during hands-on practice sessions created meaningful encounters recognized by communication theory as influential message sources, while also activating the core value recognition processes in motivational psychology. Faculty consistently described specific hands-on interactions with AI tools as transformative, and their responses demonstrated dual processing by citing both the efficacy of behavioral prediction theory and the utility assessments from motivational psychology. One faculty member's comment illustrates this integration when she explained how asking Claude to create test questions for English language learners provided credible evidence of AI capabilities through communication theory's personal experience pathway, while also demonstrating clear utility value through motivational psychology's utility assessment that "changed everything" about her view of AI. Single-theory frameworks would overlook how these processes reinforce each other.

Vicarious experiences

Vicarious experiences through facilitator demonstrations and peer sharing activate social learning mechanisms that support both communication and behavior theories, while also prompting value assessments central to motivational psychology. Faculty consistently responded positively to colleagues' implementations and valued opportunities for interdisciplinary sharing. However, their responses showed complex processing as they simultaneously evaluated message credibility, assessed the feasibility of implementation, and weighed potential benefits against costs. As one interviewee stated:

> *The best learning is when we share ideas,*

but our analysis revealed that this "learning" involved multiple theoretical processes working together to influence adoption intentions.

Verbal persuasion

Verbal persuasion conveyed through carefully chosen readings and guided discussions, appeared to influence perceived self-efficacy, as predicted by behavioral prediction theory, and value, as understood from motivational psychology, ultimately shaping behavioral intentions. Faculty discussed the research-supported arguments in the book about AI's impact on the workforce, with many citing the statement "AI will eliminate some jobs, but it is going to change every job" as a key point. However, their explanations demonstrated that this statement operated through multiple theoretical pathways by providing credible threats and opportunities framing from communication theory, modifying perceived efficacy by positioning faculty as capable agents of change rather than passive recipients, as predicted by behavioral prediction theory, and reframing AI adoption as professionally valuable rather than optional, in line with motivational psychology.

Message Processing Mediators Revealing Hidden Complexity

Our integrated approach demonstrates that faculty technology adoption involves multiple psychological processes co-occurring. Our findings explain why multi-theoretical models, such as the MMM, provide a better understanding of faculty reactions to GenAI adoption by showing how different psychological factors interact. Initially, faculty used language associated with a low sense of control from behavioral prediction theory, such as "being caught using AI" and "feeling left behind by rapid technological change." However, our integrated framework revealed that faculty viewed AI information as a threat and believed they could not effectively manage AI integration, which relates to the cognitive-behavioral outcome of aversive rejection. Responses from surveys and interviews indicated a shift toward language linked to engaged adoption, such as "I plan to," "I will implement," and "I intend to integrate." Action plans revealed that these changes involved reinterpretation of messages and improved perceptions of behavioral control. Single-theory frameworks would not have captured the complexity of these outcomes as effectively as the MMM.

Our theoretical framework predicted that perceived value would develop through targeted messages from communication theory and value assessment from motivational psychology. Faculty shifted from uncertainty about AI's relevance to a more nuanced evaluation of its utility and costs. However, this development involved shifts in perceived value about AI from motivational psychology. Many initial responses showed mixed understandings of GenAI's value and generally lower efficacy levels, linked to aversive rejection (low value and low efficacy) and discouraged hesitation (high value and low efficacy) behavioral outcomes. In contrast, post-survey answers indicated improved value assessments and increased efficacy, with faculty discussing when AI is most useful and how to maximize its benefits. Relying on a single theory would miss how these processes mutually reinforce each other.

Perceived efficacy evolved through mechanisms influenced by communication theory and reflects shifts related to behavioral prediction theory and motivational psychology, supporting our argument that faculty technology adoption requires comprehensive theoretical integration. Pre-survey responses revealed significant concerns about competence, indicating perceptions linked to aversive rejection, characterized by low efficacy and low value. Post-survey responses and implementation plans showed increased confidence in and appreciation for specific AI applications, illustrating the cognitive-behavioral outcome of engaged adoption. Teaching action plans that exhibited strong efficacy growth included ambitious strategies requiring confidence across all theoretical domains. These represent comprehensive psychological changes that our integrated framework predicted and explained.

Goal Orientation: An Intriguing Pattern for Future Investigation

Our analysis uncovered an interesting pattern regarding faculty goal orientations that emerged during the coding process. When examining open-ended survey responses, action plans, and interview transcripts, we observed that faculty members generally exhibited either intrinsic or extrinsic goal orientations, which influenced their responses to messages about GenAI integration.

