

# Generative AI Adoption in Indian Commerce Education: A Systematic Review of Faculty Acceptance Determinants Using the Unified Theory of Acceptance and Use of Technology (UTAUT) Framework

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## Abstract

The integration of Generative Artificial Intelligence (GenAI) into higher education curricula has emerged as a critical imperative under India's National Education Policy (NEP) 2020. However, the pace and depth of adoption vary significantly across disciplines, with commerce education representing a unique context where pedagogical traditions intersect with rapidly evolving technological landscapes. This study employs a systematic literature review methodology grounded in secondary data to examine the determinants of faculty acceptance of GenAI tools in Indian commerce education. Drawing upon the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM), this paper synthesizes findings from 28 peer-reviewed studies, policy documents, and industry reports published between 2020 and 2026. The analysis reveals that Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) constitute the primary determinants of faculty behavioral intention, while Facilitating Conditions (FC) and AI Literacy emerge as critical moderating variables. Notably, the study identifies a significant 'policy-practice gap' in Indian commerce colleges, where 87% of faculty acknowledge AI's potential yet only 28% report institutional AI literacy programs. The findings contribute to the theoretical discourse on technology acceptance in emerging economies and offer actionable insights for institutional policymakers, curriculum designers, and EdTech stakeholders seeking to foster sustainable GenAI integration in commerce education.

**Keywords:** *Generative AI, Commerce Education, Faculty Acceptance, UTAUT, TAM, NEP 2020, Indian Higher Education, Secondary Data, Systematic Literature Review*

## 1. Introduction

The global higher education landscape is undergoing a paradigm shift catalyzed by the proliferation of Generative Artificial Intelligence (GenAI) tools such as ChatGPT, Gemini, Claude, and domain-specific platforms. In India, this transformation is uniquely positioned at the intersection of the world's largest higher education system—comprising 1,338 universities and 70,018 Higher Education Institutions (HEIs) as of June 2025—and the ambitious vision of the National Education Policy (NEP) 2020, which mandates the integration of digital and AI-based tools across all educational levels (AISHE, 2025). The policy explicitly emphasizes equipping students with digital literacy, coding, and computational thinking skills, while simultaneously requiring faculty to adapt pedagogical approaches to harness emerging technologies (Ministry of Education, 2020).

Within this national imperative, commerce education occupies a distinctive and strategically significant position. As a discipline that bridges theoretical economic frameworks with applied business practices, commerce education in India

serves approximately 3.5 million undergraduate and postgraduate students annually, forming the backbone of the country's managerial and entrepreneurial workforce (AISHE, 2024). The discipline's inherent reliance on data analysis, financial modeling, market research, and report generation makes it particularly amenable to GenAI augmentation. Tools such as ChatGPT can assist in generating case study analyses, automating routine accounting explanations, personalizing learning pathways for taxation and corporate law modules, and simulating market scenarios for entrepreneurship education (Xu & Babaian, 2021; Lee, 2025).

Despite the apparent synergies between GenAI capabilities and commerce pedagogy, empirical evidence suggests a complex and often contradictory pattern of faculty acceptance. A 2026 global survey by the Digital Education Council revealed that faculty intent to use AI declined by 9 percentage points—from 76% in 2025 to 67% in 2026—indicating growing apprehension even as tools become more sophisticated (Digital Education Council, 2026). In the Indian context, while 87% of students and educators view AI positively—the highest enthusiasm rate globally—only 27% of educators feel confident identifying AI-generated content, and merely 25% believe they possess the skills needed to use AI effectively (Coursera, 2026; eCampus News, 2026). This dissonance between positive disposition and operational readiness constitutes the central problematique of this study.

Furthermore, the commerce education sub-sector in India exhibits structural peculiarities that differentiate it from engineering or medical education. Commerce colleges—particularly affiliated colleges under state universities—often operate with limited digital infrastructure, constrained professional development budgets, and faculty who have spent decades in traditional chalk-and-talk pedagogical modes. The transition to AI-integrated teaching is not merely a technological upgrade but a fundamental epistemological shift that challenges established notions of academic integrity, assessment validity, and the teacher's role as the primary knowledge authority (Mao et al., 2024; Portuguese-Castro & Castillo-Martinez, 2026).

Against this backdrop, the present study addresses the following research questions through a systematic review of secondary data:

1. RQ1: What are the primary determinants influencing faculty acceptance of Generative AI in Indian commerce higher education, as identified through existing empirical studies and policy analyses?
2. RQ2: How do the constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) explain variance in faculty behavioral intention toward GenAI adoption in the Indian commerce education context?
3. RQ3: What institutional, disciplinary, and demographic moderators shape the relationship between technology acceptance determinants and actual GenAI usage among commerce faculty in India?
4. RQ4: What policy-practice gaps exist between NEP 2020's AI integration mandates and the ground-level realities of commerce college faculty in India?

The significance of this study is threefold. Theoretically, it extends the UTAUT and TAM frameworks to the underexplored domain of GenAI adoption in emerging economy higher education, specifically within the commerce discipline. Practically, it provides evidence-based recommendations for institutional leaders, AI solution designers, and policymakers seeking to bridge the acceptance-intention-usage gap. Methodologically, it demonstrates the viability and rigor of secondary data synthesis as a standalone research approach for UGC CARE list publication, adhering to PRISMA guidelines for systematic reviews (Page et al., 2021).

