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Building an AI-Driven Personalized Learning System to Enhance Training Effectiveness for Primary Education Students: A Comprehensive Framework and Empirical Evaluation

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Abstract

Background/Purpose. This study aims to develop and evaluate the effectiveness of an AI-driven personalized learning system in improving learning outcomes, motivation, and pedagogical competencies of Vietnamese primary education students within the context of digital transformation in teacher education.

Methods. A mixed-methods cluster-randomized controlled trial was conducted over 18 weeks with 187 second- and third-year students from 12 intact classes at the University of Education, Vietnam National University Hanoi. The intervention comprised three components: an intelligent learning analytics system, an AI-adaptive learning environment, and a personalized competency assessment system. Data were collected through standardized achievement tests, learning motivation scales, pedagogical competency assessments, and semi-structured interviews with 60 participants (48 students, 8 instructors, 4 administrators) using systematic thematic analysis.

Results. Using multilevel modeling, the experimental group demonstrated significant improvements compared to traditional methods: a 12.3% increase in academic performance (Cohen's d = 0.62), a 18.7% increase in learning motivation (Cohen's d = 0.68), and a 15.2% enhancement in pedagogical competencies (Cohen's d = 0.56). The most significant improvements were observed in personalized lesson design capabilities (17.8%) and educational technology integration skills (16.4%).

Conclusion. The AI-driven personalized learning system significantly improved training outcomes with moderate effect sizes consistent with rigorous educational technology research. However, potential contamination effects and assessment bias represent important limitations. The study provides a scalable implementation framework emphasizing instructor digital competency development, institutional infrastructure support, and comprehensive stakeholder engagement for sustainable adoption in Vietnamese educational contexts.

1. Introduction

1.1. Background and Research Context

The Fourth Industrial Revolution is fundamentally transforming global educational systems, requiring significant restructuring of traditional pedagogical methodologies to develop 21st-century skills and lifelong learning competencies (Alenezi et al., 2023). Within this transformative context, the integration of advanced technologies with innovative educational models represents not merely an inevitable trend but a strategic imperative for enhancing educational quality, effectiveness, and accessibility. The timing of this research is particularly critical as Vietnam implements its National Digital Transformation Program (2021-2030) and faces urgent demands for digitally competent educators who can prepare children for an AI-integrated future.

Artificial Intelligence in Education (AIEd) has emerged as a powerful paradigm for revolutionizing teaching and learning processes. AIEd utilizes sophisticated algorithms to automate, personalize, and optimize both instructional delivery and learning experiences (Chiu, 2023). This technological advancement offers unprecedented opportunities to address persistent challenges in higher education, particularly in teacher preparation programs where students must develop complex pedagogical competencies while mastering diverse content areas.

Training primary school teachers represents one of the most critical areas in educational systems, as the quality of primary teachers fundamentally determines children's learning foundations and future academic success (Cotton et al., 2023). However, recent research reveals that training primary education students faces substantial challenges, including significant diversity in academic preparation levels, varied learning styles, and differential professional development needs (Kuleto et al., 2021). This priority issue affects not only immediate educational outcomes but also long-term national competitiveness, making AI-enhanced teacher preparation a strategic investment for Vietnam's educational future.

In Vietnam, the integration of digital technologies into teacher education has become increasingly urgent amid national education modernization initiatives and the growing demand for digitally competent educators. The Vietnamese Ministry of Education and Training's Strategy for Education Development 2021-2030 emphasizes the critical importance of technology integration in teacher preparation programs. However, empirical research indicates that only 21.3% of university instructors in teacher training programs possess a conceptual understanding of AI-driven personalized learning methods, while only 14.7% have practical experience implementing intelligent systems (Nguyen & Truong, 2025).

1.2. Problem Statement and Research Gap

The Primary Teaching Methods course in Vietnamese primary teacher training programs presents unique challenges due to its high integration complexity and cognitive demands. This course requires students not only to master professional knowledge but also to develop sophisticated abilities in designing and implementing developmentally appropriate teaching activities for primary school children. A comprehensive national survey across teacher-training universities found that 73% of students experience significant difficulties in personalizing teaching methods for diverse student populations.

Despite growing international research on AI applications in teacher education (Grassini, 2023), critical gaps exist in understanding how to adapt these pedagogical technologies for specific developmental characteristics of Vietnamese teacher training students. Furthermore, limited empirical evidence exists regarding the effectiveness of comprehensive AI-driven personalized learning systems specifically designed for teacher preparation contexts in developing country settings with resource constraints and infrastructure limitations.

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The complexity of implementing AI-enhanced personalized learning systems in Vietnamese educational contexts involves multiple interconnected challenges: inadequate technological infrastructure, insufficient digital competencies among instructors, limited financial resources, concerns about data privacy and algorithmic bias, and potential overreliance on technology at the expense of human interaction (Nhung et al., 2025). Additionally, there are legitimate concerns about the digital divide, equity in access to technology, and the need for culturally responsive AI systems that align with Vietnamese educational values and practices. These scalability challenges raise questions about sustainable implementation and potential for teacher resistance to technology-mediated instruction.

1.3. Research Questions

Based on the identified gaps and contextual challenges, this study addresses the following research questions:

1. How effective is a comprehensive AI-driven personalized learning system in improving academic achievement outcomes of Vietnamese primary education students compared to traditional instruction?

2. What are the effects of AI-driven personalized learning system implementation on student motivation, engagement, and self-efficacy in teacher training contexts?

3. How does the AI-driven personalized learning system influence students' pedagogical competency development, particularly in lesson design and technology integration skills?

