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Research Article

BRAIN-BASED LEARNING STRATEGIES FOR PERSONALIZED HYBRID EDUCATION

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Abstract
Personalized hybrid education offers flexible learning opportunities, yet technological adaptation alone often fails to address differences in attention, memory, cognitive load, prior knowledge, and self-regulation that shape individual learning. This study examined the effectiveness of evidence-informed brain-based learning strategies within personalized hybrid education and developed an adaptive framework for cognitively responsive instruction. A quasi-experimental mixed-methods design compared students receiving brain-informed personalized hybrid instruction with those experiencing conventional hybrid learning. The intervention integrated prior-knowledge activation, retrieval practice, spaced learning, cognitive-load management, adaptive scaffolding, formative feedback, and metacognitive reflection across physical and digital environments. Findings indicated stronger academic achievement, knowledge retention, cognitive engagement, motivation, and self-regulated learning among students receiving personalized instruction, accompanied by more manageable cognitive demands. Learning analytics and qualitative evidence further demonstrated that effective personalization required dynamic adjustments based on learner readiness, performance, progress, and support needs rather than fixed learning-style classifications. The study concludes that brain-informed personalization is most effective when grounded in credible learning science and implemented through continuous cycles of diagnosis, adaptation, retrieval, feedback, monitoring, and recalibration. The proposed framework advances personalized hybrid education by integrating cognitive responsiveness, pedagogical orchestration, and adaptive support while avoiding unsupported neuromyth-based instructional assumptions in contemporary educational practice.

Keywords: Brain-Based Learning; Cognitive Responsiveness; Hybrid Education; Personalized Learning; Self-Regulated Learning.

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INTRODUCTION

The continuing transformation of education through digital technologies has accelerated the development of hybrid learning environments that integrate face-to-face instruction with synchronous and asynchronous digital experiences (Reddy et al., 2026). Hybrid education offers greater flexibility in time, place, learning resources, and instructional interaction, yet technological flexibility alone does not guarantee meaningful learning (Murugan et al., 2025). Students differ substantially in prior knowledge, cognitive readiness, attention, motivation, self-regulation, and learning pace, creating a need for instructional systems that respond more effectively to individual variation (Lamba et al., 2025). Personalized hybrid education has consequently emerged as an important direction for designing learning experiences that adapt instructional pathways while maintaining coherent academic goals and meaningful teacher guidance.

Advances in cognitive neuroscience and the science of learning have provided increasingly sophisticated insights into how attention, memory, emotion, cognitive load, executive functions, retrieval, and neuroplasticity influence learning (Q. Xu et al., 2026). These insights suggest that effective instruction should consider the cognitive conditions under which learners encode, consolidate, retrieve, and transfer knowledge rather than relying primarily on content delivery (Wankhede et al., 2025). Brain-based learning, when grounded in credible neuroscientific and cognitive evidence, provides a framework for translating such principles into instructional strategies (Yu et al., 2025). Educational applications may include spaced learning, retrieval practice, multimodal representation, cognitive-load management, emotionally meaningful contexts, active engagement, formative feedback, movement, adequate processing intervals, and opportunities for reflection.

Personalized hybrid education provides a particularly relevant environment for applying evidence-informed brain-based strategies because digital technologies can support flexible pacing, adaptive content, continuous assessment, and differentiated learning pathways (Chen et al., 2025). Face-to-face sessions can provide social interaction, direct scaffolding, collaborative problem-solving, and emotional support, while digital components can facilitate individualized practice, retrieval schedules, adaptive feedback, and learner progress monitoring (Cui, 2025). Effective integration of these modalities could create a learning ecosystem that responds not to simplistic assumptions about fixed “brain types,” but to dynamic differences in learners’ prior knowledge, cognitive states, performance patterns, and instructional needs.

The growing adoption of personalized and hybrid learning has often been driven more strongly by technological capability than by established principles of human learning (Y. Xu et al., 2026). Adaptive platforms can recommend content, modify task difficulty, and track learner behavior, yet personalization mechanisms frequently rely on observable performance indicators without adequately considering the cognitive processes underlying those patterns (Chattopadhyay et al., 2026). A student who repeatedly performs poorly may be experiencing excessive cognitive load, weak prior knowledge, attentional difficulties, insufficient retrieval opportunities, or ineffective learning strategies (Z. Zhang et al., 2026). Personalization based only on performance data may therefore adjust what learners receive without adequately addressing why learning difficulties occur.

Brain-based learning presents its own conceptual challenges because educational discourse has sometimes incorporated oversimplified or scientifically unsupported interpretations of neuroscience (Atitallah et al., 2026). Claims concerning fixed visual, auditory, and kinesthetic learning styles, strict left-brain versus right-brain learners, or simplistic brain-based prescriptions have persisted despite limited empirical support (C. C. Volovăț et al., 2025). Such neuromyths can weaken the scientific credibility of educational innovation and lead teachers to personalize instruction according to inaccurate assumptions about learner cognition (S. R. Volovăț et al., 2024). A rigorous approach must therefore distinguish evidence-informed principles derived from cognitive neuroscience and learning science from commercially attractive but unsupported claims about how the brain learns.

Hybrid environments introduce additional cognitive challenges because learners continuously move between physical and digital learning contexts (Uthamacumaran, 2025). Notifications, multitasking, screen fatigue, fragmented attention, information overload, reduced social presence, and inconsistent self-regulation may interfere with sustained cognitive engagement (Ghahramani & Bavi, 2026). Personalized systems that increase content quantity or technological complexity without managing these demands may unintentionally intensify cognitive burden (Hussein & Jbara, 2025). The central problem is therefore how to design personalized hybrid education that adapts learning experiences while remaining aligned with reliable evidence concerning attention, memory, cognitive load, emotion, retrieval, and self-regulated learning.

