**One size does not fit all: customizing teaching and learning strategies with generative AI**

Nicolas A. Nunez1,2 (\*) and Rafael Fernandez1,2

1 Centrum Catolica Graduate Business School, Lima, Peru

2 Pontificia Universidad Catolica del Peru, Lima, Peru

(\*) Corresponding author: nnunezm@pucp.edu.pe

ORCID: 0000-0003-2193-3830

**Abstract**

Higher education institutions that implement Generative Artificial Intelligence (GAI) often assume that students will adopt these tools uniformly; however, evidence indicates considerable variation in how learners engage with AI technologies. This study develops the first empirically validated framework that combines Technological Pedagogical Content Knowledge (TPACK) and Unified Theory of Acceptance and Use of Technology (UTAUT) theories to identify distinct student profiles, moving beyond generic implementation toward targeted educational interventions. We analyzed 252 MBA students using a hybrid theoretical-empirical approach, revealing three stable profiles: Explorers (11%)—younger students who enthusiastically experiment despite lacking formal training; Moderates (68%)—systematic learners who prefer structured approaches; and Skeptics (21%)—experienced professionals who seek clear educational value before adoption. Statistical analysis showed significant differences across performance expectancy (p < 0.001), age (p < 0.001), and TPACK integration (p < 0.001), with a strong theoretical alignment (Cramer's V = 0.276, p < 0.001). Instead of treating all students the same, we propose differentiated strategies: project-based exploration for Explorers, scaffolded training sequences for Moderates, and evidence-based case studies for Skeptics. This framework addresses a practical challenge—how to effectively support diverse learners when integrating AI tools into business education. The validated typology provides concrete guidance for institutional decision-making, including resource allocation and faculty training programs. By leveraging learning analytics, institutions can automatically identify student profiles and tailor support accordingly. This research offers both theoretical advancement and practical tools for educators navigating AI integration challenges.

*Keywords:* Learning Analytics, Adaptive Learning, Generative Artificial Intelligence, Business Education, TPACK, UTAUT

**1 Introduction**

It is undeniable the impact that Generative AI (GAI) has on people's lives, from the increase in productivity derived from this technology. Several industries and economic sectors have reached new levels of efficiency by using GAI on their operations (Ebert & Louridas, 2023; Korinek, 2023; Kshetri et al., 2024). Higher education has been one of the most benefited industries by incorporating GAI into its core processes (Chan & Hu, 2023; Chiu, 2023).

While GAI offers unprecedented opportunities to personalize learning pathways in higher education, there is considerable heterogeneity in how students perceive, adopt, and use these tools. This diversity presents a significant challenge for educational institutions seeking to implement effective AI-mediated teaching and learning strategies.

Labor empowerment of graduates and the development of soft and hard skills are relevant concerns for the future of work (Healy et al., 2022; Succi & Canovi, 2020), and GAI has constituted a major driver for the workforce of the future (Firat, 2023). Companies and public agencies emphasize the need to have a critical mass of professional talent ready to tackle the challenges of this century: sustainability, climate change, innovation, and economic productivity (Brundiers et al., 2021), and the role of GAI appears to be critical to tackle these challenges.

Despite growing interest in the use of Generative AI (GAI) in higher education, there remains a notable gap in students’ capabilities and preparedness to adopt these tools effectively. This underscores the importance of examining the factors that shape their engagement with GAI. Accordingly, this study addresses the following research question: What distinctive student profiles emerge concerning the use, attitudes, and expectations toward Generative AI in the context of business education? Identifying such profiles is essential for designing differentiated educational interventions that maximize the pedagogical potential of GAI in diverse learning environments.

While scholars have highlighted the need for institutional policies and ethical guidelines to ensure the responsible integration of GAI in higher education (Michel-Villarreal et al., 2023), several pedagogical challenges remain. Among them, the customization—or even hyper-personalization—of learning pathways stands out as a central concern. In contemporary higher education, there is increasing emphasis on crafting learning journeys tailored to individual students’ needs. GAI offers promising opportunities in this regard. However, effective personalization requires a nuanced understanding of learners’ expectations, attitudes, backgrounds, and prior experience with AI tools. A uniform, "one-size-fits-all" approach may be operationally efficient from an educational management perspective, yet it risks overlooking the diverse needs and readiness levels of students.

To strike a balance between personalization and scalability, data-driven methods such as cluster analysis provide a powerful approach to identify meaningful learner profiles. In this context, our study contributes to bridging a critical gap in the literature by providing empirical evidence on the heterogeneity of student engagement with GAI and its implications for designing personalized, AI-supported instructional strategies.

The remainder of this paper is organized as follows. Section 2 presents the theoretical framework of the study. The methodology is described in section 3, and the results in section 4. We discuss the results in Section 5 and provide our conclusions in Section 6 that include implications, limitations, and future research agendas.

**2 Theoretical Framework**

**2.1 Technology Adoption in Education**

Technology adoption in educational contexts presents unique challenges that distinguish it fundamentally from workplace and consumer environments. While traditional technology acceptance research has primarily focused on organizational settings where adoption decisions follow hierarchical mandates and clear productivity metrics (Venkatesh et al., 2003), educational environments operate under different dynamics characterized by individual agency, pedagogical considerations, and learning-centered objectives (Tondeur et al., 2017).

Educational contexts differ substantially from workplace environments in several critical dimensions. Unlike organizational technology adoption driven by efficiency and competitive advantage, educational technology integration must simultaneously address learning outcomes, pedagogical alignment, and student engagement (Prestridge, 2017). Academic institutions cannot simply mandate technology use; instead, they must create conditions where both educators and learners voluntarily embrace technologies that enhance learning experiences (Bahçivan et al., 2018). This fundamental difference necessitates technology acceptance models that account for education-specific factors such as pedagogical beliefs, learning objectives, and instructional contexts.

The complexity intensifies with the advent of Generative AI (GAI) technologies, which represent a paradigm shift from passive tools to active learning partners capable of content creation, personalized tutoring, and adaptive responses (Chan & Hu, 2023). Unlike previous educational technologies that primarily facilitated existing pedagogical practices, GAI needs a fundamental reconsideration of teaching and learning processes (Michel-Villarreal et al., 2023). This transformative potential creates both unprecedented opportunities for personalized learning and significant challenges for institutional adoption strategies.

A critical gap emerges between technology acceptance and pedagogical integration. Traditional acceptance models predict whether individuals will use technology but fail to address how effectively they integrate it into educational practice (Cheng et al., 2022). Educational technology adoption requires dual-level success: initial acceptance decisions followed by meaningful pedagogical implementation. Research demonstrates that educators may accept technology yet struggle with effective classroom integration due to insufficient pedagogical knowledge or conflicting instructional beliefs (Arancibia-Herrera et al., 2024). This acceptance-integration gap suggests that educational technology adoption models must simultaneously address motivational factors influencing initial adoption and pedagogical factors determining implementation quality.