4. What institutional, technological, and pedagogical factors predict successful implementation of AI-driven personalized learning models in Vietnamese primary teacher education contexts?

1.4. Research Objectives and Significance

This research is conducted with four primary objectives:

Comprehensive Theoretical Framework Development: Develop an integrated theoretical framework combining social constructivist learning theory, adaptive learning principles, and the TPACK model, specifically calibrated for Vietnamese teacher training contexts and primary education student characteristics.

System Design and Empirical Validation: Create and rigorously evaluate a complete AI-driven personalized learning system encompassing intelligent analytics, adaptive content delivery, and competency-based assessment components.

Evidence-Based Impact Assessment: Conduct systematic empirical evaluation through cluster randomized controlled trial methodology to establish causal relationships between intervention components and multiple learning outcome domains while accounting for nested data structures.

Implementation Framework Formulation: Generate actionable guidelines and enabling-condition specifications for sustainable implementation in Vietnamese and broader Southeast Asian primary teacher education contexts.

This research is anticipated to contribute significantly to international scholarship on technology-enhanced teacher education, provide contextually relevant solutions to Vietnamese educational challenges, and establish a replicable framework for global application. The study addresses an urgent priority for modernizing the Vietnamese education system and provides evidence-based guidance for policymakers, institutional leaders, and educators considering AI integration in resource-constrained contexts.

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2. Literature Review

2.1. Theoretical Foundation of AI-Driven Personalized Learning Systems

The theoretical framework of this research is constructed upon the convergence of three fundamental educational paradigms, creating an integrated conceptual architecture that is both theoretically robust and practically applicable in higher education contexts. While these theories provide strong foundations, we acknowledge their limitations when applied to AI contexts, including challenges related to scalability, algorithmic transparency, and the risk of reducing complex pedagogical relationships to computational processes.

2.1.1. Social Constructivist Learning Theory

Vygotsky's Social Constructivist Theory provides the foundational framework through the concept of "Zone of Proximal Development" (ZPD). In AI-driven personalized learning contexts, technology functions as a sophisticated mediating tool, enabling learners to access knowledge and skills beyond their current autonomous capabilities. AI environments create dynamic scaffolding systems in which intelligent algorithms serve as cultural tools that facilitate knowledge construction (Johnson, 2021).

The integration of AI as a mediating tool must be carefully designed to support rather than replace human interaction. The system should facilitate peer collaboration and instructor guidance while providing personalized scaffolding that adapts to individual learning needs. This theoretical perspective emphasizes that learning is fundamentally social and that AI systems must be designed to enhance rather than diminish meaningful human connections in educational settings.

Recent applications demonstrate AI's effectiveness in supporting collaborative knowledge construction among teacher training students. Research shows that AI environments can effectively mediate peer collaboration during implementation sessions, aligning with Vygotskian principles of social learning and knowledge co-construction (Kasneci et al., 2023). However, critical voices warn of an over-reliance on technology that may reduce authentic social interaction, which is essential for teacher development. Potential risks include erosion of teacher-student relationships, reduced opportunities for spontaneous pedagogical mentoring, and cultural incompatibility in contexts emphasizing collective learning over individualized instruction.

2.1.2. Adaptive Learning Theory and Cognitive Load Management

Cognitive Load Theory provides the scientific foundation for digital content design principles in AI-enhanced learning environments. This theory postulates that human information processing operates through multimodal channels with limited working memory capacity. AI implementations must strategically manage cognitive load to optimize learning effectiveness while avoiding cognitive overload that can impede learning (Pardamean et al., 2022).

The theory's three types of cognitive load-intrinsic, extraneous, and germane-provide specific guidance for AI system design. Intrinsic load refers to the inherent difficulty of the learning material; extraneous load results from poor instructional design; and germane load involves the mental effort devoted to schema construction. AI systems must minimize extraneous load while managing intrinsic load appropriately and supporting germane load processes.

Empirical studies validate these principles, showing that carefully designed AI experiences following adaptive learning principles can improve learning outcomes compared to traditional instruction. However, effect sizes in rigorous studies typically range from small to moderate ($d = 0.3$-0.7), with larger effects often observed in studies with methodological limitations (Pardamean et al., 2022). Scalability challenges emerge when implementing adaptive systems across diverse learner

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populations, requiring substantial computational resources and expert instructional design capacity that may not be available in resource-constrained settings.

2.1.3. TPACK Framework Integration

The Technological Pedagogical Content Knowledge (TPACK) framework provides an organizational structure for the development of instructor competencies and for technology integration strategies. This framework recognizes that effective technology integration requires sophisticated interplay between Content Knowledge (CK), Pedagogical Knowledge (PK), and Technology Knowledge (TK), with the intersection of all three representing the most effective integration approach (Özer, 2024).

For AI-driven personalized learning systems, TPACK becomes particularly important because instructors must understand not only how to use the technology but also how AI algorithms make decisions about content presentation and student assessment. This requires a new dimension of technological knowledge, including an understanding of machine learning principles, data privacy considerations, and the potential for algorithmic bias. Teacher resistance may arise from inadequate TPACK development, fear that technology will replace human judgment, or cultural tensions between algorithmic recommendations and traditional pedagogical authority.

Research applications demonstrate that instructors with strong TPACK foundations achieve greater success in implementing AI technologies, and significant correlations exist between TPACK competency and adaptive system effectiveness in teacher-training settings. However, developing TPACK competency specifically for AI systems requires comprehensive professional development that addresses both technical and pedagogical dimensions (Rahman & Freeman, 2025).

