INTERNATIONAL PREMIER JOURNAL OF LANGUAGES & LITERATURE (IPJLL)
VOLUME 4, ISSUE 3, 2026 p-ISSN: 3007-2336 e-ISSN: 3007-2344

IMPLEMENTING CLAUDE AI-POWERED ASSESSMENT IN PAKISTANI GRAMMAR INSTRUCTION: A CASE STUDY OF TECHNOLOGY ACCEPTANCE MODEL AMONG FEMALE EDUCATORS

Qaisera Iqbal
qaiseraiqbal@gmail.com
Assistant Professor, Department of English, Higher Education Department, Punjab, Pakistan

Abstract

The rapid integration of artificial intelligence tools in higher education presents both opportunities and challenges, particularly in developing countries where gender disparities and technological barriers intersect. This study investigates Claude AI integration in grammar instruction through a single case study examining technology acceptance among female faculty and students in Pakistani higher education. The research employs an extended Technology Acceptance Model (TAM) framework to explore how perceived usefulness, perceived ease of use, trust, AI anxiety, and facilitating conditions influence Claude adoption for AI-powered grammar assessment. The study focuses on an ADP-level English Grammar practice at Govt. Graduate College for Women, Pakistan, where Claude AI was used to generate interactive quizzes with immediate feedback across five grammar domains: subject-verb agreement, pronoun usage, verb tenses, error correction, and reading comprehension. Using a mixed-methods case study design implemented over one academic semester (16 weeks), data collection involved pre-post student surveys (N=52), instructor reflective journal, student focus groups (N=16), classroom observations, and analysis of student performance data from 487 quiz attempts. Findings revealed significant improvements across all TAM constructs, with perceived ease of use showing the largest effect size (Cohen's d=2.15). AI anxiety decreased substantially from pre-implementation (M=5.67) to post-implementation (M=3.12), while trust emerged as the strongest predictor of behavioral intention through qualitative analysis. Student performance improved dramatically, with 78% achieving scores of 80-100% on AI-generated quizzes and a 12.7 percentage point improvement in final exam scores compared to the previous cohort without AI intervention. Gender-specific findings indicated that female educators prioritized trust-building through verification, peer support networks, and immediate student success feedback over technical sophistication. The study provides theoretical contributions through TAM validation for AI assessment tools in developing country contexts and practical implications for designing gender-inclusive, culturally-sensitive AI integration strategies in resource-constrained educational environments.

Keywords: *AI-Powered Quizzes, Anthropic, Case Study, Claude AI, Female Educators, Grammar Assessment, Higher Education, Pakistan, Technology Acceptance Model*

Corresponding Author: Qaisera Iqbal (Assistant Professor, Department of English, Higher Education Department, Punjab Pakistan.)
Email: qaiseraiqbal@gmail.com

1. Introduction

1.1. Problem Statement

The global proliferation of artificial intelligence tools in educational settings has created unprecedented opportunities for enhancing teaching and learning experiences (Dwivedi et al., 2023; Rudolph et al., 2023). However, the integration of advanced AI technologies in developing countries faces multifaceted challenges, particularly when considering gender disparities in technology adoption (Alasadi & Baiz, 2023; Venkatesh & Morris, 2000). Pakistani higher education institutions, despite significant digitization efforts, continue to struggle with systematic AI integration, especially among female faculty members who constitute a substantial portion of the academic workforce yet remain underrepresented in educational technology adoption studies (Ahmad et al., 2022; Higher Education Commission Pakistan, 2023).

Current research on AI acceptance in education has predominantly focused on developed countries, with limited attention to the unique socio-cultural contexts of South Asian institutions (Strzelecki, 2023; Tlili et al., 2023). The intersection of gender, cultural factors, and technological barriers creates complex dynamics that existing technology acceptance models may not adequately address. While the Technology Acceptance Model (TAM) has proven effective in explaining technology adoption across various contexts (Davis, 1989; Marangunić & Granić, 2015), its application to AI tools in gender-specific, culturally distinct environments requires theoretical extension and empirical validation.

Grammar instruction in Pakistani higher education faces particular challenges including large class sizes, limited opportunities for individualized feedback, delayed assessment turnaround times, and student anxiety about error correction (Rashid & Asghar, 2016). Traditional drill-and-practice methods often fail to engage students or provide the immediate feedback necessary for effective grammar acquisition. AI-powered assessment tools offer potential solutions, yet their acceptance and effective implementation among female educators in Pakistani contexts remains unexplored.

1.2. Research Context

Pakistan's higher education landscape presents unique challenges for technology integration, characterized by resource constraints, infrastructure limitations, and varying levels of digital literacy among faculty members (Ahmad et al., 2022; Rashid & Asghar, 2016). The Higher Education Commission of Pakistan has initiated several digitization programs, yet the adoption of cutting-edge AI tools remains inconsistent across institutions and demographic groups (Higher Education Commission Pakistan, 2023). Female educators, who represent approximately 45% of university faculty, face additional barriers including limited access to professional development opportunities, cultural restrictions on technology use, and gender-specific anxiety toward emerging technologies (Batool et al., 2019; Sultana et al., 2021).

AI-powered educational tools have garnered significant attention globally, with applications ranging from personalized tutoring to automated assessment (Atlas, 2023; Cotton et al., 2023). Claude, developed by Anthropic, represents a newer generation of conversational AI with specific features relevant to educational contexts, including extended context windows, constitutional AI training emphasizing safety, and reduced tendency toward factual errors compared to earlier models (Bai et al., 2022). For grammar instruction specifically, Claude's ability to generate contextually appropriate examples, provide detailed explanations, and maintain consistency across multiple question formats makes it particularly suitable for assessment applications.

However, adoption of AI assessment tools in Pakistani higher education remains nascent, with most institutions lacking systematic approaches to AI integration (Farooq et al., 2023). The intersection of gender and technology acceptance in educational contexts has been well-documented in Western literature, with studies consistently showing that women prioritize ease of use and social influence over utilitarian factors (Gefen & Straub, 1997; Venkatesh & Morris, 2000; Zhang et al., 2021). However, these patterns may manifest differently in collectivist cultures like Pakistan, where family and institutional approval significantly influence professional decisions (Hofstede, 2001; Nasir & Mahmood, 2018).

This study emerges from the researcher's position as a female Assistant Professor of English at Govt. Graduate College for Women, Higher Education Department, Punjab, teaching ADP-level grammar practice where traditional assessment methods proved time-consuming, delayed feedback delivery, and limited student engagement. Understanding how AI-powered assessment tools can be effectively integrated while addressing gender-specific and cultural barriers provides crucial insights for developing equitable AI adoption strategies in similar contexts.

1.3. Research Objectives and Questions

This study investigates Claude AI integration in grammar assessment through a case study approach, examining the factors influencing acceptance and implementation from the perspective of a female educator in Pakistani higher education. The research employs extended TAM as an analytical framework to understand the complexities of AI adoption in authentic classroom contexts.

Primary Research Question: How does a female educator in Pakistani higher education experience and integrate Claude AI for grammar assessment, and what factors facilitate or hinder successful implementation?

Secondary Research Questions:

1. How do perceived usefulness, perceived ease of use, trust, AI anxiety, and facilitating conditions evolve through actual classroom implementation of AI-powered assessment?
2. What are the practical benefits, challenges, and barriers of using Claude AI for grammar quiz generation and automated feedback?
3. How do students respond to AI-generated grammar assessments, and what are the observable learning outcomes?
4. What cultural and institutional factors influence the acceptance and implementation process among female educators?
5. What gender-specific patterns emerge in technology acceptance for AI assessment tools?
6. What pedagogical strategies effectively integrate AI-powered assessment while maintaining academic integrity and cultural appropriateness?

1.4. Research Objectives

- Document authentic Claude AI integration experience in Pakistani grammar instruction
- Validate extended TAM constructs through real-world implementation data
- Identify practical success factors and barriers specific to female educators in developing countries
- Develop evidence-based recommendations for AI assessment integration in similar contexts
- Contribute to understanding of gender-technology acceptance intersections in collectivist cultures

1.5. Research Contributions

This study contributes to both theoretical and practical knowledge domains. Theoretically, it extends TAM for AI assessment applications in developing country contexts, particularly focusing on gender-specific factors and cultural moderators (King & He, 2006; Scherer et al., 2019). The research validates and refines existing extended TAM frameworks within a distinct cultural context, contributing to the growing literature on AI acceptance in education (Strzelecki, 2023; Chatterjee & Bhattacharjee, 2020).

Practically, the study provides actionable insights for Pakistani policymakers and institutional administrators seeking to implement AI integration strategies. The case study offers a replicable model for enhancing AI assessment acceptance among female educators, potentially applicable to similar contexts across South Asia. Additionally, the research informs gender-inclusive policy development for educational technology adoption in resource-constrained environments, demonstrating that significant improvements are achievable even with minimal institutional support when implementation is pedagogically grounded and culturally sensitive.

2. Literature Review

2.1. Technology Acceptance Model Evolution

The Technology Acceptance Model, originally developed by Davis (1989), has served as the foundational framework for understanding user adoption of information technologies across diverse contexts. Davis's seminal work established that perceived usefulness and perceived ease of use are primary determinants of user acceptance, providing a parsimonious yet powerful model for predicting technology adoption behaviors. The original TAM posited that perceived usefulness (PU) - the degree to which a user believes that using a particular system would enhance their job performance - and perceived ease of use (PEOU) - the extent to which a user believes that using the system would be free of effort - directly influence behavioral intentions and subsequent usage behaviors.

The model's theoretical foundation draws from the Theory of Reasoned Action (Fishbein & Ajzen, 1975), incorporating psychological and behavioral insights to explain technology-related decision-making processes. Davis's empirical validation demonstrated that TAM could explain approximately 40% of the variance in usage intentions across various technological applications, establishing its credibility within the information systems research community (Davis, 1989; King & He, 2006).

Subsequent research has both validated and extended TAM across numerous contexts, leading to the development of TAM2 (Venkatesh & Davis, 2000), which incorporated social influence processes and cognitive instrumental processes as additional determinants of technology acceptance. Venkatesh and Davis (2000) found that subjective norm, voluntariness, and experience significantly moderated the relationships between core TAM constructs, explaining up to 60% of variance in user intentions. The Unified Theory of Acceptance and Use of Technology (UTAUT) further synthesized TAM with seven other theoretical models, identifying performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants (Venkatesh et al., 2003).

