IS IT ALL ABOUT FEELING? RETHINKING PERSONALIZED LEARNING FOR LASTING KNOWLEDGE

È TUTTA UNA QUESTIONE DI FEELING? RIPENSARE L'APPRENDIMENTO PERSONALIZZATO PER UNA CONOSCENZA DURATURA

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ABSTRACT

A-MEMO is an ITS module with a multi-agent architecture for the pedagogical-computational analysis of emotions in mnemonic processes. It integrates emotional markers based on prefrontal-parahippocampal neurofunctional correlates (Tallman et al., 2024; Slotnick, 2022) through: (1) sentiment analysis; (2) mnestic personalisation with emotional associations; (3) UDL principles. It overcomes methodological limitations (Twomey & Kroneisen, 2021) by exploiting evidence on cognitive enhancement via emotional mnemonic techniques (Kensinger & Ford, 2020; Wagner et al., 2021).

A-MEMO è un modulo ITS con architettura multiagente per l'analisi pedagogico-computazionale delle emozioni nei processi mnemonici. Integra marcatori emotivi basati sui correlati neurofunzionali prefrontali-paraippocampali (Tallman et al., 2024; Slotnick, 2022) attraverso: (1) sentiment analysis; (2) personalizzazione mnestica con associazioni emotive; (3) principi UDL. Supera i limiti metodologici (Twomey & Kroneisen, 2021) sfruttando le evidenze sul potenziamento cognitivo via tecniche mnemoniche emotive (Kensinger & Ford, 2020; Wagner et al., 2021).

KEYWORDS

Artificial Intelligence, Universal Design for Learning, Adaptive Learning, Intelligent Tutoring Systems, Mnemonics

Intelligenza Artificiale, Universal Design for Learning, Apprendimento Adattivo, Intelligent Tutoring Systems, Mnemotecnica.

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Introduction

The longitudinal stabilization of mnemonic traces pertaining to complex educational content represents a critical research imperative within contemporary psychopedagogical investigation. Despite the proliferation of personalized instructional technologies, specifically Intelligent Tutoring Systems (ITS), during recent decades, these computational frameworks predominantly concentrate on assessment phases and corrective feedback mechanisms (Niño-Rojas et al., 2024). The encoding phase — the critical interval during which information undergoes initial processing and consolidation within mnemonic circuits — remains comparatively under-investigated as an intervention target (Marouf et al., 2024). This methodological limitation assumes particular significance when evaluated against the substantial corpus of neuroeducational evidence establishing correlations between long-term memory stability and the co-activation of limbic structures (principally amygdala and hippocampus) and prefrontal regions responsible for cognitive control and emotional modulation (Kensinger & Ford, 2020; Tallman et al., 2024). Empirical investigations demonstrate significantly enhanced parahippocampal activity when learning stimuli possess pronounced emotional salience or motivational relevance; this neurophysiological augmentation, validated through functional neuroimaging protocols, corresponds with superior retention metrics across extended time intervals (Slotnick, 2022). Notwithstanding this evidential foundation, ITS architectural design has historically neglected the potential integration of real-time affective markers, limiting adaptive functionality primarily to exercise difficulty calibration or item sequence optimization (Maity & Deroy, 2024).

The present investigation addresses two principal research gaps. First, it establishes the technical and pedagogical feasibility of a tutoring system capable of recognizing validated affective indicators — facial valence, autonomic arousal, and blink frequency parameters — via standard input devices (webcam and microphone), subsequently utilizing these metrics to dynamically modulate the encoding phase through emotional tagging strategies. Second, it provides a practical transferability framework, delineating methodologies through which such technology can achieve scalable implementation within authentic educational contexts without necessitating specialized hardware infrastructure or advanced technical expertise from educational practitioners.

Building upon these theoretical foundations, the Affective-Mnemonic Encoding Modulator (A-MEMO) was systematically designed and evaluated through a controlled crossover pilot study. The investigation was structured around four specific research questions: (a) assessment of A-MEMO's immediate recall accuracy enhancement relative to expert human tutoring; (b) evaluation of advantage persistence at forty-eight hours post-intervention; (c) exploration of system impact on perceived cognitive load and flow state metrics; and (d) analysis of psychophysiological markers as potential mediating variables in the relationship between tutoring modality and mnemonic performance outcomes.

