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SYNAPSE model : An innovative approach to integrating human learning and artificial intelligence

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Abstract

This article presents the SYNAPSE model, a four-phase framework designed to guide the pedagogical integration of artificial intelligence (AI) in learning environments. Grounded in cognitive science, motivation theory, and self-regulated learning research, the model conceptualizes learning as a dynamic process of activation, adaptation, participation, and consolidation. Each phase corresponds to specific cognitive functions and motivational drivers, offering educators and developers a structured approach to foster learner engagement and autonomy.

Three qualitative studies conducted in upper-secondary classrooms explored how students interacted with AI-enhanced educational tools such as multimodal prompts, adaptive feedback systems, and learning dashboards. The findings reveal substantial variation in learner profiles and emphasize the crucial role of teacher mediation in shaping the pedagogical effectiveness of these tools. While AI can enhance strategic thinking and self-regulation, it cannot replace the pedagogical and ethical scaffolding necessary for deep learning.

The SYNAPSE model contributes to the responsible use of AI in education by aligning design principles with cognitive development and motivational integrity. It provides an operational framework for teacher training, tool design, and educational policy that centers human learning within technological innovation.

Keywords: SYNAPSE model; artificial intelligence in education; self-regulated learning; cognitive engagement; teacher mediation; educational technology design; motivation and autonomy; design-based research; learning dashboards; feedback ethics

1. Introduction

The rapid integration of artificial intelligence (AI) into educational settings is fundamentally transforming the design, enactment, and evaluation of learning processes. AI technologies, ranging from adaptive feedback systems to generative text tools, are increasingly present in classrooms, shaping learners' attention, cognitive engagement, and self-regulatory strategies (OECD, 2023; UNESCO, 2024). While these tools offer promising opportunities for personalization and enhanced efficiency, they simultaneously raise critical concerns regarding motivation erosion, diminished learner autonomy, and superficial engagement behaviors.

In this context, educators, researchers, and policymakers are calling for comprehensive theoretical frameworks to guide the responsible and pedagogically sound adoption of AI in education. Existing approaches often foreground technological capabilities without sufficiently addressing the complex interplay of cognitive, motivational, and ethical dimensions essential to meaningful learning experiences. This lack of integrative guidance risks the introduction of AI tools that may undermine deep engagement or inadvertently reinforce passive learning patterns.