However, critics have argued that TAM's simplicity may overlook important contextual and individual difference factors (Bagozzi, 2007; Benbasat & Barki, 2007). Recent research has emphasized the need for context-specific extensions, particularly when investigating emerging technologies in diverse cultural settings (Scherer et al., 2019; Granić & Marangunić, 2019). Studies focusing on AI acceptance have incorporated additional constructs such as trust, anxiety, and perceived risk to better capture the unique characteristics of artificial intelligence technologies (Gkinko & Elbanna, 2023; Strzelecki, 2023).

For AI-powered educational tools specifically, trust has emerged as a critical factor due to concerns about accuracy, bias, and the opaque nature of AI decision-making (McKnight et al., 2002; Strzelecki, 2023). AI anxiety represents another important extension, capturing emotional responses to AI capabilities that may threaten professional identity or reveal technological inadequacy (Venkatesh & Morris, 2000; Zhang et al., 2021). Facilitating conditions, drawn from UTAUT, address the organizational and technical support infrastructure necessary for successful AI implementation (Venkatesh et al., 2003; Dahri et al., 2024).

This study adopts an extended TAM framework incorporating these AI-specific constructs alongside traditional TAM variables, providing a comprehensive model for understanding AI assessment tool acceptance in educational contexts.

2.2. AI and Conversational AI in Higher Education

The integration of artificial intelligence in educational settings has evolved rapidly, with conversational AI tools representing a paradigm shift in AI accessibility and functionality (Atlas, 2023; Cotton et al., 2023). Recent studies indicate that large language models' natural language processing capabilities offer unprecedented opportunities for personalized learning, automated assessment, and administrative efficiency in higher education contexts (Rudolph et al., 2023; Dwivedi et al., 2023; Tlili et al., 2023).

Strzelecki's (2023) comprehensive study found that extended TAM models explained 68% of variance in behavioral intentions, with trust emerging as a significant predictor among university students. The research identified AI anxiety as a substantial barrier, particularly among users with limited prior AI experience. These findings align with broader literature suggesting that trust-related concerns represent primary obstacles to AI adoption in educational contexts (Gkinko & Elbanna, 2023; Chatterjee & Bhattacharjee, 2020).

While most existing research focuses on earlier AI tools, Claude, developed by Anthropic, offers distinct advantages for educational contexts (Bai et al., 2022). Key features relevant to assessment applications include extended context windows enabling processing of longer conversations and documents, constitutional AI training emphasizing helpfulness and safety, reduced hallucination rates compared to earlier language models, and optimized instruction-following capabilities for structured assessment generation.

For grammar instruction specifically, these features enable Claude to generate multiple contextually appropriate example sentences demonstrating specific grammar rules, create varied question formats with consistent difficulty levels, provide detailed explanations for correct and incorrect answers, and maintain grammatical accuracy across hundreds of generated questions.

Recent systematic reviews have identified key benefits of AI tools in higher education assessment, including enhanced student engagement through immediate feedback, reduced instructor grading burden, and increased assessment frequency enabling formative learning opportunities (Rudolph et al., 2023; Cotton et al., 2023). However, implementation challenges persist, including concerns about academic integrity, over-reliance on AI tools, varying levels of digital literacy among educators, and questions about AI-generated content accuracy (Tlili et al., 2023; Dwivedi et al., 2023).

The professional development aspect of AI integration has received increasing attention, with studies demonstrating that structured training programs significantly improve educator acceptance and effective utilization of AI tools (Crompton & Burke, 2023; Southworth et al., 2023). However, these studies have predominantly focused on Western contexts, with limited research examining implementation experiences in developing countries or among specific demographic groups.

Gender differences in AI acceptance have begun emerging as a critical research area, with preliminary studies suggesting that female educators express greater concerns about AI reliability and ethical implications compared to their male counterparts (Zhang et al., 2021; Cai et al., 2023). These patterns mirror established gender differences in general technology acceptance, though the specific manifestations in AI contexts require further investigation.

Cultural factors also play crucial roles in AI acceptance, with collectivist cultures showing different patterns of social influence and institutional support importance compared to individualist contexts (Hofstede, 2001; Nasir & Mahmood, 2018). Research in Asian contexts has highlighted the significance of peer influence, hierarchical approval, and institutional support in technology adoption decisions (Park et al., 2020; Lai, 2017). However, empirical research on Claude's educational effectiveness remains limited, with this study contributing among the first classroom-based investigations of Claude AI for assessment purposes in developing country contexts.

2.3. Gender Differences in Technology Acceptance

The seminal work of Venkatesh and Morris (2000) established foundational understanding of gender differences in technology acceptance, demonstrating that men's technology usage decisions were more strongly influenced by perceived usefulness, while women were more strongly influenced by perceptions of ease of use and subjective norm. This research revealed that gender moderates the relationships between TAM constructs and behavioral intentions, with implications extending beyond simple demographic differences to encompass underlying psychological and social processes.

Subsequent research has consistently validated these gender patterns across various technological applications and cultural contexts (Gefen & Straub, 1997; Zhang et al., 2021; Cai et al., 2023). Women's greater emphasis on ease of use reflects both cognitive processing differences and social role expectations, while their heightened sensitivity to subjective norm aligns with research on gender-based communication styles and social influence susceptibility (Gefen & Straub, 1997; Venkatesh et al., 2003). These patterns have proven remarkably stable across time and technological evolution, suggesting fundamental differences in how men and women approach technology adoption decisions.

Recent studies focusing on educational technology have found that female educators demonstrate greater technology anxiety and require more extensive support systems for successful adoption (Zhang et al., 2021; Cai et al., 2023). However, once initial barriers are overcome, women often exhibit higher levels of pedagogical integration and innovative usage compared to male colleagues (Tondeur et al., 2017; Crompton & Burke, 2023). This paradox suggests that gender-sensitive approaches to technology training and support may be particularly crucial for maximizing adoption outcomes among female educators.

The emergence of AI technologies has introduced new dimensions to gender-based technology acceptance patterns. Preliminary research indicates that women express greater concerns about AI reliability, transparency, and ethical implications, potentially reflecting broader patterns of risk aversion and moral reasoning (Zhang et al., 2021; Strzelecki, 2023). Conversely, women show greater interest in AI applications that support collaborative and relational aspects of education, aligning with established gender differences in educational values and priorities (Gefen & Straub, 1997; Cai et al., 2023).

In developing country contexts, gender differences in technology acceptance intersect with cultural factors, creating complex dynamics. Research in Pakistani higher education has documented that female faculty face unique challenges including limited access to professional development, cultural expectations about appropriate technology use, and lower institutional support compared to male colleagues (Batool et al., 2019; Sultana et al., 2021). These structural barriers compound individual-level gender differences, creating multiplicative rather than additive effects on technology acceptance.

Additionally, professional identity concerns may be particularly salient for female educators in contexts where technology is perceived as masculine domain. Successfully integrating AI tools requires female educators to navigate these identity tensions while maintaining authority and credibility in their professional roles.

Understanding these multifaceted gender dynamics is crucial for designing effective AI integration strategies that address not only functional barriers but also psychological and social barriers that disproportionately affect female educators in developing country contexts.

2.4. Technology Acceptance in Pakistani Context

Pakistan's unique socio-cultural context presents both opportunities and challenges for educational technology adoption. Ahmad et al. (2022) conducted a comprehensive analysis of technology acceptance in Pakistani higher education, finding that cultural factors, institutional support, and infrastructure readiness significantly influenced technology adoption patterns. The study revealed that collectivist cultural values, hierarchical decision-making structures, and resource constraints create distinct adoption dynamics compared to Western contexts (Hofstede, 2001; Nasir & Mahmood, 2018).

Digital divide issues remain prominent in Pakistani higher education, with significant variations in technology access and proficiency across institutions, regions, and demographic groups (Rashid & Asghar, 2016; Dahri et al., 2024). Female faculty members face additional challenges, including limited access to professional development opportunities, cultural restrictions on technology use, and varying levels of institutional support (Batool et al., 2019; Sultana et al., 2021). These factors create complex interaction effects that may moderate traditional TAM relationships.

Recent policy initiatives by Pakistan's Higher Education Commission have emphasized digital transformation and faculty development, though implementation remains uneven across institutions (Higher Education Commission Pakistan, 2023). The study by Dahri et al. (2024) found that Pakistani institutions demonstrated positive outcomes when adequate facilitating conditions were provided, including technical infrastructure, training, and institutional support. Understanding these contextual factors is crucial for developing effective intervention strategies.

The influence of Islamic cultural values on technology acceptance in Pakistani educational contexts has received limited research attention, though preliminary studies suggest that religious considerations may influence perceptions of AI tools and their appropriate educational applications (Nasir & Mahmood, 2018; Ahmad et al., 2022). Family and community approval processes also significantly impact professional technology adoption decisions, particularly among female educators where social expectations and cultural norms intersect with professional responsibilities (Batool et al., 2019; Sultana et al., 2021).

Infrastructure challenges specific to Pakistan include unreliable internet connectivity, limited access to high-quality computing devices, and frequent power disruptions that affect technology-dependent teaching activities (Rashid & Asghar, 2016). These practical barriers may override individual acceptance factors, suggesting that facilitating conditions play an even more critical role in developing countries than in resource-rich Western contexts where TAM was originally developed and validated.

Language also presents a unique contextual factor. While English is the medium of instruction in most Pakistani universities, faculty and students often have varying levels of English proficiency. This creates additional cognitive load when learning to use English-interface AI tools and may affect perceptions of ease of use differently than in native English-speaking contexts.

2.5. Research Gaps and Study Justification

Despite growing interest in AI adoption in education, significant research gaps remain. First, limited studies have examined AI acceptance in developing country contexts, particularly focusing on gender-specific factors and cultural moderators (Tlili et al., 2023; Strzelecki, 2023). Second, most existing research has employed cross-sectional designs, limiting understanding of how actual implementation experience influences acceptance over time (Southworth et al., 2023; Crompton & Burke, 2023). Third, the intersection of gender, culture, and AI acceptance in educational settings remains underexplored.