This study aims to develop and examine an evidence-informed framework for integrating brain-based learning strategies into personalized hybrid education (H. Zhang et al., 2024). The primary objective is to determine how established principles of learning and cognition can inform the design of personalized instructional sequences across face-to-face and digital environments (Ali et al., 2024). Particular attention is directed toward strategies involving attention management, spaced learning, retrieval practice, cognitive-load regulation, multimodal representation, formative feedback, emotional engagement, and reflective processing (Xie et al., 2025). These strategies are examined as interconnected components rather than isolated instructional techniques.

The study also seeks to investigate how learner differences can be accommodated without relying on fixed learning-style classifications or other neuromyth-based assumptions (Ting & Liu, 2024). Personalization is conceptualized as a dynamic process informed by prior knowledge, learning performance, cognitive readiness, engagement patterns, self-regulation, and progress over time (Ting & Liu, 2024). The research aims to explore whether adaptive sequencing and teacher-mediated personalization can provide appropriate levels of challenge and support while maintaining learner autonomy (Keutayeva & Abibullaev, 2024). This objective positions personalization as responsive instructional decision-making rather than permanent categorization of students.

A further objective is to examine the relationship between brain-informed instructional strategies and key educational outcomes within hybrid settings. Relevant outcomes include academic achievement, knowledge retention, cognitive engagement, motivation, self-regulation, and transfer of learning (Yao et al., 2024). The study seeks to identify whether combinations of strategies produce stronger outcomes than isolated interventions and whether their effectiveness varies according to learner characteristics and instructional contexts (Kina, 2025). The resulting analysis is expected to provide a more comprehensive explanation of how personalized hybrid education can be cognitively responsive without becoming technologically deterministic.

Existing research on hybrid learning has extensively examined flexibility, technology acceptance, student engagement, online interaction, and academic performance, yet relatively limited attention has been given to the cognitive architecture underlying effective hybrid learning design (Saranya & Menaka, 2025). Many studies evaluate platforms or instructional formats without systematically examining how attention, memory consolidation, retrieval, cognitive load, and executive control interact across physical and digital environments (Chaki & Woźniak, 2024). This gap limits understanding of why certain hybrid configurations improve learning while others create fragmentation, overload, or disengagement.

Research on personalized learning has similarly focused heavily on adaptive technologies, learning analytics, recommendation systems, and artificial intelligence (Bagherzadeh et al., 2024). These developments provide powerful mechanisms for differentiation, but technological personalization does not necessarily equal cognitive personalization (Ch Vidyasagar et al., 2024). Algorithms may adapt content difficulty or sequence based on behavioral data without incorporating well-established principles such as spacing, retrieval, desirable difficulty, prior-knowledge activation, and cognitive-load management (Song et al., 2024). A significant conceptual gap therefore exists between data-driven personalization and evidence-informed understanding of how learning develops over time.

Brain-based learning literature presents another important gap because the field contains both scientifically grounded principles and persistent neuromyths. Studies sometimes use the term “brain-based” broadly without clearly identifying the neuroscientific or cognitive mechanisms underlying instructional strategies (Khoshfekr Rudsari et al., 2025). Limited integration exists among neuroscience-informed principles, learning science, personalized instruction, and hybrid education within a unified framework (Albalawi et al., 2024). This fragmentation creates a need for a model that connects credible knowledge about cognition with practical instructional personalization while explicitly rejecting unsupported neurological classifications.

The principal novelty of this study lies in proposing an Adaptive Brain-Informed Personalized Hybrid Learning Framework that integrates evidence-informed principles of cognition with dynamic instructional personalization (Huang et al., 2024). The framework conceptualizes learning as an adaptive interaction among learner readiness, cognitive demand, instructional strategy, modality, feedback, and performance over time (Y. Xu et al., 2024). Personalization is not based on fixed neurological profiles but on continuously evolving evidence about what learners know, how successfully they process learning tasks, and what forms of support they require (Zou et al., 2024). This approach provides a scientifically cautious alternative to personalization models built around static learner categories.

A second element of novelty concerns the integration of cognitive orchestration across hybrid modalities (Devendiran & Turukmane, 2024). Face-to-face and digital learning are not treated as interchangeable delivery channels but as environments with different cognitive and social affordances (Akter et al., 2024). Direct classroom interaction may be strategically used for complex explanation, collaborative reasoning, emotional support, and immediate scaffolding, while digital environments may support spaced retrieval, adaptive practice, individualized pacing, formative feedback, and progress monitoring (Da et al., 2024). The proposed perspective therefore shifts hybrid design from distributing content across modalities toward deliberately assigning learning processes to the environments most capable of supporting them.

The study is justified by the need to bridge the persistent divide between neuroscience-inspired educational discourse, established learning science, personalized learning technologies, and practical hybrid instruction (Dan et al., 2025). Educational institutions increasingly invest in adaptive systems and digital learning environments, yet personalization should not be considered effective merely because technology can customize content (Kuo et al., 2024). Scientifically responsible personalization requires alignment with credible evidence about how learners attend, encode, practice, retrieve, regulate, and transfer knowledge (Li et al., 2024). An evidence-informed framework can therefore contribute theoretically by clarifying the mechanisms underlying personalized hybrid learning and practically by helping educators design learning experiences that are adaptive, cognitively manageable, pedagogically purposeful, and resistant to neuromyth-based practices.

RESEARCH METHOD

Research Design

This study employed a quasi-experimental mixed-methods design to investigate the effectiveness of brain-based learning strategies within personalized hybrid education

(Priyadarshini et al., 2024). The quantitative component used a pretest–posttest comparison-group design to examine changes in academic achievement, knowledge retention, cognitive engagement, motivation, self-regulated learning, and perceived cognitive load (Tang et al., 2026). The qualitative component explored how learners experienced personalized instructional sequences across face-to-face and digital learning environments (Rahman et al., 2024). This design was selected because the effectiveness of brain-informed personalization cannot be adequately understood through achievement scores alone; changes in cognitive and affective outcomes require examination alongside learners' experiences of pacing, challenge, feedback, attention, and instructional support.