Faculty who are intrinsically motivated tend to focus on pedagogical innovation and professional growth, whereas those who are extrinsically motivated emphasize problem-solving and meeting external expectations. These different orientations led to various implementation strategies, even among faculty with similar perceptions of efficacy and value. Faculty with intrinsic orientations developed action plans that centered on exploring new pedagogical possibilities and improving student learning experiences. In contrast, faculty with extrinsic orientations devised plans focused on efficiency improvements and addressing institutional priorities. For example, one intrinsically motivated faculty member designed an elaborate "AI writing tutor" system to help students develop critical thinking skills. Meanwhile, an extrinsically motivated colleague concentrated on using AI to streamline grading and administrative tasks.

This empirical finding suggests that goal orientation may serve as an additional cognitive-affective filter in the processing of messages. However, our single study cannot confirm this as a validated theoretical component. The pattern was consistent enough across our data to indicate that future research should systematically investigate whether goal orientation affects technology adoption decisions across different contexts, technologies, and faculty groups. If further research supports this, goal orientation could enhance the MMM's explanatory power by providing more detailed predictions about how faculty with similar perceptions of efficacy and value might employ different implementation strategies based on their motivational orientations.

DISCUSSION

Our findings strongly suggest that faculty technology adoption is influenced by the theoretical innovations introduced in our literature review. The MMM demonstrates its effectiveness by showing how strategic adaptation and the integration of established theories can address the complex realities of faculty decision-making in ways that single-theory approaches often overlook. This discussion examines how our theoretical contributions fill the four key gaps we identified—fragmented focus (Lu et al., 2019), context insensitivity (Sadeck, 2022), limited process understanding (Shachak et al., 2019), and intervention design limitations (Xue et al., 2024)—and what these insights mean for theory development and practical use.

Theoretical Innovation Through Strategic Framework Integration

The MMM addresses the four main limitations identified in our literature review through innovative theoretical development rather than just applying existing models. First, to address the fragmented focus issue where theories fail to integrate multiple aspects of decision-making (Lu et al., 2019), we developed a comprehensive framework that links external stimuli, message processing mediators, and behavioral outcomes within a unified system. Instead of examining isolated factors like technology acceptance or self-efficacy alone, the MMM demonstrates how personal experiences, vicarious learning, and verbal persuasion interact through perceived efficacy and value to produce consistent behavioral responses.

Second, our framework addresses context insensitivity by recognizing that academic settings have unique characteristics not captured by organizational or consumer adoption models (Sadeck, 2022). Our strategic replacement of response efficacy with locus of control reflects this academic context specificity, building on Rotter's (1966) foundational work while addressing gaps in Witte's (1992, 1994) EPPM. Faculty technology adoption involves deeper concerns about maintaining professional autonomy and pedagogical control than simply believing suggested responses will work, as Lamrabet et al. (2025) demonstrated in their research on faculty perceptions of control over technology integration. Our empirical findings support this reasoning by showing faculty transformation involved simultaneous changes in both locus of control and self-efficacy, with faculty expressing anxiety about "being caught using AI" and "feeling left behind"—language reflecting professional agency concerns rather than technology functionality, aligning with Belt and Lowenthal's (2020) observation that faculty prefer colleague learning over external mandates.

Third, to address limited process understanding where existing theories view adoption as binary outcomes rather than dynamic processes (Shachak et al., 2019), we incorporated feedback mechanisms from Fishbein and Yzer's (2003) Integrative Model of Behavior Prediction. Our framework recognizes that faculty responses evolve through ongoing interactions with rewards, barriers, and facilitators, rather than through isolated message-processing events. Previous educational technology studies by Kreijns et al. (2013) and Wang et al. (2019) demonstrated the IMBP's effectiveness in understanding how environmental factors influence the shift from intentions to behaviors in institutional settings, supporting our process-oriented approach.

Finally, regarding intervention design limitations where frameworks provide inadequate guidance for creating effective interventions (Xue et al., 2024), the MMM's integration of expectancy-value theory addresses the motivational complexity that neither communication nor behavioral prediction models alone can capture. Building on the foundational work of Eccles and Wigfield (2002) and the educational applications by Boström and Palm (2020) and Wang and Xue (2022), our framework provides specific guidance for intervention design by highlighting how external stimuli should be crafted to influence perceived efficacy and value simultaneously. Faculty described sophisticated value calculations involving utility benefits, implementation costs, and professional identity considerations—an approach our comprehensive assessment framework can systematically address in professional development, enabling faculty to move from uncertainty about GenAI's relevance to nuanced evaluations of when and how to maximize benefits while managing costs and maintaining professional integrity.

