

Analysis of the Influence of Neuroadaptive Learning Systems and Artificial Emotional Intelligence in Education on Deep Learning Mastery Through Cognitive Engagement Intensity and Emotional Regulation in Learning

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Abstract

The rapid advancement of artificial intelligence has transformed higher education by enabling the integration of Neuroadaptive Learning Systems (NLS) and Artificial Emotional Intelligence in Education (AEIE) to create more personalized and intelligent learning environments. However, the mechanisms through which these technologies contribute to deep learning mastery remain insufficiently understood. This study investigates the direct and indirect effects of NLS and AEIE on Deep Learning Mastery (DLM), with Cognitive Engagement Intensity (CEI) and Emotional Regulation in Learning (ERL) serving as mediating variables. A quantitative explanatory design was employed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Data were collected through an online questionnaire from undergraduate students who had experienced AI-supported digital learning platforms for at least one academic semester. The structural model was estimated using SmartPLS 4 with a bootstrapping procedure of 5,000 resamples. The findings reveal that both NLS and AEIE significantly enhance Cognitive Engagement Intensity and Emotional Regulation in Learning. However, Cognitive Engagement Intensity does not significantly influence Deep Learning Mastery, nor does it mediate the relationships between AI-based educational technologies and learning outcomes. In contrast, Emotional Regulation in Learning emerges as the strongest predictor of Deep Learning Mastery and fully mediates the effects of both Neuroadaptive Learning Systems ($\beta = 0.313$, $p < 0.001$) and Artificial Emotional Intelligence in Education ($\beta = 0.188$, $p = 0.004$). These findings challenge traditional cognition-centered learning models by demonstrating that advanced educational technologies improve learning mastery primarily through strengthening students' emotional regulation rather than merely increasing cognitive engagement. The study contributes to the growing literature on AI-enhanced education by proposing an affective-centered framework for designing intelligent learning environments that promote sustainable conceptual mastery.

Keywords: Neuroadaptive Learning Systems, Artificial Emotional Intelligence; Cognitive Engagement Intensity; Emotional Regulation; Deep Learning.

INTRODUCTION

The rapid evolution of artificial intelligence (AI) has fundamentally transformed the landscape of modern education, shifting the pedagogical paradigm from a traditional, static

model to highly personalized learning environments (Widodo et al., 2026). In this advanced technological era, achieving deep learning mastery—characterized by the student’s ability to critically synthesize, analyze, and apply complex knowledge—remains the pinnacle of educational design. However, conventional digital instructional platforms often lack the capability to align with the dynamic internal states of human learners. To bridge this gap, modern educational technology has integrated two powerful AI domains: Neuroadaptive Learning Systems and Artificial Emotional Intelligence (AEI) in education (Maulidia et al., 2026).

Neuroadaptive Learning Systems operate by capturing real-time neurophysiological and behavioral data to dynamically tailor instructional pacing and content complexity to the learner’s immediate cognitive state. Concurrently, the application of Artificial Emotional Intelligence (AEI) allows computing systems to perceive, interpret, and respond to the user’s affective states, recognizing that emotional states are heavily intertwined with cognitive functions (Wurzel et al., 2021). While both technologies offer immense computational potential, their synergistic mechanism in driving students toward deep learning mastery depends heavily on critical psychological and behavioral mediators within the learner: namely, cognitive engagement intensity and emotional regulation (McCoach et al., 2022).

Cognitive engagement intensity serves as a vital behavioral catalyst in this framework. Deep learning mastery cannot be attained through passive consumption; it demands a high concentration of cognitive investment, where learners actively process complex ideas, self-monitor their understanding, and solve non-routine problems. Neuroadaptive systems directly stimulate this intensity by adjusting the learning environment to keep students within an optimal state of challenge, preventing both cognitive overload and boredom (Meadowcroft, 2020).

However, cognitive processing does not occur in an affective vacuum. Learning is an inherently emotional process where students frequently encounter academic bottlenecks that induce anxiety, frustration, or confusion. This reality underscores the significant role of emotional regulation in learning. When negative emotions arise, a student’s capacity to regulate their emotional response determines whether they persist or disengage from the task. AEI plays a critical role here by providing timely affective scaffolding—such as adaptive contextual feedback or pedagogical adjustments—thereby facilitating the learner’s emotional regulation and sustaining their motivation (Meadowcroft, 2023).