The intervention was structured through an Adaptive Brain-Informed Personalized Hybrid Learning Framework integrating evidence-informed principles from cognitive neuroscience and the science of learning. Core strategies included prior-knowledge activation, attention management, cognitive-load regulation, retrieval practice, spaced learning, multimodal representation, active processing, formative feedback, emotional relevance, metacognitive reflection, and opportunities for knowledge transfer. These principles were translated into instructional practices without relying on unsupported classifications such as fixed visual–auditory–kinesthetic learning styles or left-brain/right-brain learner categories. Personalization was instead based on dynamic evidence concerning learner readiness, prior performance, progress, engagement, and demonstrated instructional needs.

The experimental group received personalized hybrid instruction based on the proposed framework, whereas the comparison group participated in conventional hybrid learning covering equivalent curriculum content, instructional duration, and learning objectives. Personalization in the experimental condition involved adaptive task difficulty, differentiated scaffolding, flexible pacing, spaced retrieval schedules, targeted formative feedback, and teacher-mediated adjustments based on learner progress. Quantitative and qualitative evidence was integrated during interpretation to determine not only whether the intervention produced measurable effects, but also which instructional mechanisms appeared to explain variations in learner outcomes.

Research Target/Subject

The target population for this study consisted of students enrolled in educational institutions that implement structured hybrid learning models, combining face-to-face instruction with synchronous and asynchronous digital activities. From this accessible population, a total of 240 students were selected from intact classes using cluster-based purposive sampling to form the quantitative sample. To minimize contamination between instructional treatments, participants were assigned at the class level into two equal groups: an experimental group (n = 120) that received brain-informed personalized hybrid instruction, and a comparison group (n = 120) that engaged in conventional hybrid learning. Eligible participants were required to have regular access to the learning management system and actively participate in both physical and online components.For the qualitative component, a subset of 24 students was purposively selected from the experimental group using maximum-variation criteria based on their prior achievement, engagement levels, self-regulation, and progress during the intervention. This qualitative sample included learners demonstrating substantial, moderate, and limited improvements to capture diverse experiences regarding personalized pacing, task difficulty, and feedback. Additionally, teachers responsible for delivering the intervention were interviewed to provide complementary insights into instructional adaptations, implementation feasibility, and classroom dynamics during the personalized hybrid learning process.

Research Procedure

The research procedure began with ethical approval, institutional permission, participant recruitment, informed consent, instrument validation, and pilot testing. Teachers implementing the experimental condition participated in preparatory sessions concerning the theoretical foundations and practical application of brain-informed learning principles. Training emphasized the distinction between evidence-supported cognitive principles and common educational neuromyths. Teachers were provided with instructional guidelines for prior-knowledge activation, retrieval practice, spacing, cognitive-load management, formative feedback, adaptive scaffolding, and reflective learning.

Baseline data were collected before the intervention through academic pretests and measures of cognitive engagement, motivation, self-regulated learning, and perceived cognitive load. Initial learner profiles were generated using prior achievement and baseline performance rather than fixed learning-style categories. Experimental-group students then received personalized instructional pathways adjusted according to demonstrated readiness, progress, and support needs. Learner profiles remained dynamic throughout the intervention and were updated based on formative assessments, task performance, retrieval accuracy, engagement indicators, and teacher observations.

The intervention was implemented through coordinated face-to-face and digital learning cycles. Face-to-face sessions emphasized concept introduction, guided explanation, collaborative reasoning, complex problem-solving, and immediate teacher scaffolding. Digital sessions provided individualized practice, spaced retrieval, adaptive task sequences, multimodal resources, formative assessment, and targeted feedback. Learning content was segmented to manage cognitive demands, while retrieval opportunities were distributed across time to strengthen memory consolidation. Short reflective activities encouraged students to evaluate their understanding, identify difficulties, and adjust learning strategies.

Quantitative analysis included descriptive statistics, tests of baseline equivalence, within-group and between-group comparisons, and appropriate inferential procedures for evaluating intervention effects. Analysis of covariance was used where appropriate to compare post-intervention outcomes while controlling for baseline differences, with effect sizes and confidence intervals reported alongside significance tests. Repeated-measures procedures examined changes across pretest, posttest, and delayed-retention measurements. Relationships among engagement, self-regulation, cognitive load, learning analytics, and academic outcomes were also examined to identify potential mechanisms associated with intervention effectiveness.

Qualitative data from interviews, observations, reflection journals, and teacher logs were analyzed thematically through systematic coding, category development, comparison, and interpretation. Particular attention was given to how students experienced personalized pacing, retrieval practice, cognitive challenge, multimodal learning, feedback, and transitions between physical and digital environments. Cases showing contrasting outcome patterns were compared to identify conditions under which the intervention appeared more or less effective. Quantitative and qualitative findings were subsequently integrated to explain convergence, divergence, and complementary patterns across data sources.

Final interpretation examined the effectiveness of the Adaptive Brain-Informed Personalized Hybrid Learning Framework as an integrated instructional system rather than attributing learning improvements directly to isolated claims about brain functioning. Evidence was interpreted through a cautious pathway connecting established findings from cognitive neuroscience and learning science with instructional principles and observable educational outcomes. This procedure enabled the study to evaluate whether personalized hybrid learning designed around attention, memory, cognitive load, retrieval, self-regulation, and adaptive support could produce more effective and sustainable learning than conventional hybrid instruction.