Student heterogeneity further complicates the adoption of educational technology. Unlike workplace environments with relatively homogeneous user populations sharing similar objectives and constraints, educational settings encompass diverse learners with varying technological backgrounds, learning preferences, and academic goals (Park & Lee, 2013). Research reveals significant individual differences in technology adoption patterns, influenced by factors such as prior experience, self-efficacy, generational characteristics, and disciplinary backgrounds (Li et al., 2019). This heterogeneity creates challenges for institutional technology implementation strategies that assume uniform user characteristics and adoption patterns.

Recent research highlights the inadequacy of one-size-fits-all approaches to educational technology adoption. Studies demonstrate that learner characteristics significantly moderate technology acceptance relationships, with factors such as technological anxiety, learning styles, and prior experience creating distinct adoption trajectories (Al-Adwan & Al-Debei, 2024). Furthermore, cultural and contextual factors introduce additional complexity, as technology adoption patterns vary across educational systems, disciplinary domains, and institutional contexts (Momenanzadeh et al., 2023).

The emergence of student typologies in educational technology research reflects growing recognition of adoption heterogeneity. Previous studies have identified distinct user profiles based on technology competence, adoption willingness, and integration success, ranging from enthusiastic early adopters to cautious skeptics requiring extensive support (Yuk & Lee, 2023). However, these typologies often focus on single technologies or lack empirical validation across diverse educational contexts, limiting their practical applicability for institutional adoption strategies.

This complexity necessitates comprehensive theoretical frameworks that simultaneously address acceptance mechanisms and pedagogical integration processes while accounting for individual difference factors. Current research lacks validated models that integrate UTAUT technology acceptance theory with TPACK pedagogical frameworks and empirically-derived user typologies. Such integration is particularly critical for GAI adoption, where the technology's transformative potential requires both initial acceptance and sophisticated pedagogical implementation across diverse learner populations. Understanding these multifaceted adoption processes becomes essential for developing effective, differentiated implementation strategies that maximize GAI's educational potential while respecting learner diversity and institutional contexts.

**2.2 UTAUT: Understanding Technology Acceptance**

The adoption of emerging technologies in higher education presents complex challenges that require robust theoretical frameworks to understand individual intentions and behaviors. The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), emerged as one of the most influential and widely validated frameworks for technology acceptance research. UTAUT synthesizes eight previous technology acceptance models, identifying four core constructs that predict usage intention and subsequent technology adoption behavior.

**2.2.1 Performance Expectancy (PE)**

Represents the degree to which individuals believe that using a technology will enhance their performance in relevant activities. In educational contexts, this translates to perceptions that GAI will improve learning outcomes, academic productivity, or assignment quality (Patterson et al., 2024; Sergeeva et al., 2025;). For MBA students, Performance Expectancy encompasses beliefs about GAI's potential to enhance analytical capabilities, improve decision-making processes, and increase professional competence

**2.2.2 Effort Expectancy (EE)**

This variable measures the perceived ease of technology use, reflecting the cognitive and temporal resources required for effective adoption (Venkatesh et al., 2003). Educational research demonstrates that perceived complexity significantly influences student technology adoption decisions, particularly for sophisticated tools like GAI that require learning new interaction paradigms (Al-Abdullatif, 2024; Tram, 2024). This construct proves especially relevant for diverse student populations with varying technological backgrounds.

**2.2.3 Social Influence (SI)**

Captures individuals' perceptions of social pressure from significant others to use technology. In educational settings, this includes influence from faculty, peers, and institutional authorities (Nikolic et al., 2024). Recent research reveals that social influence operates differently in educational versus workplace contexts, as academic environments emphasize individual agency and voluntary adoption rather than organizational mandates (Cabero-Almenara et al., 2024).

**2.2.4 Facilitating Conditions (FC)**

Refer to the perceived availability of resources and support infrastructure necessary for technology use. This encompasses technical resources, institutional support, training availability, and organizational policies (Venkatesh et al., 2003). Educational research emphasizes that facilitating conditions significantly influence not only initial adoption but also sustained integration and effective usage patterns (Khlaif et al., 2024; Perez, 2024).

UTAUT's application in educational GAI research has demonstrated strong predictive validity across diverse contexts. Studies consistently show that Performance Expectancy and Effort Expectancy serve as primary predictors of GAI adoption intentions among students and faculty (Patterson et al., 2024; Sergeeva et al., 2025). Furthermore, research reveals that pedagogical beliefs significantly moderate UTAUT relationships, with constructivist-oriented educators showing differential adoption patterns compared to transmissive-oriented instructors (Cabero-Almenara et al., 2024).

However, UTAUT's limitations in educational contexts become apparent when considering pedagogical integration complexity. The framework effectively predicts *whether* individuals will adopt technology but provides limited insight into *how* they integrate it meaningfully into educational practice (Tram, 2024). UTAUT focuses primarily on acceptance and usage intentions without addressing the pedagogical transformation necessary for effective educational technology implementation. The model cannot explain whether GAI use aligns with learning objectives, promotes critical thinking, or enhances educational outcomes within specific disciplinary contexts.

Educational contexts present unique challenges that distinguish them from workplace settings where UTAUT was originally validated. Unlike organizational environments with clear productivity metrics and hierarchical adoption mandates, educational settings require voluntary engagement and pedagogical alignment (Tondeur et al., 2017). Students must not only accept GAI technology but integrate it meaningfully into learning processes that involve content mastery, pedagogical understanding, and technological proficiency simultaneously.

This limitation underscores the necessity of complementing UTAUT with frameworks that address pedagogical integration complexity, such as TPACK, to create comprehensive understanding of both acceptance decisions and subsequent educational implementation quality. The integration of acceptance and pedagogical frameworks becomes particularly critical for GAI adoption, where transformative potential requires sophisticated understanding of technology-pedagogy-content relationships beyond simple usage intentions.

**2.3 TPACK: Pedagogical Technology Integration**

The Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006) provides a comprehensive theoretical foundation for understanding effective technology integration in educational practice. TPACK conceptualizes three fundamental knowledge domains—Content Knowledge (disciplinary mastery), Pedagogical Knowledge (instructional strategies), and Technological Knowledge (digital tool proficiency)—whose intersections create four additional domains: Technological Content Knowledge (TCK), Technological Pedagogical Knowledge (TPK), Pedagogical Content Knowledge (PCK), and the comprehensive TPACK integration.

TPACK's relevance to GAI adoption extends beyond simple technology use to encompass pedagogical transformation. Recent research has demonstrated that integrating GAI within TPACK frameworks significantly improves learning outcomes through personalized educational experiences (Bautista et al., 2024; Hava & Babayiğit, 2024; Tram, 2024). The framework's dynamic nature allows adaptation to various educational contexts while emphasizing the critical role of pedagogical considerations in technology adoption decisions (Greene & Jones, 2020; Wing Chan & Wai Tang, 2024).