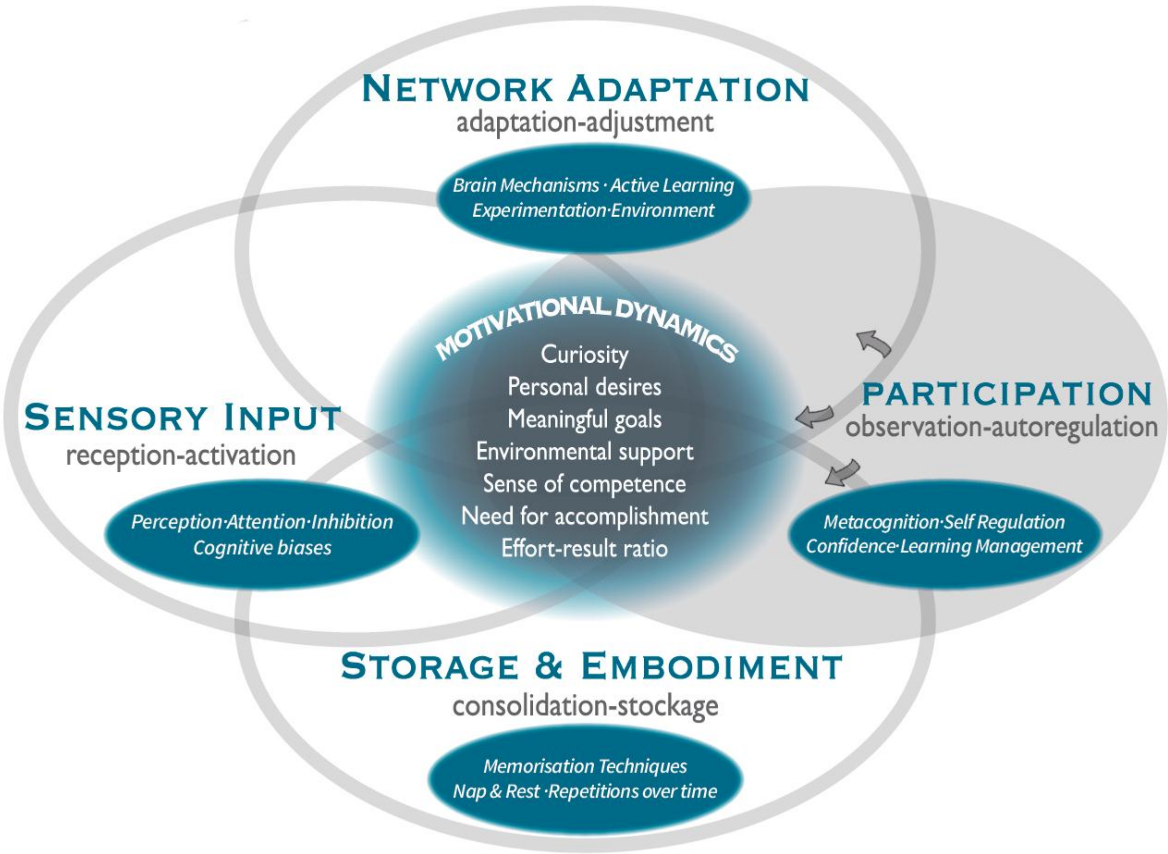
To address this gap, this article introduces the SYNAPSE model, a four-phase framework that aligns human learning processes with the affordances and constraints of AI-enhanced educational environments. Drawing from interdisciplinary research in cognitive science (Anderson, 2010; Dehaene, 2018), educational psychology (Zimmerman, 2002; Pintrich, 2004), and design-based research (Anderson & Shattuck, 2012), the model articulates learning as a dynamic sequence of interactive phases: (1) Sensory Input—activating attention and prior knowledge; (2) Network Adaptation—adjusting learning strategies and mental representations; (3) Participation—engaging metacognitive and motivational regulation; and (4) Storage and Embodiment—consolidating and transferring knowledge. Each phase corresponds to specific cognitive functions and motivational drivers and can be supported or hindered by AI tools depending on their design and integration.

This work explores how AI-enhanced educational tools interact with learners' cognitive and motivational processes and critically examines the role of teacher mediation in shaping these interactions. Specifically, it addresses three research questions: (1) How do AI tools facilitate or impede learners' attention, adaptation, and self-regulation within each SYNAPSE phase? (2) What learner profiles emerge in response to AI tool use? (3) How does teacher mediation influence the pedagogical impact of these technologies?

To investigate these questions, three qualitative studies were conducted in upper-secondary classrooms, each focusing on a distinct phase of the SYNAPSE model. A collaborative design approach was adopted in which researchers and teachers co-developed lesson sequences, ensuring that pedagogical goals guided AI tool integration rather than technological affordances driving instructional choices. This partnership enabled reflective dialogue around learner autonomy, motivation, and knowledge activation, positioning teacher mediation as a critical factor in meaningful AI use.

By offering both a descriptive and prescriptive framework, the SYNAPSE model contributes to a responsible human-centered integration of AI in education. It provides educators, developers, and policymakers with a practical tool to balance technological innovation with cognitive development and motivational integrity, ultimately fostering deeper and more autonomous learning.