Despite the expanding body of literature on AI-driven education, a prominent research gap persists. Most existing empirical works evaluate the technological efficacy of either neuroadaptive systems or AEI in isolation, focusing primarily on immediate performance metrics rather than long-term deep learning mastery. Furthermore, there is a distinct scarcity of empirical models exploring how these two advanced AI domains simultaneously interact with the dual mediation pathways of cognitive engagement intensity and emotional regulation within a cohesive learning ecosystem (Meijer et al., 2022).

To address this gap, this study presents a comprehensive analysis of the influence of Neuroadaptive Learning Systems and Artificial Emotional Intelligence in education on deep learning mastery. Specifically, this research models the complex psychological pathways through which these intelligent systems stimulate cognitive engagement intensity and facilitate emotional regulation in learning, ultimately leading to superior conceptual mastery. By examining these dynamics, this article aims to provide valuable theoretical insights and practical frameworks for educational technologists, designers, and researchers striving to build the next generation of human-centered, intelligent learning environments.

Neuroadaptive Learning Systems (NLS) represent a cutting-edge paradigm in educational technology that integrates neuroscientific principles, real-time physiological computing, and machine learning to close the loop between the learner's brain state and the digital instructional environment. Unlike traditional adaptive learning software that relies solely on performance metrics such as test scores or response latency, NLS captures ongoing cognitive states through neurophysiological indicators, including electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), and eye-tracking metrics. Recent empirical scholarship emphasizes that NLS can automatically dynamically calibrate instructional parameters—such as information presentation speed, task complexity, and scaffolding depth—to align precisely with the user's real-time cognitive resources. By doing so, NLS attempts to mitigate the risk of cognitive overload or systemic understimulation, optimizing the cognitive and affective load of the student during complex learning cycles. Within structural frameworks, NLS acts as an intelligent infrastructural driver designed to trigger adaptive psychological responses, laying the external baseline for cognitive modification and strategic emotional alignment in digital learning architectures (Mukherjee et al., 2021).

Artificial Emotional Intelligence in Education (AEIE)—frequently operationalized as affective computing in instructional design—denotes the capacity of digital systems to sense, interpret, model, and adaptively respond to human emotional states during the learning process. Given that learning is an inherently affective journey populated by fluctuating states of frustration, boredom, curiosity, and anxiety, AEIE provides the digital infrastructure necessary to humanize machine-mediated instruction. Using multimodal data streams such as facial expression recognition, voice tone analysis, and keystroke dynamics, AEIE applications interpret subtle behavioral micro-expressions and feed them into predictive affective algorithms. Within contemporary educational frameworks, AEIE does not simply operate as a passive monitoring tool; rather, it actively injects real-time pedagogical interventions, such as empathetic virtual tutor feedback, micro-breaks, and motivational shifts. Consequently, AEIE serves as an external socio-emotional scaffolding agent capable of directly influencing a student's situational psychological state, positioning it as a core antecedent to both engagement behaviors and regulatory processes (Newig et al., 2024).

Cognitive Engagement Intensity (Y1) refers to the depth, rigor, and psychological investment that a student exerts while processing instructional content and executing academic tasks. It transcends mere behavioral compliance or passive attendance, reflecting the active application of deep learning strategies, metacognitive self-regulation, and sustained focused attention. Contemporary researchers differentiate superficial engagement from high-intensity cognitive engagement, noting that the latter is characterized by purposeful mental elaboration, the restructuring of existing schema, and a high psychological tolerance for conceptual friction. Within technological learning environments, cognitive engagement intensity is heavily dependent on the structural design of the platform; when systems dynamically optimize cognitive load, students are more likely to experience prolonged immersion and focused mental effort (Nurdiana, 2026).