Empirical evidence reveals that TPACK proficiency influences both educator confidence and student engagement with GAI technologies. Studies across multiple educational contexts confirm that teachers with stronger TPACK integration demonstrate enhanced preparedness for GAI adoption and create more interactive learning environments (Ait et al., 2023; Alzahrani & Alzahrani, 2025; Yang et al., 2025). Furthermore, Ning et al.'s (2024) AI-TPACK framework identified six knowledge components that predict successful AI integration, providing a comprehensive assessment tool for large-scale implementation.

However, TPACK implementation faces significant challenges that limit its predictive power for technology adoption. Research indicates that pedagogical-technological knowledge can paradoxically create resistance to GAI adoption, as educators with stronger pedagogical expertise may perceive greater privacy concerns and compatibility issues with existing instructional practices (Alzahrani & Alzahrani, 2025; Karataş & Ataç, 2024). Additionally, factors such as limited digital infrastructure, insufficient training, and resistance to methodological change impede effective TPACK implementation (Jammeh et al., 2024).

Student profile differentiation emerges as a critical consideration within TPACK applications. Research has identified distinct technology user profiles based on TPACK competency levels, ranging from "Technological Pioneers" with high digital tool confidence to "Pedagogical Content Knowledge Specialists" with strong disciplinary expertise but limited technological proficiency (Cheng et al., 2024). Additional studies reveal profiles such as "Balanced Integrators" maintaining equilibrium across TPACK dimensions and "TPACK Laggers" showing consistently low competency levels (Li et al., 2024; Trevisan & De Rossi, 2023).

Individual difference factors significantly influence TPACK-based GAI adoption patterns. Generational differences between "digital natives" and "digital immigrants" create distinct technology interaction patterns (Hava & Babayiğit, 2024), while AI literacy levels determine users' ability to effectively evaluate and implement GAI tools (Al-Abdullatif, 2024). Furthermore, GAI-related anxiety and technological self-efficacy serve as critical psychological factors influencing adoption willingness (Wang et al., 2024).

The TPACK framework's limitations become apparent when considering technology adoption decisions. While TPACK effectively explains pedagogical integration processes, it lacks predictive power regarding initial adoption intentions and behavioral outcomes. The framework assumes technology acceptance but does not account for the motivational, social, and contextual factors that determine whether individuals choose to engage with technologies initially. This gap necessitates integration with technology acceptance models to create comprehensive understanding of both adoption decisions and subsequent pedagogical implementation—a theoretical integration that remains underexplored in GAI educational contexts.

**2.4 Integrating TPACK with UTAUT: A Comprehensive Framework for GAI Adoption**

The limitations identified in both the TPACK and UTAUT frameworks underscore the need for theoretical integration to understand GAI adoption in educational contexts comprehensively. While UTAUT effectively predicts technology acceptance intentions through motivational and contextual factors, it fails to capture the pedagogical complexity essential for meaningful educational technology integration (Al-Abdullatif, 2024; Tram, 2024). Conversely, TPACK provides a sophisticated understanding of pedagogical technology integration but lacks predictive power regarding initial adoption decisions and behavioral outcomes (Cheng et al., 2022; Wang et al., 2024). This complementary relationship suggests that integrated frameworks can address gaps inherent in single-theory approaches while providing a comprehensive understanding of educational technology adoption processes.

Theoretical integration occurs at multiple conceptual levels. UTAUT's Performance Expectancy construct directly maps onto TPACK's Technological Knowledge domain, as both address users' confidence in technology's capability to enhance educational outcomes (Ning et al., 2024). Similarly, Effort Expectancy aligns with the intersection of Technological Pedagogical Knowledge, where ease of use influences pedagogical implementation decisions (Hava & Babayiğit, 2024; Yang et al., 2025). Facilitating Conditions in UTAUT corresponds to the organizational support necessary for effective TPACK development, particularly the institutional infrastructure required for comprehensive technology-pedagogy-content integration (Malusay et al., 2025; Shin et al., 2024).

The integration addresses critical theoretical gaps by creating a sequential adoption model where UTAUT constructs predict initial GAI acceptance decisions, while TPACK dimensions explain subsequent pedagogical integration quality (Alzahrani & Alzahrani, 2025). This dual-phase approach recognizes that educational technology adoption involves both willingness to engage with technology (UTAUT domain) and capability to integrate it meaningfully into pedagogical practice (TPACK domain). Recent empirical evidence supports this integration, with studies demonstrating that pedagogical beliefs significantly moderate the relationships between UTAUT and TPACK development trajectories, while technology acceptance factors influence the latter (Cabero-Almenara et al., 2024; Karataş & Ataç, 2024).

Individual difference factors emerge as critical moderators in the integrated framework. Student characteristics such as age, professional experience, prior training, and pedagogical orientations influence both UTAUT acceptance processes and TPACK integration patterns (Li et al., 2024; Trevisan & De Rossi, 2023). These individual differences create heterogeneous adoption trajectories that necessitate differentiated implementation strategies (Cheng et al., 2024). The integrated framework suggests that successful GAI adoption requires alignment between individual acceptance factors (UTAUT) and pedagogical competency development (TPACK), with misalignment creating barriers to effective implementation (Bautista et al., 2024; Oved & Alt, 2025).

The practical implications of integration extend beyond theoretical advancements to inform institutional adoption strategies. Rather than treating acceptance and integration as separate processes, the integrated framework suggests coordinated interventions that simultaneously address motivational factors influencing adoption decisions and pedagogical factors determining implementation quality (Greene & Jones, 2020; Jammeh et al., 2024). This approach enables the prediction not only of who will adopt GAI technologies but also of how effectively they will integrate them into educational practice, providing crucial guidance for resource allocation and support system design.

The TPACK-UTAUT integration thus provides a comprehensive theoretical foundation for understanding the complexity of GAI adoption while addressing the heterogeneous needs of diverse student populations (Park & Lee, 2013). This integrated approach forms the basis for empirically identifying distinct student profiles that exhibit different patterns of technology acceptance and pedagogical integration, enabling the development of differentiated educational interventions that maximize GAI's transformative potential in business education contexts.

**2.5 Student Profiles and Differentiated Adoption Patterns**

The adoption of Generative AI (GAI) in education is inherently heterogeneous, shaped by diverse student backgrounds, technological proficiencies, and pedagogical needs (Chan & Hu, 2023; Michel-Villarreal et al., 2023). Unlike homogeneous workplace settings, educational environments encompass learners with varying levels of digital literacy, disciplinary expertise, and attitudes toward innovation (Li et al., 2024; Park & Lee, 2013). For instance, younger "digital natives" may exhibit higher exploratory behaviors with GAI, while experienced professionals often prioritize evidence-based utility (Al-Adwan & Al-Debei, 2024; Yang et al., 2025). This heterogeneity challenges institutional strategies that assume uniform adoption pathways, necessitating frameworks that account for multidimensional differences in technology acceptance *and* pedagogical integration (Celik, 2023; Cheng et al., 2024).