1. Methodology

1.1. Evolutionary trajectory of Intelligent Tutoring Systems: from rele-based to generative paradigms

The developmental trajectory of Intelligent Tutoring Systems (ITS) reveals significant architectural transformations since their inception, with pioneering systems from the late 1970s characterized by computational rigidity and constrained interaction modalities. Subsequent technological advancements have facilitated the progressive incorporation of sophisticated artificial intelligence methodologies and machine learning algorithms (Alkhatlan & Kalita, 2018). The integration of neural network architectures and, more recently, Large Language Models (LLMs) has fundamentally transformed ITS functionality, establishing educational environments with generative capabilities and contextual semantic analysis proficiency (Virvou & Tsihrintzis, 2023). Contemporary scientometric analyses demonstrate that while ITS research demonstrates continued expansion as a disciplinary field, the interdisciplinary synthesis of computer science, psychological theory, and educational praxis remains instrumental for developmental advancement (Guo et al., 2021). Specifically, current-generation systems emphasize interactive learning environments, student modeling frameworks, and adaptive instructional strategization. Despite substantial empirical evidence documenting ITS efficacy in enhancing learning outcomes — particularly within STEM educational contexts (Ilić, Ivanović & Klašnja-Milićević, 2024) — a significant methodological gap persists regarding metacognitive and motivational factor integration. Furthermore, analytical evaluations of implementations within authentic educational settings have revealed contradictory outcomes, suggesting the necessity for more nuanced consideration of the multidimensional complexity inherent in genuine learning environments (Wang et al., 2023).

1.2. Affective Marker Integration in Educational Systems: Multimodal Recognition and Adaptation Mechanisms

Research investigating adaptive learning mediated through affective markers represents a promising yet nascent investigative domain, wherein affective computing methodologies are progressively transforming learning environments by enabling systems to recognize and respond to students' emotional states with increasing sophistication (Lauc et al., 2023). Recent empirical investigations have explored affective interface implementation within game-based learning systems, demonstrating enhancements in student motivation and satisfaction metrics through content adaptation contingent upon detected facial expressions (Tsai, Lo, & Chen, 2012). Cutting-edge research has established that the integration of physiological data streams — including eye-tracking parameters and heart rate variability (HRV) metrics — can effectively detect cognitive load fluctuations and stress manifestations within virtual reality environments, facilitating dynamic real-time adaptations (Nastri, 2025). However, the majority of these systems necessitate specialized hardware configurations, presenting significant implementation barriers for large-scale educational deployment (Marsico, Barbieri & Piceci, 2023; Nastri, 2025). Indeed, while the adaptation of facial expression recognition between adult and pediatric populations through deep neural networks represents a promising innovation, applications integrating this methodological approach to adaptively modify learning encoding phases in real-time remain exceptionally rare (Megan et al., 2022).

1.3. Emotional tagging and mnemonic consolidation

The theoretical construct of emotional tagging, which postulates that associating emotionally salient stimuli with neutral information enhances memorization processes, finds robust substantiation within cognitive neuroscience. Recent investigations into emotional memory consolidation modulation have identified the causal role of the medial prefrontal cortex (mPFC) in processing emotionally-valenced memories; specifically, empirical evidence demonstrates that mPFC stimulation during encoding interacts with consolidation processes to selectively enhance memory retention for negatively-valenced objects after a 24-hour interval encompassing a sleep cycle (Yeh et al., 2021). Despite extensive experimental validation, the systematic application of these neurobiological principles within educational contexts remains markedly limited, with few educational systems deliberately incorporating emotional tagging mechanisms within instructional design architectures (Lauc et al., 2023).

1.4. Universal design for learning and perceptual-affective personalization

The Universal Design for Learning (UDL) framework constitutes a theoretically robust approach for inclusive education design, oriented toward minimizing learning barriers through systematic environmental modifications (Sewell et al., 2022). This conceptual framework promotes tripartite diversification: in information representation modalities, in student action and expression mechanisms, and in engagement strategy implementation (Ecker, 2023). UDL implementation within digital learning environments has demonstrated significant potential for enhancing accessibility and engagement through the integration of diverse multimedia formats including textual, auditory, visual, interactive graphical, and augmented reality modalities (Zakariyah et al., 2023). However, despite increasing UDL framework dissemination, numerous practical implementations merely provide content in multiple formats without implementing genuine perceptual-affective personalization. Consequently, the direct integration between neuroscientific principles and personalized learning approaches, particularly through UDL framework application, remains a fertile yet relatively unexplored domain within quotidian educational practice (Triana & Supena, 2023).