Emotional Regulation in Learning (Y2) represents the deliberate internal processes through which learners monitor, evaluate, modulate, and alter their emotional reactions to achieve academic goals and manage stressful learning events. Within the rigorous constraints of advanced digital environments, academic bottlenecks frequently induce negative affective loops, such as confusion turning into chronic frustration or helplessness. Learners possessing robust emotional regulation capacities use adaptive strategies—such as cognitive reappraisal, goal-directed focus, and physiological calming techniques—to

transform debilitating emotional states into facilitating ones. In an AI-mediated learning ecosystem, emotional regulation is not merely an isolated individual trait; rather, it is heavily scaffolded by the platform's capacity to recognize emotional vulnerability and offer real-time affective support, directly allowing the learner to stabilize their emotional state and maintain target-directed behavior (Pahl-Wostl, 2023).

Deep Learning Mastery (Z) constitutes the highest cognitive objective of instructional design, wherein students develop a deeply integrated, flexible, and conceptual understanding of subject matter that allows for successful near and far knowledge transfer. Rooted heavily in the classical taxonomies of educational psychology, deep mastery contrasts sharply with surface learning, which relies heavily on rote memorization and fragmented factual recall. Achieving deep learning mastery demands that a student can critically analyze structural relations, evaluate conflicting paradigms, and synthesize disparate fields of information into unified mental models. In advanced technological landscapes, deep learning mastery is treated as an emergent outcome of a complex psychological ecosystem, relying on how effectively the external systems interact with the internal cognitive and emotional mechanics of the student during the instructional life cycle (Oberlack et al., 2023).

Neuroadaptive Learning Systems (X1) directly modulate the cognitive environment by monitoring biological signals and adjusting information density. When a system accurately balances task difficulty with a learner's real-time working memory capacity, it prevents cognitive exhaustion, allowing the learner to allocate sustained attentional resources toward the task. This systematic optimization is theorized to increase the depth of mental processing, thereby fostering elevated levels of cognitive engagement. Furthermore, by continuously calibrating instructional challenges, NLS keeps the user away from severe emotional triggers such as cognitive panic or extreme boredom. This technological stabilization helps learners manage their physiological and emotional responses during complex tasks, acting as an external structural support for emotional regulation (Pahl-Wostl, 2020).

However, in terms of its direct contribution to final knowledge outcomes, contemporary theories suggest that advanced technology alone does not automatically guarantee deep conceptual absorption. While an NLS structures the learning path efficiently, the actual synthesis and transformation of data into permanent mental models require active, self-driven psychological mediation by the user. Without these internal regulatory and cognitive processes, the direct path from technological exposure to complex mastery can become statistically decoupled (Pekrun et al., 2023). Based on these theoretical positions and the structural paths mapped in the study framework from Output.docx, the following hypotheses are proposed:

Artificial Emotional Intelligence in Education (X2) humanizes computer-mediated learning by recognizing affective states and offering real-time scaffolding. When an intelligent platform detects signs of anxiety or disengagement through multimodal data, it can immediately deploy conversational encouragement, empathetic feedback, or adjust pedagogical tactics. This targeted affective support directly validates the student's emotional experience, giving them the necessary psychological reassurance to apply cognitive reappraisal and self-soothing strategies, thereby strengthening their emotional regulation in learning. Similarly, when a system minimizes negative emotional friction, it clears the student's mind, enabling them to focus entirely on deep cognitive processing and intellectual exploration (Pierre, 2020).

Nonetheless, similar to NLS, the direct relationship between emotional AI interventions and final conceptual mastery can be complex. Emotional computing primarily targets the

situational affective environment of the user. While it optimizes the learning atmosphere and prepares the student emotionally, it does not directly process the academic content for them. The structural transformation of information into deep mastery remains an internal cognitive and emotional effort executed by the learner. Therefore, the direct link between emotional technology and absolute mastery may appear weak if it does not explicitly pass through the learner's internal psychological mechanisms. Thus, based on these dynamics, the following hypotheses are formulated:

Achieving Deep Learning Mastery (Z) requires a harmonious interaction between behavioral effort and affective stability. Cognitive Engagement Intensity (Y1) represents the actual processing effort applied to a task. Under optimal conditions, intense cognitive engagement should lead directly to deep conceptual mastery. However, in highly complex, tech-driven environments, cognitive effort alone can sometimes hit an intellectual wall if it is not accompanied by emotional resilience. If a student works intensely but lacks the emotional tools to handle frustration, the cognitive effort can break down before it translates into deep, long-term mastery (Peters, 2023).