Prior research has proposed student typologies based on technology adoption (e.g., "innovators" vs. "laggards"; Rogers, 2003) or TPACK competency, like "Technological Pioneers" vs. "Pedagogical Specialists" (Trevisan & De Rossi, 2023). However, these classifications often suffer from two key limitations: (a) they focus on *either* acceptance (UTAUT) *or* integration (TPACK), failing to bridge the gap between intent and practice (Cheng et al., 2022; Karataş & Ataç, 2024); and (b) they lack empirical validation in GAI contexts, relying instead on theoretical proxies (Ning et al., 2024). For example, while Cabero-Almenara et al. (2024) identified educator profiles using UTAUT, their model omitted TPACK’s pedagogical dimensions, limiting actionable insights for classroom implementation. Similarly, TPACK-based typologies (e.g., Hava & Babayiğit, 2024) rarely incorporate behavioral predictors like performance expectancy or social influence, despite their proven role in adoption decisions (Venkatesh et al., 2012).

Therefore, to address these gaps, our study integrates UTAUT and TPACK to derive *empirically grounded* student profiles that reflect both adoption drivers and pedagogical readiness. This approach aligns with recent calls for hybrid frameworks in educational technology research (Murphy et al., 2024; Wang et al., 2024). By anchoring profiles in both UTAUT (e.g., behavioral intention) and TPACK (e.g., technological pedagogical knowledge), we offer a scalable model for personalized interventions, advancing beyond the "one-size-fits-all" paradigm (Tondeur et al., 2017; Tram, 2024).

**3 Methodology**

**3.1 Sample, Variables, and Calibration**

The sample consisted of 252 valid observations collected from MBA students enrolled in a Peruvian business school. After implementing systematic data quality controls and removing incomplete responses, all cases retained complete information across critical variables, ensuring robust analytical foundations for cluster validation. Demographic characteristics revealed a gender distribution of 69.3% men and 30.7% women. Regarding employment sectors, 90.8% of respondents worked in the private sector, 6.4% in the public sector, and 2.8% in non-profit organizations. In terms of professional experience, 59.0% had more than 10 years of work experience, 21.9% between 6 and 10 years, and 19.1% between 3 and 5 years. Participants came from diverse industries, with the most represented being mining (15.5%), education (11.6%), and banking and financial services (10.8%). The "Other" category, which includes sectors such as consulting, healthcare, and manufacturing, accounted for 35.5% of the sample.

Age distribution ranged from 25 to 55 years (M = 36.9, SD = 7.8), providing adequate representation across different generational cohorts relevant to technology adoption research. This demographic diversity, particularly the variation in age and professional experience, provides a robust foundation for identifying differentiated student profiles in the context of GAI adoption, as these variables are theoretically central to TPACK framework applications (Cheng et al., 2024).

Therefore, sampling adequacy for cluster analysis was confirmed through multiple criteria: (1) sample size exceeding recommended minimum of 2k observations per expected cluster (Hair et al., 2019), (2) complete data across all critical UTAUT constructs, and (3) sufficient variance in key theoretical variables to enable meaningful profile differentiation. The final sample of 252 participants provides adequate statistical power for robust cluster validation and cross-validation analyses. Instrument calibration was conducted through a comprehensive validation process. All UTAUT constructs demonstrated acceptable to excellent internal consistency (Cronbach's α ranging from 0.731 to 0.946), with Performance Expectancy (α = 0.901), Facilitating Conditions (α = 0.894), and Motivation (α = 0.946) showing robust reliability. Social Influence reliability was improved from 0.685 to 0.731 through systematic item analysis and removal of one poorly performing item, consistent with psychometric best practices (Nunnally & Bernstein, 1994).

**3.2 Data processing**

Data preparation followed a systematic process to ensure analytical rigor and theoretical consistency. After comprehensive data cleaning and outlier detection, we implemented variable recoding to align the scales, ensuring that higher values consistently indicated more positive attitudes across all constructs.

We employed a hybrid approach that combines empirical clustering with theoretical validation, addressing recent criticisms regarding the interpretability of educational technology clustering research (Park & Lee, 2013; Cheng et al., 2024). Rather than relying solely on data-driven methods, we implemented theoretically informed classification based on established TPACK and UTAUT literature. Composite variables for all UTAUT constructs were constructed using validated psychometric procedures, with items aggregated using mean scores after confirming acceptable internal consistency.

Profile classification combined quantile-based cutoff points with theoretical criteria. Skeptics were identified as individuals with low Performance Expectancy (≤33rd percentile) and higher age/professional experience (≥50th percentile), reflecting experienced professionals requiring evidence-based persuasion. Explorers exhibited high Performance Expectancy (≥66th percentile), absence of formal AI training, and younger age (≤50th percentile), consistent with digital native adoption patterns. Moderates comprised the remaining participants, representing the theoretically expected intermediate profile.

**3.2.1 Cluster Validation**

Our validation strategy addressed methodological rigor through four complementary dimensions: theoretical-empirical concordance, statistical significance testing, internal cluster quality metrics, and stability analysis (Murphy et al., 2024). K-medoids clustering was selected over k-means due to robustness to outliers and interpretable cluster representatives, valuable in educational research contexts.

Theoretical-empirical validation examined concordance between theoretical profiles and empirical clusters using contingency table analysis. Cramer's V measured association strength, while Chi-square tests provided significance testing. Internal validation included silhouette analysis and bootstrap stability analysis using 100 resampling iterations. We employed Euclidean distance on standardized variables and multiple random initializations to ensure robustness. This comprehensive approach ensures both statistical soundness and theoretical interpretability for educational intervention design.

**3.3 Study variables**

Our variable selection and operationalization were grounded in the TPACK model (Mishra & Koehler, 2006) and the UTAUT framework (Venkatesh et al., 2003), both of which were applied to GAI adoption in higher education. Table 1 presents the comprehensive variable structure organized by theoretical construction.

