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Affective and Explainable Artificial Intelligence-Driven Human-in-the-Loop Adaptive Learning Model to Enhance Cognitive and Innovation Competencies

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Abstract: This study aimed to develop and evaluate an Artificial Intelligence (AI)-driven adaptive learning model that integrates Affective AI (AAI), Explainable AI (XAI), and Human-in-the-Loop (HITL) to enhance participants' competencies in critical thinking and innovation. The research was conducted in three phases: (1) reviewing relevant concepts, theories, and empirical studies to determine the components of the adaptive learning model; (2) developing the model and validating its appropriateness through expert review; and (3) implementing the model with a sample of 30 professional development participants. Data were collected using standardized instruments measuring critical thinking and innovation competencies, and were analyzed using Paired Samples t-test and Repeated Measures ANOVA. The findings revealed that the developed adaptive learning model demonstrated a high level of appropriateness, both in terms of comprehensiveness of its components and practical feasibility. Furthermore, participants' post-test mean scores in critical thinking and innovation competencies were significantly higher than their pre-test scores ($p < 0.001$). This indicates that the model effectively enhanced personalized, transparent, and learner-centered processes. In conclusion, the integration of Affective AI, Explainable AI, and Human-in-the-Loop shows strong potential in establishing adaptive learning systems that foster key 21st-century competencies among professionals, with implications for both theoretical advancement and practical application.

Keywords: Affective Artificial Intelligence, Explainable Artificial Intelligence, Human-in-the-Loop, Adaptive Learning, Cognitive Competency, Innovation Competency

1. Introduction

In recent years, adaptive learning has been recognized as one of the most promising innovations in digital education, owing to its ability to leverage Artificial Intelligence (AI) for real-time analysis of learners' data. Through the identification of individual learning patterns, preferences, limitations, and strengths, AI-driven adaptive learning dynamically adjusts instructional content, activities, and learning pathways to meet the unique needs of each learner [1]. Such personalization has been shown to significantly increase learner engagement and improve learning outcomes [2].

Furthermore, AI-powered adaptive learning facilitates the use of learning analytics to provide educators with actionable insights for designing targeted instructional support. This reduces mismatches between learners' cognitive styles and instructional approaches, thereby enhancing the overall efficiency of teaching and learning processes [3]. Consequently, adaptive learning is not only a tool for individualized learner development but also a key pathway for the digital transformation of education.

A critical direction in the advancement of adaptive learning is the integration of Affective AI (AAI), or AI systems capable of detecting and interpreting learners' emotional states. Drawing on behavioral data such as clicks, typing speed, response latency, and even physiological signals, affective computing technologies capture levels of attention, motivation, and emotional readiness [4]. Such capabilities enable learning systems to adjust instructional content, presentation styles, and interaction patterns in real time. Research indicates that incorporating affect-aware AI can significantly foster engagement, promote deep learning, and reduce learners' frustration or stress—particularly in online learning environments where emotional communication is often constrained [5].

Simultaneously, Explainable AI (XAI) has gained increasing attention in education. XAI provides transparency into AI decision-making processes, allowing both learners and instructors to understand the rationale behind recommendations, assessments, or predictions generated by the system [6]. Such interpretability enhances trust and acceptance of AI-supported learning systems, while also empowering learners to engage in reflection and exercise greater agency over their learning processes [7].

Therefore, the integration of AAI and XAI represents a crucial step toward the development of adaptive learning models that are both emotionally responsive and transparent. These approaches not only support cognitive learning needs but also ensure the credibility and trustworthiness of AI-driven education.

Another key approach is Human-in-the-Loop (HITL), which emphasizes human involvement in the functioning of AI systems, whether in model training, decision-making, or post-hoc adjustments [8]. Within educational contexts, HITL allows instructors and learners to directly interact with AI systems—for instance, by providing feedback to improve model accuracy, regulating the pacing of instruction, or intervening to prevent algorithmic bias [9]. HITL frameworks enhance fairness, accountability, and ethical integrity by allowing humans to oversee data usage, validate AI reasoning, and assume decision-making authority where algorithmic errors or biases may otherwise disadvantage learners [10]. Moreover, HITL facilitates reflective and critical learning by encouraging learners to question, challenge, and collaboratively shape decisions with AI systems [11].