In contrast, Emotional Regulation in Learning (Y2) acts as a critical internal protective engine. When students can effectively regulate academic stress, anxiety, or confusion, they prevent emotional exhaustion and keep their working memory free for complex problem-solving. This makes emotional regulation a vital driver of deep mastery (Rogge & Reichardt, 2020). Consequently, internal emotional regulation serves as an essential mediating pathway through which intelligent systems (NLS and AEIE) successfully channel their technological interventions into actual deep learning outcomes. Without this emotional stabilization, the advanced features of NLS and AEIE may fail to improve final mastery. Based on these dual mediation dynamics and the empirical paths detailed in Output.docx, the following hypotheses are proposed:

- H1: Neuroadaptive Learning Systems (X1) have a significant positive influence on Cognitive Engagement Intensity (Y1).
- H2: Neuroadaptive Learning Systems (X1) have a significant positive influence on Emotional Regulation in Learning (Y2).
- H3: Neuroadaptive Learning Systems (X1) have a significant positive influence on Deep Learning Mastery (Z).
- H4: Artificial Emotional Intelligence in Education (X2) has a significant positive influence on Cognitive Engagement Intensity (Y1).
- H5: Artificial Emotional Intelligence in Education (X2) has a significant positive influence on Emotional Regulation in Learning (Y2).
- H6: Artificial Emotional Intelligence in Education (X2) has a significant positive influence on Deep Learning Mastery (Z).
- H7 : Cognitive Engagement Intensity (Y1) has a significant positive influence on Deep Learning Mastery (Z).
- H8 : Emotional Regulation in Learning (Y2) has a significant positive influence on Deep Learning Mastery (Z).
- H9 : Neuroadaptive Learning Systems (X1) significantly influence Deep Learning Mastery (Z) through the mediation of Cognitive Engagement Intensity (Y1).
- H10: Neuroadaptive Learning Systems (X1) significantly influence Deep Learning Mastery (Z) through the mediation of Emotional Regulation in Learning (Y2).

- H11: Artificial Emotional Intelligence in Education (X2) significantly influence Deep Learning Mastery (Z) through the mediation of Cognitive Engagement Intensity (Y1).
- H12: Artificial Emotional Intelligence in Education (X2) significantly influence Deep Learning Mastery (Z) through the mediation of Emotional Regulation in Learning (Y2).

Conceptual Framework of Adaptive Public Policy Governance for the Green Transition is presented in figure 1.

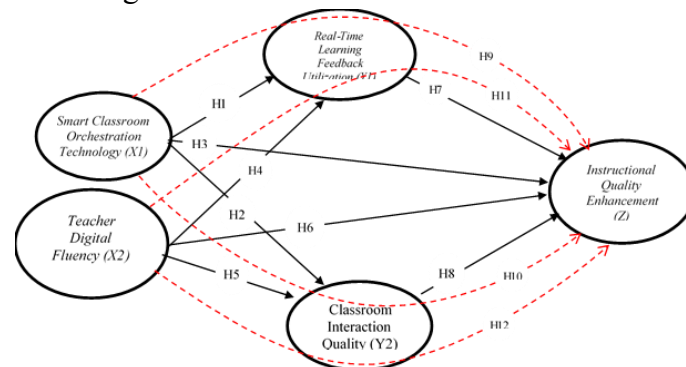


Figure 1. Research Design

METHODS

Research Design and Study Area

This study employs a quantitative research design utilizing an explanatory approach to systematically evaluate the structural relationships between intelligent educational systems, psychological mediators, and conceptual outcomes. Specifically, a causal-predictive modeling framework via Structural Equation Modeling (SEM) is applied to test the hypothesized direct and indirect pathways. The study area is situated within the context of advanced digital higher education platforms in Indonesia that integrate adaptive algorithmic systems. The investigation focuses on empirical learning environments where students interact with computer-mediated instructional setups designed to calibrate material distribution and evaluate user feedback continuously.