**Table 1**

*Variable Structure and Theoretical Mapping*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Construct | Items | α | TPACK Mapping | Key Indicators |
| Performance Expectancy (PE) | 9 | 0.901 | Technological Knowledge (TK) | Academic performance enhancement, learning efficiency |
| Effort Expectancy (EE) | 10 | 0.735 | TK ∩ Pedagogical Knowledge | Perceived ease of use, learning complexity |
| Social Influence (SI) | 4 | 0.731 | Educational context factor | Peer/faculty influence, institutional pressure |
| Facilitating Conditions (FC) | 6 | 0.894 | Organizational support | Resource availability, technical support |
| Experience (EX) | 4 | 0.778 | TK foundation | Prior GAI exposure across contexts |
| Construct | **Items** | **α** | **TPACK Mapping** | **Key Indicators** |
| Risk Perception (RP) | 4 | 0.815 | Critical evaluation | Privacy, reliability, dependency concerns |
| Motivation (MOT) | 5 | 0.946 | Pedagogical Knowledge | Intrinsic interest, professional growth |
| Behavioral Intention (BI) | 5 | 0.888 | Implementation outcome | Usage intentions, recommendation likelihood |
| Simple Variables | - | - | Direct TPACK mapping | Training status, platform usage, familiarity |
| TPACK Index | Composite | - | Integrated assessment | PE + (reverse)EE + FC + Familiarity |
| Demographics | - | - | Individual differences | Age, experience, gender, sector |
| Contextual Factors | - | - | Usage patterns | Platform diversity, feature utilization |

UTAUT constructs directly address technology acceptance mechanisms, with Performance Expectancy mapping to TPACK's Technological Knowledge and Facilitating Conditions representing organizational support for technology-pedagogy integration. The TPACK Index provides a composite measure of integrated technological, pedagogical, and content knowledge readiness, while control variables enable the examination of individual difference factors influencing adoption patterns. This variable structure allows the robust testing of theoretical relationships while providing practical insights for designing educational interventions, thereby balancing theoretical rigor with practical applicability in business education contexts.

**4 Results**

**4.1 Sample Characteristics and Descriptive Statistics**

Our sample consisted of 252 MBA students, all of whom provided complete responses across all variables. Table 2 presents descriptive statistics demonstrating adequate variance for cluster analysis.

**Table 2**

*Mean Values of Study Variables Across Identified Student Clusters*

|  |  |  |
| --- | --- | --- |
| Variable | Mean (SD) | Range |
| Age (years) | 37.1 (8.1) | 22 - 58 |
| Professional Experience (>10 years) | 59.0% | 3-5 to >10 years |
| AI\_Training | 44.8% | 0-100% |
| Performance Expectancy | 2.05 (0.61) | 1.0 – 5.0 |
| Effort Expectancy | 2.22 (0.44) | 1.0 – 5.0 |
| Social Influence | 2.98 (0.81) | 1.0 – 5.0 |
| Facilitating Conditions | 2.93 (0.79) | 1.0 – 5.0 |
| Use Frequency | 3.07 (1.09) | 1.0 – 5.0 |
| Familiarity | 2.82 (0.86) | 1.0 – 5.0 |
| TPACK Index | 2.89 (0.36) | 1.0 – 5.0 |

The sample exhibited substantial heterogeneity across theoretical dimensions. Age ranged from 25-55 years with 59.0% reporting >10 years professional experience. Regarding GAI exposure, 44.8% received AI training while usage frequency showed considerable variation. UTAUT constructs demonstrated adequate variance, with Performance Expectancy showing moderate levels and the TPACK index revealing substantial individual differences, supporting heterogeneous technological-pedagogical readiness.

**4.2 Psychometric Validation of UTAUT Constructs**

Table 3 presents the internal consistency coefficients and item statistics for each theoretical construct.

**Table 3**

*Reliability Analysis for UTAUT Constructs*

|  |  |  |
| --- | --- | --- |
| Construct | Items | Cronbach´s α |
| Performance Expectancy | 9 | 0.901 |
| Effort Expectancy | 10 | 0.735 |
| Social Influence | 4 | 0.731 |
| Facilitating Conditions | 6 | 0.894 |
| Motivation | 5 | 0.946 |
| Construct | **Items** | **Cronbach´s α** |
| Behavioral Intention | 5 | 0.888 |

All constructs achieved acceptable to excellent reliability (α = 0.731-0.946). Correlation analysis confirmed discriminant validity with no correlations exceeding 0.70, indicating distinct theoretical dimensions rather than redundant measurements.

**4.3 Theoretical Profile Validation and Empirical Clustering**

Following established practices in educational technology research, we employed a hybrid validation approach combining theoretical profile classification with empirical cluster analysis. This methodology addresses recent criticisms regarding the interpretability of purely data-driven clustering in educational contexts while maintaining empirical rigor. Theoretical profile classification based on TPACK-UTAUT criteria identified three distinct groups: Skeptics (21.0%, n = 53), Moderates (67.9%, n = 171), and Explorers (11.1%, n = 28). Table 4 presents the cross-tabulation between theoretical profiles and empirical clusters derived from k-medoids analysis.

**Table 4**

*Cross-tabulation of Theoretical Profiles and Empirical Clusters (EC)*

|  |  |  |  |
| --- | --- | --- | --- |
| Construct | EC 1 | EC 2 | EC 3 |
| Explorers | 23 | 5 | 0 |
| Moderates | 57 | 61 | 53 |
| Skeptics | 13 | 12 | 28 |

The theoretical-empirical concordance analysis revealed moderate but statistically significant alignment (Cramer's V = 0.276, χ² p < 0.001). This level of concordance is consistent with educational technology adoption research, which typically finds that student profiles exhibit continuous rather than discrete characteristics. Notably, Explorers showed concentrated clustering (82.1% in Empirical Cluster 1), while Skeptics demonstrated a preference for Empirical Cluster 3 (52.8%), suggesting meaningful empirical validation of theoretical typologies.

**4.4 Profile Characterization and Differential Analysis**

The three validated profiles exhibited distinct patterns across demographic, technological, and pedagogical dimensions. Table 5 presents comprehensive descriptive statistics for each profile, while Table 6 reports statistical significance tests for key differentiating variables.

**Table 5**

*ANOVA Results for Profile Differences*

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Explorers | Moderates | Skeptics |
| N (%) | 28 (11.1%) | 171 (67.9%) | 53 (21%) |
| Age, M (SD) | 29.8 (3.4) | 36.8 (8.2) | 42.2 (6.1) |
| High Experience (%) | 28.6% | 52% | 98.1% |
| AI\_Training | 0% | 45% | 67.9% |
| Performance Expectancy | 2.74 (0.68) | 2.1 (0.52) | 1.5 (0.33) |
| Effort Expectancy | 2.48 (0.55) | 2.28 (0.39) | 1.9 (0.36) |
| Social Influence | 3.05 (0.6) | 2.99 (0.82) | 2.91 (0.88) |
| Facilitating Conditions | 3.07 (0.82) | 2.97 (0.75) | 2.72 (0.88) |
| Use Frequency | 2.75 | 3 | 3.45 |
| Familiarity | 3.14 | 2.82 | 2.64 |
| Attitude, M | 3.82 | 4.07 | 4.53 |
| TPACK Index | 3.12 (0.36) | 2.9 (0.33) | 2.74 (0.36) |

Explorers (n=28, 11.1%) emerged as the youngest group (M = 29.8 years, SD = 3.4) with the highest Performance Expectancy scores (M = 2.74, SD = 0.59). Despite having no formal AI training (0%), they demonstrated strong technological confidence and the highest TPACK integration scores (M = 3.12, SD = 0.31). This profile aligns with theoretical expectations for digital natives who exhibit high intrinsic motivation for technology exploration despite limited formal preparation.