Instruments, and Data Collection Techniques

Academic learning outcomes were measured using curriculum-aligned achievement and retention tests developed according to the instructional objectives addressed during the intervention. The achievement test assessed conceptual understanding, application, analysis, and problem-solving rather than simple factual recall. A delayed retention assessment was administered after the intervention to determine the durability of learning. Content validity was established through expert review, while item difficulty, discrimination, reliability, and construct alignment were evaluated during pilot testing before the instruments were used in the main study.

Cognitive and affective variables were assessed using structured scales measuring cognitive engagement, perceived cognitive load, learning motivation, self-regulated learning, and metacognitive awareness. Cognitive engagement indicators examined sustained attention, active processing, elaboration, and persistence. Cognitive-load measures distinguished perceived mental effort and unnecessary processing demands where appropriate. Self-regulated learning measures assessed planning, monitoring, strategy adjustment, time management, and reflective evaluation. All instruments were adapted from established theoretical constructs and subjected to validity and reliability assessment before data collection.

Digital learning analytics provided behavioral evidence concerning learner interaction with personalized hybrid activities. Recorded indicators included task completion, learning frequency, time-on-task, retrieval-practice participation, response accuracy, feedback utilization, revision behavior, and progression through differentiated activities. These data were used as indicators of learning behavior rather than direct measures of neurological activity. No inference about individual brain states was made solely from digital behavioral traces, thereby maintaining a clear distinction between observable learning behavior and neuroscientific interpretation.

Qualitative instruments included semi-structured interview protocols, classroom observation sheets, learner reflection journals, and teacher implementation logs. Interviews explored learners' perceptions of task difficulty, pacing, feedback, attention, motivation, retrieval activities, and transitions between face-to-face and digital learning. Observation protocols documented instructional implementation and learner responses during selected activities. Instrument credibility was strengthened through expert validation, pilot testing, triangulation across data sources, member checking where appropriate, and systematic documentation of qualitative coding procedures.

Data Analysis Technique

Quantitative data analysis involved both descriptive and inferential statistical methods to evaluate intervention outcomes and ensure baseline equivalence between the experimental and comparison groups. Analysis of Covariance (ANCOVA) was employed to compare posttest academic achievement, knowledge retention, cognitive engagement, motivation, self-regulated learning, and perceived cognitive load while controlling for baseline pretest scores. Repeated-measures procedures were used to track performance trajectory across pretest, posttest, and delayed-retention assessments. Furthermore, effect sizes and confidence intervals were reported alongside statistical significance tests, and relational analyses were conducted to examine connections among digital learning analytics, engagement indicators, self-regulation, and overall academic outcomes.

Qualitative data gathered from semi-structured interviews, classroom observations, learner reflection journals, and teacher logs were analyzed using systematic thematic analysis. The coding process involved identifying patterns, developing categories, and comparing themes to understand how students experienced personalized pacing, spaced retrieval, cognitive challenge, and transitions between face-to-face and online environments. Comparative case analysis was conducted across high-, medium-, and low-performing student profiles to highlight variations in intervention effectiveness. Ultimately, quantitative and qualitative findings were integrated during interpretation to explain convergence, divergence, and the instructional mechanisms underlying learner outcomes.

RESULTS AND DISCUSSION

The quantitative analysis included 240 students distributed equally between the experimental group receiving Adaptive Brain-Informed Personalized Hybrid Learning and the comparison group receiving conventional hybrid instruction. Baseline analysis showed relatively comparable academic performance between the experimental group (M = 62.84, SD = 8.17) and the comparison group (M = 63.21, SD = 8.04). Post-intervention scores increased to 82.46 (SD = 7.12) in the experimental group and 74.38 (SD = 7.86) in the comparison group. Delayed-retention scores remained relatively stable in the experimental group (M = 79.73, SD = 7.35), whereas a larger decline was observed in the comparison group (M = 69.92, SD = 8.11), indicating different patterns of learning durability across instructional conditions.

Table 1. Descriptive Statistics of Learning Outcomes and Psychological Variables

Variable	Experimental Group Pretest M (SD)	Experimental Group Posttest M (SD)	Comparison Group Pretest M (SD)	Comparison Group Posttest M (SD)
Academic Achievement	62.84 (8.17)	82.46 (7.12)	63.21 (8.04)	74.38 (7.86)
Cognitive Engagement	3.31 (0.56)	4.18 (0.48)	3.34 (0.54)	3.67 (0.52)
Learning Motivation	3.48 (0.58)	4.21 (0.46)	3.51 (0.57)	3.76 (0.51)
Self-Regulated Learning	3.27 (0.61)	4.09 (0.50)	3.30 (0.59)	3.63 (0.55)
Perceived Cognitive Load	3.62 (0.64)	2.91 (0.57)	3.59 (0.62)	3.38 (0.60)

Descriptive patterns across psychological variables showed greater improvement in the experimental group. Cognitive engagement increased from 3.31 to 4.18, motivation increased from 3.48 to 4.21, and self-regulated learning increased from 3.27 to 4.09. Perceived cognitive load declined from 3.62 to 2.91, suggesting that students experienced learning tasks as more cognitively manageable after participating in the intervention. Changes in the comparison group were positive but consistently smaller, particularly for cognitive engagement, self-regulation, and cognitive-load reduction.

The improvement in academic achievement appears to reflect the cumulative contribution of several interconnected instructional strategies rather than the influence of a single technique. Prior-knowledge activation helped students connect new information with existing cognitive structures, while segmented learning materials reduced unnecessary processing demands. Retrieval practice required students to actively reconstruct previously learned information instead of repeatedly reviewing content, and spaced learning distributed these retrieval opportunities across time. Personalized scaffolding further adjusted task complexity according to demonstrated learner readiness.

The lower perceived cognitive load observed in the experimental condition did not indicate that learning tasks became academically easier. Students continued to engage with complex concepts and problem-solving activities, but instructional demands were more systematically organized. Learners received targeted support when difficulties emerged and gradually encountered more demanding tasks as their competence increased. This pattern suggests that effective personalization may optimize cognitive challenge rather than simply minimize difficulty, creating conditions in which mental effort is directed toward meaningful learning rather than avoidable confusion.