2.2. AI Applications in Teacher Education: Critical Perspectives

International research on AI applications in teacher education reveals both promising opportunities and significant challenges across different educational contexts. While systematic reviews indicate that AI interventions typically focus on three primary areas-content personalization, assessment automation, and learning analytics-the evidence base reveals considerable variation in effectiveness and implementation success (Zawacki-Richter et al., 2019).

2.2.1. Evidence Base and Effect Sizes

Studies from developed educational systems show effect sizes ranging from 0.42 to 0.78 for AI applications in teacher preparation programs, with most rigorous studies reporting moderate effects ($d = 0.58 - 0.72$) (Wang et al., 2024; Zawacki-Richter et al., 2019). However, these findings primarily emerge from contexts with robust technological infrastructure and high levels of instructor digital competency, raising important questions about transferability to developing educational systems.

Meta-analytic evidence suggests that adaptive learning systems can increase student engagement by 15-22% and improve retention rates by 12-18% compared to traditional approaches (Wang et al., 2024). However, these effects vary considerably based on implementation quality, instructor competency, and institutional support systems.

2.2.2. Implementation Challenges and Negative Impacts

Critical perspectives highlight several significant challenges in AI implementation. Privacy concerns arise from the extensive data collection required for personalization, including data on learning behaviors, performance patterns, and personal preferences. Algorithmic bias represents another critical concern, as AI systems may perpetuate or amplify existing educational inequalities if training data reflects historical biases (Dignum, 2021).

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The digital divide poses particular challenges in developing countries, where unequal access to technology and internet connectivity can exacerbate educational inequalities. In Vietnam specifically, rural-urban disparities in technological infrastructure may limit equitable implementation of AI-enhanced learning systems (Nhung et al., 2025).

Over-dependence on technology represents an additional concern, particularly in teacher education, where human modeling and mentoring relationships are fundamental to professional development. Critics argue that excessive reliance on AI systems may reduce opportunities for authentic human interaction, which is essential for developing the interpersonal skills required for effective teaching (Johnson, 2021).

2.2.3. Mixed and Contradictory Results

The research literature reveals mixed results regarding AI effectiveness in educational contexts. While some studies report substantial improvements, others show minimal effects or even negative outcomes. A recent systematic review found that 34% of AI education interventions showed no significant effects, while 12% reported negative impacts on student outcomes (Wang et al., 2024).

Factors associated with unsuccessful implementations include inadequate instructor training, poor system usability, insufficient technical support, and misalignment between AI capabilities and educational goals. These findings underscore the importance of comprehensive implementation support rather than focusing solely on technological features.

2.3. Digital Transformation in Vietnamese Education: Opportunities and Constraints

Vietnam's efforts to digitalize education have accelerated significantly following the COVID-19 pandemic and national digital transformation initiatives. The Ministry of Education and Training's comprehensive strategy emphasizes technology integration across all educational levels, with particular focus on teacher preparation programs (Nguyen & Mai, 2023).

2.3.1. National Policy Context

The Vietnamese government has invested substantially in educational technology infrastructure through initiatives such as the National Digital Transformation Program and the Education Development Strategy 2021-2030. These policies emphasize the need for digitally competent teachers and technology-enhanced learning environments.

However, implementation challenges persist at multiple levels. Rural universities often lack adequate internet connectivity and technical support infrastructure. Many faculty members require extensive professional development to effectively integrate new technologies into their teaching practice (Sklyarov et al., 2020).

2.3.2. Cultural and Contextual Considerations

Vietnamese educational culture emphasizes respect for authority, collaborative learning, and holistic student development. AI systems must be designed to align with these cultural values rather than imposing Western educational paradigms. This requires careful attention to how AI systems mediate teacher-student relationships and support rather than undermine traditional Vietnamese educational strengths.

Research indicates substantial variation in digital readiness across Vietnamese educational institutions, with urban universities demonstrating significantly higher implementation capacity than rural counterparts. Successful AI implementation requires comprehensive support systems addressing technical infrastructure, professional development, and institutional culture change (Honcharuk et al., 2024).

The most effective implementations combine technological innovation with culturally responsive pedagogical practices that honor Vietnamese educational traditions while embracing beneficial technological enhancements (Honcharuk et al., 2024).

3. Methodology

3.1. Research Design Framework

This investigation employed a mixed-methods research design, incorporating both quantitative experimental methodology and qualitative inquiry, to comprehensively evaluate the effectiveness of an AI-driven personalized learning system. The study used a cluster-randomized controlled trial (cRCT) design with pre- and post-measurements over an 18-week intervention period to address concerns about contamination between participants.

The methodological approach was specifically calibrated to address the complexity of technology-enhanced pedagogical interventions while maintaining scientific rigor appropriate for university education contexts. The research design incorporated multiple validity safeguards, systematic bias controls, and comprehensive outcome measurement protocols to ensure the reliability and generalizability of the findings.

3.2. Participants and Setting

The study was conducted at the University of Education, Vietnam National University Hanoi, with 187 second and third-year students enrolled in primary education programs across 12 intact classes. Cluster randomization was employed to assign entire classes to the experimental (6 classes, $n = 93$) and control (6 classes, $n = 94$) conditions, using computer-generated randomization sequences generated in R.

Inclusion criteria comprised: (1) enrollment in a primary education teacher training program, (2) completion of foundational pedagogy courses, (3) basic computer literacy demonstrated through a standardized assessment, (4) voluntary informed consent with understanding of study requirements, and (5) commitment to full participation throughout the 18 weeks.

Exclusion criteria included concurrent enrollment in other educational technology research studies, severe learning disabilities that would interfere with technology use, and planned extended absences during the intervention period.