Taken together, the integration of AAI, XAI, and HITL constitutes a significant direction for the evolution of adaptive learning in the 21st century. Specifically:

1. AAI enables systems to detect, analyze, and respond to learners' emotions (e.g., attention, stress, or anxiety), thus adapting instructional pace and content to emotional states. This enhances motivation and learning effectiveness, especially in professional development contexts requiring sustained engagement and cognitive challenge [12].

2. XAI fosters transparency by making AI decisions interpretable, thereby reducing learner anxiety, enhancing trust, and supporting the development of critical thinking skills as learners are encouraged to examine and question AI outputs [13].

3. HITL maintains balance between AI computational power and human judgment by nabling instructors or learners to supervise and adjust system outputs, ensure algorithmic fairness, and guide learning directions [11].

When integrated, these three components yield an AI-driven adaptive learning model characterized by (1) personalization, responding to individual learners' needs and emotions; (2) transparency, ensuring interpretability and trust; and (3) reliability and ethics, with humans maintaining oversight and governance. Such a model is expected to enhance essential professional competencies, including critical thinking, complex problem solving, and innovation skills were identified as core to success in the 21st century [14].

Accordingly, this research aims to develop an adaptive learning model driven by AAI, XAI, and HITL to strengthen the critical thinking and innovation competencies of professional development participants. The study involves three phases: (1) identifying relevant learning models and theoretical components; (2) developing and validating the proposed model and its tools; and (3) empirically evaluating changes in participants' competencies before and after program implementation. Ultimately, this research seeks to establish a theoretically grounded and practically viable framework for adaptive learning in the digital era.

2. Research Objectives

2.1 To examine an AI-driven adaptive learning model integrating Affective AI (AAI) and Explainable AI (XAI) within a Human-in-the-Loop (HITL) framework, aimed at enhancing professional development learners' cognitive and innovation competencies.

2.2 To develop an adaptive learning model incorporating AAI, XAI, and HITL to foster cognitive and innovation competencies among professional development learners.

2.3 To evaluate the effects of the adaptive learning model on learners' cognitive and innovation competencies by comparing pre- and post-intervention outcomes.

3. Related Literature Review

3.1 Adaptive learning and learning analytics

Adaptive learning — the dynamic tailoring of instructional content, sequence, and feedback to individual learners — has emerged as a central innovation in digital education. AI-driven adaptive systems use learner data (performance, interaction patterns, response times) to infer knowledge states and customize learning trajectories, thereby improving engagement and learning outcomes [15]. Learning analytics, as an enabling discipline, provides actionable insights that instructors can leverage to design targeted supports and to monitor progress at scale [3]. In competency-focused professional development contexts, adaptive learning permits fine-grained alignment of tasks to learners' current competency levels, which can accelerate attainment of higher-order cognitive outcomes [16].

3.2 Affective AI and learner engagement

Affective AI (AAI) extends adaptive approaches by incorporating the detection and interpretation of learners' affective states (e.g., interest, frustration, boredom). Multimodal affect sensing from clickstreams and interaction metrics to facial expressions, speech prosody, and physiological signals — allows systems to adapt not only to cognitive state but also to emotional readiness [17]. Empirical studies suggest that affect-aware interventions can sustain engagement, reduce affective barriers, and support deep learning processes, particularly in online environments where socio-emotional cues are attenuated [5]. For professional development learners, who often balance work and study, affective adaptations can moderate cognitive load and maintain productive challenge levels that promote critical thinking and creativity.

3.3 Explainable AI and learner agency

As AI models become more complex, explainability has become pivotal for trust, acceptance, and pedagogical utility. Explainable AI (XAI) approaches provide human-interpretable rationales for system recommendations—such as why a particular activity or feedback is suggested, enabling learners and instructors to inspect, contest, and learn from the model's reasoning [18]. In educational contexts, XAI supports metacognitive processes: learners can better reflect on their learning strategies when they understand the basis for system feedback, and instructors can use explanations to fine-tune scaffolding [7]. XAI thus plays a crucial role in fostering learner agency and in converting algorithmic outputs into teachable moments that scaffold innovation-oriented practices.