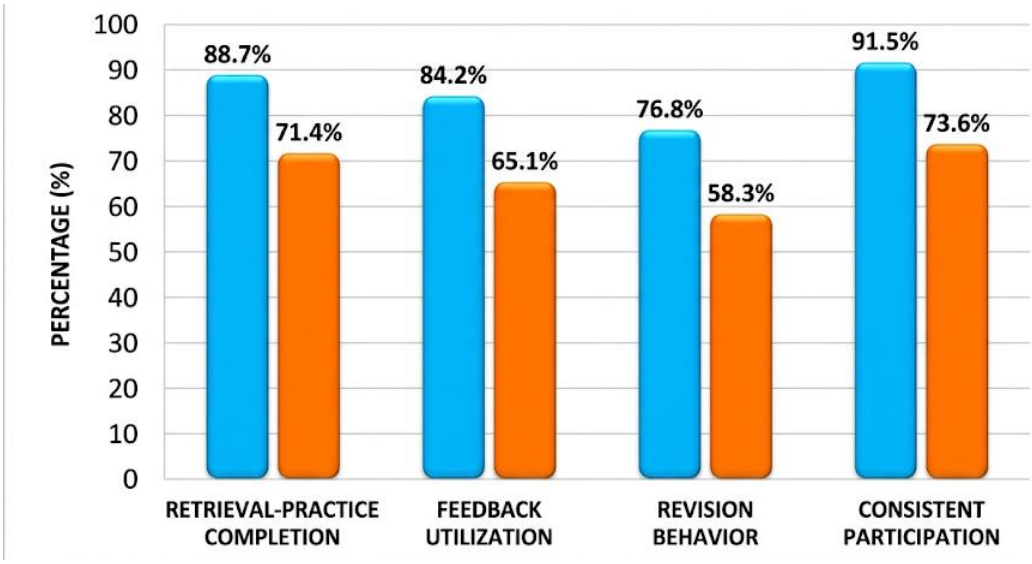

Figure 1. Comparative Behavioral Engagement Across Instructional Conditions

Learning analytics revealed meaningful differences in behavioral engagement across instructional conditions. Students in the experimental group completed approximately 88.7% of assigned retrieval-practice activities compared with 71.4% in the comparison condition. Feedback utilization reached 84.2% among experimental participants, while revision behavior after formative feedback was recorded in 76.8% of eligible learning episodes. Students receiving personalized instruction also demonstrated more consistent participation across face-to-face and digital components, with fewer incomplete digital learning sequences.

Patterns of adaptive task progression showed substantial individual variation within the experimental group. Approximately 34% of learners progressed rapidly to advanced tasks, 46% required moderate scaffolding before advancing, and 20% required sustained instructional support across several learning cycles. These differences demonstrate that personalization did not produce a uniform learning pathway. Students reached common curriculum objectives through different combinations of pacing, task difficulty, retrieval frequency, feedback, and scaffolding.

Analysis of covariance controlling for baseline achievement demonstrated a statistically significant difference in posttest performance between the experimental and comparison groups, $F(1, 237) = 68.42$, $p < .001$, partial $\eta^2 = .224$. The adjusted posttest mean remained significantly higher for students receiving brain-informed personalized hybrid instruction. Repeated-measures analysis across pretest, posttest, and delayed-retention assessments also revealed a significant group-by-time interaction, $F(2, 474) = 39.17$, $p < .001$, partial $\eta^2 = .142$, indicating that patterns of learning development differed systematically between instructional conditions.

Multivariate analyses identified significant intervention effects for cognitive engagement, learning motivation, self-regulated learning, and perceived cognitive load. The strongest standardized differences were observed for cognitive engagement and self-regulation, while the reduction in cognitive load represented a moderate effect. Delayed-retention analysis showed that experimental-group students maintained a significantly greater proportion of their post-intervention learning gains than comparison-group students ($p < .001$). These results indicate that the intervention influenced not only immediate performance but also the durability and regulation of learning.

Correlation analysis showed that cognitive engagement was positively associated with posttest achievement ($r = .58$, $p < .001$), while self-regulated learning demonstrated a similarly positive relationship ($r = .55$, $p < .001$). Retrieval-practice completion was positively related to delayed retention ($r = .61$, $p < .001$), representing one of the strongest relationships identified in the analysis. Feedback utilization was also associated with academic improvement ($r = .49$, $p < .001$), suggesting that students who actively responded to formative information tended to demonstrate greater learning progress.

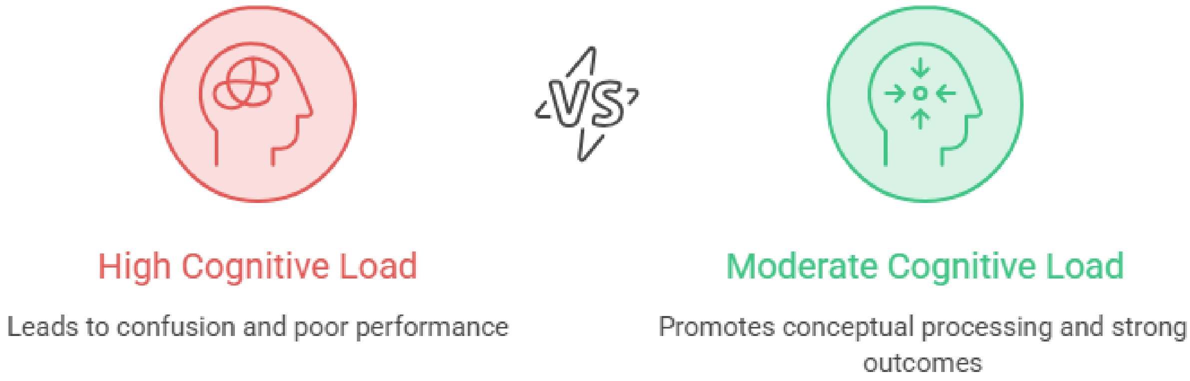

Figure 2. How to Optimize Cognitive Load for Effective Learning

Perceived cognitive load showed a moderate negative relationship with achievement ($r = -.41$, $p < .001$), although this relationship varied according to the nature of the reported mental effort. Students experiencing persistent confusion, fragmented information, or navigation difficulties generally performed less effectively, whereas learners reporting substantial but manageable intellectual effort often demonstrated strong outcomes. This distinction suggests that cognitive demand itself was not inherently detrimental. Learning quality depended on whether mental resources were directed toward productive conceptual processing or unnecessary instructional complexity.