Empirical Validation of Integrated Theoretical Innovation

Our MMM-guided intervention proved effective, comparable to other theory-based professional development methods, while offering additional advantages through comprehensive theoretical integration. Similar to Lee et al.'s (2022) AI book club, which combines cognitive load theory, communities of practice, and design justice principles, and Nazaretsky et al.'s (2022) trust-focused intervention that integrates trust theory, cognitive bias research, and decision-making studies, our approach achieved positive outcomes through systematic application of theory rather than the atheoretical practical experience that Mercader and Gairín (2020) describe as common in many faculty development efforts.

Our data offers initial evidence that the MMM framework effectively explains faculty responses to GenAI faculty development. Two key findings support our theoretical design choices. First, we observed the predicted interaction effects between perceived efficacy and value that confirm our combined approach. Faculty with similar efficacy and value ratings consistently demonstrated similar cognitive-behavioral outcomes, suggesting that responses result from the interplay of multiple mediators rather than individual psychological factors. For example, faculty with high technological efficacy but low perceived value for GenAI in their teaching contexts exhibited passive acceptance behaviors. They made statements like "I could use it, but I don't see why I would change what already works," which indicates that high confidence alone was insufficient to promote meaningful integration without aligned value perceptions. This interaction effect validates our belief that behavioral outcomes depend on the concurrent consideration of multiple psychological factors as mediators.

Second, our framework identified and measured the four distinct cognitive-behavioral outcomes we theorized would result from different efficacy-value combinations. Survey data confirmed engaged adoption among faculty who developed both high efficacy and high value perceptions, discouraged hesitation among those with high value but low efficacy beliefs, passive acceptance among faculty with high efficacy but low value, and aversive rejection among those with both low efficacy and low value. These survey-measured patterns consistently aligned with faculty action plans, validating our theoretical predictions. Engaged adopters proposed specific implementation strategies, discouraged faculty requested additional support resources, passive faculty suggested minimal changes, and aversive faculty avoided GenAI-related modifications entirely. Crucially, faculty consistently described the combination of personal experiences, peer demonstrations, and authoritative readings as essential, with no single stimulus being sufficient for meaningful adoption. This finding provides evidence that successful faculty development requires comprehensive, multi-domain theoretical approaches that address the full spectrum of psychological factors influencing adoption outcomes.

Goal Orientation Discovery Supporting Theoretical Innovation

Our analysis revealed goal orientation patterns that emerged because our integrated framework could track complex psychological interactions that single-theory approaches would miss, extending motivational psychology applications that Eccles (2005) and Wigfield and Eccles (2020) developed in other educational contexts. Faculty exhibited either intrinsic or extrinsic motivational orientations that influenced how they processed messages about GenAI integration, formed behavioral intentions, and assessed technology value in systematically different ways, even among faculty with similar perceptions of efficacy and value.

This empirical discovery supports our argument from the literature review that faculty technology adoption involves psychological complexities, requiring integrated theoretical approaches rather than the fragmented, single-theory applications that Kimmons et al. (2020) criticized as “anarchic.” Understanding how goal orientation influences faculty responses required our comprehensive framework to analyze its effects across communication, behavioral, and motivational processes simultaneously. While our single study cannot establish goal orientation as a validated theoretical component, this pattern warrants systematic investigation to determine whether it consistently functions as an additional mediating factor in faculty technology adoption.

Implications for Institutional Support and Institutional Strategy

Our findings provide educational leaders and faculty development professionals with guidance on supporting technology adoption through evidence-based approaches. Understanding how the MMM framework functions in practice allows institutions to move beyond traditional training methods toward comprehensive strategies that address the psychological complexity of faculty decision-making.

Technology infrastructure and policy development

Institutions should provide access to technology while recognizing that resources alone only remove environmental barriers and do not influence the message processing, behavioral prediction, or motivational assessment that ultimately determine adoption outcomes. As Polly et al. (2021) demonstrated, simply providing access to technology is not enough for meaningful adoption. Instead, institutions should develop clear policies that serve multiple theoretical functions simultaneously: offering behavioral guidance that influences faculty perceptions of control, providing trustworthy sources of information that shape message interpretation, and establishing frameworks that help faculty recognize the value of technology. These policies should explicitly address the cognitive-affective filters our framework identifies as key to adoption decisions, building on Belt and Lowenthal's (2020) findings that faculty development requires systematic rather than ad hoc approaches.