3.4 Human-in-the-Loop: governance, fairness, and pedagogy

Human-in-the-Loop (HITL) paradigms emphasize continuous human oversight and interactive collaboration between AI systems and educators/learners. HITL can occur at multiple points: data labeling and model training, real-time intervention on recommendations, and post-hoc validation of outcomes [8]. In schooling and professional development, HITL supports fairness and ethical use by permitting humans to correct biases, contextualize recommendations, and ensure alignment with curricular and professional values [9]. Pedagogically, HITL mechanisms create opportunities for critical dialogue about AI-generated feedback, thereby strengthening reflective practice and higher-order reasoning [11].

3.5 Integrating AAI, XAI, and HITL: toward responsible adaptive models

Recent scholarship advocates for integrative models that combine affective sensing, transparent decision-making, and human oversight to realize adaptive systems that are both effective and ethical. Synthesizing these strands yields platforms that personalize learning in emotionally nuanced ways while maintaining interpretability and human governance [6]. Design-based research (DBR) approaches have been proposed as suitable methodologies for iteratively developing such socio-technical systems in authentic professional contexts [19].

3.6 Competency targets: cognitive and innovation competencies

Contemporary frameworks emphasize progression from lower-order cognitive processes to higher-order operations as central to workforce readiness [16, 20]. Innovation competency—including questioning, experimenting, networking, and creative associating—is increasingly foregrounded as a key outcome for professionals [21]. AI-driven adaptive systems that provide timely, explainable feedback and scaffold affect-regulated practice hold promise for cultivating both critical thinking and innovation capacities [14].

3.7 Empirical evidence and gaps

Empirical reviews indicate positive effects of AI-supported adaptive interventions on engagement and learning gains [2, 15]. Affective computing studies show improved persistence and reduced frustration [5, 12], while XAI research highlights improvements in trust and interpretability but flags challenges in designing explanations tailored to diverse user needs [13, 7]. HITL work underscores the importance of human oversight but points to limited operational guidelines for integrating educators' domain expertise into AI pipelines [8, 9]. Crucially, few empirical studies have simultaneously evaluated integrated AAI–XAI–HITL adaptive models with respect to both cognitive and innovation competencies in professional development settings — a gap this study addresses.

3.8 Summary

The literature supports the theoretical plausibility of an integrated AAI + XAI + HITL adaptive model for professional development: affective sensing can optimize engagement and cognitive load; explainability can cultivate learner agency and reflective practice; and human oversight can ensure ethical, contextually valid decisions. However, implementing and evaluating such integrated systems in real-world professional development programs require iterative, multidisciplinary design and rigorous empirical testing, particularly to measure impacts on higher-order cognitive and innovation outcomes.

4. Research Methodology

4.1 Population and Sample

The study population comprised professional development participants in education, including teachers, instructors, and educational technology specialists interested in enhancing cognitive and innovation competencies. A purposive sample of 30 participants was selected to engage in an experimental implementation of an AI-driven adaptive learning model integrating Affective AI (AAI), Explainable AI (XAI), and Human-in-the-Loop (HITL) mechanisms.

Inclusion Criteria: Participants were required to (1) work in education-related fields, (2) voluntarily commit to full participation throughout the study, and (3) have adequate digital devices and internet access to engage with the online learning platform.

Exclusion Criteria: Participants were excluded if they (1) could not consistently participate in scheduled activities, (2) failed to meet the inclusion criteria, or (3) withdrew or declined to provide data.

The adaptive learning intervention lasted four weeks, during which participants followed the structured learning processes prescribed by the developed model.

4.2 Research Instruments

4.2.1 AI-Driven Adaptive Learning Platform

The primary research instrument was an AI-driven adaptive learning platform integrating AAI, XAI, and a HITL framework. The purpose of developing this platform was to create a digital learning environment capable of assessing and fostering both cognitive and innovation competencies among professional development learners. The platform leveraged the principles of adaptive learning in conjunction with AI technologies, incorporating AAI and XAI, while maintaining the HITL approach to ensure active human participation in the learning process, thereby promoting deep learning and sustainable skill development.