Figure 1: SYNAPSE MODEL



2. The SYNAPSE Model

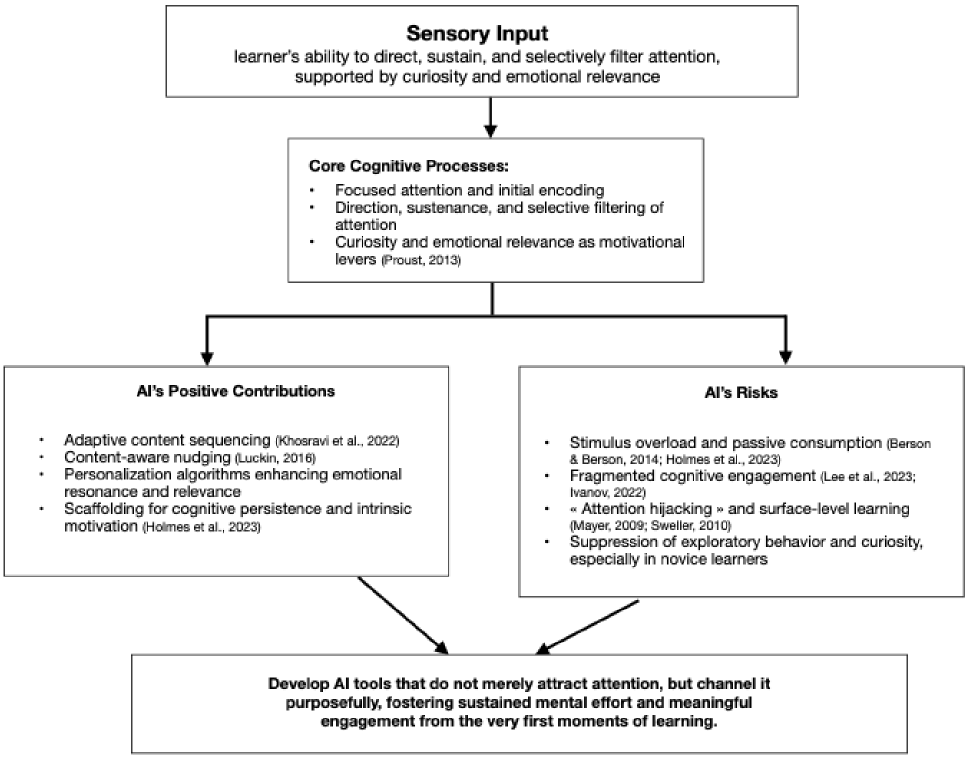
The SYNAPSE model provides a comprehensive, four-phase framework to structure human learning within AI-enhanced environments by integrating cognitive, motivational, and self-regulatory processes. Influenced by foundational research in cognitive science (Anderson, 2010; Dehaene, 2018), educational psychology (Zimmerman, 2002; Pintrich, 2004), and design-based educational research (Anderson & Shattuck, 2012), SYNAPSE positions itself as a tool to guide both ethical and effective AI adoption in educational contexts.

2.1 Phase 1: Sensory Input – Cognitive Activation and Attentional Engagement

Learning begins with perception and attentional orientation. At this stage, learners process stimuli that activate prior knowledge and trigger curiosity (Loewenstein, 1994; Dehaene, 2018). Emotional salience plays a key role: stimuli that are autobiographically relevant or surprising increase dopamine release and support hippocampal encoding (Gruber, Gelman, & Ranganath, 2014). The goal is to establish a state of "readiness to learn," where working memory and attentional focus are aligned with incoming information (Baddeley, 2012).

AI tools can support this phase through adaptive multimodal environments—combining video, sound, and short textual prompts—to trigger curiosity and focus (Mayer, 2014). Eye-tracking data or click latency can inform real-time adjustments to stimuli. However, the risk of cognitive overload remains high if multimodal inputs are not calibrated to the learner's cognitive load capacity (Sweller, 2011). Moreover, opaque recommendation algorithms can reinforce existing biases, limiting epistemic openness (Zhai, Wibowo, & Li, 2024).