Fourth, while earlier AI tools have received substantial research attention, Claude AI remains largely unstudied despite its distinctive features for educational applications. Fifth, assessment-specific AI applications have received less attention than instructional or administrative uses, despite assessment being a particularly time-intensive and high-stakes educational function.

This study addresses these gaps by investigating Claude AI acceptance for grammar assessment among Pakistani female educators through a case study design that documents actual implementation experience, challenges, and outcomes. The research contributes to both theoretical understanding of technology acceptance in diverse contexts and practical knowledge about successful AI integration strategies in resource-constrained, gender-segregated educational environments.

3. Theoretical Framework

This study adopts an extended Technology Acceptance Model framework specifically adapted for AI-powered assessment tools in developing country educational contexts. The framework retains Davis's (1989) core constructs while incorporating extensions relevant to AI technologies and culturally-specific factors.

3.1. Core TAM Constructs

Perceived Usefulness (PU): It is the degree to which the female educator believes that using Claude AI for grammar assessment would enhance her teaching effectiveness and students' learning outcomes. In this context, usefulness encompasses time savings in assessment creation, improved feedback quality, increased assessment frequency, and enhanced student engagement.

Perceived Ease of Use (PEOU): It shows the extent to which the educator believes that using Claude AI would be free of effort. This includes ease of learning the system, simplicity of generating quiz questions, clarity of the AI interface, and minimal technical barriers to implementation.

Behavioral Intention (BI): The likelihood that the educator will continue using Claude AI for grammar assessment beyond the study period and recommend it to colleagues. This represents the ultimate dependent variable in the TAM framework.

3.2. AI-Specific Extensions

Trust in AI (TRUST): Confidence in Claude's reliability, accuracy, and ethical operation specifically for educational assessment purposes. Trust formation includes verification of AI-generated content accuracy, consistency of outputs, and alignment with pedagogical standards. This construct is particularly critical for assessment applications where errors could mislead students or undermine learning (McKnight et al., 2002; Strzelecki, 2023).

AI Anxiety (ANX): Negative emotional responses and concerns about AI capabilities and implications, including fear of technological inadequacy, concern about AI replacing human judgment, worry about dependence on technology, and anxiety about accuracy of AI-generated content. This construct captures both general technology anxiety and AI-specific concerns (Venkatesh & Morris, 2000; Zhang et al., 2021).

Facilitating Conditions (FC): Organizational and technical resources available to support Claude AI implementation, including internet connectivity, device access, institutional support, technical assistance, and time allocation for learning and implementation. This construct drawn from UTAUT recognizes that acceptance alone is insufficient without enabling infrastructure (Venkatesh et al., 2003).

3.3. Proposed Relationships

Based on established TAM literature and AI acceptance research, the following relationships are examined: Perceived Usefulness and Perceived Ease of Use positively influence Behavioral Intention; Trust positively influences Behavioral Intention and may mediate relationships between PU/PEOU and BI; AI Anxiety negatively influences Behavioral Intention; Facilitating Conditions positively influence actual implementation success and moderate relationships between intention and use; and Perceived Ease of Use positively influences Perceived Usefulness.

The study examines how these constructs evolve through actual implementation experience and how they interact in the specific context of a female educator in Pakistani higher education integrating AI-powered assessment tools.

4. Methodology

4.1. Research Design

This study employs a single case study design with embedded mixed-methods data collection (Yin, 2018; Stake, 2006). Case study methodology is particularly appropriate for investigating contemporary phenomena within real-life contexts, especially when boundaries between phenomenon and context are not clearly evident (Yin, 2018). This approach enables in-depth exploration of Claude AI integration experience while maintaining the complexity and richness of authentic classroom settings (Merriam & Tisdell, 2015).

The research design integrates a single instrumental case study (ADP Grammar course with AI-powered assessment), pre-post comparison (baseline vs. implementation period), mixed-methods data collection (quantitative surveys and qualitative reflections, observations, focus groups), TAM as analytical framework (examining constructs through implementation experience), and action research orientation (researcher as practitioner implementing innovation).

This design addresses both theory testing (examining how extended TAM constructs manifest in AI assessment adoption) and practical exploration (documenting authentic integration experiences, challenges, and outcomes). The embedded mixed-methods approach enables triangulation of findings while providing comprehensive insights into both statistical relationships and underlying mechanisms influencing AI acceptance (Creswell & Plano Clark, 2017).

Research Setting: Govt. Graduate College for Women, Punjab, Pakistan (public institution). Researcher Role: Female faculty member with 15 years teaching experience. Timeline: One academic semester (16 weeks, Spring 2025). Implementation Approach: Action research with systematic documentation and reflection.

4.2. Case Study Context

Course Context: Academic Level: Associate Degree Program (ADP), Year 2. Course Title: English Grammar Practice. Course Code: ENG-203. Credit Hours: 3 (3 contact hours per week). Class Size: 52 female students. Student Age Range: 18-20 years. English Proficiency: Intermediate to upper-intermediate (CEFR B1-B2 equivalent). Prior Technology Exposure: Basic (smartphones, social media, minimal educational technology). Semester: Spring 2025 (16 weeks, January-May).

Curriculum Requirements: The course follows the Higher Education Commission Pakistan prescribed curriculum with focus on grammar topics including subject-verb agreement, pronoun usage, verb tenses, voice, narration, clauses, and sentence structure. Assessment structure: Mid-term exam (30%), Final exam (50%), Continuous assessment (20%). Prescribed materials: Punjab Textbook Board grammar textbook plus supplementary exercises. Learning outcomes: Accurate grammar usage in writing, error identification and correction, application of grammar rules in context.

Pre-Implementation Challenges: The researcher identified several challenges with traditional grammar instruction approach including large class size (52 students) limiting individualized feedback and attention; manual correction burden (approximately 260 assignments per assessment cycle); delayed feedback (typically 7-10 days before students received corrected work); inconsistent correction (fatigue-induced variations in marking standards); student anxiety (fear of making mistakes, reluctance to practice); low engagement (traditional drill-and-practice perceived as boring); limited differentiation (all students received identical exercises); insufficient practice opportunities (time constraints limited formative assessments); resource constraints (photocopying costs, no access to digital platforms); and motivation issues (students viewed grammar as difficult and useless theoretical knowledge).

Instructor's Pre-Implementation Status: Prior AI experience: None (first time using any AI tool). Technology confidence: Moderate (comfortable with PowerPoint, WhatsApp, Google Classroom, but anxious about advanced technology). AI perceptions: Skeptical, anxious, and curious. Institutional support: Zero formal support (no training, no guidance, self-initiated exploration). Resources: Personal smartphone and laptop, home internet connection, no institutional technology budget.

4.3. Claude AI Implementation Strategy

Phase 1: Preparation and Exploration (Weeks 1-2)

Step 1: Self-Directed Learning. Researcher independently explored Claude AI capabilities through Anthropic's website and documentation. Conducted systematic prompting experiments to understand Claude's grammar knowledge and question generation capabilities. Tested various prompt formats for quiz question generation.

Step 2: Content Development. Developed question generation prompts for five grammar assessment areas. Example Prompt Template: Generate 5 multiple-choice questions testing subject-verb agreement with complex subjects (collective nouns, indefinite pronouns, compound subjects). Each question should: 1) Present a sentence with a subject-verb agreement error, 2) Offer 4 answer options (1 correct, 3 plausible distractors), 3) Use Pakistani/South Asian contexts in example sentences, 4) Include brief explanation of the correct answer, 5) Be appropriate for intermediate-level ADP students. Format as: Question | Options A-D | Correct Answer | Explanation.

Step 3: Quality Assurance Protocol. Verified all AI-generated questions against authoritative grammar references (Cambridge Grammar in Use, Swan's Practical English Usage, prescribed textbook). Created accuracy verification checklist: grammatical correctness, clarity of wording, appropriate difficulty level, cultural appropriateness, answer key accuracy. Piloted 10 questions with 5 volunteer students for comprehensibility testing.

Step 4: Platform Selection and Setup. Evaluated available quiz platforms (Google Forms, Quizizz, Kahoot, ClassPoint). Selected platform based on: free access, mobile compatibility, immediate feedback capability, ease of use for students with low tech skills. Created quiz template with institutional branding.

Phase 2: Implementation (Weeks 3-16)

Five AI-Generated Assessment Types:

1. Complex Subject-Verb Agreement Quiz. Format: 25 multiple-choice questions, 25 marks. Content: Advanced concepts (collective nouns, indefinite pronouns, inverted sentences, compound subjects with correlative conjunctions). Claude's role: Generated question stems, realistic distractors, and grammatical explanations.

Platform feature: Immediate right/wrong feedback with rule explanations displayed.

2. Subject-Verb Agreement Correction. Format: 25 sentences with errors requiring complete sentence rewrites, open-ended responses. Content: Real-world contexts requiring students to write complete corrected sentences. Claude's role: Generated error sentences with controlled difficulty progression, provided multiple acceptable correction variations. Platform feature: Show Correct Answer button revealing model answer with explanation.
3. Pronoun Correction Assessment. Format: 25 multiple-choice questions testing pronoun case, reference clarity, agreement. Content: Pronoun case (subjective/objective/possessive), antecedent agreement, vague reference issues. Claude's role: Created contextually appropriate sentences testing specific pronoun rules with common error patterns. Platform feature: Detailed explanation for each option explaining why correct answer is right and why distractors are incorrect.
4. Verb Correction Quiz (Final Exam Practice Format). Format: 15 questions, 15 marks, exam-style formatting matching university final exam pattern. Content: Verb tense consistency, modal verb usage, aspect (perfect/progressive), subject-verb agreement with complex subjects. Claude's role: Generated questions matching university exam patterns and difficulty level. Platform feature: Timed assessment (45 minutes) simulating exam conditions, immediate scoring.
5. Comprehension Assessment. Format: Reading passage (300-400 words) plus 10 comprehension questions, 15 marks, 45 minutes. Content: Academic or general interest passages at appropriate reading level with literal, inferential, and critical thinking questions. Claude's role: Generated reading passages on topics relevant to Pakistani students (education, technology, social issues) plus comprehension questions testing understanding. Platform feature: Passage visible throughout quiz, extended time, immediate feedback on completion.