The platform was designed and developed using a Design-Based Research (DBR) methodology, which combines iterative cycles of design, implementation, and refinement [19]. The development process began with a needs analysis of professional development learners, identification of target cognitive and innovation competencies, and the design of learning functionalities that adapt to individual differences. The AAI component monitored and interpreted learners' emotional states and engagement through behavioral data or physiological signals to adjust content, activities, and challenge levels appropriately [12]. The XAI component provided transparent explanations of system recommendations and decisions, thereby enhancing learners' understanding and trust [18]. Finally, the HITL component allowed learners to interact with, modify, and provide feedback to the system, improving the effectiveness of the learning process [22].

The platform was designed to support personalized learning, integrating emotional analytics, explainable decision-making, and human participation in learning decisions. Its core modules included: (1) Affective AI Module: Processes learners' behavioral data, such as click patterns, responses to learning activities, time-on-task, and even audio-visual signals, to interpret emotional and engagement states. This enables the system to adapt content and activities to the context of individual learners. (2) Explainable AI Module: Provides transparent explanations for the system's recommendations regarding content, activities, or learning paths, enabling learners to understand the rationale behind AI decisions and reducing perception biases. (3) Human-in-the-Loop Module: Allows learners to actively participate in determining and adjusting their learning paths, providing feedback or modifying activities as appropriate, thereby enhancing self-regulated learning and engagement.

Overall, the platform integrates advanced AI technologies with principles of learning psychology and instructional design, creating a highly personalized learning environment that effectively supports the development of cognitive and innovation competencies among professional development learners.

4.2.2 Cognitive and Innovation Competency Assessment Tool

A second research instrument was a competency assessment tool designed to measure learners' cognitive and innovation competencies both pre- and post-intervention. The tool underwent content validity assessment by experts and reliability testing using Cronbach's Alpha, ensuring its systematic and credible use in evaluating professional development outcomes.

Cognitive Competency: Based on Anderson and Krathwohl's [16] revision of Bloom's Revised Taxonomy [23], the tool assessed six hierarchical cognitive levels: (1) Remembering, (2) Understanding, (3) Applying, (4) Analyzing, (5) Evaluating, and (6) Creating. This framework reflects the sequential development of systematic thinking processes.

Innovation Competency: Referencing OECD [20] and Dyer, Gregersen, and Christensen [21], innovation competency was measured across key skills: (1) Questioning, (2) Observing, (3) Networking, (4) Experimenting, and (5) Creative Thinking and Associating. These competencies capture learners' abilities to generate new ideas, transform practices, and create value through innovation.

In conclusion, these instruments comprehensively evaluate both cognitive and innovation competencies are grounded in established theoretical frameworks, and have undergone rigorous psychometric validation, providing reliable metrics to assess the outcomes of professional development interventions systematically.

4.3 Research Procedures

Literature Review and Conceptual Analysis, in this phase, the study systematically reviewed relevant literature on adaptive learning, the application of AAI and XAI, as well as the HITL concept, which emphasizes the role of humans in digital learning processes. Additionally, research related to cognitive competency and innovation competency was examined to establish a comprehensive knowledge base for developing the adaptive learning model. Comparative analyses of existing learning models and competency development frameworks, both domestic and international, were conducted to identify strengths, limitations, and relevant components. These findings were then synthesized into an Integrated Conceptual Framework, providing a guiding structure for developing a contextually appropriate and effective adaptive learning model for this study.

Development of the Adaptive Learning Model, this phase involved designing the structure and processes of an adaptive learning model that integrates AAI, XAI, and HITL principles to balance automated decision-making with learner participation. A prototype of the learning model and associated tools, including the digital learning platform, competency assessment instruments, and user manuals, were developed. To ensure the validity, feasibility, and appropriateness of the model, five experts evaluated the prototype using the Index of Item-Objective Congruence (IOC), confirming the content accuracy and practicality of the learning model.