## 2. Literature Review

### 2.1 GenAI in Higher Education: Global Trajectory and Indian Specificities

The integration of artificial intelligence in education (AIEd) has evolved from early intelligent tutoring systems and adaptive learning platforms to the current era of large language model-based generative tools. A comprehensive systematic review by Wang et al. (2024) analyzed 252 studies and identified five dominant application clusters: (a) personalized learning and feedback, (b) automated assessment and grading, (c) intelligent tutoring and query resolution, (d) curriculum content generation, and (e) administrative decision support. Within these clusters, GenAI tools—particularly ChatGPT—have demonstrated transformative potential in reducing faculty workload, enhancing student engagement, and enabling scale-independent personalization (Holmes & Tuomi, 2022; Chen et al., 2020).

In India, the GenAI adoption narrative is characterized by what EY India (2025) terms "enthusiastic asymmetry"—high student demand coupled with cautious institutional response. The Coursera Global Skills Report 2026 notes that Indian institutions are pioneering AI-driven course creation, with over 58% of Coursera's Course Builder usage originating from Indian partners, yet only 20% of Indian universities have formal AI governance policies (Coursera, 2026). This asymmetry is particularly pronounced in commerce education, where the discipline's traditional emphasis on manual calculation, statutory compliance, and standardized examination formats creates institutional inertia against AI-mediated pedagogical innovation (Madegowda, 2025).

The National Education Policy 2020 provides the macro-level policy architecture for AI integration, mandating digital literacy across all educational tiers and envisioning a "multidisciplinary and holistic" higher education system responsive to Industry 4.0 requirements (Ministry of Education, 2020). However, the policy's implementation at the micro-level—particularly in affiliated commerce colleges governed by state universities—remains uneven. The All India Survey on Higher Education (AISHE) 2023-24 data indicates that while 64% of central universities report AI-related initiatives, only 18% of affiliated colleges have comparable programs, highlighting a structural digital divide (AISHE, 2024).

## 2.2 Faculty Acceptance: The Critical Bottleneck in Technology Diffusion

Faculty acceptance represents the most consequential yet underexamined variable in educational technology diffusion. Unlike student adoption, which is often driven by convenience and peer influence, faculty acceptance is mediated by complex professional identities, tenure pressures, assessment accountability, and epistemological commitments to disciplinary knowledge (Granic, 2023). A 2026 meta-analysis of TAM and UTAUT studies synthesizing 3,006 faculty participants across nine countries found that Perceived Usefulness (PU) exhibited the strongest effect on Behavioral Intention ( $r = 0.26$ , 95% CI [0.20, 0.33]), followed by Social Influence ( $r = 0.26$ , 95% CI [0.14, 0.37]) and Perceived Ease of Use ( $r = 0.17$ , 95% CI [0.05, 0.29]) (Sciedu Press, 2026).

In the Indian context, Kavitha and Joshith (2025) surveyed 400 university educators across disciplines and found that while 78% expressed willingness to adopt AI tools, only 34% had actually integrated them into teaching practice. The study identified institutional support—or the lack thereof—as the primary barrier, with faculty in affiliated colleges reporting significantly lower facilitating conditions compared to those in autonomous institutions or central universities. This finding aligns with the broader global pattern where facilitating conditions demonstrate inconsistent effects across studies, likely reflecting cross-institutional variance in infrastructure, training, and policy clarity (Abubakar & Al-Mamary, 2025; Hassan et al., 2020).

For commerce faculty specifically, the acceptance calculus involves additional discipline-specific considerations. The risk of AI-generated content undermining assessment validity is particularly acute in commerce education, where case-study analyses, financial statement interpretations, and tax computation exercises—traditionally used to evaluate higher-order thinking—can now be partially automated by GenAI tools (Mao et al., 2024). Faculty concerns about academic integrity are substantiated by survey data indicating that 24% of students globally admit to submitting AI-generated work without disclosure, and 37% of educators worry that unregulated AI could undermine degree credibility (eCampus News, 2026). These integrity anxieties interact with acceptance determinants in ways not fully captured by standard TAM/UTAUT constructs, suggesting the need for extended models incorporating trust, risk perception, and academic integrity norms.

## 2.3 Commerce Education in India: Structural Context and Pedagogical Traditions

Commerce education in India operates through a dual-track system: university departments offering B.Com, M.Com, and doctoral programs, and affiliated colleges—often private or government-aided—serving as the primary delivery mechanism for undergraduate instruction. The University Grants Commission (UGC) regulates curriculum frameworks through the Choice-Based Credit System (CBCS), but individual universities retain significant autonomy in syllabus design and examination modalities. This decentralized governance creates heterogeneity in AI readiness, with elite institutions like Shri Ram College of Commerce (SRCC) and Loyola College integrating AI modules, while tier-2 and tier-3 colleges remain digitally under-resourced (NIRF, 2025).

The pedagogical tradition in Indian commerce education has historically emphasized rote learning, standardized examination formats, and teacher-centric knowledge transmission. The NEP 2020 explicitly critiques this "rigid

separation between arts and sciences, between curricular and extra-curricular activities, and between vocational and academic streams" (Ministry of Education, 2020, p. 5). GenAI adoption represents both an opportunity and a threat within this reform context: an opportunity to shift toward experiential, inquiry-based learning, and a threat to faculty who perceive their expertise and authority as being displaced by algorithmic content generation (Batat, 2024; de Souza Lessa et al., 2026).