In synthesis, the extant literature identifies a significant research-practice gap: the paucity of ITS-guided adaptive systems that integrate multimodal affective markers with emotional tagging strategies to personalize learning encoding phases according to UDL principles. The proposed A-MEMO framework endeavors to address this gap by synthesizing recent advancements across these interconnected research domains.

2. A-MEMO module: theoretical framework, system architecture and implementation paradigms

2.1. Epistemological and neuro-pedagogical foundations

The A-MEMO module's theoretical architecture is predicated upon three empirically substantiated hypotheses derived from the analyzed literature corpus.

The primary theoretical postulate asserts that emotional salience, characterized by predominantly positive valence coupled with moderate arousal parameters, facilitates mnemonic consolidation through enhanced activation of limbic structures, specifically the amygdala-hippocampal complex, and prefrontal regions responsible for cognitive-emotional modulation (Kensinger & Ford, 2020; Slotnick, 2022; Tallman et al., 2024). This neurobiological mechanism constitutes the foundational substrate upon which the system's affective components are constructed. The secondary hypothesis addresses the dynamic regulation of cognitive load, continuously monitored through real-time physiological indicators; this methodological approach aims to maintain learners within their proximal development zone, thereby facilitating flow state induction, the psychological condition characterized by optimal attentional allocation and intrinsic motivational engagement, thus maximizing learning efficacy through attention optimization and working memory allocation (Nastri, 2025). This hypothesis operationalizes contemporary cognitive load theory within an adaptive computational framework. The tertiary theoretical proposition adheres to Universal Design for Learning (UDL) principles, which systematically diversify educational content representation modalities to minimize perceptual and cognitive barriers, thereby enhancing accessibility and inclusivity across diverse learner populations (Ecker, 2023; Sewell et al., 2022; Zakariyah et al., 2023). This framework facilitates the implementation of multimodal representation strategies that accommodate varying cognitive processing preferences and capabilities.

2.2. Multi-Agent architectural framework and functional distribution

The technical architecture of A-MEMO employs a hierarchical tri-level structure engineered to facilitate effective and dynamic instructional process management. At the highest architectural level, the orchestrator agent, implemented through a Large Language Model (GPT-4o), coordinates interactions among three specialized agents, ensuring pedagogical coherence and communicative efficacy throughout the system's operational cycles (Wang et al., 2024). The primary dialogic agent, designated as Albert (Barbieri et al., 2024), manages direct student communication, interpreting inquiries and generating pedagogically coherent responses through sophisticated natural language processing mechanisms. The secondary agent, the mnemonic agent, selects and implements contextually appropriate mnemonic encoding strategies based on collected affective and cognitive indicators, facilitating optimal information processing and retention. The tertiary agent, specialized in visuospatial processing tasks, generates dynamic graphical representations, providing visual support for informational content and facilitating spatial comprehension of complex conceptual structures (Alkhatlan & Kalita, 2018; Ilić, Ivanović & Klašnja-Milićević, 2024). Each agent incorporates dual memory systems: a semantic memory repository maintaining stable didactic information, and an episodic memory architecture tracking and recording historical interactions and student affective states, enabling contextually appropriate responses based on longitudinal interaction patterns (Xu et al., 2025).

2.3. Multi-modal sensory pipeline and engagement quantification methodology

A-MEMO implements a sensory pipeline engineered to detect real-time affective and cognitive indicators through commonly available sensor technologies, specifically webcam and microphone inputs. The webcam captures facial landmarks utilizing the OpenFace 2.0 framework (Baltrusaitis et al., 2018) to extract emotional valence and arousal metrics, while the microphone analyzes prosodic parameters correlated with emotional states. Additionally, blink-rate frequency and, when available, pupillary dilation are monitored as indirect cognitive load indicators, providing a comprehensive physiological data stream for real-time analysis. These sensory data undergo processing within standardized fifteen-second temporal windows, generating three normalized metrics: valence (V, ranging from -1 to +1), arousal (A, ranging from 0 to 1), and estimated cognitive load (C, ranging from 0 to 1). Weighting coefficients were empirically determined during pilot phase validation. Upon calculation of the composite engagement index (CEI), the system employs dynamic thresholds, continuously updated based on historical student performance metrics, to determine optimal timing and typology of adaptive interventions, ensuring contextually appropriate pedagogical responses to observed physiological states.