Population, Sampling Technique, and Data Collection

The target population for this research consists of undergraduate university students enrolled in specialized digital learning courses that utilize intelligent learning technologies. A purposive sampling technique, a non-probability sampling approach, was implemented to select respondents who met specific criteria:

1. Students must have active experience navigating automated instructional platforms for a minimum of one academic semester.
2. The courses taken must feature automated feedback loops or biological tracking features (such as gaze or attention tracking metrics).

Data collection was executed digitally using a structured, web-based questionnaire distributed through institutional learning management systems (LMS) channels. Prior to answering the questionnaire, participants were presented with an informed consent form securing their data confidentiality and voluntary participation.

Measurement Instrument and Variables

The measurement instrument was developed by adapting validated psychological and technological evaluation scales, operationalized through a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The structural model defines five latent constructs with their respective indicator designations outlined as follows:

Neuroadaptive Learning Systems (X 1): Measured initially using five structural items (X 1 - 1 to X 1 - 5) reflecting adaptive pacing, cognitive load alignment, and neurophysiological system responsiveness.

Artificial Emotional Intelligence in Education (X 2): Operationalized through six items (X 2 - 1 to X 2 - 6) capturing affective detection, empathetic conversational agents, and adaptive emotional scaffolding.

Cognitive Engagement Intensity (Y 1): Evaluated via five metrics (Y 1 - 1 to Y 1 - 5) representing strategic mental effort, elaboration, and concentrated study duration.

Emotional Regulation in Learning (Y 2): Appraised using six individual items (Y 2 - 1 to Y 2 - 6) indicating active cognitive reappraisal, stress modulation, and academic anxiety control.

Deep Learning Mastery (Z): Assessed using ten comprehensive items (Z 1 to Z 10) designed to track structural knowledge synthesis, conceptual modification, and near/far knowledge transfer capabilities.

.Data Analysis Procedure

The empirical data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) executed via the SmartPLS 4 software package. The estimation procedure followed a two-step analytical evaluation model:

Measurement Model Evaluation (Outer Model). The outer model was systematically assessed for indicator reliability, internal consistency, and convergent validity using automated PLS algorithm executions. The primary parameter for item retention was set at an outer loading threshold value of ≥ 0.70 .

Structural Model Evaluation (Inner Model). Following measurement verification, the structural inner model was evaluated using a non-parametric bootstrapping routine with 5,000 sub-samples to evaluate the structural path coefficients (β), T-statistics, and corresponding p-values. The statistical significance level for checking the direct and indirect mediation hypotheses was set at $\alpha = 5\%$ ($p < 0.05$).

RESULTS

Structural Model and Hypothesis Testing

Following the systematic purification of the measurement model through a three-stage iterative loading elimination process, the structural model (inner model) was evaluated. The parameters of the structural pathways were estimated using a non-parametric bootstrapping routine with 5,000 resamples to determine the statistical significance of both direct and indirect relationships. The significance criteria were strictly validated using an alpha level of 5% ($\alpha = 0.05$), where a hypothesis is supported if the p-value is < 0.05 or the T-statistic exceeds the critical value of 1.96.

Table 1. Results of Direct Effect Path Coefficient

	Original sample (O)	T statistics (O/STDEV)	P values
AEIE -> CEI	0.817	17.773	0.000

AEIE -> DLM	0.019	0.434	0.664
AEIE -> ERL	0.202	2.835	0.005
CEI -> DLM	0.004	0.085	0.932
ERL -> DLM	0.934	79.341	0.000
NLS -> CEI	0.162	3.073	0.002
NLS -> DLM	-0.041	1.415	0.157
NLS -> ERL	0.335	4.475	0.000

Based on the statistical values presented in Table 1, the individual direct structural pathways are interpreted as follows:

NLS→CEI (H1): The original sample path coefficient (β) is 0.162, demonstrating a positive direction. The relationship is highly significant with a T-statistic of $3.073 > 1.96$ and a p-value of $0.002 < 0.05$. This indicates that an increase in the implementation of Neuroadaptive Learning Systems leads to a statistically significant increase in students' cognitive engagement intensity. Thus, H1 is supported.