Comprehensive faculty development design

Professional development programs should incorporate all three external stimulus types identified by our framework as essential for altering faculty perceptions. These programs must offer meaningful personal experiences through hands-on practice, create opportunities for vicarious learning via peer demonstrations and interdisciplinary sharing, and provide credible verbal persuasion through carefully selected readings and expert guidance. Our findings show that faculty consistently require multiple stimulus types working together, as no single approach alone is sufficient for engaged adoption. This combined strategy addresses both perceived efficacy and perceived value simultaneously, establishing the psychological conditions necessary for behavior change.

Sustainable community building and long-term support

Long-term integration requires comprehensive sustainability strategies that address all relevant psychological mechanisms working together, extending the community-building approaches demonstrated by Lee et al. (2022) in their AI book club model. Institutions should create opportunities for faculty to showcase successful implementations, providing ongoing vicarious experiences that reinforce perceptions of value while building collective efficacy across disciplines. Follow-up workshops and continuing education opportunities would maintain faculty's exposure to new developments, enabling them to develop advanced skills and more nuanced value assessments. These ongoing touchpoints ensure that the psychological transformations achieved through initial professional development continue to evolve rather than diminish over time, supporting the dynamic feedback mechanisms that our framework identifies as crucial for sustained adoption.

Limitations and Future Research

Our study offers insights into faculty technology adoption through the MMM framework, but several limitations highlight key areas for future research. Most notably, our findings are based on faculty experiences at a single public Midwest university, which restricts the generalizability of the results to different institutional settings, regions, and organizational cultures. While the theoretical foundations of the MMM framework are rooted in established psychological theories that should generally apply, the specific ways external stimuli, feedback mechanisms, and cognitive-behavioral outcomes appear may differ across diverse institutional environments with varying levels of technology support, professional development resources, and cultures of innovation. Additionally, our focus on implementation intentions rather than actual classroom practices limits our ability to determine whether the psychological changes observed translate into lasting behavioral changes over time. Our self-selected participant sample from a single institution may have introduced bias toward faculty with positive initial attitudes, potentially making our test of the MMM's theoretical integration conservative rather than fully representative of the range of faculty responses to GenAI adoption initiatives.

Future research should examine MMM applications in different types of institutions, regions, and cultural contexts to validate the framework broadly and identify necessary adaptations. Long-term studies should investigate how message processing, behavioral prediction, and motivation evolve in response to ongoing technology use, thereby aiding in understanding sustained adoption over time. Research should also incorporate comparison groups with varying initial perceptions and institutional backgrounds to assess how the MMM framework performs across different faculty populations and environments.

Despite the limitations, our findings demonstrate that the MMM's combination of communication theory, behavioral prediction, and motivational psychology offers clear advantages over single-theory approaches to understanding faculty technology adoption. The framework addresses important theoretical gaps while providing practical guidance for designing comprehensive professional development programs that consider the full complexity of faculty decision-making processes.

CONCLUSION

This study demonstrates that the Mediated Message Model effectively addresses key limitations in faculty technology adoption research by uncovering psychological complexities often overlooked by single-theory frameworks. Our integrated approach identified four distinct behavioral response patterns—engaged adoption, discouraged hesitation, impassive acceptance, and aversive rejection—that arise from specific combinations of perceived efficacy and value, rather than from individual psychological factors alone. These findings support our prediction that faculty technology adoption involves simultaneous processes across communication, behavioral, and motivational domains.

Our research indicates that successful educator training necessitates coordinated efforts across multiple theoretical domains. Faculty consistently reported the need for a mix of personal experiences, peer demonstrations, and authoritative readings, with no single stimulus being sufficient for meaningful adoption. This evidence supports our systematic approach of establishing value perceptions first, then developing skills while incorporating diverse external stimuli to influence psychological mediators. Additionally, our analysis identified goal orientation patterns indicating that intrinsic versus extrinsic motivational tendencies influence how faculty interpret AI integration messages and form implementation intentions, suggesting further investigation into this as a potential mediating factor.

The MMM provides faculty development leaders with specific, theory-based strategies that address the full complexity of technology adoption. Leaders can develop interventions that blend hands-on experience for credible personal learning, peer demonstrations for social learning and modeling, and well-structured readings that highlight opportunities while simultaneously enhancing efficacy and perceived value. This comprehensive approach offers clear guidance for designing professional development that extends beyond traditional training to foster engaged adoption. As GenAI continues to reshape academic work, institutions need strategies grounded in theory that view faculty technology adoption as a complex psychological process requiring an integrated understanding rather than isolated interventions targeting separate factors. The MMM framework advances both theoretical insight and practical implementation by showing how communication theory, behavioral prediction, and motivational psychology can be systematically combined to support meaningful faculty development in an era of rapid technological change.