A representative case involved a student who entered the intervention with below-average prior achievement, inconsistent digital participation, and limited confidence in independent learning. Initial diagnostic assessment indicated gaps in prerequisite knowledge rather than a fixed deficit in learning ability. The personalized pathway therefore provided shorter content segments, targeted prerequisite review, guided retrieval exercises, immediate formative feedback, and a slower progression toward complex problem-solving tasks. Face-to-face sessions were used for teacher scaffolding and clarification, while digital activities provided repeated retrieval opportunities at scheduled intervals.

The student's achievement increased from 56 on the pretest to 80 on the posttest and remained at 77 on the delayed-retention assessment. Learning logs showed a progressive increase in independent task completion and a decline in requests for direct instructional assistance. Reflection entries indicated that repeated retrieval initially felt more demanding than rereading but gradually increased confidence in remembering and applying concepts. Teacher observations also documented greater participation in collaborative problem-solving after foundational knowledge became more stable.

The case illustrates how personalization can operate as dynamic instructional adaptation rather than classification according to presumed learning styles. The student was not categorized as a particular type of learner or assigned a fixed instructional modality. Support was adjusted according to evidence from prior knowledge, retrieval performance, formative assessment, learning behavior, and demonstrated progress. Scaffolding was gradually reduced as competence increased, allowing the learner to assume greater responsibility for planning, monitoring, and completing learning activities.

Qualitative findings from the broader participant group reinforced this pattern. Students commonly described spaced retrieval as initially challenging but increasingly useful for recognizing what they genuinely understood and what required further study. Personalized feedback was perceived as valuable when it provided specific guidance rather than simply indicating correctness. Teachers reported that learning analytics became most useful when interpreted alongside classroom observations and direct interaction with students. Behavioral data alone were insufficient to explain why learners struggled, reinforcing the importance of combining digital evidence with professional pedagogical judgment.

The findings indicate that the Adaptive Brain-Informed Personalized Hybrid Learning approach was associated with stronger academic achievement, knowledge retention, cognitive engagement, motivation, self-regulated learning, and more manageable cognitive load than conventional hybrid instruction. The results do not support the interpretation that these improvements resulted from tailoring instruction to fixed neurological or learning-style categories. Stronger outcomes emerged from evidence-informed strategies involving retrieval, spacing, prior-knowledge activation, cognitive-load management, formative feedback, adaptive scaffolding, and dynamic adjustment based on learner progress.

The overall pattern supports an Adaptive Brain-Informed Personalized Hybrid Learning Framework in which effective personalization operates through continuous cycles of diagnosis, instructional adaptation, active processing, retrieval, feedback, monitoring, and recalibration. Face-to-face and digital modalities contributed different but complementary functions within this cycle. The central interpretation is that personalized hybrid education becomes more effective when adaptation is grounded in observable learning needs and credible principles of cognition rather than technological customization alone. Brain-informed personalization should therefore be understood as the pedagogical orchestration of learning conditions that support attention, memory, cognitive challenge, self-regulation, and durable knowledge development.

The findings indicate that the integration of evidence-informed brain-based learning strategies within personalized hybrid education was associated with meaningful improvements in academic achievement, knowledge retention, cognitive engagement, learning motivation, and self-regulated learning. Students participating in the adaptive intervention demonstrated stronger post-intervention performance than those receiving conventional hybrid instruction, while delayed assessment suggested greater durability of acquired knowledge. The overall pattern indicates that personalized hybrid learning becomes more effective when instructional adaptation is grounded in established principles of cognition and learning rather than technological customization alone.

The reduction in perceived cognitive load represents another important finding because it occurred alongside improvements in academic performance rather than through simplification of learning objectives. Students continued to engage with conceptually demanding tasks, yet instructional information was more systematically segmented, sequenced, and supported. Personalized scaffolding allowed learners to receive assistance according to demonstrated needs, while progressive task complexity maintained meaningful intellectual challenge. This pattern suggests that effective instruction should optimize cognitive demand rather than merely reduce mental effort.

Learning analytics further revealed that retrieval-practice completion, feedback utilization, revision behavior, and consistent participation were associated with stronger learning outcomes. Students did not follow identical pathways toward common educational objectives. Some progressed rapidly toward advanced tasks, while others required repeated retrieval, prerequisite review, additional feedback, or sustained scaffolding. Such variation demonstrates that personalization is most appropriately understood as a dynamic adjustment of instructional conditions rather than the assignment of learners to permanent categories.

Qualitative findings reinforced the quantitative results by showing how students gradually developed greater awareness of their own learning processes. Retrieval practice was initially perceived by some participants as more demanding than passive review, yet repeated experience helped them recognize gaps in understanding and monitor their progress more accurately. Teachers also reported that learning analytics became educationally meaningful only when interpreted alongside classroom observations, formative assessment, and direct interaction. Personalized learning therefore emerged as a process combining data-informed adaptation with professional pedagogical judgment.