2.4. Adaptive Intervention Taxonomy and UDL Integration Framework

The system implements specific adaptive strategies in response to data obtained through the sensory pipeline. Upon detection of increased cognitive load or decreased emotional valence, A-MEMO automatically initiates interventions through three principal pedagogical mechanisms: narrative prompts designed to enhance positive emotional valence (Shuyuan, 2022); utilization of schemas, diagrams, or step-by-step guidance on mind palace development and application to facilitate mnemonic consolidation of complex content (Blunt et al., 2021; Wagner et al., 2021; Poupard, 2023); and micro-respiratory pauses to temporarily mitigate cognitive load and reestablish optimal learning conditions (Quek et al., 2021; Bishara, 2022; Gupta & Prashar, 2024). Concurrently, the visuospatial agent implements dynamic graphical layers on the virtual whiteboard to emphasize essential elements of the didactic content through visual salience manipulation. In accordance with UDL principles, the system simultaneously offers multiple representational channels (vocal explanations, written text, and graphical annotations), enables students to annotate and interactively manipulate visual content, and utilizes affective modulation to maintain elevated engagement and intrinsic motivation throughout the learning process (Fishbach & Woolley, 2022), thus creating a comprehensive, multi-modal learning environment optimized for diverse cognitive processing preferences.

3. Methodological Framework: Experimental Protocol

3.1. Expermental Design

The empirical validation of the proposed framework was operationalized through a pilot investigation structured as a counterbalanced crossover design implementing Williams' Latin Square (AB/BA sequences), thereby systematically controlling for sequence effects and practice-induced variability. This methodological approach necessitated that each participant engage with both instructional modalities, the adaptive A-MEMO system and a reference human tutor, separated by a fifteen-minute washout (sudoku exercise) interval strategically implemented to attenuate inter-condition interference effects. The primary statistical unit of analysis was designated as the experimental phase, methodologically treated as a within-subject repeated measure to maximize statistical power while controlling for individual difference variables.

3.2. Participant Demographics and Selection Criteria

The pilot sample comprised ten male volunteers affiliated with a chess organization, exhibiting a mean chronological age of forty-five years (SD = 2.7) and mean Elo rating of 1045 points (SD = 37). All participants self-reported absence of uncorrected visual impairments and demonstrated routine familiarity with computational devices. Pupillometric data of sufficient quality for analytical purposes was obtainable from only one participant due to webcam resolution constraints and environmental confounding variables; for the remaining subjects, cognitive load estimation and affective state assessment relied on blink-rate quantification and facial expression analysis via computational algorithms.

3.3. Psychometric Instrumentation and Data Acquisition Protocols

The experimental protocol was executed on a MacBook Pro M1 connected to an external 24-inch display monitor. Facial expressions were captured via the integrated 720p webcam, while an external microphone recorded vocal parameters. The memory task comprised sixteen novel chess configurations systematically balanced for material and tactical complexity according to established quantitative metrics (Bilalić et al., 2009). Performance assessment employed a standardized scoring protocol whereby two points were allocated for each correctly positioned chess piece, yielding a maximum potential score of thirty-two points. Cognitive load was quantified through blink frequency measurements, calculated on a frame-wise basis and normalized across thirty-second temporal windows. Where available, z-standardized pupillary dilation provided supplementary psychophysiological data. Affective states were assessed using the validated Positive and Negative Affect Schedule in its brief Italian version (I-PANAS-SF), administered at three temporal junctures: baseline, post-condition 1, and post-condition 2 (Jahanvash et al., 2011). Experiential flow states were measured using the Flow Short Scale (FSS), administered through integrated contextual windows. Baseline mnemonic capacities were evaluated through standardized Digit Span (forward and backward protocols) and Corsi Block-Tapping tasks to establish fundamental visuospatial memory parameters.

3.4. Procedural Implementation

Following completion of background questionnaires, preliminary psychometric assessments, and necessary calibration procedures for facial and vocal recognition, each participant completed an initial reconstruction task using a diagram from an actual chess game to establish baseline competency. This assessment was supplemented by reconstruction of a novel configuration devoid of recognized patterns, thereby establishing baseline visuospatial memory capacity independent of semantic context (Chase & Simon, 1973). During the training phase, participants allocated to condition A received mnemonic instruction from the virtual tutor, while remaining participants interacted with the human tutor; this procedural sequence was subsequently inverted for the second experimental phase. Throughout the diagram study period, both virtual and human tutors provided exclusively strategic support designed to facilitate deep processing, systematically avoiding solution disclosure. Immediate recall assessment (T0) was administered upon completion of both experimental phases; forty-eight hours later, participants completed an online reconstruction task (T+48h) with single-session authentication protocols to ensure data integrity.