Participant Demographic Characteristics: The final sample ($N=187$) consisted of 142 females (75.9%) and 45 males (24.1%) students with a mean age of 20.3 years ($SD=1.2$, range 18-23). Regarding socioeconomic background, 34.2% came from urban areas, 41.7% from suburban areas, and 24.1% from rural areas. The digital experience assessment revealed that 28.3% reported high prior technology experience, 51.3% moderate experience, and 20.4% limited experience. Baseline computer literacy scores averaged 7.8/10 ($SD=1.4$) with no significant between-group differences ($p=0.742$). These demographic variables were included as covariates in multilevel analyses to control for potential confounding effects.

Power analysis calculations using optimal design software for cluster randomized trials determined the minimum required sample size of 144 participants across 12 clusters ($ICC = 0.10$, $\alpha = 0.05$, power = 0.80, anticipated effect size $d = 0.6$). The final sample of 187 students provided adequate statistical power (power = 0.87) while accommodating potential attrition rates of 15-20%.

3.3. Contamination Control Strategies and Limitations

Given the single-site design, complete contamination prevention was not feasible. However, several comprehensive strategies were implemented to minimize cross-group information sharing while acknowledging inherent limitations of the research context.

Implemented Contamination Control Measures: The research team employed multiple strategies, including separate scheduling for experimental and control classes to reduce direct contact, instructor isolation protocols where different instructors taught each condition with explicit instructions not to discuss methods, confidentiality agreements signed by students, and social media monitoring of class-specific groups for evidence of cross-contamination.

Acknowledged Methodological Limitations: Despite control efforts, students from both groups shared dormitories, dining facilities, and library spaces where informal discussions inevitably occurred. Some instructors taught courses outside the study that included students from both groups; university-wide events created opportunities for information sharing; and no objective measure of the extent of contamination was implemented.

Impact Assessment and Conservative Bias: Post-study interviews revealed that 23% of control group students reported hearing about “some kind of computer system” from experimental group peers, though specific details were reportedly limited. This contamination likely introduced conservative bias, leading the observed effects to represent lower-bound estimates of true intervention effectiveness.

3.4. AI-Driven Personalized Learning System: Technical Specifications

The intervention system comprised three integrated components designed according to evidence-based principles and theoretical frameworks, with detailed technical specifications provided to ensure replicability and transparency.

Component 1: The Intelligent Learning Analytics System used a comprehensive machine learning architecture, including TensorFlow 2.8 with the Keras API for deep learning models, Python 3.9 with scikit-learn 1.1 for traditional ML algorithms, and data processing with Pandas 1.4 and NumPy 1.21. Personalization algorithms included K-means clustering ($k = 5$) based on learning-style inventory responses, collaborative filtering using matrix factorization, Item Response Theory for difficulty adaptation, and a Q-learning algorithm for learning path optimization. The system was trained on historical performance data from 2,847 student records, expert annotations of 1,250 content items, 45,000 interaction records from pilot testing, and outcome correlations based on 5 years of student grade data.

Component 2: AI-Adaptive Learning Environment featured an adaptive content delivery system with 847 learning objects across multiple formats, real-time content selection based on student performance and engagement, multimodal presentation based on learning style preferences, and a comprehensive gamification framework with 15 badge categories and 73 total achievements. The immediate feedback system used natural language processing with a BERT-base model fine-tuned on educational feedback data, template-based feedback generation with 247 patterns, and delivered 95% of feedback within 30 seconds of student submission.

Component 3: Personalized Competency Assessment System employed automated scoring algorithms including BERT-based transformer models fine-tuned on 2,000 expert-scored pedagogical reflections, computer vision models for analyzing teaching demonstration videos, and multi-criteria decision analysis combining rubric scores with peer evaluation data. Quality assurance measures included monthly calibration studies, statistical monitoring for scoring pattern changes, and formal student appeal processes for AI-generated score review.

3.5. Data Collection Instruments

Academic Achievement Assessment utilized a comprehensive test battery comprising 60 items across multiple formats aligned with Vietnamese Teacher Education Standards. Content domains included child development psychology (15 items, Cronbach’s $\alpha = 0.84$), personalized teaching

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methods (18 items, Cronbach's α = 0.87), educational technology integration (12 items, Cronbach's α = 0.81), and assessment and evaluation principles (15 items, Cronbach's α = 0.85). Psychometric properties included content validity, established through expert panel review (Content Validity Index = 0.92); overall internal consistency (Cronbach's α = 0.89); test-retest reliability (r = 0.84 over a 2-week interval); and confirmatory factor analysis supporting a four-factor structure (CFI = 0.94, RMSEA = 0.063).

The Learning Motivation and Engagement Scale employed a modified instrument adapted for Vietnamese university contexts, comprising 35 items across six dimensions, each measured on a 5-point Likert scale. Psychometric validation included cultural adaptation through a translation-back-translation procedure, pilot testing with 120 students not included in the main study, confirmatory factor analysis (CFI = 0.92, RMSEA = 0.067), subscale reliability ranging from 0.78 to 0.86, and scalar invariance confirmed across gender and class year.

Pedagogical Competency Assessment used performance-based evaluation to measure capacity across six pedagogical domains, employing multiple assessment methods to minimize bias. Enhanced blinding procedures included anonymous submissions through a digital platform, technology skill separation from other domains, temporal separation with randomized scoring order, and independent validation through 25% double-scoring by external raters. Bias detection analysis monitored technology-skill correlations, evaluator consistency patterns, and competency-area analysis to identify potential sources of bias.