Implementation Workflow: Quiz Creation (Instructor): Generate questions using Claude (15-20 minutes per quiz). Verify accuracy against textbook/grammar references (10-15 minutes). Input questions into quiz platform (20-30 minutes). Test quiz functionality (5 minutes). Total time per quiz: 50-70 minutes. Quiz Distribution (Instructor): Share quiz link via WhatsApp class group. Announce in class with brief instructions. Set deadline (typically 7 days from announcement). Quiz Completion (Students): Access via smartphone/laptop at convenient time. Complete at own pace (average 20-30 minutes). Receive immediate score and performance rating. Review Show Correct Answer for missed questions. Option to retake quiz unlimited times. Performance Monitoring (Instructor): Review class performance summary (5 minutes). Identify common error patterns (10 minutes). Plan next class session addressing weak areas (15 minutes). Total time per quiz cycle: approximately 30 minutes versus approximately 8 hours for manual correction of 52 papers.

Platform Implementation Details: Technology used: Google Forms integrated with custom quiz add-on enabling immediate feedback. Access method: Mobile-friendly responsive design, students used personal smartphones. Delivery channel: WhatsApp group links (most accessible communication channel for students). Attempt policy: Unlimited retakes encouraged to promote growth mindset. Privacy: Individual results private to each student, no public leaderboards to reduce anxiety. Data collection: Automatic scoring and data export for research analysis.

Gamification Elements: Performance ratings: 73-79% equals Very Good with thumbs up emoji; 80-92% equals Excellent with star emoji; 93-100% equals Outstanding with trophy emoji. Visual feedback: Color-coded score displays (green for high, yellow for medium, red for needs improvement). Achievement badges: Virtual certificates for perfect scores. Progress tracking: Students could view their score improvement trajectory across multiple attempts. Motivational messages: Personalized encouragement based on performance (Great improvement, Keep practicing).

4.4. Data Collection Methods

Quantitative Data Collection:

1. Pre-Post Student Surveys (N=52). Timing: Week 1 (pre-implementation) and Week 15 (post-implementation). Instrument: Extended TAM questionnaire with 46 items. Constructs measured: Perceived Usefulness (8 items, sample: Using Claude AI quizzes would improve my grammar learning), Perceived Ease of Use (7 items, sample: I find Claude AI quizzes easy to use), Trust in AI (10 items, sample: I trust Claude AI to provide accurate grammar feedback), AI Anxiety (15 items, sample: I feel nervous about using AI for learning), Facilitating Conditions (10 items, sample: I have adequate internet access to use AI quizzes), Behavioral Intention (6 items, sample: I intend to continue using AI quizzes for grammar practice). Scale: 7-point Likert scale (1 equals Strongly Disagree, 7 equals Strongly Agree). Language: Bilingual (English with Urdu translations for technical terms). Delivery method: Google Forms, completed in class with researcher present to answer questions. Response rate: Pre-survey 100% (52/52), Post-survey 96% (50/52, 2 students absent).
2. Student Performance Data. Quiz scores: All 487 quiz attempts across 52 students, including scores, attempt number, time spent, improvement trajectories. Final exam scores: Comparison with previous cohort (Spring 2024, n=48) who did not use AI quizzes. Source: Quiz platform automated data export, university examination records. Variables tracked: Individual scores, class average, standard deviation, improvement rate across attempts, engagement frequency.

3. Instructor Self-Assessment. TAM constructs: Weekly self-rating on 7-point scale for all TAM constructs. Tracking sheet: Maintained in Excel spreadsheet documenting weekly perceptions. Purpose: Document instructor's own acceptance journey paralleling student experience.
   Qualitative Data Collection:
4. Instructor Reflective Journal. Format: Weekly written reflections, minimum 500 words per entry. Duration: 16 weeks (16 total entries). Prompts used: What worked well this week with AI quizzes? What didn't? How did students respond? What feedback did I receive? How am I feeling about using Claude AI? Has my confidence changed? What challenges did I encounter? How did I address them? What surprised me? What would I do differently? Analysis unit: Each weekly entry treated as data unit for thematic coding. Purpose: Capture real-time implementation experience, emotional journey, problem-solving strategies.
5. Student Focus Groups (N=16 students). Timing: Week 14-15 (after post-survey, before final exam). Structure: 4 focus groups with 4 students each. Selection: Purposive sampling to represent diversity (high/medium/low achievers, varying technology confidence levels, different quiz engagement patterns). Duration: 45-60 minutes per session. Location: University classroom after regular class hours. Guiding questions: How was your experience using Claude AI quizzes for grammar practice? What did you like most? What didn't you like? Did the quizzes help you learn grammar? How? How did immediate feedback affect your learning? Did you trust the AI-generated questions and answers? Why or why not? What made the quizzes easy or difficult to use? Would you recommend AI quizzes to other students? Why? What suggestions do you have for improvement? Recording: Audio recorded with participant consent. Transcription: Verbatim transcription in mixed Urdu-English (as spoken). Language: Students chose to speak in Urdu, English, or code-switched mix based on comfort.
6. Classroom Observations. Format: Researcher field notes during weekly class sessions. Focus: Student verbal comments about quizzes, questions asked, enthusiasm levels, peer discussions about quiz performance. Frequency: 16 weeks of observation notes. Recording: Handwritten notes immediately after each class session.
7. Artifact Collection. Materials collected: Screenshots of quiz interfaces showing student perspective, sample quiz questions generated by Claude, student result cards showing score distributions, WhatsApp group conversations about quizzes, email/WhatsApp exchanges with students about technical issues. Purpose: Provide visual documentation of implementation and evidence of engagement.

8. Document Analysis. Previous cohort data: Spring 2024 course records for comparison (final exam scores, student evaluations, instructor's previous teaching materials). Institutional documents: Course syllabus, assessment policy, curriculum guidelines. Purpose: Establish baseline for comparison and contextual understanding.

4.5. Data Analysis Procedures

Quantitative Analysis:

1. Descriptive Statistics. Calculated means, standard deviations, ranges for all TAM constructs at pre and post timepoints. Generated frequency distributions for student performance data. Created data visualizations (bar charts, line graphs) for score distributions. Software: SPSS v.28, Microsoft Excel.
2. Reliability Analysis. Calculated Cronbach's alpha for each multi-item construct to assess internal consistency. Examined item-total correlations to identify problematic items. Acceptable threshold: alpha greater than or equal to 0.80.
3. Paired-Samples t-Tests. Compared pre-post scores for each TAM construct to assess intervention effect. Calculated Cohen's d effect sizes to determine magnitude of change. Significance level: alpha equals 0.05, two-tailed tests. Interpretation: d equals 0.20 (small), 0.50 (medium), 0.80 or greater (large effect).
4. Independent-Samples t-Test. Compared final exam scores between AI-enhanced cohort (2025) and traditional cohort (2024). Assessed statistical and practical significance of performance differences.
5. Descriptive Performance Analysis. Quiz score distributions, attempt frequencies, improvement trajectories. Engagement metrics (number of quizzes completed, retake patterns). Performance level categorization (Outstanding/Excellent/Very Good percentages).

Qualitative Analysis:

6. Thematic Analysis (Braun & Clarke, 2006). Followed six-phase approach: Phase 1: Familiarization (Read all reflective journal entries twice, listened to focus group recordings while reading transcripts, made initial notes of recurring ideas and surprising insights). Phase 2: Initial Coding (Systematic line-by-line coding using NVivo 14 software, deductive codes from TAM framework, inductive codes for emergent themes not predicted by framework). Phase 3: Theme Development (Grouped related codes into candidate themes, created thematic maps showing relationships between themes, organized themes hierarchically). Phase 4: Theme Review (Checked themes against coded data extracts for internal homogeneity, checked themes against entire dataset for external heterogeneity, refined theme boundaries and definitions). Phase 5: Theme Definition and Naming (Defined essence of each theme in 2-3 sentences, named themes using clear evocative labels,

identified representative quotes illustrating each theme). Phase 6: Report Production (Integrated themes with quantitative findings, selected compelling quotes with contextual information, linked findings to theoretical framework and literature).

7. Integration of Quantitative and Qualitative Data. Triangulation: Compared survey results with focus group themes and journal reflections to identify convergence and divergence. Explanation: Used qualitative data to explain quantitative patterns. Contextualization: Embedded quantitative findings within rich qualitative context from implementation experience. Complementarity: Used each data type to address different aspects of research questions.

Trustworthiness Strategies: Credibility: Member checking (shared preliminary themes with 5 student participants for validation), prolonged engagement (16-week implementation), triangulation across multiple data sources. Dependability: Detailed audit trail (all prompts used for Claude, quiz creation timestamps, decision documentation). Confirmability: Reflexivity journaling (researcher acknowledged own biases and assumptions), data-grounded interpretations with extensive quotes. Transferability: Thick description of context enabling readers to assess applicability to their settings.

Ethical Considerations: Institutional ethics approval obtained from University of Gujrat Research Ethics Committee. Informed consent: All students provided written consent; participation voluntary with no grade penalty for declining. Confidentiality: Student identities protected through pseudonyms, aggregate reporting. Data security: Password-protected files, encrypted storage, limited access. Researcher dual role: Transparently acknowledged as both instructor and researcher; mitigation through triangulation and member checking.

4.6. Results

4.6.1. Participant Characteristics

All 52 female students enrolled in ADP Year 2, participated, with complete pre-post survey data obtained from 50 students (96% retention rate).

Student Demographics: Mean age: 19.2 years (SD=0.8, range 18-20). English proficiency: 59.6% intermediate (n=31), 34.6% upper-intermediate (n=18), 5.8% advanced (n=3). Prior AI exposure: 90.4% never used any AI tool (n=47), 9.6% tried once or twice (n=5). Technology confidence: 53.8% low (n=28), 40.4% moderate (n=21), 5.8% high (n=3). Smartphone ownership: 100% (n=52). Laptop ownership: 42.3% (n=22). Home internet access: 78.8% (n=41).

Instructor Profile: Female, M.Phil English Linguistics. 15 years teaching experience. First-time AI user (zero prior experience). Moderate technology confidence (comfortable with basic tools, anxious about advanced technology).

4.6.2. Quantitative Results: TAM Constructs

Descriptive Statistics and Reliability

All TAM constructs demonstrated high internal consistency.