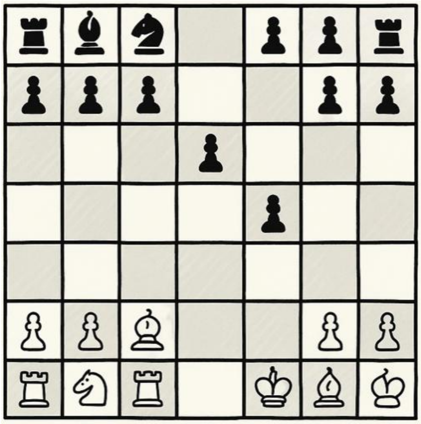

Figure 1. (Chess position independent of semantic context)

3.5. Statistical Analytical Framework

Given the exploratory nature of this pilot investigation and the limited sample size (N = 10), statistical analyses were conducted primarily to evaluate feasibility parameters and preliminary efficacy indicators of the A-MEMO framework, precluding generalization of obtained results. Performance differentials between A-MEMO and human tutor conditions were calculated for each participant and subjected to paired-samples t-tests, accompanied by Cohen's effect size metric for repeated measures (dz). Prior to implementation of parametric statistical procedures, distributional normality was verified using the Shapiro-Wilk test to ensure methodological rigor. Exploratory relationships between affective indicators and recall accuracy were examined using Pearson correlation coefficients, acknowledging methodological limitations imposed by sample size constraints. For the single participant with complete pupillometric data, a preliminary partial mediation model was constructed using bootstrap procedures (5,000 samples). All statistical interpretations must be approached with considerable caution due to the substantial Type I error risk associated with the limited participant cohort. Statistical significance threshold was established at $\alpha = .05$.

4. Results: empirical evaluation of A-MEMO system efficacy

Initial distribution analysis of immediate and delayed recall scores revealed kurtosis and skewness values ranging between −0.8 and 0.7, indicating approximately normal distributions suitable for parametric statistical procedures. No extreme outliers were identified using the ±3 SD criterion, enhancing the internal validity of subsequent analyses. The A-MEMO condition demonstrated superior immediate recall performance ($M = 24.72$, $SD = 2.41$) compared to the human tutor condition ($M = 20.04$, $SD = 2.78$), yielding a mean differential of 4.68 points. This performance enhancement reached statistical significance ($t(9) = 4.79$, $p = .001$) with a large effect size ($d_z = 1.52$) according to Cohen's conventions; while these findings appear promising, they must be interpreted cautiously within the context of limited statistical power and restricted sample size inherent to this pilot investigation.

4.1. Memory Retention Dynamics: Temporal Stability of Learning Effects

Longitudinal analysis at the 48-hour assessment point revealed persistent performance advantages in the A-MEMO condition ($M = 21.19$, $SD = 2.67$) compared to the human tutor condition ($M = 17.66$, $SD = 3.01$), maintaining a mean differential of 3.53 points. Although formal statistical testing was not conducted due to inadequate statistical power, this exploratory finding demonstrated remarkable consistency, with 80% of participants maintaining superior performance in the A-MEMO condition at the delayed assessment interval. This retention pattern suggests potential long-term efficacy of the emotion-enhanced encoding mechanisms implemented within the A-MEMO framework.