Figure 2: Phase 1-Sensory Input



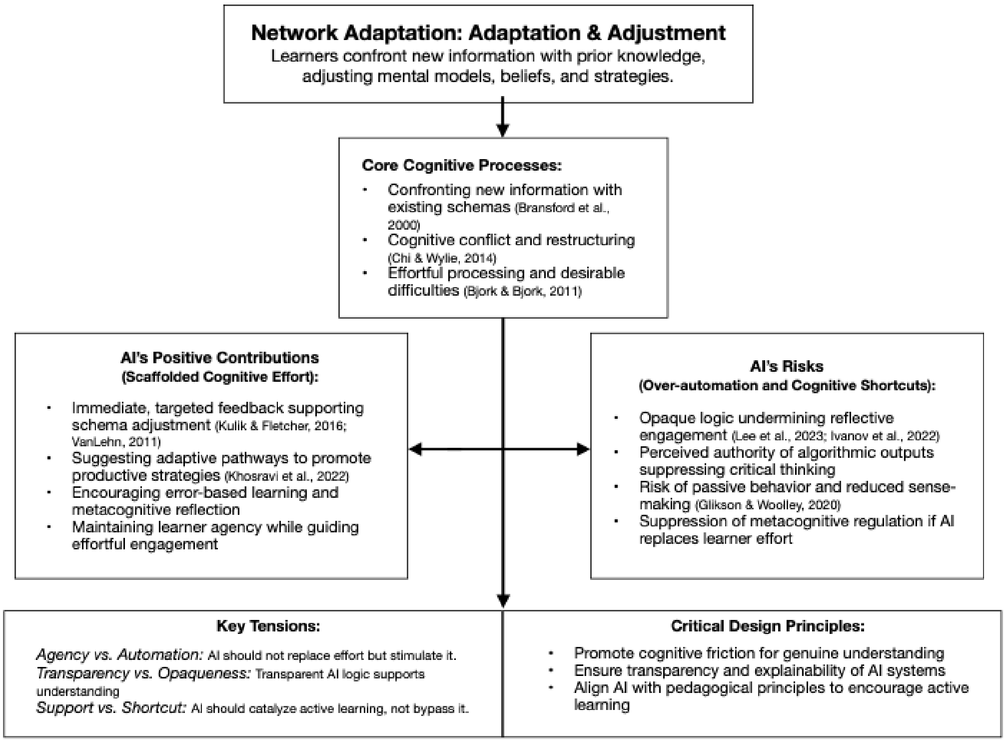
2.2 Phase 2: Network Adaptation – Strategic Adjustment and Cognitive Remodeling

Once learners are engaged, they begin to modify and refine mental representations. This process, supported by the brain's executive functions and long-term potentiation mechanisms, involves inhibiting incorrect responses, testing hypotheses, and adjusting strategies based on feedback (Diamond, 2013; Hebb, 1949).

AI can enhance this phase through intelligent tutoring systems that provide process-level feedback—explaining why a response was incorrect and offering pathways for improvement (Aleven et al., 2016). Adaptive sequencing and error-sensitive scaffolding help learners navigate complex tasks with support that fades over time (Roll & Winne, 2015). However, over-reliance on hints or automation can lead to passivity, where learners bypass reflective reasoning and adopt "click-through" behaviors (Koedinger & Aleven, 2007).

Motivationally, this phase thrives on the perception of competence. Learners are more likely to persist when challenges are matched to their current level with an optimal level of difficulty—what Bjork and Bjork (2022) term "desirable difficulty." Effective AI design should thus aim to balance challenge and support, enabling the development of flexible and transferrable problem-solving skills.