3.6. Implementation Procedures

Experimental Group Protocol involved participants receiving instruction using the complete AI-driven personalized learning system across four thematic modules delivered over 18 weeks: Child Development Psychology (4 weeks), Personalized Teaching Methods (5 weeks), Educational Technology Integration (5 weeks), and Assessment and Evaluation (4 weeks). Implementation fidelity monitoring included a 40-hour instructor certification program, automated usage analytics with weekly reports, a 15-item fidelity checklist completed after each session, and weekly student engagement surveys measuring satisfaction with system usage.

The control group protocol provided traditional instruction covering identical curriculum content using conventional pedagogical approaches. Fidelity assurance measures included instructor isolation during planning meetings, 20-hour professional development focused on enhancing conventional teaching methods, detailed curriculum mapping to ensure identical learning objectives, and equivalent instructor contact time with attention-control activities. Contamination monitoring involved weekly instructor interviews, bi-weekly student surveys about exposure to alternative methods, and informal monitoring of cross-group student interactions.

3.7. Data Analysis Strategy

Multilevel Modeling for Clustered Data employed comprehensive statistical approaches using the lme4 package in R to account for nested structure of students within classes. Model specifications included Level 1 (Student) and Level 2 (Class) equations with appropriate covariates. Intraclass correlation coefficients were calculated for academic achievement (ICC = 0.12), learning motivation (ICC = 0.08), and pedagogical competency (ICC = 0.15). The model-building strategy progressed from unconditional models to treatment-effect models, then to final covariate-adjusted models selected using likelihood ratio tests and information criteria.

Systematic Qualitative Analysis followed enhanced thematic analysis framework incorporating six phases: data familiarization with multiple readings and memo writing, systematic initial coding using both deductive and inductive approaches, theme development through thematic networks and pattern recognition, theme review and refinement ensuring internal homogeneity and external heterogeneity, theme definition and naming with detailed descriptions and exemplar selection, and report production with integration strategy and member checking with 20% of interview participants.

3.8. Ethical Considerations

Research protocols received approval from the Institutional Review Board at Vietnam National University Hanoi (Protocol 2024-VNU-IRB-127). All procedures complied with Vietnamese research ethics regulations and international standards for educational research.

Enhanced Privacy Protections included data minimization limited to variables essential to the research questions, purpose limitation with clear specification of data use purposes and a prohibition on secondary uses, retention limits with automatic deletion after a 7-year retention period, and participant rights with clear procedures for data access, correction, and deletion requests.

4. Results

4.1. Participant Characteristics and Baseline Equivalence

Statistical analysis confirmed successful cluster randomization, with no significant between-group differences in demographic variables or baseline measures. Multilevel analysis accounting for clustering revealed no significant differences in baseline academic performance (experimental clusters: M = 7.41, SD = 1.18; control clusters: M = 7.44, SD = 1.15; $t(10) = 0.17$, $p = 0.867$, Cohen's d = 0.03).

Cluster-level characteristics showed balanced assignment, with average class size (experimental = 15.5 ± 2.3, control = 15.7 ± 2.1, $p = 0.89$), instructor experience (experimental = 8.2 ± 3.1 years, control = 7.9 ± 2.8 years, $p = 0.74$), and similar technology access across all clusters.

Attrition analysis revealed that of 187 initial participants, 179 (95.7%) completed all assessments. Attrition was balanced across conditions (experimental: n = 4, control: n = 4) and unrelated to baseline characteristics (all $p > 0.05$). Missing data handling used maximum likelihood estimation within multilevel models.

4.2. Primary Outcome Analysis: Academic Achievement

Practical Significance of Academic Achievement Gains: The 12.3% improvement in academic achievement (Cohen's d = 0.62) translates to approximately 0.91 points on the 10-point Vietnamese grading scale. In practical terms, this gain represents the difference between a typical "good" performance (7.4/10) and approaching "very good" performance (8.3/10). In teacher preparation contexts, this improvement indicates greater mastery of essential pedagogical concepts, a stronger ability to design developmentally appropriate lessons, and better integration of educational technology into teaching practice. Students demonstrating these gains show greater readiness for practicum teaching experiences and a higher likelihood of successful first-year teaching performance, based on historical correlation analyses ($r = 0.58$, $p < 0.001$).

Table 1: Academic Achievement Results by Thematic Module (Multilevel Analysis)

Module	Experimental M(SD)	Control M(SD)	β (SE)	95% CI	p-value	Cohen's d
Child Development	8.42 (1.08)	7.51 (1.21)	0.91 (0.22)	[0.47, 1.35]	< 0.001	0.79
Teaching Methods	8.31 (0.97)	7.41 (1.15)	0.90 (0.21)	[0.48, 1.32]	< 0.001	0.82
Technology Integration	8.28 (1.12)	7.38 (1.24)	0.90 (0.23)	[0.44, 1.36]	0.001	0.75
Assessment Methods	8.31 (1.06)	7.39 (1.19)	0.92 (0.22)	[0.48, 1.36]	< 0.001	0.81

Model diagnostics confirmed that assumptions were met, with residuals normal (Shapiro-Wilk test, $p = 0.23$), homoscedasticity (Levene's test, $p = 0.41$), and acceptable multicollinearity (all VIF values < 2.5).

4.3. Secondary Outcome Analysis: Learning Motivation and Engagement

Multilevel MANOVA revealed significant multivariate treatment effect ($F(6, 5) = 12.34$, $p = 0.008$) with moderate effect size (partial $\eta^2 = 0.94$). Intraclass correlation for composite motivation score was ICC = 0.08 (95% CI: 0.03, 0.17).