The improvement in achievement and retention is consistent with research in cognitive psychology demonstrating the value of retrieval practice and distributed learning. Repeated retrieval requires learners to reconstruct knowledge from memory rather than simply re-expose themselves to information, strengthening accessibility and supporting longer-term retention. Spacing learning opportunities across time similarly reduces dependence on short-term familiarity and encourages repeated reconstruction of knowledge. The present findings support the educational value of integrating these principles systematically into hybrid instructional sequences.

The results also align with cognitive load theory, particularly the principle that instructional design should minimize unnecessary processing while preserving intellectually productive challenge. Students in the experimental condition experienced lower perceived cognitive burden despite engaging with demanding academic content. Segmentation, prerequisite activation, adaptive scaffolding, and clearer sequencing may have reduced processing demands unrelated to the learning objectives. Such findings reinforce the distinction between productive cognitive effort and extraneous cognitive burden.

Existing personalized learning research has often emphasized adaptive platforms, learning analytics, artificial intelligence, and algorithmic recommendation systems. The current findings extend this literature by suggesting that technological adaptation alone is insufficient to define meaningful personalization. Adaptive systems can change task difficulty or recommend resources, but effective personalization requires decisions about when learners should retrieve, practice, receive scaffolding, revisit prerequisites, obtain feedback, or progress toward more complex tasks. The educational value of personalization therefore depends on the principles guiding adaptation rather than on adaptation itself.

The findings differ from educational approaches that interpret brain-based learning through fixed learner classifications, particularly visual–auditory–kinesthetic learning styles or left-brain/right-brain distinctions. No such categories were required to produce meaningful differences in learning outcomes. Adaptation was instead based on prior knowledge, demonstrated performance, retrieval success, engagement patterns, and evolving support needs. This distinction is theoretically important because it positions brain-informed education within evidence-supported learning science rather than neuromyth-based instructional prescriptions.

The findings signify a need to reconceptualize personalization as dynamic cognitive responsiveness. Personalized learning should not mean creating a permanent instructional profile for each learner based on presumed preferences or fixed characteristics. Learner needs change as knowledge develops, misconceptions are corrected, confidence increases, and self-regulatory capacity improves. Effective personalization therefore requires continuous cycles of diagnosis, adaptation, monitoring, and recalibration.

The results also signify that difficulty should not automatically be interpreted as evidence of ineffective learning. Students initially described retrieval practice as demanding because reconstructing information from memory requires greater effort than rereading familiar material. Such effort can be educationally productive when appropriately calibrated. Learning experiences that feel easy may create an illusion of mastery, whereas carefully designed challenges can strengthen retention and transfer. Personalized instruction should therefore optimize desirable cognitive difficulty rather than maximize immediate comfort.

The improvement in self-regulated learning signifies that personalization can potentially develop learner autonomy rather than create dependence on adaptive systems. Students became increasingly capable of identifying knowledge gaps, responding to feedback, monitoring progress, and adjusting learning behavior. Effective personalization should gradually transfer responsibility from external instructional regulation toward learner self-regulation. Adaptive support becomes most educationally valuable when it functions as temporary scaffolding that strengthens learners' capacity to manage their own learning.

The complementary roles of face-to-face and digital environments signify that hybrid education should be designed according to cognitive and pedagogical functions rather than simple scheduling arrangements. Physical classroom interaction provided opportunities for complex explanation, collaborative reasoning, immediate clarification, and relational support, while digital environments supported spaced retrieval, flexible pacing, repeated practice, and individualized feedback. Hybrid education therefore becomes more meaningful when modalities are intentionally orchestrated according to what each environment can contribute to learning.

The theoretical implication concerns the relationship among cognitive neuroscience, learning science, and instructional design. Neuroscientific knowledge should not be translated directly into classroom prescriptions without intermediate theoretical and empirical validation. A more defensible pathway moves from understanding cognitive mechanisms to identifying evidence-supported principles of learning and then translating those principles into instructional strategies. This pathway protects brain-informed education from reductionism while preserving the potential value of interdisciplinary knowledge.

The pedagogical implication is that teachers should personalize instruction according to dynamic evidence of learning rather than assumed learner types. Diagnostic assessment, retrieval performance, formative feedback, task completion, misconceptions, engagement, and observed progress provide more defensible foundations for adaptation than fixed preference categories. Teachers can adjust pacing, scaffolding, task complexity, feedback, and practice schedules while maintaining common learning objectives. Personalization therefore requires sophisticated instructional decision-making rather than simply offering students different content formats.

The technological implication is that personalized learning systems should move beyond content recommendation toward cognitively informed orchestration. Digital platforms could support adaptive retrieval schedules, prerequisite diagnosis, spacing algorithms, formative feedback, mastery monitoring, and scaffold adjustment. Such systems should remain transparent enough for teachers to understand why particular recommendations are generated. Technology should strengthen professional decision-making rather than obscure instructional reasoning behind automated personalization.

The institutional implication concerns teacher professional development. Educators require opportunities to understand attention, memory, retrieval, spacing, cognitive load, metacognition, feedback, and self-regulation while also learning to distinguish credible research from popular neuromyths. Professional learning should not present neuroscience as a collection of simplified facts about the brain. Teachers need frameworks for critically evaluating educational claims and translating reliable evidence into contextually appropriate instructional decisions.

The improvement in academic achievement can be explained by the interaction of prior-knowledge activation, adaptive scaffolding, active processing, and repeated retrieval. New information becomes easier to understand when learners can connect it with relevant existing knowledge. Diagnostic evidence allowed instructional support to address prerequisite gaps before students encountered increasingly complex tasks. Retrieval subsequently required active reconstruction, strengthening access to learned information and revealing areas requiring additional practice.