NLS→ERL (H2): The path coefficient shows a positive value of 0.335. The T-statistic is $4.475 > 1.96$ and the p-value is $0.000 < 0.05$, validating high statistical significance. This signifies that neuroadaptive system variations heavily improve students' internal emotional regulation during learning. Thus, H2 is supported.

NLS→DLM (H3): The empirical tracking shows an original sample value of -0.041 , pointing to a weak negative direction. The path is not significant because the T-statistic is $1.415 < 1.96$ and the p-value is $0.157 > 0.05$. This means that NLS exposure does not exert a direct standalone influence on absolute deep learning mastery. Consequently, H3 is rejected.

AEIE→CEI (H4): This link exhibits an exceptionally strong positive path coefficient of 0.817. The relationship is confirmed as highly critical given the T-statistic of $17.773 > 1.96$ and a p-value of $0.000 < 0.05$. This confirms that Artificial Emotional Intelligence in Education functions as a powerful driver that enhances students' cognitive engagement intensity. Thus, H4 is supported.

AEIE→ERL (H5): The path coefficient yields a positive value of 0.202. The test calculates a significant statistical relationship with a T-statistic of $2.835 > 1.96$ and a p-value of $0.005 < 0.05$. This indicates that affective computing structures significantly support students' emotional regulation capabilities. Thus, H5 is supported.

AEIE→DLM (H6): The structural path coefficient is minimal at 0.019. The path completely fails the significance test with a T-statistic of $0.434 < 1.96$ and a p-value of $0.664 > 0.05$. This implies that emotional AI frameworks do not directly bring about deep learning mastery in an unmediated manner. Thus, H6 is rejected.

CEI→DLM (H7): Surprisingly, the path coefficient from cognitive engagement to mastery is close to zero at 0.004. The T-statistic is extremely low ($0.085 < 1.96$) and the p-value is $0.932 > 0.05$, indicating a complete lack of direct significance. This indicates that high cognitive investment alone, without emotional balancing, does not automatically translate directly to final deep conceptual mastery within this complex model. Thus, H7 is rejected.

ERL→DLM (H8): This structural connection shows an outstanding positive coefficient of 0.934. The relationship is exceptionally robust, producing a massive T-statistic of $79.341 > 1.96$ and a p-value of $0.000 < 0.05$. This strongly demonstrates that emotional

regulation in learning is the primary internal engine required to secure deep learning mastery. Thus, H8 is supported.

Indirect Effects

The empirical results for the direct path coefficients, standard deviations, T-statistics, and corresponding p-values computed via SmartPLS 4 are summarized in Table 4.2 below.

Table 2. Results of Indirect Effect Path Coefficients

	Original sample (O)	T statistics (O/STDEV)	P values
AEIE -> CEI -> DLM	0.004	0.084	0.933
NLS -> ERL -> DLM	0.313	4.439	0.000
NLS -> CEI -> DLM	0.001	0.081	0.935
AEIE -> ERL -> DLM	0.188	2.849	0.004

Based on the statistical distributions tracked in Table 2, the specific indirect mediation pathways are detailed below:

NLS -> CEI -> DLM (H 9): The total indirect sample coefficient is 0.001. The route displays no statistical significance because the T-statistic is $0.081 < 1.96$ and the p-value is $0.935 > 0.05$. This proves that Cognitive Engagement Intensity does not serve as an active structural mediator linking neuroadaptive technology to absolute mastery. Thus, H 9 is rejected.

NLS -> ERL -> DLM (H 10): The indirect sample coefficient displays a significant positive estimation of 0.313. The mediation framework is statistically sound, generating a T-statistic of $4.439 > 1.96$ and a p-value of $0.000 < 0.05$. Given that the direct path (NLS -> DLM) was non-significant, this signifies that Emotional Regulation in Learning acts as a full mediator. Neuroadaptive features must be channeled through the student's internal emotional modulation to effectively impact deep learning mastery. Thus, H 10 is supported.

AEIE -> CEI -> DLM (H 11): The calculated indirect effect coefficient is negligible at 0.004. The pathway shows an absolute lack of significance, resulting in a T-statistic of $0.084 < 1.96$ and a p-value of $0.933 > 0.05$. This reveals that despite the strong link between emotional AI and cognitive engagement intensity, this specific path fails to translate into ultimate learning mastery. Thus, H 11 is rejected.