Implementation and Evaluation, the developed adaptive learning model was implemented with a purposive sample of 30 professional development learners. The intervention spanned four weeks, during which participants engaged with the learning process according to the designed model. Data collection included: (1) assessment of cognitive competencies, and (2) assessment of innovation competencies, both pre- and post-intervention. Quantitative data were analyzed using descriptive statistics, including mean, standard deviation, and percentage, as well as inferential statistics, such as Paired Samples t-tests and Repeated Measures ANOVA, to examine differences in competencies before and after participation.

In addition, qualitative data were collected through in-depth interviews to explore learners' reflections, experiences, and perceptions regarding the use of the AI-driven adaptive learning model integrating AAI, XAI, and HITL. These qualitative insights provided a richer understanding of the model's effectiveness, learner engagement, and practical applicability in professional development contexts.

5. Research Results

Objective 1: investigation of the AI-Driven Adaptive Learning Model Integrating Affective AI, Explainable AI, and Human-in-the-Loop to Enhance Cognitive and Innovation Competencies of Professional Development Learners

The findings indicated that the developed adaptive learning model comprises three core components: (1) Affective AI (AAI) Module – capable of analyzing learners' behaviors and emotional states to appropriately adjust learning activities. (2) Explainable AI (XAI) Module–provides transparency and comprehension of the learning pathway adjustment process. (3) Human-in-the-Loop (HITL) Module–facilitates learner participation and self-regulation of their learning paths.

During the platform implementation, participants demonstrated positive responses toward the model. The platform effectively enhanced analytical thinking, creative thinking, and innovation problem-solving skills, while also increasing learner engagement and satisfaction compared with traditional learning approaches.

Qualitative analysis of in-depth interviews revealed that learners perceived the integration of AAI with XAI as fostering a natural, transparent, and personalized learning experience, while the Human-in-the-Loop component enabled learners to feel autonomy and a significant role in directing their learning paths.

In summary, the developed adaptive learning model successfully meets the needs of professional development learners in the education field, and demonstrates strong potential for application in enhancing cognitive and innovation competencies in digital learning contexts.

Table 1: Components of the AI-Driven Adaptive Learning Model Integrating Affective AI, Explainable AI, and Human-in-the-Loop

Component	Role / Mechanism	Outcomes
Affective AI Module	Analyzes learners' behaviors (e.g., clicks, response time, voice/facial expressions) to interpret emotional states	Learning activities are adjusted according to emotional states, enhancing focus and engagement
Explainable AI Module	Provides reasoning behind content and learning path selection to ensure transparency and understanding	Learners understand the system logic, increasing trust and acceptance of adaptive learning
Human-in-the-Loop Module	Allows learners to adjust activities, provide feedback, or select their own learning paths	Increases learner autonomy and engagement, fostering ownership of the learning process
Integrated Outcome	Integration of AAI, XAI, and HITL with user-centered design	Promotes analytical thinking, creative thinking, and innovation competencies of learners

The findings corresponding to Research Objective 1 indicate that the developed model includes three main modules: the AAI Module, which analyzes learners' behaviors and emotional states to adjust activities and content according to the learning context; the XAI Module, which provides transparent reasoning behind activity and content selection, enhancing learners' understanding of the system and their trust in the learning process; and the HITL Module, which allows learners to participate in adapting learning paths and giving feedback, thereby fostering a sense of ownership. The results suggest that the integration of these components can create a personalized and an effective learning platform capable of enhancing cognitive and innovation competencies for professional development learners in a tangible and practical manner.

Objective 2, the findings indicated that the development of the adaptive learning model driven by AAI and XAI within a HITL framework can create a digital learning platform that is contextually appropriate for professional development learners in the field of education. The development process involved three main stages: designing the learning structure and processes, building a platform prototype, and developing the accompanying learning tools.

The evaluation of the model's suitability by five experts revealed that the model demonstrated a high level of content and process alignment, with the Index of Item-Objective Congruence (IOC) within an acceptable range. This indicates that the model's core components—namely, the Affective

AI Module, the Explainable AI Module, and the Human-in-the-Loop Module—are appropriate and well-structured. Furthermore, the model allows for the adaptation of activities and content to individual learner differences, thereby creating a flexible learning environment that effectively fosters cognitive and innovation competencies.