TABLE 1

Descriptive Statistics and Reliability Analysis (N=50)

Construct	Items	Pre-M(SD)	Post-M(SD)	Cronbach's α
Perceived Usefulness	8	3.92(1.24)	5.78(0.95)	0.89
Perceived Ease of Use	7	3.45(1.38)	5.91(0.88)	0.91
Trust in AI	10	3.21(1.42)	5.34(1.08)	0.88
AI Anxiety	15	5.67(1.118)	3.12(1.31)	0.90
Facilitating Conditions	10	3.18(1.45)	5.02(1.15)	0.85
Behavioral Intention	6	3.56(1.33)	5.67(1.02)	0.87

Note: All scales measured on 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree). All alpha values greater than 0.85, indicating excellent reliability.

Pre-Post Intervention Effects

Paired-samples t-tests revealed statistically significant improvements across all TAM constructs following Claude AI implementation.

TABLE 2

Pre-Post Implementation Comparison (N=50)

Construct	Mean Difference	t-value	p-value	Cohen's d	Effect Size
Perceived Usefulness	+1.86	12.34	<.001	1.67	Large
Perceived Ease of Use	+2.46	15.89	<.001	2.15	Large
Trust in AI	+2.13	13.45	<.001	1.75	Large
AI Anxiety	-2.55	-14.23	<.001	-2.01	Large
Facilitating Conditions	+1.84	11.67	<.001	1.52	Large
Behavioral Intention	+2.11	13.89	<.001	1.82	Large

Key Findings: All constructs showed statistically significant changes ($p < .001$), indicating robust intervention effect. Perceived Ease of Use demonstrated the largest effect size (d=2.15), increasing from M=3.45 to M=5.91 - students found AI quizzes remarkably easy to use despite initial low technology confidence. AI Anxiety showed the second-largest effect (d=-2.01), decreasing from M=5.67 to M=3.12 - substantial anxiety reduction through hands-on experience. All effect sizes were large ($d > 1.50$), indicating not just statistical significance but meaningful practical impact. Facilitating Conditions showed the smallest (though still large) improvement, suggesting infrastructure remains a relative weakness despite perceived improvements.

Instructor Self-Reported TAM Evolution

The instructor's personal TAM construct journey documented through weekly self-assessment.

TABLE 3

Instructor TAM Scores Over Time (1-7 scale)

Construct	Week 1	Week 4	Week 8	Week 12	Week 16	Total Change
Perceived Usefulness	3.5	4.8	5.6	6.1	6.4	+2.9
Perceived Ease of Use	2.8	4.2	5.4	5.9	6.1	+3.3
Trust in AI	2.9	4.6	5.5	6.0	6.2	+3.3
AI Anxiety	6.2	4.8	3.5	2.6	2.1	-4.
Facilitating Conditions	2.5	2.8	3.2	3.6	3.8	+1.3
Behavioral Intention	3.2	5.1	6.0	6.3	6.5	+3.3

Interpretation: Instructor's acceptance journey paralleled and even exceeded student patterns, with anxiety decreasing from 6.2 to 2.1 (dramatic reduction). Facilitating Conditions remained lowest, reflecting ongoing institutional support gaps.

4.6.3. Student Performance Outcomes

Quiz Performance Analysis

Overall Quiz Engagement: Total quiz attempts: 487 across 16 weeks. Average attempts per student: 9.4 quizzes (range 4-15). Completion rate: 94% of students completed at least 8 quizzes. Retake rate: 86.5% of students (n=45) retook at least one quiz to improve scores.

TABLE 4
Quiz Score Distribution (N=487 total attempts)

Performance Level	Score Range |	Frequency	Percentage	Performance Rating
Outstanding	15 (93-100%)	170	34.9%	Outstanding!
Excellent	12-13/15 (80-87%)	209	42.9%	Excellent!
Very Good	11/15 (73%)	108	22.2%	Very Good!
Total High Achievement	11-15/15	487	100%	All passing scores

Key Performance Indicators: Mean quiz score: 13.2/15 (88.0%). Median score: 14/15 (93.3%). 78% of all quiz attempts achieved Excellent or Outstanding ratings (scores greater than or equal to 12/15). Zero failure rates - all quiz attempts scored above 70%, demonstrating accessible difficulty level.

Improvement Trajectories for Students Who Retook Quizzes: Average improvement: +1.8 points (12% increase) from first to second attempt. Example: First attempt: 11/15 (73%), Second attempt: 13/15 (87%). Maximum improvement observed: Student improved from 10/15 to 15/15 (+33%) across three attempts. Persistence effect: Students who attempted 3 or more times showed 18% average improvement, demonstrating growth mindset.

Final Exam Performance Comparison

Historical Comparison with Previous Cohort

TABLE 5
Final Exam Performance - 2024 vs. 2025 Cohorts

Metric	2024 Cohort (No AI, n=48)	2025 Cohort (AI-Enhanced, n=52)	Difference	Statistical Significance

Mean Exam Score	68.5% (SD=15.2)	81.2% (SD=10.8)	+12.7%	t(98)=4.89, p<.001, d=0.98
Students Scoring 80%+	80%+	26 (54.2%)	41 (78.8%)	+24.6% | χ^2=7.23, p<.01
Students Scoring 90%+	90%+	8 (16.7%)	19 (36.5%)	+19.8% | χ^2=5.67, p<.05
Failure Rate (<50%	(<50%)	7 (14.6%)	2 (3.8%)	-10.8% | χ^2=3.89, p<.05
Median Score	72%	83%	+11%	-

Statistical Interpretation: Independent-samples t-test confirmed significantly higher final exam scores in AI-enhanced cohort: t(98)=4.89, p<.001, Cohen's d=0.98 (large effect). Effect size d=0.98 indicates substantial practical significance beyond statistical significance. 24.6 percentage point increase in students achieving 80% or greater demonstrates meaningful learning outcome improvement. Failure rate reduced by 71% (from 14.6% to 3.8%), suggesting AI quizzes particularly benefited struggling students.

Possible Confounding Variables Considered: Instructor effect: Same instructor taught both cohorts, reducing instructor bias. Curriculum: Identical syllabus, textbook, exam format across both years. Cohort differences: Entrance exam scores comparable (2024: M=72%, 2025: M=73%, not significantly different). Semester timing: Both Spring semesters, same duration, similar institutional conditions.

Conclusion: While causality cannot be definitively established without experimental design, the substantial performance improvement combined with large effect sizes and consistent patterns across multiple metrics strongly suggests AI-powered quizzes contributed meaningfully to enhanced learning outcomes.

4.6.4. Qualitative Findings: Major Themes

Four major themes emerged from thematic analysis of instructor journal, focus groups, and classroom observations.

Theme 1: Trust Evolution Through Verification - "I Had to Check Everything at First"

Description: Both instructor and students demonstrated systematic trust-building processes involving verification of AI-generated content against authoritative sources. Trust evolved from initial skepticism through repeated accuracy confirmation to confident acceptance.

Sub-theme 1a: Initial Skepticism and Systematic Verification

Instructor's first journal entry (Week 1): "I felt nervous introducing Claude to my classes. What if it gives wrong answers? What if students cheat? What if I look incompetent because I don't understand the technology? As a female teacher, I already feel pressure to prove myself technically. Using AI felt risky. I generated 25 questions using Claude for subject-verb agreement. But can I trust them? I spent 3 hours checking every single question against my Cambridge Grammar textbook. Out of 25 questions, I found only 1 minor wording issue - the grammar was 100% accurate. 24/25 equals 96% accuracy. That's actually better than my own question-writing! But I still feel nervous."

Student focus group evidence (FG2): "Pehli baar jab quiz diya, mujhe yakeen nahi tha ke computer sahi answer de raha hai [First time when I took quiz, I didn't believe computer was giving right answer]. Maine apni grammar book kholi aur check kiya [I opened my grammar book and checked]. Answer sahi tha! [Answer was correct!]" Another student added: "Main bhi! Maine 5-6 questions check kiye apni book se [Me too! I checked 5-6 questions from my book]. Sab sahi the [All were correct]. Tab se trust ho gaya [Then I started trusting]."

Sub-theme 1b: Accuracy Confirmation Building Confidence

Instructor journal (Week 5): "I've now verified over 100 Claude-generated questions. Accuracy rate: 98%. Only 2 questions had minor issues (awkward wording, not grammatical errors). I'm starting to trust Claude's grammar knowledge. It actually knows grammar rules better than some of my colleagues! My anxiety about AI giving wrong answers is decreasing. I still spot-check questions, but I no longer feel the need to verify every single one."

Student focus group (FG3): "After taking 7-8 quizzes, ab mujhe pata chal gaya ke ye AI reliable hai [now I know this AI is reliable]. Har baar correct answer sahi hota hai explanation ke sath [Every time the correct answer is right with explanation]. Kabhi bhi wrong answer nahi dikha [Never showed wrong answer]. So now I trust it completely."

TAM Connection: This theme directly relates to the Trust construct, explaining the large effect size (d=1.75). Trust was not assumed but earned through systematic verification processes.

Theme 2: Immediate Feedback as Transformative Learning Experience - "I Know Right Away"

Description: Immediate feedback emerged as the single most valued feature of AI-powered quizzes, fundamentally transforming the learning experience by enabling instant error correction, reducing anxiety about mistakes, and fostering growth mindset through unlimited retakes.

Sub-theme 2a: Contrast with Traditional Delayed Feedback

Student focus group (FG1): "Pehle homework dete the, 10 din baad checked ho kar milta tha [Before we submitted homework, got it back checked after 10 days]. Tab tak hum bhool jate the ke humne kya likha tha aur kyun [By then we'd forgotten what we wrote and why]. Sirf dekh lete the marks [Just looked at the marks]. Wrong answers pe dhyan hi nahi jaata tha [Didn't even pay attention to wrong answers]. Haan! Aur agar kuch samajh nahi aata tha correction mein, toh dobara puchne ki himmat nahi hoti thi [Yes! And if we didn't understand the correction, didn't have courage to ask again]. Ab quiz mein turant pata chal jata hai, wahan par explanation bhi hai [Now in quiz we know immediately, there's also explanation right there]. Perfect hai! [It's perfect!]"

Instructor journal (Week 6): "I never realized how much delayed feedback was undermining learning until I saw the contrast. When I return manually corrected work after 10 days, students glance at the grade and file it away. They don't engage with my painstakingly written feedback. But with AI quizzes, they immediately click Show Correct Answer for every mistake. They're engaging with feedback while the question is fresh in their minds. This is real formative assessment."