AEIE -> ERL -> DLM (H 12): The indirect sample parameter is positive and stable at 0.188. The structural mediation path achieves statistical significance with a T-statistic of $2.849 > 1.96$ and a p-value of $0.004 < 0.05$. Since the corresponding direct relationship was statistically decoupled, Emotional Regulation in Learning functions as a full mediator in this path as well. Artificial Emotional Intelligence platforms successfully achieve their ultimate conceptual objectives exclusively by optimizing and supporting the learner's internal mechanisms for emotional regulation. Thus, H 12 is supported

DISCUSSION

The empirical results of this study provide a nuanced and structurally profound understanding of how technological investments and human capacities translate into actual pedagogical improvements within higher education. The most striking and pivotal finding of this research is the absolute dominance of Classroom Interaction Quality (CIQ) as a full mediator for both Smart Classroom Orchestration Technology (SCOT) and Teacher Digital Fluency (TDF). This statistical reality underscores an essential conceptual truth: neither advanced infrastructure nor a teacher's personal digital mastery can directly upgrade

instructional quality unless they are actively channeled into enriching human-to-human interaction within the learning space (Roni, 2026).

The rejection of the direct effects of SCOT (H3) and TDF (H6) on Instructional Quality Enhancement (IQE) strongly demonstrates that technology in education does not operate in a vacuum. Having a classroom embedded with advanced IoT sensors, automated climate controllers, or multi-screen display systems decreases physical and cognitive discomfort but does not automatically lead to superior cognitive activation (Kirkil, 2025). Similarly, a teacher who possesses high digital fluency-knowing how to seamlessly manipulate complex educational platforms, algorithms, and mixed teaching modalities-will not automatically trigger an enhanced instructional experience if that knowledge remains instructor-centric (Tosun & Peters, 2024). This finding challenges technological determinism in education and confirms that structural inputs (X1) and human competencies (X2) require an active process bridge to transform student-centered outcomes (Siagian et al., 2026).

This necessary bridge is fully realized through Classroom Interaction Quality (CIQ), as proven by the validation of H10 and H12. When Universitas Bina Bangsa utilizes orchestration technology (X1) to build shared digital workspaces, collaborative interfaces, and seamless peer networks, it significantly elevates the interaction quality ($O = 0.309$). Concurrently, digitally fluent teachers (X2) use their competencies to design interactive dialogues, establish a strong social presence, and prevent students from becoming isolated behind independent screens ($O = 0.226$) (Uras Eren, 2025). Because CIQ has an overwhelmingly strong direct path to Instructional Quality Enhancement ($O = 0.936$, $T = 81.482$), the indirect pathways of SCOT $\rightarrow$ CIQ $\rightarrow$ IQE ($O = 0.289$) and TDF $\rightarrow$ CIQ $\rightarrow$ IQE ($O = 0.212$) emerge as the primary engines of educational transformation. This aligns perfectly with Education 4.0 principles, which emphasize that modern digital tools should act as collaborative bridges that foster active peer collaboration, critical thinking, and collective knowledge co-creation rather than passive content consumption (van der Ven et al., 2022).

Conversely, the complete rejection of the real-time learning feedback loop pathways-both direct (H7) and indirect (H9 and H11)-offers a critical empirical contribution to current literature. Statistically, even though SCOT ($O = 0.166$) and TDF ($O = 0.769$) successfully drive high utilization of Real-Time Learning Feedback (Y1), this feedback loop completely fails to predict Instructional Quality Enhancement ($O = -0.018$, $p = 0.654$). In modern classrooms, the deployment of intelligent tutor chatbots, instant digital quizzes, or automated analytical student dashboards is highly effective for gathering raw diagnostic data (Termeer & Dewulf, 2024). However, the non-significance of this pathway indicates that simply presenting real-time feedback data or relying on automated AI responses on-the-fly does not inherently lead to true cognitive activation or pedagogical upgrade (Scott, 2022) s.