Figure 3: Phase 2-Network Adaptation



2.3 Phase 3: Participation – Metacognitive Monitoring and Self-Regulated Learning

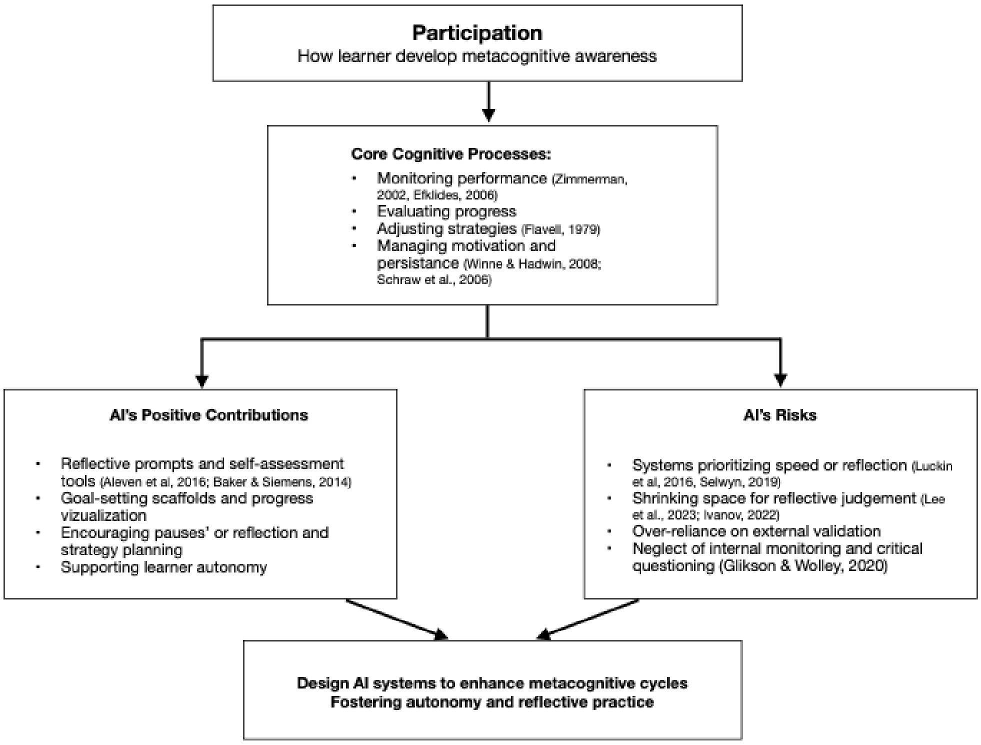
The third phase centers on learners' capacity to monitor and regulate their own learning. It involves setting goals, evaluating progress, selecting strategies, and seeking help when necessary (Zimmerman, 2018; Winne & Hadwin, 2008). Metacognitive processes such as planning, self-questioning, and revision are essential for developing cognitive autonomy (Efklides, 2006).

AI-supported dashboards and conversational agents can scaffold this phase by making learning processes visible and reflective. Learning analytics tools can display performance trends, trigger alerts, and suggest actions based on usage data (Kay, Leung, & Reilly, 2022). Chatbots can prompt learners with reflective questions like "Why did you choose that approach?" or "What would you try next?"

Nevertheless, without explicit training, students may misinterpret dashboards or use them for superficial purposes, such as checking off tasks without evaluating strategy quality (Lee, Park, & Lodge, 2023). Additionally, the collection of fine-grained behavioral data raises ethical concerns about learner privacy and surveillance (Holstein et al., 2019). The role of the teacher is critical in modeling dashboard use and in embedding metacognitive routines into instruction.

Motivation in this phase is often tied to relatedness and agency. Learners who feel connected to a learning community and perceive control over their trajectory are more likely to engage in sustained regulation (Deci & Ryan, 2000).

Figure 4: Phase 3 - Participation



2.4 Phase 4: Storage & Embodiment – Consolidation and Transfer

The final phase involves stabilizing learning through memory consolidation and embodied engagement. During slow-wave sleep, hippocampal traces are transferred to neocortical networks, strengthening long-term retention (Wamsley, 2022). Active recall, spaced repetition, and varied practice enhance this process (Ebbinghaus, 1885; Bransford, Brown, & Cocking, 2000). At the same time, embodied learning—through gestures, simulations, or mental imagery—activates sensorimotor networks, grounding abstract concepts in physical experience (Barsalou, 2008).

AI tools can support this phase through spaced-repetition algorithms that optimize recall intervals (Papamitsiou & Economides, 2014), immersive virtual environments that simulate real-world scenarios, or reflective prompts that encourage transfer to personal contexts. However, overdependence on notifications, automation of revision tasks, or excessive externalization of memory functions can hinder deeper encoding and internalization (Zhai, Wibowo, & Li, 2024).