Table 2: Learning Motivation Results (Multilevel Analysis)

Dimension	Experimental M(SD)	Control M(SD)	β (SE)	95% CI	p-value	Cohen's d
Intrinsic Motivation	4.12 (0.64)	3.47 (0.71)	0.65 (0.14)	[0.36, 0.94]	< 0.001	0.93
Learning Confidence	4.08 (0.68)	3.52 (0.69)	0.56 (0.15)	[0.25, 0.87]	0.002	0.81
Engagement Level	4.15 (0.62)	3.51 (0.74)	0.64 (0.14)	[0.35, 0.93]	< 0.001	0.93
Technology Attitude	4.02 (0.71)	3.49 (0.76)	0.53 (0.16)	[0.20, 0.86]	0.004	0.71
Self-Efficacy	3.98 (0.73)	3.54 (0.74)	0.44 (0.16)	[0.11, 0.77]	0.013	0.60
Academic Satisfaction	4.05 (0.66)	3.58 (0.72)	0.47 (0.15)	[0.16, 0.78]	0.006	0.66
Composite Score	4.07 (0.67)	3.52 (0.73)	0.55 (0.13)	[0.28, 0.82]	< 0.001	0.79

All effects remained significant after Bonferroni correction for multiple comparisons ($\alpha = 0.008$).

4.4. Tertiary Outcome Analysis: Pedagogical Competency Development

Analysis of Technology Integration Bias: A detailed bias-detection analysis revealed concerning patterns suggesting potential evaluator bias favoring participants in the experimental group. Technology integration scores showed a significantly higher correlation with overall ratings ($r=0.67$, $p<0.001$) than with other competency areas ($r=0.48$-0.55, all $p<0.001$). Inter-rater reliability analysis indicated lower agreement on technology integration assessments (ICC=0.71) compared to other domains (ICC=0.82-0.88). Post-hoc interviews with evaluators revealed that 40% reported difficulty maintaining blinding due to technology-specific terminology and references in student submissions. These patterns emerged despite enhanced blinding procedures, suggesting a risk of systematic bias.

Sources and Impact of Bias: Potential bias may have arisen from: (1) Evaluators unconsciously associating technology sophistication with overall pedagogical competence; (2) Experimental group students naturally incorporating more technology references in their work, inadvertently revealing group membership; (3) Evaluator expectations about AI training effects influencing scoring decisions; (4) Halo effect where strong technology skills influenced ratings across all competency domains. To address these concerns, conservative estimates excluding technology integration maintained substantial overall effect sizes ($d=0.72$), suggesting that bias, while present, did not fully account for observed improvements. However, true effect sizes for technology integration may be inflated by 15-20% due to assessment bias.

Pedagogical Process Implications: The observed bias highlights fundamental challenges in objectively assessing technology-integrated teaching competencies. As digital tools become integral to pedagogical practice, distinguishing between technology skills and pedagogical expertise becomes increasingly complex. This methodological challenge reflects broader conceptual questions about the nature of teaching competence in technology-rich environments and whether traditional competency frameworks adequately capture 21st-century teaching requirements.

Table 3: Pedagogical Competency Results with Bias Analysis

Competency Area	Experimental M(SD)	Control M(SD)	β (SE)	Cohen's d	Potential Bias Risk
Lesson Design	4.08 (0.58)	3.46 (0.72)	0.62 (0.13)	0.94	Low
Content Knowledge	3.96 (0.64)	3.48 (0.69)	0.48 (0.14)	0.72	Low
Technology Integration	4.01 (0.61)	3.44 (0.71)	0.57 (0.14)	0.86	High
Assessment Methods	3.92 (0.66)	3.46 (0.74)	0.46 (0.15)	0.66	Low
Classroom Management	3.89 (0.69)	3.42 (0.71)	0.47 (0.15)	0.67	Low
Reflection Skills	3.91 (0.63)	3.47 (0.68)	0.44 (0.14)	0.67	Low
Overall (excluding tech)	3.95 (0.64)	3.46 (0.71)	0.49 (0.13)	0.72	Low

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Bias Detection Results revealed no systematic differences in scoring patterns between anonymized groups ($F(1, 177) = 0.82$, $p = 0.367$). However, technology integration scores showed a higher correlation with overall ratings ($r = 0.67$) than with other competencies ($r = 0.48$-0.55), suggesting potential bias. Conservative estimates, excluding technology integration, maintained a substantial overall effect size ($d = 0.72$).

4.5. Implementation Predictor Analysis

Multilevel regression analysis identified predictors of intervention effectiveness using student-level and cluster-level variables. The model explained 58.3% of the between-cluster variance in academic outcomes.

Table 4: Implementation Effectiveness Predictors (Multilevel Model)

Predictor Variable	β	SE	t-value	p-value	95% CI
Cluster Level					
Instructor Digital Competency	0.42	0.12	3.50	0.006	[0.15, 0.69]
Technical Infrastructure	0.31	0.13	2.38	0.039	[0.02, 0.60]
Student Level					
Prior Technology Experience	0.18	0.07	2.57	0.011	[0.04, 0.32]
Learning Motivation (baseline)	0.22	0.08	2.75	0.007	[0.06, 0.38]
System Usability Rating	0.28	0.09	3.11	0.002	[0.10, 0.46]

Cluster-level predictors showed stronger effects than individual-level variables, emphasizing the importance of institutional factors for successful implementation.

4.6. Qualitative Findings: Comprehensive Thematic Analysis

Systematic thematic analysis of 60 interviews (students n=48, instructors n=8, administrators n=4) conducted between weeks 16-18 of the intervention revealed six major themes reflecting both positive and negative implementation experiences. Interview protocols included semi-structured questions addressing system usability, pedagogical effectiveness, implementation challenges, cultural adaptation, and recommendations for improvement. Interviews averaged 45 minutes (range: 30-75 minutes), were audio-recorded with participant consent, and transcribed verbatim by trained research assistants. Data were analyzed using NVivo 12 software following Braun and Clarke's six-phase thematic analysis framework.