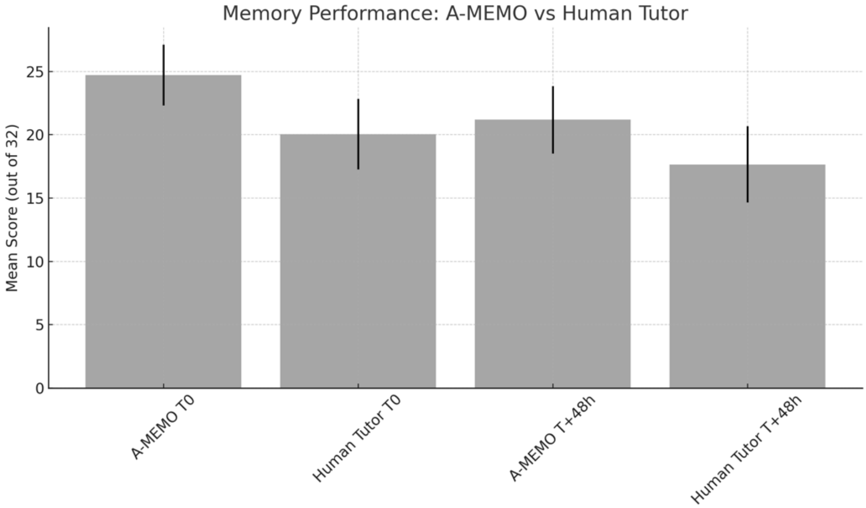

Figure 2. (Memory Performance A-MEMO vs Human Tutor)

4.2. Psychophysiological Correlates of Cognitive Processing

Analysis of blink frequency dynamics revealed a substantial reduction from 17.3 (±2.1) to 14.2 (±1.8) blinks/minute during the A-MEMO condition, potentially indicating decreased cognitive load through enhanced processing efficiency. This physiological marker aligns with theoretical predictions regarding optimized cognitive resource allocation during emotional tagging processes. For the single participant with complete pupillometric data, mean pupillary dilation showed a reduction of 0.55 z-score units in the A-MEMO condition, providing preliminary convergent validation of the cognitive load reduction hypothesis. While limited by single-subject availability, this finding offers methodological proof-of-concept for future investigations incorporating more sophisticated pupillometric instrumentation. Experiential flow assessment using the Flow Short Scale (FSS) demonstrated a mean increase of 4.1 points in the A-MEMO condition, approaching marginal statistical significance ($t(9) = 2.08$, $p = .067$). This trend suggests enhanced psychological engagement and attentional focus during the adaptive learning process. Concurrently, positive affect measured via PANAS increased by 3.8 points ($p = .093$), while negative affect remained stable across experimental conditions, indicating selective enhancement of positive emotional states during A-MEMO interaction. Exploratory correlational analysis revealed a moderate relationship between flow state metrics and immediate mnemonic accuracy ($r = .43$, $p = .059$), suggesting potential mechanistic pathways through which enhanced attentional engagement might facilitate memory consolidation. While not reaching conventional significance thresholds, this correlation provides preliminary evidence supporting the theoretical framework underlying A-MEMO's design. In the exploratory mediation model conducted with pupillometric data from the single subject with complete measurements, approximately 32% of A-MEMO's positive effect on performance appeared mediated by pupillary dilation reduction. While this finding must be interpreted with extreme caution due to its single-subject nature, it offers a preliminary mechanistic hypothesis regarding the relationship between cognitive load modulation and memory enhancement that warrants investigation in larger-scale studies.

5. Discussion

5.1. Synthesis of empirical findings and theoretical contextualization

The present pilot investigation provides preliminary validation of the hypothesis that dynamic integration of affective markers during mnemonic encoding processes can substantially enhance both immediate and short-term recall performance. The observed effect magnitude (dz = 1.52) suggests that real-time emotional tagging techniques supported by physiological parameters yield performance benefits that substantially exceed those typically reported in conventional Intelligent Tutoring Systems literature. These empirical outcomes demonstrate conceptual alignment with established neuroeducational evidence emphasizing the critical role of limbic-hippocampal co-activation in facilitating mnemonic consolidation (Kensinger & Ford, 2020; Slotnick, 2022). The observed reduction in blink-rate frequency as a cognitive load proxy demonstrates compatibility with previously documented physiological correlates of optimized information processing, underscoring the importance of precise and temporally appropriate adaptations (Biondi et al., 2023). Furthermore, the positive trend observed in flow state metrics, although statistically marginal, provides empirical support for theoretical models positing that optimal equilibrium between cognitive challenge and competence parameters facilitates enhanced mnemonic performance (Alameda et al., 2022).