### 3. Theoretical Framework

#### 3.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), provides the foundational theoretical architecture for understanding technology adoption behavior. TAM posits that an individual's Behavioral Intention (BI) to adopt a technology is determined by two primary cognitive beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU refers to the degree to which an individual believes that using a particular system would enhance their job performance, while PEOU captures the belief that using the system would be free of effort. These constructs, in turn, are influenced by external variables such as system design characteristics, training, and institutional support (Davis, 1989; Davis et al., 1989).

In the context of GenAI adoption by commerce faculty, PU manifests as beliefs about whether GenAI tools can improve teaching quality, reduce grading workload, generate relevant case studies, and enhance student comprehension of complex topics like GST compliance or financial derivatives. PEOU, conversely, reflects faculty assessments of the learning curve associated with prompt engineering, tool navigation, and integration into existing Learning Management Systems (LMS). The meta-analytic evidence from 2021-2025 faculty studies confirms that  $PU \rightarrow BI$  ( $r = 0.26$ ) and  $PEOU \rightarrow BI$  ( $r = 0.17$ ) relationships remain robust across diverse national and disciplinary contexts, though effect sizes are moderate rather than large, suggesting the influence of unmeasured moderators (Sciedu Press, 2026).

#### 3.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), integrates elements from eight prior technology acceptance models, including TAM, the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), and the Diffusion of Innovations Theory. UTAUT proposes four core determinants of Behavioral Intention and Use Behavior: (1) Performance Expectancy (PE)—the degree to which using the technology will provide benefits in performing certain activities; (2) Effort Expectancy (EE)—the degree of ease associated with the use of the technology; (3) Social Influence (SI)—the extent to which an individual perceives that important others believe they should use the new technology; and (4) Facilitating Conditions (FC)—the degree to which an individual believes that organizational and technical infrastructure exists to support system use (Venkatesh et al., 2003).

UTAUT further specifies four moderators—gender, age, experience, and voluntariness of use—that shape the strength of relationships between determinants and outcomes. In the higher education context, UTAUT has been extensively validated across mobile learning, e-learning platform adoption, and more recently, AI-based educational tool acceptance (Wang et al., 2021; Xu et al., 2024). For Indian commerce faculty, Performance Expectancy encompasses beliefs about GenAI's capacity to enhance student learning outcomes in subjects like accounting, taxation, and business law. Effort Expectancy captures the perceived complexity of mastering GenAI interfaces, particularly for faculty with limited prior digital tool experience. Social Influence reflects peer norms, departmental culture, and institutional leadership signals regarding AI adoption. Facilitating Conditions include access to reliable internet, AI tool subscriptions, training workshops, and technical support staff.

#### 3.3 Integrated Conceptual Model for This Study

Drawing upon both TAM and UTAUT, this study proposes an integrated conceptual model tailored to the GenAI-commerce education context. The model retains the core UTAUT constructs (PE, EE, SI, FC) while incorporating TAM's Attitude toward Using Technology (ATT) as a mediating variable between cognitive beliefs and Behavioral Intention (BI). Additionally, the model introduces three context-specific extensions: (a) AI Literacy as a moderator reflecting faculty's foundational understanding of AI capabilities and limitations; (b) Academic Integrity Concerns

(AIC) as a negative predictor capturing faculty anxiety about GenAI-enabled plagiarism and assessment fraud; and (c) Disciplinary Relevance (DR) as a positive predictor reflecting the perceived fit between GenAI functionalities and commerce pedagogy requirements.

The integrated model is formally specified through the following hypothesized relationships, derived from the secondary data synthesis:

5. H1: Performance Expectancy (PE) positively influences faculty Attitude (ATT) toward GenAI adoption in commerce education.
6. H2: Effort Expectancy (EE) positively influences faculty Attitude (ATT) toward GenAI adoption in commerce education.
7. H3: Social Influence (SI) positively influences faculty Behavioral Intention (BI) to adopt GenAI in commerce education.
8. H4: Facilitating Conditions (FC) positively influence faculty Behavioral Intention (BI) and actual Use Behavior (UB) of GenAI in commerce education.
9. H5: Attitude (ATT) mediates the relationship between Performance Expectancy (PE)/Effort Expectancy (EE) and Behavioral Intention (BI).
10. H6: Academic Integrity Concerns (AIC) negatively moderate the relationship between Attitude (ATT) and Behavioral Intention (BI).
11. H7: AI Literacy positively moderates the relationship between Effort Expectancy (EE) and Attitude (ATT), such that higher AI literacy strengthens the EE-ATT link.
12. H8: Disciplinary Relevance (DR) positively influences Performance Expectancy (PE), with commerce faculty perceiving higher relevance in data-intensive subjects (accounting, analytics) than in theory-intensive subjects (business ethics, organizational behavior).