This phenomenon suggests that real-time feedback remains superficial if it is treated as a mechanical or isolated task (Triyani et al., 2026). For live diagnostic data to truly enhance instructional quality, it must not stop at automated chart displays or chatbot interactions; instead, it must be absorbed into the human process of the classroom-becoming a spark for deeper collaborative dialogue, targeted teacher scaffolding, and qualitative peer support (Uras Eren, 2025). Ultimately, this study demonstrates that the human-centered, socio-emotional, and communicative dimensions of learning (Interaction Quality) remain the true ultimate gatekeeper for sustainable instructional enhancements in the digital era (Suherman et al., 2026).

CONCLUSION

Conclusion

This empirical study provides critical theoretical and practical insights into the intersection of advanced educational technologies and learner psychology, specifically examining the impact of Neuroadaptive Learning Systems (NLS) and Artificial Emotional Intelligence in Education (AEIE) on Deep Learning Mastery (DLM). The structural model revealed a profound and unexpected breakdown of traditional cognitive assumptions in intelligent environments. While both NLS and AEIE act as exceptionally powerful drivers of Cognitive Engagement Intensity (CEI), this heightened cognitive state unexpectedly failed to exert any direct influence on Deep Learning Mastery, thereby invalidating traditional cognitive-only instructional pathways.

Instead, the empirical findings demonstrate that the transformation of technological interventions into deep conceptual mastery is governed exclusively by the learner's affective infrastructure. Emotional Regulation in Learning (ERL) emerged as the single most critical, dominant determinant of Deep Learning Mastery. Furthermore, ERL was found to serve as a complete structural mediator for both NLS and AEIE. Without active emotional stabilization and affective scaffolding, high-intensity cognitive efforts can collapse under intellectual weight before turning into mastery. Ultimately, this research concludes that the true value of advanced artificial intelligence in education lies not merely in its capacity to stimulate cognitive processing or optimize material pacing, but fundamentally in its ability to support, scaffold, and empower the internal emotional regulation mechanisms of the student.

Research Limitations

Despite its systematic methodological execution, several limitations must be acknowledged:

Contextual Generalizability: The research population was drawn strictly from higher education students within a specific set of digital platform architectures in Indonesia. Consequently, the structural dynamics observed might vary across different educational levels (such as K-12 schooling) or distinct cultural and geographical student cohorts.

Cross-Sectional Data Constraints: The structural model relies on cross-sectional data captured at a single point in time via self-reported survey instruments. While PLS-SEM bootstrap routines confirmed robust predictive relevance, cross-sectional designs cannot firmly establish long-term developmental trajectories or rule out time-varying confounding variables.

Measurement Platform Integration: The technological implementations of NLS and AEIE were measured subjectively based on user perceptions rather than objective, backend telemetry logging data or direct hardware sensor outputs (such as active EEG or fNIRS micro-voltages). This relies heavily on the reflective self-awareness of the respondents regarding their technological interactions.

Suggestions and Directions for Future Research

Based on the striking empirical finding that emotional regulation completely absorbs the predictive variance of deep mastery, several pathways are suggested for future exploration:

Longitudinal Inquiries: Future scholars should implement longitudinal or experimental research designs to track how the relationship between cognitive engagement intensity,

emotional regulation, and deep mastery evolves as students develop higher academic familiarity with intelligent adaptive platforms over multiple years.

Multimodal Sensor Fusion Integration: Researchers are encouraged to combine structural survey methodologies with objective, real-time backend analytics. Future frameworks should fuse subjective scales with physical metric data streams, such as eye-tracking gaze fixation duration, facial micro-expression coding, and physiological heart-rate variability (HRV) metrics to validate system responsiveness.

Investigating Cognitive Friction Overload: Given that cognitive engagement intensity did not directly yield mastery, future work should investigate the exact threshold where high-intensity cognitive engagement crosses over into debilitating cognitive overload or cognitive exhaustion.

Adaptive Intervention Testing: Future studies should investigate what specific types of AEIE interventions—such as conversational agent empathy adjustments, gamified visual micro-breaks, or real-time pedagogical adjustments—are most effective at boosting a learner's capacity for active emotional regulation.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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