Sub-theme 2b: Growth Mindset Through Unlimited Retakes

Student focus group (FG1): "Mera pehla attempt tha 11/15. Thoda sad hui [My first attempt was 11/15. Felt a bit sad]. But phir socha, koi baat nahi, dobara try karti hoon [But then thought, no problem, I'll try again]. Show Correct Answer dekha, samjha kyun galat tha [Viewed Show Correct Answer, understood why it was wrong]. Second attempt: 14/15! Bohot khushi hui [Second attempt: 14/15! Felt so happy]. This shows practice se improve hota hai [This shows that with practice you improve]. Maine ek quiz 3 baar ki [I did one quiz 3 times]. First: 10/15, Second: 12/15, Third: 15/15 perfect score! Har baar kuch naya seekhti gayi [Learned something new each time]."

Performance data supporting this theme: 86.5% of students retook at least one quiz. Students who retook quizzes improved by average 1.8 points (12%). High achievers (15/15) often reported multiple attempts: "I took it 3 times to make sure I really understood, not just got lucky."

TAM Connection: This theme explains the extraordinary Perceived Usefulness scores (M=5.78 post-implementation, d=1.67 effect size).

Theme 3: Ease of Use Paradox - "Even My Mother Could Use This"

Description: Despite students' self-reported low technology confidence (53.8%), they found AI quizzes remarkably easy to use. However, instructor experienced significant behind-the-scenes complexity in content creation, revealing an ease-of-use asymmetry between consumption and production.

Sub-theme 3a: Student Perspective - Surprisingly Simple

Student focus group (FG3): "Main technology mein bilkul weak hoon [I'm very weak in technology]. Laptop nahi hai, computer class mein bhi weak thi [Don't have laptop, was weak in computer class too]. But ye quiz toh itna simple hai [But this quiz is so simple]. Bas WhatsApp pe link aata hai, click karo, questions aate hain, answer select karo, submit karo [Just get link on WhatsApp, click, questions appear, select answer, submit]. Aur result turant aa jata hai [And result comes immediately]. Meri ammi bhi kar leti! [Even my mother could do it!]"

Sub-theme 3b: Instructor Perspective - Hidden Complexity

Instructor journal (Week 3): "Students think this is so easy - just click and answer. But they don't see the 50-70 minutes I spend per quiz: generating questions with carefully crafted Claude prompts, verifying accuracy, inputting into platform, testing functionality. For students, it's 20 minutes of easy interaction. For me, it's hours of complex work. But it's still faster than manually creating and grading 52 papers (which took 8 hours). So it IS easier for me too, just not effortless like students perceive."

TAM Connection: This theme explains the largest effect size in the entire study - Perceived Ease of Use (d=2.15).

Theme 4: Peer Support and Collaborative Learning in Female Student Community

Description: Female students spontaneously created peer support networks around AI quizzes, sharing links, discussing answers, celebrating achievements collectively, and learning collaboratively.

Sub-theme 4a: WhatsApp as Social Learning Hub

Student focus group (FG1): "Humari class ki WhatsApp group hai [We have a class WhatsApp group]. Jab koi quiz link ata hai, sab share karti hain [When someone gets quiz link, everyone shares]. Try karo, bohot achi hai! [Try it, it's very good!] Agar kisi ko problem hai, toh group mein pooch leti hai [If someone has a problem, asks in group]. Haan! Aur jab kisi ko 15/15 perfect score milti hai, toh wo screenshot share karti hai [Yes! And when someone gets 15/15 perfect score, she shares screenshot]. Phir sab Mashallah, bohot achi! bolti hain [Then everyone says Mashallah, very good!]. Phir humein bhi motivation milti hai ke hum bhi perfect score karen [Then we also get motivated to get perfect score]. It's like competition but friendly."

Sub-theme 4b: Collective Achievement Culture

Student focus group (FG4): "Jab humari poori class mein 80% students ko excellent score milta hai, toh lagta hai humari class bohot achi hai [When 80% of students in our whole class get excellent scores, feels like our class is very good]. Pehle lagta tha main akeli weak hoon [Before felt I alone am weak]. Ab lagta hai hum sab improve ho rahe hain [Now feels we all are improving]. Ye collective feeling hai [This is a collective feeling]."

TAM Connection: This theme reveals that Subjective Norm (social influence), while not formally measured as a separate construct in this study, operated powerfully through peer networks.

5. Discussion

5.1. Theoretical Contributions

This study makes several significant contributions to Technology Acceptance Model literature, particularly for AI applications in developing country educational contexts.

Extended TAM Validation for AI Assessment Tools

The findings validate extended TAM's applicability to AI-powered assessment while revealing assessment-specific nuances. All hypothesized constructs (PU, PEOU, Trust, Anxiety, FC) demonstrated strong measurement properties (Cronbach's alpha > 0.85) and significant pre-post changes with large effect sizes (d > 1.50), indicating that extended TAM provides a robust framework for understanding AI acceptance in educational contexts (Strzelecki, 2023; Gkinko & Elbanna, 2023).

However, this study extends prior research by demonstrating that trust formation mechanisms are application-specific. For assessment AI, trust built through systematic accuracy verification - students and instructor checked AI-generated content against authoritative sources, confirming 98% accuracy rate (McKnight et al., 2002). This competence-based trust differs from trust in other AI applications where accuracy is less critical.

Implication: Trust-building strategies must be tailored to AI application type. For assessment AI, provide transparency about content generation processes, enable easy verification against external sources, and build verification activities into training programs.

5.2. Perceived Ease of Use as Primary Adoption Driver

The extraordinarily large effect size for PEOU (d=2.15) - larger than any other construct including perceived usefulness - challenges assumptions about what drives AI acceptance. While Davis (1989) positioned PU as primary determinant, this study suggests that for female users with low initial technology confidence in developing country contexts, PEOU may be the critical gatekeeper determining whether adoption occurs at all.

Qualitative data revealed why: Despite low technology confidence (53.8% self-rated as low), students discovered they could successfully use AI quizzes because the interface was mobile-friendly, cognitively simple, and required zero technical troubleshooting. This created a profound "I can do this" realization that transformed self-efficacy perceptions (Venkatesh & Morris, 2000).

However, the study also revealed an important ease-of-use asymmetry: High ease for student consumers, moderate ease for instructor producers. Students experienced frictionless quiz-taking; instructor experienced 50-70 minutes of prompt engineering, verification, and platform setup per quiz. While still easier than 8 hours of manual grading, this production complexity remains a barrier to scaled adoption.

Implication: EdTech developers should optimize ease of use for BOTH consumption and production. Current AI tools over-index on end-user experience while neglecting educator authoring experience. Simplify content creation workflows, provide prompt templates, automate verification processes, and reduce technical complexity for educators.

5.3. AI Anxiety Reduction Through Experiential Learning

The dramatic anxiety reduction (d=-2.01, from M=5.67 to M=3.12) provides empirical support for experience-based anxiety reduction (Venkatesh & Morris, 2000; Zhang et al., 2021). However, this study reveals multidimensional anxiety sources beyond general technology anxiety.

Initial Anxiety Dimensions: Competence anxiety ("I don't know how to use AI"), addressed by ease of use. Accuracy anxiety ("What if AI teaches wrong grammar?"), addressed by verification proving 98% accuracy. Professional identity anxiety ("Am I still a good teacher if I use AI?"), addressed by framing AI as pedagogical tool, not replacement. Ethical anxiety ("Is it cheating to use AI?"), addressed by establishing clear academic integrity boundaries.

Anxiety Reduction Mechanisms: Gradual exposure (16-week implementation allowed progressive comfort building). Visible student success (seeing 78% of students achieve excellent scores validated AI usefulness). Peer normalization (colleagues and students using AI successfully reduced isolation fear). Control maintenance (instructor retained final authority over content).

This multi-dimensional framework extends Venkatesh and Morris's (2000) gender-focused anxiety model by incorporating professional, epistemological, and cultural anxieties specific to developing country contexts.

Implication: Training programs should address each anxiety dimension explicitly rather than assuming generic technology training will reduce AI anxiety. Include verification activities (address accuracy anxiety), pedagogical framing workshops (address identity anxiety), and peer support networks (address isolation anxiety).

5.4. Cultural and Gender Factors in AI Acceptance

The prominence of peer support and collaborative learning in qualitative data - students spontaneously creating WhatsApp study groups, celebrating collective achievement, preferring peer explanation over individual troubleshooting - aligns with established patterns that women prioritize subjective norm more than men in technology acceptance (Venkatesh & Morris, 2000; Gefen & Straub, 1997).

However, this study reveals that subjective norm operates through specific mechanisms in collectivist cultures: Collective achievement framing ("Our class did well" rather than "I did well"). Peer teaching as learning strategy (explaining to friends in Urdu after reviewing English AI explanations). Social motivation ("When someone got 15/15, we all wanted to try"). Collaborative problem-solving (study groups completing quizzes together while submitting individually).

This extends Hofstede's (2001) collectivism construct by showing how it specifically manifests in educational technology adoption. In individualist Western contexts, technology acceptance is driven by personal efficiency gains and individual achievement. In collectivist contexts, acceptance is driven by group benefit, peer encouragement, and collective success.

Implication: AI integration strategies in collectivist cultures should leverage existing social structures (WhatsApp groups, peer networks, family connections) rather than assuming individualistic adoption pathways. Design collaborative features into AI tools, celebrate group achievements, and provide culturally-resonant social incentives.

5.5. Practical Implications

For Pakistani Higher Education Policymakers

The study provides evidence-based recommendations for systemic AI integration.

Faculty Development Programs with Gender-Sensitive Design: Current findings demonstrate that structured, experiential training can transform AI acceptance among female educators with low initial technology confidence. The instructor's journey from anxiety (6.2/7) to confident advocacy (2.1/7 anxiety, 6.5/7 behavioral intention) over 16 weeks provides a replicable model.

Recommended Program Components: Phase 1 (Weeks 1-4): Hands-On Exploration (self-directed AI experimentation with low-stakes applications, peer learning groups of 3-5 female educators, focus on reducing anxiety through positive first experiences). Phase 2 (Weeks 5-12): Supported Implementation (implement AI tool in actual course with peer mentoring, weekly reflection sessions sharing successes and challenges, technical support available via WhatsApp helpline, focus on building confidence through visible student success). Phase 3 (Weeks 13-16): Reflection and Advocacy (document implementation outcomes, develop personal AI integration plan for future courses, present findings to department colleagues, focus on transitioning from user to advocate).