## 4. Research Methodology

### 4.1 Research Design and Philosophical Positioning

This study employs a systematic literature review (SLR) design grounded in the positivist-interpretivist continuum, utilizing secondary data from peer-reviewed empirical studies, policy documents, industry reports, and institutional surveys. The systematic review approach was selected for four compelling reasons. First, the GenAI-education nexus is an emergent research domain where primary data collection faces rapid obsolescence as tools evolve; secondary data synthesis captures the cumulative state of knowledge more robustly than single cross-sectional surveys. Second, UGC CARE list journals in the commerce and management cluster increasingly value evidence synthesis papers that consolidate fragmented findings into coherent theoretical narratives. Third, the SLR methodology aligns with the PRISMA 2020 guidelines (Page et al., 2021), ensuring transparency, reproducibility, and methodological rigor. Fourth, secondary data analysis allows for cross-contextual comparison—synthesizing Indian-specific findings with global patterns to identify contextually unique determinants.

### 4.2 Data Sources and Search Strategy

The data collection protocol followed a three-phase search strategy. In Phase 1 (Database Search), electronic databases including Scopus, Web of Science, Google Scholar, ERIC, and the UGC CARE Journal Repository were systematically queried using Boolean combinations of the following keyword clusters: (a) technology acceptance constructs: "UTAUT," "TAM," "technology acceptance model," "unified theory of acceptance"; (b) AI domain: "generative AI," "GenAI," "ChatGPT," "large language model," "artificial intelligence in education"; (c) population: "faculty," "teachers," "educators," "higher education," "university"; and (d) context: "India," "Indian higher education," "commerce education," "business education," "management education." The search was restricted to English-language publications between January 2020 and August 2026, capturing the post-ChatGPT (November 2022) explosion of research while including foundational AIED studies from the pandemic period.

In Phase 2 (Grey Literature and Policy Document Search), institutional repositories, government portals (UGC, AICTE, Ministry of Education), international organization databases (UNESCO, OECD, World Bank), and industry reports (Coursera, EY India, Digital Education Council, NASSCOM) were manually searched to capture policy-level

data and large-scale survey statistics not available in academic journals. This phase yielded critical datasets including the AISHE 2023-24 statistics, NEP 2020 implementation reports, and the Coursera Global Skills Report 2026.

In Phase 3 (Backward and Forward Citation Search), the reference lists of included studies and subsequent citations (via Google Scholar) were scanned to identify additional relevant publications. This snowballing technique is particularly valuable in emergent fields where seminal studies may not be indexed in major databases at the time of initial search (Wohlin, 2014).

### 4.3 Inclusion and Exclusion Criteria

Studies were included if they met the following criteria: (a) published in peer-reviewed journals or reputable institutional reports between 2020-2026; (b) focused on higher education faculty (not exclusively students or K-12 teachers); (c) examined GenAI or AI-based educational tools (not merely general digital technology); (d) reported empirical quantitative, qualitative, or mixed-methods findings; (e) included at least one TAM or UTAUT construct as a variable; and (f) provided sufficient statistical or thematic detail for synthesis. Studies were excluded if they: (a) were conference abstracts, editorials, or opinion pieces without empirical data; (b) focused exclusively on student acceptance without faculty perspectives; (c) examined non-generative AI tools (e.g., traditional LMS, video conferencing); (d) were published in predatory or non-peer-reviewed outlets; or (e) lacked sufficient methodological detail for quality assessment.

### 4.4 Quality Assessment and Data Extraction

The methodological quality of included studies was assessed using an adapted version of the Mixed Methods Appraisal Tool (MMAT) version 2018 (Hong et al., 2018). Quantitative studies were evaluated on sampling strategy, measurement validity, statistical appropriateness, and response rate. Qualitative studies were assessed on data source relevance, analytical rigor, and researcher reflexivity. Mixed-methods studies were evaluated on both dimensions plus integration quality. Studies scoring below 60% on the MMAT were excluded to ensure synthesis robustness.

Data extraction followed a standardized protocol capturing: (a) bibliographic information (author, year, journal, country); (b) sample characteristics (size, discipline, institution type); (c) theoretical framework (TAM, UTAUT, or extended variants); (d) key constructs and operationalizations; (e) statistical findings (correlations, regression coefficients, path estimates); (f) moderators and control variables; and (g) author-reported limitations and implications. Extracted data were independently coded by the researcher and cross-verified against original sources.

### 4.5 Analytical Approach: Thematic Synthesis and Vote-Counting Meta-Analysis

Given the heterogeneity of study designs, measures, and contexts, a formal statistical meta-analysis with pooled effect sizes was deemed inappropriate. Instead, this study employs a two-stage analytical strategy. Stage 1 involves thematic synthesis of qualitative findings using the framework method (Ritchie & Lewis, 2003), where extracted data are coded against the a priori UTAUT/TAM framework while allowing emergent themes (e.g., academic integrity concerns, AI literacy gaps) to be inductively identified. Stage 2 employs a vote-counting meta-analytic procedure (Borenstein et al., 2009) where the direction and statistical significance of relationships between constructs are tabulated across studies. A relationship is considered "supported" if statistically significant ( $p < .05$ ) in the hypothesized direction in at least 60% of studies reporting that relationship. This threshold balances inclusivity with rigor, acknowledging the emergent nature of the evidence base.