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APPENDIX A

Book club outline and description

Book club design as faculty-teaching-faculty professional development

- Five core sessions (75–90 minutes each) plus showcase session
- “Teaching with AI” (Bowen & Watson) as the core text
- Supplementary resources aligned with the MMM components

Multi-modal implementation aligned with MMM components

***Diverse tool selection to address various faculty needs*:**

- Large language models: Claude, ChatGPT, Gemini, Microsoft Copilot
- Research-focused tools: Elicit, SciSpace, Consensus
- Creative tools: Canva AI image generator

Balanced approach to content and practice

- Theoretical discussions based on readings
- Practical demonstrations with real-time tool use
- Structured hands-on activities
- Faculty-led exploration within disciplinary contexts

Implementation phases with specific activities

Session 1: GenAI for teaching, research, and professional practice

- Introduction to GenAI definitions and key concepts
- Exploration of GenAI’s potential in higher education contexts
- Discussion of K-12 GenAI literacy frameworks as models
- Hands-on practice with basic GenAI prompts

Session 2: Thinking with GenAI

- Prompt engineering fundamentals with TFVC framework
- Iteration and refinement of prompts
- Techniques for managing GenAI responses
- Practice creating discipline-specific prompts

Session 3: GenAI as a personal assistant

- Research question generation and exploration
- Use of specialized research tools (Elicit, SciSpace, Consensus)
- Creating outlines and presentation materials
- Integration of visual elements with Canva AI

Session 4: GenAI as a teaching assistant

- Student interaction simulations
- Creating discussion questions and rubrics
- Assignment design and customization
- Course improvement strategies
- GenAI writing tutor implementation

Session 5: Learning with GenAI

- Academic integrity considerations
- Assignment redesign for the GenAI era
- Action plan development guidance

Showcase session: Implementation and community building

- Faculty presentations of implementation plans
- Peer feedback and idea exchange
- Recognition of innovative approaches
- Establishment of an ongoing community of practice

APPENDIX B

Survey & interview questions

Pre-Survey

Quantitative Scales

Participants rated their agreement with the following statements on a scale of 0 (Strongly Disagree) to 5 (Strongly Agree):

Perceived Efficacy

1. I am confident that I can master new educational technologies, even if they initially seem complex or unfamiliar.
2. I have the skills necessary to incorporate AI tools into my course design and instruction effectively.
3. When faced with technical difficulties using AI tools, I am confident in my ability to troubleshoot and find solutions.
4. The effectiveness of AI tools in my teaching depends primarily on how well I learn to use them rather than on the tools themselves.

Perceived Value.

1. I value the potential for AI tools to meaningfully improve the quality of my instruction and course delivery.
2. The time savings I could gain from using AI tools in my research and professional work would be highly valuable to me.
3. I see great value in using AI tools to enhance the quality and timeliness of feedback I provide to students.
4. The potential benefits of learning to use AI tools outweigh the time and effort required to develop these skills.

Open-Ended Items

1. What are your main concerns about using AI in your teaching, research, or professional duties?
2. What tasks or challenges do you hope AI could help with in your work?
3. What would motivate you to integrate AI into your teaching, research, and professional practice?

Postsurvey

Quantitative Scale

Participants rated their agreement with the following statements on a scale of 0 (Strongly Disagree) to 5 (Strongly Agree):

Workshop Evaluation.

1. The workshop effectively addressed my concerns about AI in higher education.
2. The content was presented in a way that matched my learning style and needs.
3. I recommend this professional development series to colleagues.

Open-Ended Items

1. What specific changes, if any, do you plan to make in your professional practice as a result of this faculty development series?
2. What barriers do you anticipate in implementing AI in your teaching, and how might you overcome them?
3. What additional support or resources would help you feel more confident about using AI in education?
4. Any additional comments on how the professional development series influenced your perspective on AI in higher education?

Interview Questions

1. What were your initial attitudes and beliefs on AI in higher education?
   a. Please comment first on its role in supporting student learning.
   b. Next, please comment on using it for teaching, research, and professional practice.
2. What changes do you plan to make in your teaching due to the AI Book Club?
3. What changes do you plan to make in your research due to the AI Book Club?
4. What specific changes do you plan to make in any of your other professional duties because of the AI Book Club?
5. What barriers do you anticipate in implementing AI in your teaching, research, or other professional duties, and how might you overcome them?
6. What additional support or resources would help you feel more confident about using AI? What barriers do you anticipate in implementing AI in your teaching, and how might you overcome them?