Stronger retention likely resulted from the temporal distribution of learning opportunities. Conventional instruction often concentrates learning within relatively short periods, creating strong immediate familiarity that may decline rapidly. Spaced retrieval repeatedly reactivates knowledge after partial forgetting has occurred, requiring greater reconstruction and strengthening subsequent accessibility. Hybrid environments are particularly suitable for this approach because digital components can distribute retrieval opportunities between classroom sessions without requiring continuous synchronous instruction.

Improved cognitive engagement and self-regulation can be explained by the active role learners assumed within the personalized learning cycle. Students received information about their performance, encountered tasks calibrated to their current readiness, revised responses after feedback, and monitored progress over time. Such processes encouraged learners to become participants in regulating learning rather than passive recipients of instructional content. Visible progress may also have strengthened perceived competence and motivation.

Lower perceived cognitive load likely resulted from better alignment among task complexity, learner readiness, instructional sequencing, and available support. Students with prerequisite gaps received additional scaffolding, while learners demonstrating mastery progressed toward more complex tasks. This adjustment reduced situations in which students encountered either overwhelming difficulty or unnecessary repetition. Cognitive resources could consequently be directed more efficiently toward relevant conceptual processing.

Future research should isolate the relative contributions of individual components within the integrated intervention. The current framework combines retrieval practice, spacing, prior-knowledge activation, cognitive-load management, adaptive scaffolding, formative feedback, and self-regulatory support. Factorial and dismantling designs could determine which components produce independent effects, which operate synergistically, and which are most effective for particular learner populations. Such research would prevent the effectiveness of a multicomponent intervention from being incorrectly attributed to a single “brain-based” mechanism.

Longitudinal studies should examine whether improvements in achievement, retention, and self-regulation persist across semesters and transfer to new academic contexts. Personalized systems may produce short-term performance improvements without necessarily developing durable independent learning capacities. Future research should therefore assess far-transfer, long-term retention, autonomous strategy use, and learners’ ability to regulate learning after adaptive scaffolding is gradually removed.

Research should also investigate how artificial intelligence can support cognitively informed personalization without creating excessive automation or learner dependence (Arshad Choudhry et al., 2025). AI systems could analyze retrieval patterns, identify prerequisite gaps, recommend spacing intervals, and suggest adaptive scaffolds, yet algorithmic recommendations should remain subject to teacher judgment. Future studies should examine how human–AI collaboration can combine computational pattern recognition with contextual pedagogical expertise while preserving transparency, fairness, privacy, and learner agency.

Future educational practice should ultimately move from loosely defined brain-based learning toward evidence-informed cognitively responsive personalization (Del Pup et al., 2025). The strongest contribution of this perspective is not the claim that neuroscience provides direct formulas for teaching, but the recognition that instructional design should respect reliable knowledge about attention, memory, cognitive load, retrieval, feedback, and self-regulation (Umirzakova et al., 2025). Personalized hybrid education can become more scientifically defensible when adaptation responds dynamically to observable learning needs, hybrid modalities are assigned purposeful cognitive functions, and technological innovation remains subordinate to sound principles of human learning.

CONCLUSION

The most significant finding of this study is that personalized hybrid education becomes more effective when instructional adaptation is grounded in evidence-informed principles of human learning rather than fixed learner classifications or technological personalization alone. The integration of prior-knowledge activation, retrieval practice, spaced learning, cognitive-load management, adaptive scaffolding, formative feedback, and metacognitive reflection was associated with stronger academic achievement, knowledge retention, cognitive engagement, motivation, and self-regulated learning, alongside more manageable cognitive demands. Students benefited from different combinations of pacing, practice, feedback, and instructional support while progressing toward shared learning objectives, demonstrating that personalization should function as a dynamic process rather than a permanent categorization of learners. The findings therefore redefine brain-based personalization as dynamic cognitive responsiveness, in which instructional decisions continuously adapt to observable evidence of learner readiness, performance, progress, and support needs while deliberately avoiding unsupported assumptions derived from learning-style or hemispheric-dominance neuromyths.

The principal contribution of this study is conceptual and methodological through the development of an Adaptive Brain-Informed Personalized Hybrid Learning Framework that connects credible principles from cognitive neuroscience and learning science with personalized instructional design across physical and digital environments. Conceptually, the framework establishes a scientifically cautious pathway from cognitive mechanisms to evidence-supported learning principles and subsequently to pedagogical strategies, thereby avoiding the direct and potentially misleading translation of neuroscientific findings into classroom prescriptions. Methodologically, the integration of quasi-experimental evidence, delayed-retention assessment, learning analytics, classroom observation, learner reflection, and qualitative inquiry provides a multidimensional approach for examining not only whether personalized learning improves performance but also how learners engage with adaptive instructional processes. The framework further introduces cognitive orchestration across hybrid modalities, positioning face-to-face learning for complex explanation, collaborative reasoning, and responsive scaffolding while using digital environments strategically for adaptive practice, spaced retrieval, individualized pacing, progress monitoring, and formative feedback.

The limitations of this study concern its quasi-experimental design, reliance on selected educational contexts, relatively limited intervention duration, partially self-reported psychological measures, and the difficulty of isolating the independent effects of individual strategies within a multicomponent intervention. The study did not directly measure neurological processes; consequently, observed educational improvements should not be interpreted as evidence of specific changes in brain functioning. Future research should employ longitudinal, randomized, factorial, and dismantling designs to identify the relative and interactive contributions of retrieval practice, spacing, cognitive-load management, scaffolding, feedback, and metacognitive support. Further investigations should examine long-term retention, transfer of learning, learner autonomy, diverse educational populations, and the role of artificial intelligence in dynamically adapting instructional pathways without reducing teacher judgment or student agency. Such research can advance the field from broadly defined brain-based instruction toward evidence-informed cognitively responsive personalization, providing a more rigorous foundation for designing hybrid education that is adaptive, scientifically defensible, pedagogically meaningful, and sustainable across diverse learning contexts.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used Grammarly to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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