Theme 1: Enhanced Personalized Learning emerged from 89% of participants, with positive experiences (72% of references) highlighting that the system better understood individual learning styles than traditional methods and provided analytics that helped identify learning gaps. Representative quotations included: "The system seemed to know exactly what I struggled with and gave me extra practice" (Student 23); "I could see my progress in real-time, which motivated me to keep improving" (Student 35). Negative experiences (28% of references) noted mechanical recommendations and occasional pedagogically inappropriate suggestions requiring instructor

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override. “Sometimes the AI recommended activities that didn't fit my students' developmental level” (Student 42).

Theme 2: Technology Integration Challenges was reported by 76% of participants, with implementation difficulties including initial system crashes, insufficient training, and internet connectivity problems that disrupted sessions. “The first three weeks were frustrating with constant technical issues” (Student 18); “I felt overwhelmed by all the features initially” (Instructor 3). However, gradual adaptation occurred with most participants becoming comfortable with system features by month three. “Once I understood the logic, it became much easier to use” (Student 29).

Theme 3: Motivation and Engagement. Variations showed 84% participation, with the high-engagement subgroup (67%) appreciating immediate feedback and real-time progress monitoring. “Getting instant feedback kept me engaged and helped me learn faster” (Student 31). While low engagement subgroup (33%) preferred face-to-face instructor feedback over AI responses. “I missed the personal touch and detailed explanations from my instructor” (Student 47).

Theme 4: Instructor Professional Development Needs was identified by 100% of instructors, highlighting competency gaps in understanding AI recommendation mechanisms and in balancing AI assistance with traditional teaching methods. “I needed much more training on how AI makes decisions and when to override its recommendations” (Instructor 5); “Finding the right balance between technology and human interaction was difficult” (Instructor 7).

Theme 5: Institutional Support Variations revealed that substantial infrastructure investment was necessary but created steeper learning curves than anticipated, though technical support effectiveness improved significantly after initial implementation period. “The technical team became very responsive by month two” (Administrator 2); “Initial infrastructure problems frustrated everyone” (Instructor 4).

Theme 6: Cultural Adaptation Considerations aligned with Vietnamese educational values by supporting collaborative learning while adding personalized elements, though some cultural tensions emerged when AI recommendations conflicted with traditional respect for instructor authority. “Sometimes the system suggested approaches that contradicted my instructor's teaching, which felt uncomfortable” (Student 38); “We learned to appreciate both individual progress tracking and group learning activities” (Student 44).

Member checking results showed that 82% of participants agreed with the preliminary theme descriptions, and refinements were made based on detailed feedback from 12 participants.

4.7. Contamination Impact Assessment

Post-study contamination analysis revealed evidence of cross-group information sharing, likely resulting in conservative effect size estimates.

Detected Contamination Effects included: 23% of control group students reporting awareness of AI system features; 15% demonstrating knowledge of specific AI capabilities; and social media analysis revealing 8 instances of cross-group discussion about study methods. This contamination likely reduced observed effect sizes by increasing control-group performance, creating null-hypothesis bias against finding significant differences, and suggesting that true intervention effects may be 15-25% larger than observed.

Sensitivity analysis using per-protocol analysis, excluding contaminated participants, showed slightly larger effect sizes (d = 0.68-0.74), supporting a conservative bias interpretation and strengthening confidence in the intervention's effectiveness.

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5. Discussion

5.1. Academic Achievement Effects in Context

The moderate academic achievement improvement (Cohen's d = 0.62, 12.3% gain) aligns well with effects reported in rigorous AI and personalized learning research. Recent meta-analyses of adaptive learning studies report average effect sizes of d = 0.58-0.72 for well-implemented interventions (Wang et al., 2024; Zawacki-Richter et al., 2019), placing our findings within the expected range for high-quality educational technology research.

Contamination Considerations: The observed effects are likely conservative estimates due to single-site contamination across groups. The fact that 23% of control group participants reported hearing about AI system features suggests that true intervention effects may be larger than observed. This conservative bias strengthens confidence in the findings' validity and clinical significance.

Multilevel Modeling Advantages: The use of cluster randomization and multilevel analysis provides more appropriate statistical inference than previous studies using individual randomization. The observed ICC values (0.08-0.15) confirm the necessity of accounting for clustering effects, as failing to do so would have inflated Type I error rates.

5.2. Methodological Contributions and Limitations

This study addresses several methodological gaps in educational technology research while acknowledging important limitations.

Methodological Strengths include cluster randomization to reduce contamination risk compared to individual randomization, multilevel analysis providing appropriate statistical methods for nested data structure, comprehensive outcome measurement across multiple domains with validated instruments, implementation fidelity monitoring through systematic tracking of intervention adherence, and bias-aware assessment recognizing and analyzing potential evaluation bias.

Critical Limitations encompass single-site design, limiting generalizability and enabling contamination despite cluster randomization; assessment bias, where evaluators may have detected group membership through technology integration artifacts; temporal constraints, with an 18-week period insufficient for long-term sustainability assessment; and cultural specificity, where the Vietnamese context may limit international transferability.

5.3. Technological Implementation Insights

AI system effectiveness varied significantly across different components and user groups, providing important insights for future implementations.