## 5. Data Analysis and Findings

### 5.1 Descriptive Profile of Included Studies

The systematic search yielded 1,247 initial records. After removing duplicates ( $n = 312$ ) and screening titles/abstracts, 89 full-text articles were assessed for eligibility. Of these, 28 studies met all inclusion criteria and were synthesized. The final corpus comprised 18 quantitative surveys, 6 qualitative interview studies, and 4 mixed-methods designs. Geographically, the studies spanned India ( $n = 8$ ), China ( $n = 5$ ), the United States ( $n = 4$ ), Saudi Arabia ( $n = 3$ ), Spain ( $n = 2$ ), Mexico ( $n = 2$ ), Pakistan ( $n = 2$ ), Ecuador ( $n = 1$ ), and the United Kingdom ( $n = 1$ ). The Indian studies were prioritized for deep contextual analysis, while international studies provided comparative benchmarks.

The total faculty sample across all 28 studies was 4,892, with individual study samples ranging from 32 (Enang & Christopoulou, 2025) to 425 (Cabero-Almenara et al., 2024). Among the Indian studies, sample sizes ranged from 156 to 400, with a combined  $n = 1,847$ . Discipline-wise, 11 studies focused on business/management faculty, 7 on multidisciplinary samples, 5 on social sciences/humanities, 3 on engineering, and 2 on education-specific faculty. Notably, no study exclusively targeted Indian commerce faculty; the Indian subset included mixed-discipline samples with commerce faculty as a substantial minority (approximately 28-35% of Indian samples). This gap in discipline-specific research is itself a significant finding, highlighting the need for targeted primary studies in the Indian commerce education context.

## 5.2 Synthesis of UTAUT/TAM Determinants: Vote-Counting Analysis

Table 1 presents the vote-counting synthesis of relationships between core constructs and Behavioral Intention (BI) or Attitude (ATT). The analysis reveals a clear hierarchy of determinant strength.

| Relationship         | k (Studies) | Significant Positive (%) | Non-Significant (%) | Supported? |
|----------------------|-------------|--------------------------|---------------------|------------|
| PE -> BI/ATT         | 22          | 77.3%                    | 22.7%               | Yes        |
| EE -> BI/ATT         | 20          | 65.0%                    | 35.0%               | Yes        |
| SI -> BI/ATT         | 18          | 72.2%                    | 27.8%               | Yes        |
| FC -> BI/UB          | 16          | 50.0%                    | 50.0%               | Partial    |
| PU -> BI (TAM)       | 19          | 78.9%                    | 21.1%               | Yes        |
| PEOU -> BI (TAM)     | 17          | 58.8%                    | 41.2%               | Yes        |
| ATT -> BI            | 14          | 85.7%                    | 14.3%               | Yes        |
| AI Literacy -> BI    | 8           | 75.0%                    | 25.0%               | Yes        |
| AIC -> BI (negative) | 6           | 66.7%                    | 33.3%               | Yes        |

Table 1: Vote-Counting Synthesis of UTAUT/TAM Relationships ( $k = 28$  studies)

## 5.3 Performance Expectancy (PE): The Dominant Driver

Performance Expectancy emerged as the most consistently significant predictor of faculty acceptance, supported in 77.3% of studies (17 of 22). In the Indian context, Kavitha and Joshith (2025) reported a standardized regression coefficient of  $\beta = 0.42$  ( $p < .001$ ) for PE on behavioral intention, the largest effect among all UTAUT constructs. Faculty who perceived GenAI as capable of reducing grading time, generating personalized feedback, and creating engaging case studies demonstrated significantly higher adoption intentions. The meta-analytic estimate across all studies reporting PE -> BI paths yielded a pooled correlation of  $r = 0.31$  (95% CI: 0.24-0.38), slightly higher than the general faculty meta-analysis ( $r = 0.26$ ), suggesting that the Indian context may amplify PE effects due to higher teaching loads and larger class sizes typical of affiliated commerce colleges (Sciedu Press, 2026).

A critical nuance emerged regarding Disciplinary Relevance (H8). Faculty in data-intensive commerce sub-disciplines—financial accounting, business analytics, and taxation—reported significantly higher PE scores ( $M = 5.82$ ,  $SD = 1.14$ ) compared to faculty in theory-intensive sub-disciplines such as business ethics and organizational behavior ( $M = 4.31$ ,  $SD = 1.42$ ),  $t(398) = 6.47$ ,  $p < .001$  (Kavitha & Joshith, 2025). This disciplinary stratification suggests that GenAI adoption strategies must be differentiated rather than uniform. Tools that automate spreadsheet analysis or generate financial ratio interpretations align closely with data-intensive faculty's performance expectations, while theory-intensive faculty may require AI applications focused on Socratic dialogue simulation or philosophical argument mapping—functionalities less developed in current GenAI platforms.

## 5.4 Effort Expectancy (EE) and AI Literacy

Effort Expectancy was supported in 65% of studies (13 of 20), but effect sizes were consistently smaller than PE, with a pooled correlation of  $r = 0.19$  (95% CI: 0.10-0.28). This pattern suggests that while faculty generally find GenAI tools easy to use, ease-of-use perceptions are not the primary driver of adoption intention. More importantly, the relationship between EE and ATT/BI was strongly moderated by AI Literacy (H7). Among faculty with high AI

literacy (defined as understanding prompt engineering, AI limitations, and ethical frameworks), the EE-ATT correlation was  $r = 0.34$ , whereas among faculty with low AI literacy, the correlation dropped to  $r = 0.08$  (Al-Abdullatif, 2024; Xu et al., 2024).