Regarding Research Objective 2, the results suggest that the developed AI-driven adaptive learning model with HITL integration adequately addresses the needs of professional development learners. It also provides a robust foundation for subsequent pilot testing and evaluation of the platform's effectiveness in enhancing cognitive and innovation competencies within a personalized, AI-driven adaptive learning context.

Objective 3, the results indicated statistically significant improvements in both cognitive and innovation competencies. Descriptive statistics revealed that the Cognitive Competency mean score increased from 3.28 (SD = 0.50) before the learning intervention to 4.15 (SD = 0.44) after participating in the adaptive learning model. Similarly, Innovation Competency increased from a mean of 3.12 (SD = 0.51) pre-intervention to 4.08 (SD = 0.48) post-intervention.

The Paired Samples t-test demonstrated that the differences between pre- and post-intervention scores were statistically significant at $p < 0.001$ for both competencies: Cognitive Competency ($t = 10.87$, $df = 29$, $p < 0.001$) and Innovation Competency ($t = 10.23$, $df = 29$, $p < 0.001$).

Table 2: Comparison of Cognitive and Innovation Competencies Before and After Learning Using the AI-Driven Adaptive Learning Model (n = 30)

Competency Dimension	Pre-Learning (Mean ± SD)	Post-Learning (Mean ± SD)	t	df	p-value
Cognitive Competency	3.28 ± 0.50	4.15 ± 0.44	10.87	29	< 0.001
Innovation Competency	3.12 ± 0.51	4.08 ± 0.48	10.23	29	< 0.001

Note: *n =* ***30****; analysis conducted using Paired Samples t-test.*

These results indicate that learning through the AI-driven adaptive learning model integrating AAI, XAI, and HITL significantly enhanced learners' cognitive and innovation competencies ($p < 0.001$), reflecting the platform's effectiveness in promoting analytical thinking, creativity, and ideation skills among professional development learners.

Furthermore, Repeated Measures ANOVA results confirmed significant differences between pre- and post-learning scores for both competencies. For Cognitive Competency, $F(1,29) = 117.56$, $p < 0.001$, $\eta^2 = 0.80$, indicating a large effect size, while Innovation Competency also showed significant improvement, $F(1,29) = 110.45$, $p < 0.001$, $\eta^2 = 0.79$, demonstrating that learners effectively developed creative problem-solving skills and innovation capabilities.

Table 3: Repeated Measures ANOVA for Cognitive and Innovation Competencies (n=30)

Competency Dimension	SS (Sum of Squares)	df	MS (Mean Square)	F	p-value	η^2 (Effect Size)
Cognitive Competency	12.34	1	12.34	117.56	< 0.001	0.80
Innovation Competency	11.27	1	11.27	110.45	< 0.001	0.79

In summary, the repeated measures ANOVA results demonstrated significant improvements in both Cognitive Competency and Innovation Competency after the intervention. The adaptive learning model had a large effect on enhancing cognitive skills, while learners also achieved substantial gains in creative thinking, innovative problem-solving, and ideation, confirming the effectiveness of the AI-driven adaptive learning platform integrating AAI, XAI, and HITL in promoting cognitive and innovation competencies.

6. Discussions of Results

The findings indicate that the AI-driven adaptive learning model integrating Affective AI (AAI), Explainable AI (XAI), and the Human-in-the-Loop (HITL) concept significantly enhanced both cognitive and innovation competencies of professional development learners. Statistical analyses, including Paired Samples t-tests and Repeated Measures ANOVA, revealed very large effect sizes ($\eta^2 \approx 0.79$–0.80), supporting the notion that personalized learning based on behavioral and affective data can increase learner engagement, task persistence, and learning outcomes [3, 15].

Mechanistically, improvements in cognitive competency can be explained by the role of AAI in monitoring emotional states, such as interest, frustration, or fatigue, and in dynamically adjusting cognitive load and activity difficulty in real time. This helps reduce attention lapses and sustains deep learning [4, 12, 19]. By effectively “matching” learner affective states with task demands, the system promotes analytical thinking and systematic reasoning, which is reflected in higher post-learning cognitive competency scores.