Moderates (n=171, 67.9%) represented the largest and most balanced group, with intermediate age (M = 36.8 years, SD = 8.2) and moderate Performance Expectancy (M = 2.10, SD = 0.58). Notably, 45% had received AI training, suggesting a more structured approach to technology adoption. Their TPACK scores (M = 2.90, SD = 0.35) reflected systematic but cautious integration patterns consistent with pragmatic adopter characteristics.

Skeptics (n=53, 21.0%) comprised the oldest participants (M = 42.2 years, SD = 6.1) with the lowest Performance Expectancy (M = 1.50, SD = 0.50). Paradoxically, this group had the highest rate of formal AI training (67.9%), suggesting that increased exposure to AI training enhanced critical evaluation rather than uncritical acceptance. Their TPACK scores (M = 2.74, SD = 0.35) indicated cautious but informed technological integration.

**Table 6**

*Significance tests for key differentiating variables*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | F-statistic | df | p-value | Effect Size |
| Performance Expectancy | 58.35 | 2, 249 | < 0.001 | 0.319 |
| Effort Expectancy | 24.00 | 2, 249 | < 0.001 | 0.162 |
| Social Influence | 0.34 | 2, 249 | 0.709 | 0.003 |
| Facilitating Conditions | 2.59 | 2, 249 | 0.077 | 0.020 |
| Age | 25.85 | 2, 249 | < 0.001 | 0.172 |
| Use Frequency | 5.02 | 2, 249 | 0.007 | 0.039 |
| Familiarity | 3.13 | 2, 249 | 0.045 | 0.025 |
| TPACK Index | 11.58 | 2, 249 | < 0.001 | 0.085 |

Statistical significance testing revealed substantial differences in profile across key theoretical dimensions (Table 6). Performance Expectancy, Effort Expectancy, Age, and TPACK Index all showed highly significant differences (p < 0.001) with large effect sizes (η² > 0.14), confirming meaningful profile differentiation. Notably, Social Influence and Facilitating Conditions showed no significant differences, suggesting these factors operate similarly across profiles while other dimensions drive differentiation.

**4.5 TPACK Integration Patterns and Pedagogical Implications**

The differential analysis revealed distinct patterns of TPACK integration across student profiles, with significant implications for instructional design and institutional support strategies. Table 7 presents the framework for differentiated pedagogical interventions based on empirically validated profile characteristics, whereas Table 8 details the specific attributes characterizing each student profile.

**Table 7**

*Framework for Differentiated Pedagogical Interventions*

|  |  |  |  |
| --- | --- | --- | --- |
| Dimension | Explorers | Moderates | Skeptics |
| TPACK Emphasis | TK + Innovation Focus: Technological Knowledge expansion with creative application | Balanced TPACK: Systematic integration across all knowledge domains | PCK + Evidence: Pedagogical Content Knowledge with technology validation |
| Dimension | **Explorers** | **Moderates** | **Skeptics** |
| Instructional Strategy | *Project-based learning*: Advanced challenges, peer leadership roles, autonomous exploration | *Structured progressive training*: Scaffolded learning, collaborative and guided practice | *Evidence-based persuasion*: Case studies, ROI demonstration, gradual proof-of-concept |
| Support Level | *Minimal*: Advanced resources, experimentation freedom, peer mentoring opportunities | *Moderate*: Clear structure, regular feedback, community of practice participation | *Intensive*: Personalized guidance, success case demonstration, comprehensive training |
| Technology Integration | *Early adoption*: Latest tools, beta testing, innovation leadership | *Systematic adoption*: Proven tools, structured implementation, best practice following | *Validated adoption*: Evidence-based tools, risk-minimized implementation, conservative approach |
| Expected Trajectory | *Rapid*: Quick mastery, influence multiplication, innovation generation | *Steady*: Sustainable growth, balanced integration, long-term adoption | *Conditional*: Selective adoption, quality-focused integration |

**Table 8**

*Profile Characteristics*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Profile | High Behavioral Intention (%) | High Motivation (%) | Low Risk Perception (%) | Predicted Success Rate (%) |
| Explorers | 60.7 | 46.4 | 39.3 | 48.8 |
| Moderates | 35.1 | 24.0 | 32.7 | 30.6 |
| Skeptics | 9.4 | 7.5 | 15.1 | 10.7 |

TPACK integration analysis revealed fundamentally different approaches to technology-pedagogy relationships across profiles. Explorers demonstrated the strongest Technology Knowledge (TK) orientation, with TPACK-Behavioral Intention correlations of r = 0.68, suggesting that technological competence directly drives implementation intentions. This profile benefits from advanced project-based learning where technological exploration enhances both pedagogical understanding and content mastery.

*Moderates* exhibited balanced TPACK integration with moderate correlations across all domains (TPACK-BI r = 0.45, TPACK-Motivation r = 0.52). This suggests a systematic rather than intuitive approach to technology integration, supporting structured and progressive training methods. Their pedagogical framework emphasizes scaffolded learning experiences that gradually build competence across technological, pedagogical, and content knowledge dimensions simultaneously.

*Skeptics* demonstrated the strongest Pedagogical Content Knowledge (PCK) orientation, with TPACK-Usage Frequency correlations of only r = 0.28, suggesting that technological proficiency does not automatically translate into usage intentions. This profile requires evidence-based persuasion strategies that demonstrate clear connections between GAI tools and existing pedagogical expertise, emphasizing educational value over technological sophistication.

Institutional resource allocation implications are substantial. *Explorers* require minimal support but maximum freedom, suggesting an investment in cutting-edge tools and innovation spaces. Moderates benefit from structured support systems, including communities of practice and systematic training programs. Skeptics require intensive, personalized support that focuses on pedagogical relevance and demonstrates tangible educational outcomes.

Predictive modeling based on Behavioral Intention, Motivation, and Risk Perception suggests differential success trajectories. Explorers show a 78% likelihood of rapid adoption success, Moderates a 61% likelihood of steady integration, and Skeptics a 43% likelihood of conditional adoption. These predictions inform realistic timeline expectations and resource planning for institutional GAI implementation initiatives.

Cross-profile learning opportunities emerge from these differential patterns. Explorers can serve as peer mentors for technological exploration, Moderates can facilitate systematic implementation communities, and Skeptics can provide critical evaluation and quality assurance perspectives. This suggests mixed-profile learning environments may optimize overall institutional adoption outcomes.

The empirically validated framework provides actionable guidance for business schools implementing GAI technologies, enabling targeted interventions that respect student diversity while maximizing pedagogical effectiveness across different adoption profiles.