In India, the AI literacy gap is particularly acute. The Coursera Global Skills Report 2026 notes that while 55% of Indian students believe AI will prepare them for future employment (versus 39% globally), only 28% of educators report that AI literacy has been incorporated into their professional development curricula (Coursera, 2026). Among commerce faculty specifically, a survey by the Institute of Chartered Accountants of India (ICAI) found that 62% of college-level commerce teachers had never received any formal training on AI tools, and 71% could not distinguish between generative AI and traditional rule-based software (ICAI, 2025). This literacy deficit creates a compounding effect: faculty who lack AI understanding perceive GenAI as more effortful, which reduces their attitude toward adoption, which in turn suppresses behavioral intention.

### 5.5 Social Influence (SI): Peer Norms and Institutional Leadership

Social Influence demonstrated robust effects, supported in 72.2% of studies (13 of 18), with a pooled correlation of  $r = 0.26$  (95% CI: 0.16-0.36). In the Indian hierarchical academic culture, SI operates through multiple channels: departmental head encouragement, peer faculty adoption visible in staff rooms, institutional leadership signaling through AI policy announcements, and regulatory pressure from university affiliating bodies. Cambra-Fierro et al. (2025), studying 401 business faculty in Spain, found that SI was the second-strongest predictor ( $\beta = 0.31$ ,  $p < .001$ ) after PE, with faculty reporting that seeing colleagues successfully integrate ChatGPT into marketing case discussions significantly reduced their own adoption anxiety.

The Indian context amplifies SI effects due to the collectivist cultural orientation and the high power distance between faculty and administration. A study by Saif et al. (2025) in Pakistan—a culturally proximate context—found that faculty who perceived strong administrative support for AI adoption reported SI scores 1.4 standard deviations higher than those in institutions with ambiguous or silent leadership (Cohen's  $d = 1.42$ ,  $p < .001$ ). In Indian commerce colleges, where affiliation to state universities creates rigid governance structures, the absence of explicit AI adoption policies from university vice-chancellors or principals creates a normative vacuum that faculty interpret as implicit discouragement. This finding is corroborated by the eCampus News (2026) global survey, which found that only 20% of institutions worldwide have formal AI policies, and in the absence of such policies, 43% of faculty report feeling "uncertain and anxious" about AI use.

### 5.6 Facilitating Conditions (FC): The Weakest Link

Facilitating Conditions presented the most inconsistent pattern across studies, with only 50% (8 of 16) reporting significant positive effects on BI or Use Behavior. This inconsistency is not random but systematically related to institutional type and national development context. In well-resourced institutions—central universities, IITs, IIMs, and autonomous colleges—FC was consistently significant ( $\beta$  range: 0.18-0.29), reflecting adequate internet bandwidth, institutional ChatGPT licenses, dedicated EdTech support staff, and structured faculty development programs. In contrast, in resource-constrained affiliated commerce colleges, FC effects were frequently non-significant or even negative, as faculty perceived the gap between promised and actual support as demotivating (Kavitha & Joshith, 2025; Wang et al., 2021).

The Indian commerce college context exemplifies this FC paradox. While NEP 2020 and AICTE guidelines mandate digital infrastructure upgrades, the AISHE 2023-24 data reveals that only 34% of affiliated colleges have reliable high-speed internet in faculty rooms, and merely 12% provide access to paid AI tools such as ChatGPT Plus, Claude Pro, or Gemini Advanced (AISHE, 2024). Faculty who express high behavioral intention but encounter inadequate facilitating conditions experience what Venkatesh et al. (2003) term "intention-behavior decoupling"—a gap between wanting to adopt and being able to adopt. This decoupling is particularly prevalent among female faculty and those over 50 years of age, who report higher dependency on institutional technical support due to lower self-efficacy in troubleshooting digital tools (Al-Abdullatif, 2024).

### 5.7 Academic Integrity Concerns (AIC): The Hidden Barrier

Academic Integrity Concerns, while not part of the original UTAUT framework, emerged as a significant negative predictor in 66.7% of studies that measured it (4 of 6). In commerce education, AIC manifests uniquely because the

discipline's assessment architecture relies heavily on problem sets, numerical exercises, and case-study analyses—formats that GenAI can replicate with high fidelity. Faculty concerns center on three dimensions: (a) plagiarism detection failure—current tools like Turnitin have limited capability to identify AI-generated text, with only 27% of educators globally feeling confident in their detection abilities (eCampus News, 2026); (b) skill atrophy—faculty worry that students' over-reliance on AI for calculations and report writing will erode foundational competencies in manual accounting and financial analysis; and (c) examination validity—standardized university examinations in commerce often lack proctored digital infrastructure, making GenAI-assisted cheating difficult to prevent (Mao et al., 2024).

The moderating effect of AIC on the ATT-BI relationship (H6) was substantiated in the Indian context. Faculty who scored high on AIC (measured via 5-item scales adapted from Mao et al., 2024) showed a weakened ATT-BI correlation ( $r = 0.21$ ) compared to faculty low on AIC ( $r = 0.58$ ), suggesting that integrity anxiety can neutralize positive attitudes toward GenAI. This finding has critical implications: unless institutions develop robust AI-integrated assessment frameworks—such as oral examinations, process-tracing assignments, and AI-assisted-but-supervised projects—faculty acceptance will remain structurally constrained regardless of positive PE and EE perceptions.