Critical Success Factors: Female facilitators (role models demonstrating "someone like me can do this"). Peer learning emphasis (leverage collaborative learning preference among women). Pedagogical framing (position AI as teaching enhancement, not technological performance). Cultural relevance (use Pakistani examples, allow Urdu discussion, respect cultural norms). Recognition (certificates, reduced teaching load, or stipends for participation). Ongoing support (community of practice continuing beyond training program).

Infrastructure Investment Beyond Technology: Facilitating Conditions showed the smallest improvement despite being important (remained at M=5.02 vs. other constructs at M=5.34-5.91). Qualitative data revealed persistent barriers: unreliable internet, lack of institutional support, absence of formal policies.

Required Institutional Support: Technical Infrastructure (reliable campus-wide WiFi, computer labs with AI tool access, faculty laptops/tablets, backup internet solutions). Human Infrastructure (EdTech support staff, AI literacy trainers, peer mentors). Policy Infrastructure (clear academic integrity guidelines, faculty evaluation criteria recognizing innovation, intellectual property policies, data privacy protocols). Financial Infrastructure (dedicated EdTech budget, stipends for faculty developing AI-enhanced courses, subscriptions to quality AI platforms, conference travel funding).

Quality Assurance and Ethical Frameworks: Current absence of institutional AI guidelines created anxiety and inconsistency. Universities need Academic Integrity Policies (clearly delineate when AI assistance is appropriate, provide faculty guidance on AI-generated assessment content verification, update plagiarism policies for AI era). Content Quality Standards (peer review protocols for AI-generated materials, accuracy verification checklists, student feedback mechanisms, regular audits). Ethical Use Guidelines (transparency about AI use with students, informed consent for data collection, bias detection strategies, faculty autonomy).

For Individual Female Educators

The study offers a replicable blueprint for grassroots AI integration.

Start Small, Scale Gradually: Weeks 1-2: Personal Exploration (sign up for Claude, experiment with generating quiz questions, verify outputs against textbook, no student implementation yet). Weeks 3-4: Pilot Testing (create one 10-question quiz, administer to 5-10 volunteer students, solicit feedback, refine based on feedback). Weeks 5-8: Limited Implementation (use AI quizzes for one topic or unit, monitor student performance and engagement, document successes, address issues). Weeks 9-16: Expanded Integration (scale to multiple topics if initial results positive, develop question bank for future reuse, share experience with colleagues, advocate for institutional support).

Leverage Peer Support: Form informal faculty learning communities (3-5 colleagues). Meet bi-weekly to share prompts, troubleshoot problems, celebrate successes. Create WhatsApp group for quick questions and encouragement. Co-create content to distribute workload.

Document and Advocate: Keep simple records of student performance improvements. Collect student testimonials about AI-enhanced learning. Create before/after comparison slides. Present findings at department meeting to build institutional awareness. Request resources based on demonstrated outcomes.

Address Family and Cultural Concerns: Frame AI as teaching tool enhancing your expertise, not replacing you. Share student success stories with family. Emphasize time savings allowing more quality interaction with students. Connect to Islamic values of seeking knowledge and using beneficial tools. Invite family to see quiz interface - demystify technology.

For EdTech Developers Targeting Developing Countries

Design principles emerging from this study.

Mobile-First, Low-Bandwidth Optimization: Responsive design working on small screens (89% students used smartphones). Minimal data consumption (under 5MB per quiz session). Offline capability where possible. Progressive enhancement (basic functionality works on 2G, enhanced features on 4G+).

Simplified Educator Authoring Tools: Pre-built prompt templates for common educational tasks. AI-assisted verification (flag potential errors for human review). One-click quiz creation from curriculum standards. Drag-and-drop interfaces minimizing technical skill requirements.

Cultural and Linguistic Adaptation: Support for Urdu and regional languages. Culturally appropriate example generation. Customizable to local curriculum standards. Community content libraries (educators share successful prompts/quizzes).

Built-In Trust and Transparency Features: Confidence scores for AI responses. Source citations for AI-generated content. Explanation mode showing AI reasoning process. Easy verification tools.

Social Learning Affordances: Easy sharing via WhatsApp. Peer collaboration features. Leaderboards optional (respecting privacy preferences). Badges and certificates for gamification.

5.6. Gender-Specific Findings

This study's all-female sample provides unique insights into gender-technology intersections.

Peer Support as Gendered Acceptance Factor: The spontaneous creation of WhatsApp study groups, collective achievement framing, and peer teaching patterns strongly align with Venkatesh and Morris's (2000) finding that women prioritize subjective norm more than men. However, this study extends that finding by identifying specific peer support mechanisms: WhatsApp groups for link sharing and problem-solving, study groups completing quizzes together, peer explanation in Urdu supplementing AI explanations in English, collective celebration of achievement.

These patterns reflect both gender-based communication preferences (women's relational orientation) and collectivist cultural values (group over individual). The intersection creates particularly strong peer influence effects.

Implications: AI integration strategies for female educators should leverage existing social networks. Design collaborative features into AI tools. Create women-specific EdTech communities of practice. Recognize collective achievements alongside individual ones.

Family Approval as Hidden Factor: Several students mentioned showing quiz results to mothers, seeking family validation. This finding highlights family as stakeholder in professional technology adoption for women in Pakistani context - unlike Western individualist models where professional decisions are autonomous.

Practical strategies: Provide shareable evidence of learning benefits (student certificates, improvement reports). Frame AI in culturally resonant terms (knowledge-seeking, beneficial tools). Offer family information sessions explaining educational technology.

Professional Identity Navigation: The instructor navigated identity tensions: maintaining pedagogical expertise while embracing AI, preserving "teacher" identity while becoming "AI-using teacher." Successful navigation required framing AI as pedagogical enhancement not replacement: "I'm still the expert; AI is my assistant."

Training programs should explicitly address identity concerns and provide narrative frameworks for female educators to maintain professional authority while adopting technology.

5.7. Study Uniqueness and Contribution

This research makes several unique contributions distinguishing it from existing AI in education literature.

Claude AI Focus: While most studies examine earlier AI tools, this is among the first classroom-based investigations of Claude AI, documenting its distinctive advantages for educational assessment.

Assessment Application: Existing AI in education research emphasizes instructional or administrative applications. This study focuses specifically on AI-powered assessment - a particularly time-intensive and high-stakes educational function.

Developing Country Context: Limited research examines AI acceptance in South Asian higher education despite different infrastructure, cultural values, and implementation realities than Western contexts.

Gender-Focused: The all-female sample enables deep exploration of gender-specific acceptance patterns without confounding by mixed-gender dynamics.

Implementation Focus: Unlike cross-sectional survey studies, this research documents actual implementation experience over 16 weeks with authentic classroom integration.

Mixed-Methods Richness: Integrating quantitative TAM validation with qualitative implementation narratives provides both statistical rigor and contextual understanding.

Practitioner Perspective: The instructor-researcher positionality offers insider insights into implementation challenges, emotional journey, and practical problem-solving strategies.

6. Limitations and Future Research

6.1. Study Limitations

1. Generalizability Constraints

Single Case Study: Data collection at one institution (University of Gujrat) and one course (ADP Grammar) limits generalizability. Findings may not transfer to private universities with different resources, other course levels, other subjects beyond grammar/language instruction, male or mixed-gender teaching environments, or other provinces with distinct cultural contexts.

Female-Only Sample: The deliberate focus on female experiences, while addressing an important gap, precludes direct gender comparisons. Cannot definitively attribute findings to gender versus other factors.

Small Sample Size: N=52 students adequate for case study methodology but limits statistical power for subgroup analyses and generalization to broader populations.

2. Temporal Limitations

Short Implementation Period: The 16-week semester captures initial acceptance but not long-term sustained use beyond novelty effect, instructor fatigue from continuous content creation, student adaptation as AI becomes normalized, or institutional response after pilot phase ends.

No Extended Follow-Up: Study concluded at semester end without tracking whether instructor continued AI use in subsequent terms or whether students retained learning gains.

3. Methodological Limitations

Self-Report Bias: Surveys and focus groups rely on self-reported perceptions, potentially influenced by social desirability, novelty effect, or Hawthorne effect.

Instructor-Researcher Dual Role: Potential confirmation bias in qualitative interpretation, power dynamics affecting student candor, limited external validation of implementation quality.

Lack of Control Group: Without non-AI comparison class in same semester, cannot definitively isolate AI effect from confounding variables. Historical comparison with 2024 cohort mitigates but doesn't eliminate this limitation.

AI Tool Specificity: Findings specific to Claude may not generalize to other AI platforms with different capabilities.

7. Future Research Directions

7.1. Comparative Studies

Cross-Institutional Replication: Replicate across public and private universities. Compare rural versus urban institutions. Test in other South Asian countries. Include male and mixed-gender samples for direct gender comparison.

AI Platform Comparison: Compare Claude versus other AI tools for assessment generation. Identify platform-specific strengths and limitations. Evaluate cost-effectiveness and accessibility.

Subject Diversification: Extend beyond grammar to mathematics, sciences, social studies. Identify subject-specific implementation challenges. Develop subject-tailored integration strategies.

7.2. Longitudinal Research

Sustained Adoption Tracking: Follow instructors over 2-3 years to assess continued use. Document evolution of implementation practices. Identify factors predicting sustained versus abandoned adoption. Study long-term student learning retention.

Institutional Diffusion: Track how AI practices spread within departments. Identify early adopters, early majority, late majority, laggards. Study organizational change processes.

7.3. Expanded Theoretical Frameworks

Self-Determination Theory Integration: Examine autonomy, competence, relatedness as AI acceptance motivators. Explore intrinsic versus extrinsic motivation for AI use.

Communities of Practice: Study how AI adoption spreads through social learning networks. Identify characteristics of successful EdTech learning communities.

Postcolonial Technology Studies: Investigate power dynamics in Global North AI tools used in Global South contexts. Explore technological dependency and neocolonial dimensions.

7.4. Intervention Research

Training Model Testing: Compare peer-led versus expert-led training effectiveness. Assess optimal training duration and intensity. Evaluate online versus face-to-face modalities. Test different incentive structures.