5.2. Advanced Mnemonic Methodologies and Emotional Tagging Integration

A primary methodological innovation within the A-MEMO framework involves the active implementation of adaptive mnemonic techniques for regulating emotional states and cognitive load parameters. The strategies employed in this investigation, while theoretically established in their foundational formulation (e.g., associative narratives, method of loci), demonstrate significant efficacy when dynamically and contextually applied in response to learner-specific requirements. For instance, instructional prompts to generate associative narratives between chess pieces and their respective board positions, or visualization exercises involving familiar spatial locations to reduce cognitive processing demands, produced encouraging results regarding both performance metrics and emotional engagement indicators. These findings suggest that future developmental iterations might prioritize predictive adaptive systems based on validated mnemonic and metacognitive technique repertoires over real-time physiological data acquisition. Such systems could leverage standardized psychological state assessment instruments including PANAS and FSS as primary adaptation mechanisms, potentially simplifying technological implementation while maintaining performance benefits.

5.3. Methodological Limitations and Generalizability Constraints

Despite the encouraging empirical trajectory delineated herein, several substantive limitations warrant consideration when interpreting the present findings. Primarily, the restricted sample size (N=10) significantly constrains result generalizability and statistical power. Additionally, sample homogeneity (exclusively male chess players) and limited pupillometric data availability present considerable obstacles for extending these findings to more diverse demographic populations and educational contexts. While preliminary patterns demonstrating coherence between blink-rate frequency, positive affective states, and performance outcomes appear promising, rigorous validation within more methodologically robust experimental paradigms remains essential before drawing definitive conclusions regarding underlying mechanisms.

5.4. Educational Implications and Future Research Trajectories

The technical feasibility demonstrated by the A-MEMO module indicates promising prospects for future educational applications. Initial deployment may utilize consumer-grade hardware components (standard webcams and microphones) within controlled environments, with subsequent developmental goals focusing on distilling adaptive models capable of operating on common devices without specialized infrastructure requirements. A promising practical evolution involves integration with widely implemented Learning Management Systems (LMS), potentially transitioning from real-time physiological data acquisition to predictive modeling of students' affective and cognitive requirements through natural language sentiment analysis of learner-generated textual content. The diversification of interaction modalities represents a particularly promising avenue for future development: interactive and immersive educational platforms such as Minecraft Education, three-dimensional virtual environments, and augmented reality technologies could be integrated to further enhance instructional efficacy and emotional engagement while maintaining effective adaptive personalization of the learning process across multiple representational modalities. To improve reliability and validity in subsequent investigations, several methodological refinements merit consideration as imperative priorities. These include: implementation of experimental designs with larger and more demographically diverse samples; utilization of high-resolution eye-tracking instrumentation; and incorporation of extended longitudinal follow-up assessments (e.g., at one-month and three-month intervals) to evaluate long-term retention of acquired information. These methodological enhancements would substantially strengthen the evidential foundation supporting the efficacy of emotion-enhanced adaptive learning systems in authentic educational contexts.

Conclusions

This pilot investigation provides preliminary empirical evidence supporting both the technical feasibility and pedagogical efficacy of adaptive systems incorporating real-time emotional tagging methodologies during mnemonic encoding processes. The A-MEMO framework demonstrates promising potential for advancing educational neuroscience applications in learning environments through the strategic integration of affective markers, cognitive load monitoring, and adaptive instructional sequencing. Despite acknowledged methodological constraints inherent to pilot-scale investigations, the observed performance enhancements suggest significant transformative potential for contemporary educational practices. The substantial effect size documented in immediate recall performance, coupled with preliminary evidence of sustained retention advantages at 48-hour assessment, indicates that emotion-enhanced encoding strategies may offer substantive benefits compared to traditional instructional methodologies. Nevertheless, the transition from experimental prototype to scalable educational implementation necessitates further rigorous investigation. Future research agendas should prioritize: (1) large-scale validation studies with diverse learner populations; (2) longitudinal assessment of retention dynamics across extended time intervals; (3) systematic comparison with existing intelligent tutoring methodologies; and (4) thorough examination of implementation parameters in authentic educational environments.

The integration of affective computing, neurocognitive principles, and adaptive learning systems represents a promising frontier in educational technology research and, as demonstrated by this preliminary investigation, the deliberate application of emotional tagging during encoding processes may significantly enhance learning outcomes across diverse educational domains, potentially transforming contemporary pedagogical approaches through evidence-based technological innovation.

Author contributions

U.B. conceptualized the study, developed the methodology, designed the software architecture, performed data analysis, managed resources, and wrote the methodology and results sections; A.F. conducted literature review focused on pedagogical aspects and UDL framework, contributed to resource management, and participated in manuscript editing; L.P. supervised the project, administered project activities, and wrote the introduction section. All authors reviewed and approved the final version of the manuscript.

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