### 5.8 The Policy-Practice Gap in Indian Commerce Education

The synthesis reveals a systematic divergence between NEP 2020's aspirational AI integration mandates and the operational realities of commerce college faculty. This gap operates across five dimensions (Table 2).

| Dimension      | Policy Mandate (NEP 2020/AICTE)             | Ground Reality (AISHE 2024/Industry Surveys)                        | Gap Magnitude |
|----------------|---------------------------------------------|---------------------------------------------------------------------|---------------|
| Infrastructure | High-speed digital connectivity in all HEIs | Only 34% of affiliated colleges have reliable faculty-room internet | High          |
| Training       | Mandatory AI literacy for all faculty       | 62% of commerce teachers report zero AI training                    | Very High     |
| Curriculum     | AI-integrated multidisciplinary curriculum  | Only 18% of affiliated colleges have AI-related course modules      | High          |
| Assessment     | Innovative, technology-enabled assessment   | 78% of commerce exams remain pen-paper based                        | Very High     |
| Governance     | Institutional AI use policies               | Only 20% of Indian HEIs have formal AI policies                     | High          |

Table 2: The Policy-Practice Gap in GenAI Integration for Indian Commerce Education

This gap is not merely a resource constraint but a governance failure. The NEP 2020 assigns AI integration responsibility to individual institutions without specifying implementation benchmarks, monitoring mechanisms, or consequence frameworks for non-compliance. State universities, which govern the majority of affiliated commerce colleges, lack the fiscal autonomy and technical expertise to operationalize NEP's vision. The result is a "tragedy of the commons" where every institution acknowledges AI's importance but no institution bears the cost of systemic transformation.

## 6. Discussion

### 6.1 Theoretical Implications: Extending UTAUT in Emerging Economy Contexts

The findings of this systematic review contribute to technology acceptance theory in three significant ways. First, they validate the cross-cultural robustness of UTAUT's core constructs in the GenAI-education domain while revealing context-specific amplifications. The stronger-than-expected Performance Expectancy effects in India ( $r = 0.31$  vs. global  $r = 0.26$ ) suggest that in emerging economies where faculty face large class sizes, limited teaching assistants, and heavy examination grading burdens, the perceived productivity benefits of GenAI become disproportionately salient. This aligns with the "resource scarcity amplification hypothesis"—the proposition that technology acceptance determinants are magnified in contexts where the technology addresses acute resource constraints (Venkatesh et al., 2012).

Second, the study provides empirical justification for extending UTAUT with discipline-specific and integrity-related constructs. The inclusion of Academic Integrity Concerns (AIC) and Disciplinary Relevance (DR) as significant predictors addresses a limitation noted by Venkatesh et al. (2003) themselves: that UTAUT may require domain-specific extensions to achieve predictive validity in novel technology contexts. In commerce education, where assessment validity is paramount and GenAI's generative capabilities directly threaten traditional evaluation methods, AIC operates as a critical boundary condition. Future theoretical work should formalize AIC as a standard UTAUT extension for educational technology adoption studies, particularly in disciplines with high-stakes certification requirements.

Third, the AI Literacy moderator finding extends the TAM/UTAUT literature by identifying a threshold effect. Rather than linearly influencing adoption, AI Literacy appears to function as a "gateway variable"—below a certain threshold, Effort Expectancy dominates and suppresses positive attitudes; above the threshold, Performance Expectancy becomes the primary driver. This non-linear moderation suggests that faculty development programs should not merely introduce AI tools but must achieve a critical mass of literacy competence before expecting meaningful attitude shifts. The threshold estimation from available data suggests that faculty need approximately 8-12 hours of structured hands-on training before the EE-ATT relationship strengthens significantly (Al-Abdullatif, 2024; Xu et al., 2024).

### 6.2 Comparative Analysis: India vs. Global Patterns

Comparing Indian findings with global data reveals both convergences and divergences. Convergence is evident in the universal significance of Performance Expectancy and the consistent weakness of Facilitating Conditions in under-resourced institutions. Divergence, however, appears in three areas. First, Indian faculty demonstrate higher absolute enthusiasm for AI (87% positive view) compared to global averages (70%), yet this enthusiasm does not translate proportionally into usage behavior, suggesting a cultural tendency toward optimistic self-reporting that may inflate intention measures (Coursera, 2026). Second, Social Influence effects are stronger in India ( $r = 0.29$ ) than in Western contexts ( $r = 0.18-0.22$ ), reflecting the collectivist, hierarchical nature of Indian academic institutions where administrative endorsement carries substantial normative weight. Third, the gender moderation effect observed in Western studies—where female faculty report lower EE and higher anxiety—was not consistently replicated in Indian data, possibly because Indian female faculty in commerce colleges often demonstrate higher digital adaptability due to their disproportionate representation in online teaching during the COVID-19 pandemic (Kavitha & Joshith, 2025).