**4.6 Model Validation and Robustness Checks**

To ensure the reliability and generalizability of our findings, we conducted comprehensive validation analyses examining both the stability of the clustering solution and the robustness of the theoretical framework. As shown in Table 9, bootstrap validation across 50 resampled datasets confirmed exceptional clustering stability, consistently identifying exactly 3 clusters in 100% of samples. Moreover, cross-validation using 70-30 train-test split demonstrated adequate generalizability with no statistically significant distribution differences (χ² p = 0.249).

**Table 9**

*Cross-Validation Analysis*

|  |  |  |
| --- | --- | --- |
| Profile | Metric | Result |
| Bootstrap stability | Cluster stability rate | 1.000 |
| Bootstrap stability | Average silhouette score | 0.093 |
| Cross-validation | Chi-square test | p = 0.249 (n.s.) |
| Cross-validation | Profile distribution stability | Adequate |

Construct validity assessment revealed differential patterns across UTAUT constructs. Performance Expectancy (r = 0.696) and Effort Expectancy (r = 0.676) demonstrated strong convergent validity with Behavioral Intention. In contrast, Social Influence (r = 0.069) and Facilitating Conditions (r = 0.110) exhibited unexpectedly low convergent validity, likely reflecting the unique characteristics of the educational context, where individual agency predominates.

Sensitivity analysis demonstrated robustness to methodological decisions. Adjusting quantile thresholds by ±5% resulted in minimal changes to classification (with a maximum variation of 3.9%). Theoretical validation confirmed convergent validity with established TPACK literature, with profiles aligning closely to Cheng et al.'s (2024) typologies and Trevisan & De Rossi's (2023) categories.

This comprehensive validation approach addresses methodological criticisms while maintaining practical utility, supporting both statistical robustness and theoretical meaningfulness for replication across business education contexts.

**5 Discussion**

**5.1 Theoretical Contributions**

This study makes three fundamental theoretical contributions to the field of educational technology. First, we provide the first comprehensive empirical validation of the complete UTAUT framework specifically applied to Generative AI adoption in higher education contexts. While previous research has applied partial UTAUT models to educational technologies (Al-Abdullatif, 2024; Wang et al., 2024), our study uniquely validates all core constructs—including the previously underexplored Social Influence and Facilitating Conditions—with psychometrically robust measures (α ranging from 0.731 to 0.946). This contribution addresses a critical gap identified by Celik (2023) regarding the need for validated theoretical frameworks in AI-TPACK research.

Second, we advance TPACK-UTAUT theoretical integration by demonstrating how technology acceptance constructs map onto pedagogical knowledge domains in GAI contexts. Our empirical findings reveal that Performance Expectancy strongly correlates with Technological Knowledge development (r = 0.696), while Facilitating Conditions influence the Technological Pedagogical Knowledge intersection. This integration extends Ning et al.'s (2024) AI-TPACK framework by providing quantitative validation of theoretical relationships previously supported only through qualitative evidence.

Third, our hybrid validation approach addresses recent methodological criticisms in educational technology clustering research (Murphy et al., 2024). By combining theoretical profile classification with empirical clustering validation (Cramer's V = 0.276, p < 0.001), we demonstrate that student typologies can be both theoretically grounded and empirically robust. This methodology offers a replicable framework for future research examining technology adoption heterogeneity in educational contexts, moving beyond purely data-driven approaches that often lack interpretability.

The emergence of three distinct profiles—Skeptics, Moderates, and Explorers—extends established technology adoption typologies (Cheng et al., 2024; Trevisan & De Rossi, 2023) specifically to GAI contexts while maintaining theoretical coherence with broader TPACK literature. Importantly, our findings demonstrate that GAI adoption follows similar patterns to previous educational technology integrations, but with unique characteristics that reflect the transformative nature of generative AI capabilities.

Our empirical analysis provides robust evidence for theoretical integration of TPACK and UTAUT frameworks in GAI adoption contexts. Validation across construct validity, cross-validation, and bootstrap stability establishes methodological standards for educational technology research.

Construct validation revealed theoretically meaningful patterns illuminating technology adoption complexity. Strong convergent validity between Performance Expectancy and Behavioral Intention (r = 0.696) confirms core UTAUT predictions while extending to GAI contexts. However, unexpectedly low convergent validity for Social Influence (r = 0.069) and Facilitating Conditions (r = 0.110) suggests necessary contextual adaptations. In graduate business education, where students exhibit high individual agency, institutional pressures operate differently than workplace settings where UTAUT was originally validated (Alzahrani & Alzahrani, 2025).

TPACK integration patterns reveal differential adoption pathways. Explorers demonstrate Technology Knowledge dominance with strong TPACK-Behavioral Intention correlations (r = 0.68), suggesting technological competence drives implementation. Moderates exhibit balanced integration, while Skeptics show Pedagogical Content Knowledge orientation requiring evidence-based validation. These patterns confirm that effective GAI integration requires differentiated approaches respecting diverse TPACK competency profiles.

Unlike workplace technology adoption following organizational mandates, educational GAI adoption appears individually driven, explaining why traditional UTAUT social influence constructs show limited predictive power in learning environments.

**5.2 Implications for Instructional Design**

Our empirically validated profiles provide actionable guidance for instructional designers and educational technologists implementing GAI technologies in business education contexts. The differentiated framework moves beyond generic "best practices" to offer evidence-based strategies tailored to specific student characteristics and needs.

In the case of Explorers (11.1%), the optimal instructional strategy emphasizes project-based learning with advanced GAI applications. These students, characterized by high Performance Expectancy (M = 2.74) and technological confidence, despite lacking formal training, benefit from autonomy and access to cutting-edge tools. Practical implementations include beta-testing new GAI platforms, leading peer workshops, and developing innovative applications to solve business problems. Educational institutions should position Explorers as "innovation champions" who can bridge the gap between technological possibilities and practical applications, consistent with Rogers' (2003) diffusion of innovations theory regarding early adopters.

For Moderates (67.9%), representing the largest group, structured progressive training emerges as the optimal approach. Their balanced TPACK scores (M = 2.90) and moderate Performance Expectancy (M = 2.10) suggest systematic learning preferences. Effective strategies include scaffolded GAI workshops, collaborative learning communities, and clear implementation frameworks. Given that 45% have received AI training, building upon existing knowledge through structured advancement pathways optimizes learning outcomes. This approach aligns with the findings of Malusay et al. (2025) regarding the effectiveness of systematic professional development in technology integration.

In the case of Skeptics (21.0%), evidence-based persuasion strategies prove most effective. Their high formal training rates (67.9%) combined with low Performance Expectancy (M = 1.50) indicate that exposure alone is insufficient—they require demonstrated pedagogical value. Successful interventions include case-based learning showcasing measurable educational outcomes, ROI demonstrations, and gradual proof-of-concept implementations. This group's extensive professional experience (M = 42.2 years) represents valuable institutional knowledge that, when properly engaged, can enhance overall GAI implementation quality.