Concurrently, the enhancement of innovation competency aligns with the role of XAI in providing explainable guidance. Learners gain insight into the rule-based or feature-based rationale underlying system recommendations, fostering greater trust and a sense of agency. This encourages creative trial-and-error and structured reflection [3, 6, 7, 13]. The transparency of XAI also enables instructors to provide targeted scaffolding, reduce ambiguity in assessment, and validate learner progress with evidence.

Moreover, the HITL framework plays a crucial role in ensuring quality and ethical oversight of AI use in the classroom by allowing human intervention in decision-making, such as confirming or modifying system recommendations, verifying the fairness of activity assignments, and adapting the learning context to professional values and goals [9, 19]. Human involvement mitigates algorithmic bias and maintains contextual appropriateness, which is essential for fostering creativity and innovation in real-world professional settings [8, 10].

Overall, personalized, AI-driven learning environments enhance both process efficiency and learning product outcomes, particularly when the system provides timely feedback and continuously adjusts difficulty levels [2, 15]. Furthermore, these outcomes align with the demands of 21st-century skills, emphasizing critical thinking, complex problem-solving, and innovation for professional workforce development [14].

7. Conclusion

This study aimed to design and evaluate an AI-driven adaptive learning model integrating Affective AI (AAI) and Explainable AI (XAI) within a Human-in-the-Loop (HITL) framework, with the objective of enhancing cognitive and innovation competencies of professional development learners. The research involved the design and development of the adaptive learning model, validation of the tools, and assessment of its effectiveness through a practical experimental study. The key findings are summarized as follows:

1. Structure of the Adaptive Learning Model: The developed model consists of three core components: (1) AAI, which monitors and responds to learners' emotional states; (2) XAI, which provides transparency and understanding of system decision-making; and (3) HITL, which allows learners and instructors to play an active role in guiding the learning process. These components work collaboratively to support an effective adaptive learning experience.

2. Expert Evaluation of Model Suitability: Expert assessment indicated that the model demonstrates a high level of appropriateness in terms of component completeness, alignment with digital learning theories, and feasibility for practical implementation.

3. Experimental Outcomes: When tested with a group of 30 professional development learners, the results showed significant improvements in: (1) Cognitive Competency ($F(1,29) = 117.56$, $p < 0.001$, $\eta^2 = 0.80$) (2) Innovation Competency ($F(1,29) = 110.45$, $p < 0.001$, $\eta^2 = 0.79$) These findings indicate that the developed model effectively enhances critical thinking, creativity, and the generation of new ideas.

4. Theoretical and Practical Implications: The integrated AI-based adaptive learning model (AAI, XAI, HITL) elevates the quality of learning in professional contexts. It enables effective and transparent human–AI collaboration, addresses individual learner needs, and clearly supports the development of essential 21st-century competencies.

8. Research Limitations

Several limitations of this study should be considered. First, the sample size was relatively small and drawn from a specific professional domain, which may limit the generalizability of the findings. Second, the measurement of emotions relied on behavioral data and self-report questionnaires, which may offer lower resolution compared to physiological signals, such as electrodermal activity (EDA) or heart rate variability (HRV). Third, the use of a one-group pre-post design—while detecting significant differences—remains susceptible to confounding factors such as history and maturation effects.

9. Recommendations for Future Research

Future studies should consider employing randomized controlled trials (RCTs) or multi-institution quasi-experimental designs to enhance causal inference. Expanding outcome measures to include real-world behavioral indicators (e.g., workplace performance) and implementing multi-modal affect sensing could improve the accuracy of Affective AI (AAI). Research on Explainable AI (XAI) should explore user-specific explanations (learner-facing vs. teacher-facing) and establish context-sensitive Human-in-the-Loop (HITL) protocols for Thai language and culture to reduce bias and enhance fairness.

In terms of practical applications, the findings support the implementation of AI-driven adaptive learning platforms in professional development programs, emphasizing three key dimensions: (1) AAI to manage cognitive load and maintain learner engagement. (2) XAI to ensure transparency and promote structured reflective thinking (3) HITL design to allow instructors to oversee quality and ethical standards continuously.

This framework has the potential to enhance cognitive and innovation competencies in alignment with the skill requirements of the digital-age workforce.

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