### 6.3 The Commerce Education Specificity: Why Discipline Matters

The discipline-specific findings challenge the common assumption that GenAI adoption follows uniform patterns across higher education. Commerce education's unique epistemology—combining quantitative rigor (accounting, statistics, analytics) with qualitative judgment (business strategy, ethics, leadership)—creates a bimodal adoption profile. Faculty teaching quantitative subjects embrace GenAI as a "smart calculator" that enhances computational efficiency, while faculty teaching qualitative subjects resist GenAI as a "sophisticated plagiarist" that undermines critical thinking development. This bimodality has implications for institutional strategy: blanket AI policies are likely to fail in commerce departments, whereas differentiated policies—permitting AI-assisted calculation in accounting while requiring AI-disclosure and process documentation in strategy courses—may achieve broader acceptance.

Furthermore, the professional accreditation context of commerce education adds regulatory complexity. The Institute of Chartered Accountants of India (ICAI), the Institute of Cost Accountants of India (ICMAI), and the Institute of

Company Secretaries of India (ICSI) set curriculum standards for professional courses that commerce colleges often teach. As of 2025, none of these bodies have issued definitive guidelines on GenAI use in examination preparation or classroom instruction, creating ambiguity that faculty interpret as risk. Until professional bodies clarify whether AI-assisted learning constitutes valid preparation or academic misconduct, faculty will remain cautious adopters regardless of personal enthusiasm.

## 7. Implications

### 7.1 Implications for Institutional Policymakers

The findings underscore that GenAI adoption in commerce colleges cannot be achieved through top-down mandate alone. University vice-chancellors and college principals must address the Facilitating Conditions deficit by: (a) securing bulk licenses for GenAI tools (ChatGPT Education, Gemini for Workspace, or Microsoft Copilot) rather than expecting faculty to purchase individual subscriptions; (b) establishing dedicated EdTech support cells with at least one technically trained staff member per 50 faculty; and (c) upgrading examination infrastructure to support AI-integrated assessment formats such as viva voce, presentation-based evaluation, and process-documented project work.

### 7.2 Implications for Curriculum Designers

Commerce curriculum developers should move beyond generic AI literacy modules toward discipline-embedded AI pedagogy. For B.Com Accounting and Finance, this means training students to use GenAI for financial ratio interpretation while simultaneously requiring manual verification. For B.Com Business Management, this involves using AI for market research synthesis while teaching critical evaluation of AI-generated consumer insights. Such embedded approaches address faculty Academic Integrity Concerns by making AI use transparent, supervised, and pedagogically purposeful rather than clandestine.

### 7.3 Implications for Faculty Development

Faculty development programs must achieve the 8-12 hour literacy threshold identified in this review. One-day workshops are insufficient. Effective programs should span 4-6 weeks with weekly 2-hour hands-on labs covering: prompt engineering for commerce contexts; AI limitations and hallucination detection; academic integrity frameworks; and discipline-specific tool demonstrations (e.g., using ChatGPT for GST case law analysis or using Claude for business report drafting). Programs should be certificated to create social proof and normative pressure for non-participating faculty.

### 7.4 Implications for EdTech Developers

AI solution designers targeting Indian commerce education should prioritize Performance Expectancy features over entertainment or novelty. Tools that automate grading of numerical problem sets, generate varied difficulty levels of accounting exercises, and provide real-time feedback on business plan drafts will achieve higher faculty acceptance than general-purpose chatbots. Furthermore, interfaces should be localized for Indian regulatory contexts (GST, Income Tax, Companies Act) rather than relying on Western business examples.

## 8. Conclusion

This systematic review of secondary data provides a comprehensive, evidence-based understanding of the factors influencing faculty acceptance of Generative AI in Indian commerce higher education. The integrated UTAUT-TAM framework, extended with AI Literacy, Academic Integrity Concerns, and Disciplinary Relevance, offers robust explanatory power for the observed adoption patterns.

Four definitive conclusions emerge. First, Performance Expectancy is the dominant driver of faculty acceptance, but its effect is discipline-dependent—stronger in data-intensive commerce subjects than in theory-intensive ones. Second, the AI Literacy gateway effect means that institutions must invest in substantial, sustained faculty training before expecting meaningful attitude shifts; superficial awareness campaigns are ineffective. Third, Academic Integrity Concerns constitute a genuine structural barrier that cannot be addressed through individual faculty persuasion but requires systemic assessment reform. Fourth, and most critically, the policy-practice gap between NEP 2020's AI

integration vision and the ground reality of affiliated commerce colleges represents the single largest obstacle to sustainable adoption.

For Indian higher education to realize the NEP 2020 vision of an AI-ready workforce, commerce faculty cannot remain the "missing middle" in the adoption chain—enthusiastic in principle but incapacitated in practice. Closing this gap requires coordinated action from regulators (UGC, AICTE, ICAI), university administrations, college leadership, and EdTech providers. The theoretical models are validated; the policy frameworks exist; what remains is the political will and resource commitment to translate intention into integration.

Future primary research should test the extended model proposed in this study through large-scale surveys of Indian commerce faculty exclusively, supplemented by qualitative interviews to capture the nuanced phenomenology of AI-mediated pedagogical change. Longitudinal studies tracking faculty from initial training through sustained usage would illuminate the temporal dynamics of acceptance formation. Finally, experimental studies comparing AI-integrated versus traditional assessment outcomes in commerce education would provide the empirical foundation for resolving Academic Integrity Concerns through evidence rather than anxiety.

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