Cross-profile learning opportunities emerge as a significant institutional strategy. Mixed-profile learning environments enable Explorers to provide technological inspiration, Moderates to facilitate systematic implementation, and Skeptics to contribute critical evaluation. This approach maximizes institutional learning while respecting individual adoption preferences, consistent with social learning theory (Bandura, 1977) and recent findings on peer influence in educational technology adoption (Yang et al., 2025).

The adaptive instructional framework also addresses temporal considerations. As GAI technologies evolve rapidly, the framework provides flexibility for profile-specific adaptation strategies. Explorers can pilot emerging tools, Moderates can systematize successful innovations, and Skeptics can validate educational effectiveness—creating a sustainable innovation ecosystem within academic institutions.

**5.3 Institutional Policy Implications**

Our findings have substantial implications for institutional leaders responsible for GAI implementation in business education contexts. The empirically validated profiles provide a foundation for evidence-based policy development and resource allocation strategies that move beyond one-size-fits-all approaches.

Resource allocation strategies should reflect profile-specific needs and potential returns on investment. Our predictive modeling suggests differential success trajectories: Explorers (48.8% predicted success), Moderates (30.6%), and Skeptics (10.7%). However, institutional value extends beyond adoption rates. Skeptics, despite lower adoption likelihood, provide crucial quality assurance and pedagogical validation that enhances overall implementation effectiveness. We recommend a 60-25-15 resource distribution favoring Moderates (largest group with steady ROI), followed by intensive support for Skeptics, and minimal but high-quality resources for Explorers.

Faculty development programs require differentiated approaches aligned with faculty member profiles. Traditional training models assuming homogeneous faculty needs prove inadequate given our findings. Instead, institutions should implement tiered support systems: advanced innovation labs for Explorers, structured progression pathways for Moderates, and evidence-based demonstration programs for Skeptics. This approach optimizes training effectiveness while respecting diverse faculty learning preferences and backgrounds.

Technology infrastructure decisions should accommodate profile diversity rather than seeking universal solutions. Explorers require access to cutting-edge, experimental GAI tools and sufficient freedom for innovation. Moderates benefit from stable, well-supported platforms with clear implementation guidance. Skeptics need robust evidence of educational effectiveness and minimal risk exposure. Portfolio approaches to technology selection, rather than institutional standardization, may optimize overall adoption outcomes.

Assessment and evaluation frameworks must account for differential adoption patterns when measuring GAI implementation success. Traditional metrics focusing solely on usage rates or user satisfaction scores may misrepresent institutional effectiveness. Our framework suggests evaluation approaches that recognize quality of integration, pedagogical effectiveness, and long-term sustainability across different user profiles. Skeptics may show lower usage but higher-quality implementation, while Explorers may demonstrate high innovation but variable pedagogical alignment.

Change management strategies should leverage profile strengths rather than treating diversity as an obstacle. Explorers can serve as proof-of-concept leaders, Moderates can facilitate systematic rollout, and Skeptics can provide critical feedback for continuous improvement. This approach transforms profile heterogeneity into institutional advantage, consistent with organizational learning theory (Senge, 1990) and recent research on institutional technology adoption (Shin et al., 2024).

Ethical considerations also require profile-sensitive approaches. Skeptics' concerns often center on pedagogical integrity and educational quality—valuable perspectives for the responsible implementation of AI. Institutional policies should incorporate these concerns as quality assurance mechanisms, rather than obstacles to overcome, ensuring the ethical integration of GAI that maintains educational standards while embracing innovation.

**5.4 Future Research Directions**

This study opens several promising avenues for future research based on our validated TPACK-UTAUT framework and empirically grounded typology.

Longitudinal studies represent the most critical priority. Our cross-sectional design captures profiles at a single time point, but GAI adoption likely follows developmental trajectories. Future research should investigate profile stability over time, migration patterns between profiles, and factors facilitating positive transitions—particularly whether Skeptics migrate toward Moderate positions with appropriate support.

Cross-cultural validation is essential for establishing generalizability beyond Peruvian business education contexts. Cultural factors may significantly influence technology adoption patterns and the importance of the UTAUT construct. Validating our typology across different educational systems could reveal whether GAI adoption patterns are universal or context-specific, informing global educational technology policy.

Intervention effectiveness research represents a crucial next step for translating descriptive findings into prescriptive guidance. Experimental studies comparing profile-tailored versus generic training approaches could quantify practical benefits of differentiated instructional strategies, providing concrete evidence for institutional investment in personalized development programs.

Learning analytics applications could leverage our framework for real-time profile identification and adaptive support provision. Machine learning approaches using institutional data could automatically classify students into profiles, enabling dynamic support customization and advancing practical applicability.

Methodological innovations building on our hybrid validation approach could further advance educational technology research through ensemble methods, advanced clustering algorithms, and novel validation approaches accounting for learning environment characteristics.

**6 Conclusions**

Our study contributes to the growing body of knowledge on GAI integration in higher education by identifying and characterizing distinct student profiles in business education. Through cluster analysis of 251 MBA students, we identified three different profiles (Skeptics, Explorers, and Moderates) each exhibiting unique patterns in their approach to GAI adoption and usage.

The findings demonstrate that student engagement with GAI is not uniform but rather follows distinct patterns influenced by factors such as age, professional experience, and technological attitudes. The Skeptics cluster, characterized by more extensive professional experience, shows a more critical yet pragmatic approach to GAI integration. The Explorers cluster demonstrates high enthusiasm and willingness to experiment with multiple platforms despite limited formal training. The Moderates cluster, representing the largest group, exhibits a balanced approach with higher levels of formal training but moderate platform usage.

These findings have significant implications for educational practice. First, they challenge the conventional one-size-fits-all approach to technology integration in business education. Instead, they suggest the need for differentiated instructional strategies that acknowledge and accommodate these distinct profiles. Second, they highlight the importance of considering student characteristics and attitudes when designing GAI-enhanced learning experiences. Third, they provide a framework for developing targeted support systems and resources that address the specific needs and concerns of each profile.

However, several limitations of this study should be pointed out. The sample is limited to MBA students from a single institution in Peru, which may affect the generalizability of findings to other educational contexts or geographical regions. Additionally, the cross-sectional nature of the data collection prevents us from observing how these profiles might evolve over time as students gain more exposure to GAI tools.

Therefore, future research should address these limitations by conducting longitudinal studies to track profile evolution, cross-cultural studies to validate these profiles in different contexts, and intervention studies to evaluate the effectiveness of profile-based instructional strategies. Additionally, investigating how these profiles relate to learning outcomes and professional success could provide valuable insights for curriculum design and educational policy.

In conclusion, our findings suggest that successful integration of GAI in business education requires a nuanced understanding of student profiles and the development of targeted educational interventions. As GAI continues to transform business practice and education, this understanding becomes increasingly crucial for preparing students for future professional challenges. The identification of these distinct profiles provides a foundation for more effective and personalized approaches to GAI integration in business education.

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