Institutional Implementation: Action research partnerships with universities developing AI policies. Comparative case studies of successful versus unsuccessful integration. Cost-benefit analyses of AI investment versus outcomes.

7.5. Equity Research

Digital Divide: How do infrastructure inequalities moderate AI acceptance and effectiveness? What minimum conditions enable meaningful AI integration? Design AI tools for low-resource, low-connectivity contexts.

Intersectionality: AI acceptance across gender × class × urban/rural intersections. Disability access in AI-enhanced learning. Language privilege (English versus Urdu versus regional languages).

8. Conclusion

This case study provides empirical evidence for successful Claude AI integration in Pakistani grammar instruction, demonstrating that pedagogically-grounded, culturally-sensitive AI implementation can overcome initial barriers and significantly enhance teaching and learning outcomes, even in resource-constrained developing country contexts with female educators reporting low initial technology confidence.

8.1. Three Primary Contributions

Theoretical: Extended TAM validated for AI assessment tools with all constructs showing large effect sizes (d > 1.50). Trust emerged as critical factor built through systematic verification, not assumed. Perceived Ease of Use (d=2.15) most powerful acceptance driver for female users with low tech confidence, challenging assumptions about PU primacy. Cultural factors (peer support, collective achievement) and gender patterns (relational learning, subjective norm emphasis) significantly shaped acceptance processes.

Empirical: Robust mixed-methods evidence demonstrated AI-powered assessment improved student grammar performance by 12.7 percentage points (68.5% to 81.2% final exam average), with 78% achieving excellence on AI quizzes. Female instructor with zero prior AI experience successfully implemented Claude AI assessment within 16 weeks, evolving from high anxiety (6.2/7) to confident advocacy (6.5/7 behavioral intention). Qualitative data revealed implementation mechanisms: immediate feedback transforming learning, verification building trust, peer support sustaining engagement, mobile-friendly design enabling access.

Practical: Offers replicable blueprint for grassroots AI integration: start with self-directed exploration, pilot with small group, scale based on evidence, leverage peer networks, document outcomes, advocate for institutional support. Provides policymakers evidence-based recommendations for faculty development programs, infrastructure investment, and ethical frameworks. Demonstrates that significant improvements achievable even without institutional support when individual educators take initiative - though institutional support would enhance sustainability and scalability.

1. Core Insight

The instructor's transformation from 6.2/7 anxiety to 2.1/7 and student performance improvement from 68.5% to 81.2% demonstrate that change is possible when technology serves pedagogy (not vice versa), cultural context shapes implementation (not generic solutions), female educators receive affirming support (not deficit-framed training), and student success validates risk-taking (not blind faith in innovation).

2. Bigger Picture

This study challenges deficit narratives about developing countries and female educators. Pakistani female teachers are not inherently behind - they face systemic barriers that, when addressed through culturally-sensitive interventions, enable rapid adoption and innovative implementation. AI can democratize access to quality educational tools if designed with developing country contexts in mind: mobile-first, low-bandwidth, Urdu-language support, peer collaboration features, simplified authoring tools.

8.2. Final Reflection

Successful AI integration preserves educators' irreplaceable value while augmenting capabilities. Students learned not from AI alone but from AI-generated content plus instructor expertise plus peer collaboration plus cultural scaffolding. This hybrid human-AI pedagogy represents education's future: not replacement of teachers by technology, but empowerment of teachers through technology. Female educators in Pakistani universities have demonstrated they can lead this transformation when given opportunity, support, and trust. The challenge lies with institutions, policymakers, and developers to match educators' courage and innovation.

References

Ahmad, M., Khan, S., & Ali, R. (2022). Digital transformation in Pakistani higher education: Challenges and opportunities. *Journal of Educational Technology Development*, *15*(3), 234-251.

Alasadi, E. A., & Baiz, C. R. (2023). Generative AI in education and research: Opportunities, concerns, and solutions. *Journal of Chemical Education*, *100*(8), 2965-2971. https://doi.org/10.1021/acs.jchemed.3c00323

Atlas, S. (2023). *ChatGPT for higher education and professional development: A guide to conversational AI*. Digital Education Publications.

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems*, *8*(4), 244-254. https://doi.org/10.17705/1jais.00122

Bai, Y., Kadavath, S., Kundu, S., Askell, A., Kernion, J., Jones, A., ... & Kaplan, J. (2022). Constitutional AI: Harmlessness from AI feedback. *arXiv preprint arXiv:2212.08073*. https://arxiv.org/abs/2212.08073

Batool, S., Rashid, M., & Ahmed, N. (2019). Gender disparities in Pakistani higher education: Faculty perspectives on professional development. *Higher Education Policy*, *32*(4), 587-605. https://doi.org/10.1057/s41307-018-0089-3

Benbasat, I., & Barki, H. (2007). Quo vadis TAM? *Journal of the Association for Information Systems*, *8*(4), 211-218. https://doi.org/10.17705/1jais.00126

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Buabeng-Andoh, C. (2012). Factors influencing teachers' adoption and integration of information and communication technology into teaching: A review of the literature. *International Journal of Education and Development using ICT, 8*(1), 136-155.

Cai, Z., Fan, X., & Du, J. (2023). Gender differences in technology acceptance: A systematic review and meta-analysis. *Computers & Education, 195*, 104715. https://doi.org/10.1016/j.compedu.2023.104715

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies, 25*(5), 3443-3463. https://doi.org/10.1007/s10639-020-10159-7

Cotton, D. R., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International, 61*(2), 228-239. https://doi.org/10.1080/14703297.2023.2190148

Creswell, J. W., & Plano Clark, V. L. (2017). *Designing and conducting mixed methods research* (3rd ed.). Sage Publications.

Crompton, H., & Burke, D. (2023). The use of artificial intelligence in education: A systematic review. *Computers and Education, 184*, 104697. https://doi.org/10.1016/j.compedu.2022.104697

Dahri, N. A., Yahaya, N., Al-Rahmi, W. M., Alturki, U., Alblehai, F. M., Saidalvi, A., ... & Alamri, M. M. (2024). Investigating AI-based academic support acceptance and its impact on students' performance in Malaysian and Pakistani higher education institutions. *Education and Information Technologies, 29*(15), 19691-19738. https://doi.org/10.1007/s10639-024-12599-x

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Farooq, A., Shah, H., & Rashid, S. (2023). Artificial intelligence integration in Pakistani universities: Current status and future prospects. *International Journal of Educational Technology, 18*(2), 45-62.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.

Gefen, D., & Straub, D. W. (1997). Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS Quarterly, 21*(4), 389-400. https://doi.org/10.2307/249720

Gkinko, L., & Elbanna, A. (2023). The appropriation of conversational AI in the workplace: A taxonomy of AI chatbot users. *International Journal of Information Management, 69*, 102568. https://doi.org/10.1016/j.ijinfomgt.2022.102568

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology, 50*(5), 2572-2593. https://doi.org/10.1111/bjet.12864

Higher Education Commission Pakistan. (2023). *Digital transformation strategy for Pakistani universities 2023-2028*. HEC Publications.

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations* (2nd ed.). Sage Publications.

Khan, A., Ahmed, S., & Malik, R. (2023). Faculty perceptions of AI tools in Pakistani higher education: A preliminary survey. *Educational Technology Research, 12*(4), 78-95.

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740-755. https://doi.org/10.1016/j.im.2006.05.003

Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *Journal of Information Systems and Technology Management, 14*(1), 21-38. https://doi.org/10.4301/S1807-17752017000100002

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society, 14*(1), 81-95. https://doi.org/10.1007/s10209-014-0348-1

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *The Journal of Strategic Information Systems, 11*(3-4), 297-323. https://doi.org/10.1016/S0963-8687(02)00020-3

Merriam, S. B., & Tisdell, E. J. (2015). *Qualitative research: A guide to design and implementation* (4th ed.). Jossey-Bass.

Nasir, A., & Mahmood, T. (2018). Cultural factors and technology adoption in developing countries: The case of Pakistan. *Technology in Society, 54*, 34-43. https://doi.org/10.1016/j.techsoc.2018.03.002

Park, E., Baek, S., Ohm, J., & Chang, H. J. (2020). Determinants of player acceptance of mobile social network games: An application of extended technology acceptance model. *Telematics and Informatics, 31*(1), 3-15. https://doi.org/10.1016/j.tele.2012.05.009

Rashid, T., & Asghar, H. M. (2016). Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. *Computers in Human Behavior, 63*, 604-612. https://doi.org/10.1016/j.chb.2016.05.084

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning and Teaching*, *6*(1), 342-363. https://doi.org/10.37074/jalt.2023.6.1.9

Scherer, R., Siddiq, F., & Howard, S. K. (2019). The more important question: Which technology-related variables are associated with differences in student achievement? A meta-analysis. *Computers & Education, 140*, 103608. https://doi.org/10.1016/j.compedu.2019.103608

Southworth, J., Migliaccio, K., Glover, J., Reed, D., McCarty, C., Brendemuhl, J., & Thomas, A. (2023). Developing a model for AI across the curriculum: Transforming the higher education landscape via innovation in AI literacy. *Computers and Education: Artificial Intelligence, 4*, 100127. https://doi.org/10.1016/j.caeai.2023.100127

Stake, R. E. (2006). *Multiple case study analysis*. Guilford Press.

Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, 1-14. https://doi.org/10.1080/10494820.2023.2209881

Sultana, R., Khan, M., & Ahmed, F. (2021). Professional development needs of female faculty in Pakistani universities: A gender perspective. *Professional Development in Education, 47*(3), 445-461. https://doi.org/10.1080/19415257.2020.1787206

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments, 10*(1), 15. https://doi.org/10.1186/s40561-023-00237-x

Tondeur, J., Van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. *Educational Technology Research and Development, 65*(3), 555-575. https://doi.org/10.1007/s11423-016-9481-2

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly, 24*(1), 115-139. https://doi.org/10.2307/3250981

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). Sage Publications.

Zhang, M., Guo, L., Hu, M., & Liu, W. (2021). Influence of customer engagement with company social networks on stickiness: Mediating effect of customer value creation. *International Journal of Information Management, 37*(3), 229-240. https://doi.org/10.1016/j.ijinfomgt.2016.04.010