Most Effective Features included personalized content recommendation (84% user satisfaction), immediate feedback systems (78% satisfaction), and learning progress visualization (81% satisfaction). Problematic Features comprised complex analytics dashboards (43% satisfaction), repetitive recommendation patterns (38% negative feedback), and technical reliability issues (23% experienced regular problems).

Professional Development Implications: The finding that instructor digital competency was the strongest implementation predictor ($\beta = 0.42$) validates TPACK framework predictions while highlighting the substantial investment required for effective AI integration in education.

5.4. Cultural and Contextual Considerations

Vietnamese educational context presented both opportunities and challenges for AI implementation.

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Cultural Alignment included emphasis on collaborative learning supported by AI-mediated peer interaction, respect for structured learning environments compatible with AI-guided instruction, and high technology adoption rates among younger students facilitating system acceptance.

Cultural Tensions involved traditional authority relationships complicated when AI recommendations conflicted with instructor preferences, individual personalization sometimes conflicted with collective learning values, and privacy concerns related to extensive data collection for personalization.

5.5. Implementation Scalability Challenges

Resource requirements for successful implementation were substantial, raising important questions about scalability and accessibility.

Human Capital Requirements encompassed a 40-hour instructor training program, dedicated technical support staff (minimum 0.5 FTE), instructional design expertise for content adaptation, and data analysis capabilities for system optimization.

Institutional Readiness Factors include leadership commitment to innovation and change management, faculty willingness to adapt teaching practices, student access to technology and digital literacy, and robust technical infrastructure with reliable internet connectivity.

5.6. Theoretical Implications

Social Constructivist Theory Validation: The study confirms AI's potential as a mediating tool for learning, though the importance of human interaction remained paramount. Students consistently valued instructor feedback more highly than AI-generated responses, suggesting complementary rather than substitutional roles.

TPACK Framework Extension: Results demonstrate that effective AI integration requires a new dimension of technological knowledge including understanding of algorithmic decision-making, data privacy, and bias detection. Traditional TPACK competencies were necessary but insufficient for optimal AI implementation.

Adaptive Learning Theory Confirmation: The moderate effect sizes observed align with theoretical predictions about cognitive load optimization rather than dramatic learning transformation. The theory's emphasis on managing extraneous cognitive load proved particularly relevant for AI system design.

5.7. Future Research Directions

Longitudinal Studies are critically needed to assess long-term learning retention, skill transfer, and sustainability of AI-enhanced approaches. The 18-week intervention period was insufficient to evaluate lasting impacts on the development of teaching competency.

Multi-site Replication with true prevention of contamination could provide less conservative effect size estimates and stronger generalizability evidence. Cross-cultural validation in different educational contexts would enhance international applicability.

Economic Evaluation Research examining cost-effectiveness and return on investment could inform policy decisions about large-scale implementation. Current resource requirements may limit accessibility for resource-constrained institutions.

Individual Difference Research investigating optimal personalization strategies for different learner characteristics could enhance system effectiveness. The current study's broad approach may have masked important subgroup variations.

6. Conclusion

This cluster randomized controlled trial provides robust empirical evidence for the moderate effectiveness of AI-driven personalized learning in Vietnamese teacher education, while acknowledging important methodological limitations and implementation challenges.

6.1. Key Findings Summary

Primary Outcomes: Academic achievement improvements (d = 0.62) and motivation enhancements (d = 0.79) represent meaningful effects consistent with rigorous educational technology research, though contamination likely resulted in conservative estimates.

Implementation Insights: Instructor digital competency emerged as the strongest predictor of success, emphasizing human capital development over technological sophistication alone. Cultural adaptation and comprehensive support systems proved essential for effective implementation.

Methodological Contributions: The use of cluster randomization and multilevel analysis provides more appropriate methodology for educational technology research, while systematic bias detection offers important lessons for future studies.

6.2. Implications for Practice and Policy

Evidence-Based Recommendations include phased implementation with substantial professional development investment, realistic expectations aligned with moderate effect sizes typical of quality interventions, comprehensive support systems addressing technical, pedagogical, and cultural factors, and continuous evaluation with attention to bias detection and contamination control.

Policy Implications: Large-scale implementation requires significant resource commitment and institutional change management. The substantial investment required may limit accessibility without targeted funding support.

6.3. Study Limitations and Future Directions

Acknowledged Limitations include single-site design, which can lead to contamination despite cluster randomization; potential assessment bias favoring technology-trained students; limited generalizability beyond Vietnamese higher education contexts; and insufficient duration for long-term impact assessment.

Future Research Priorities include multi-site replication with contamination prevention, long-term follow-up studies assessing skill retention and transfer, economic evaluation of implementation costs and benefits, and cross-cultural validation in diverse educational contexts.

6.4. Final Conclusions

This research demonstrates that AI-driven personalized learning can provide meaningful improvements in teacher education when implemented with appropriate support systems and realistic expectations. The moderate effect sizes observed represent achievable benefits that justify continued development and refinement of AI educational applications.

However, the substantial implementation requirements, potential for bias, and contamination challenges highlight the complexity of educational technology integration. Success requires comprehensive approaches addressing human, technological, and institutional factors rather than focusing solely on AI capabilities.

The study offers valuable methodological insights for educational technology research and provides evidence-based guidance for practitioners and policymakers considering AI integration in teacher preparation programs.

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Declarations

Author Contributions. [Author Name]: conceptualization, methodology, validation, formal analysis, investigation, writing-original draft, visualization. [Co-Author Name]: methodology, validation, resources, writing-review and editing, supervision, project administration. All authors have read and approved the final manuscript.
Conflicts of Interest. The authors declare no conflicts of interest. The AI system used in this study was developed independently without commercial partnerships or financial incentives that could bias the research.
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