Learner motivation at this stage is fueled by the perception of progress and mastery. When learners recognize improvements, they gain confidence and are more likely to persist in increasingly complex tasks (Ryan & Deci, 2020).

Figure 5: Phase 4 - Storage & Embodiment (Consolidation)

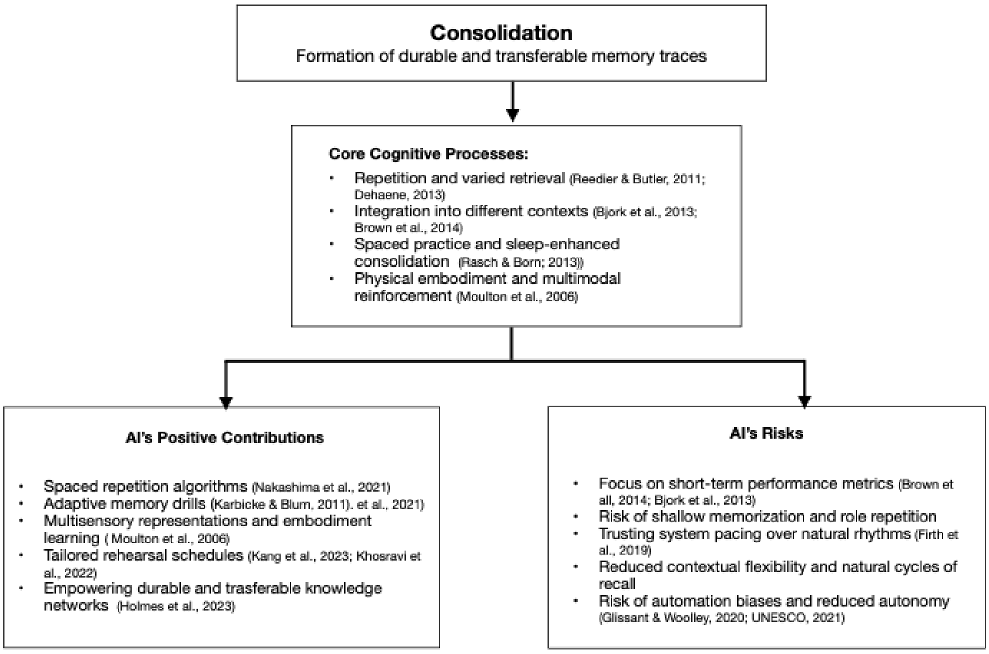


Table 1: 4 Phases Description SYNTHESIS

Phase	Cognitive mechanisms	AI functions	Main risks	Design principles
1 SENSORY INPUT (reception and activation)	Selective attention, affective salience, knowledge activation	Multimodal stimuli, curiosity prompts, immediate low-stakes feedback	Cognitive overload, filter bubbles, biased primers	Create varied stimuli, pace the flow of information, integrate metacognitive cues such as: *Why am I seeing this?*
2 NETWORK ADAPTATION (Adaptation & Adjustment)	Cognitive flexibility, use of working memory, executive and attentional control, inhibition	Giving fundamental information, proposing exercises, adaptive sequencing, feedback at process level, scaffolding in case of error	Information overload, over-reliance on cues, premature automation, loss of strategy diversity, learner passivity	Gradually remove scaffolding, highlight reasoning pathways, encourage "*explain your choice*" reflections.
3 PARTICIPATION (Metacognition & self-regulation)	Goal-setting, monitoring, strategic help-seeking, social co-regulation	Learning analysis dashboards, chatbot reflection partners, peer annotation layers	Consistent, individual learner tracking (dashboard myopia), outsourcing the learning process (via AI), privacy concerns	Explaining how it works, dashboard awareness, combining external metrics with self-explanatory messages, protecting data transparency
4 STORAGE & EMBODIMENT (Consolidation and transfer)	Rehearsal of knowledge to be consolidated, spaced retrieval, embodiment loops, transfers	Spaced repetition algorithms, immersive simulations, performance monitoring	Cognitive outsourcing, fragmented attention, standardized "one-size-fits-all" practice.	Mix technology-generated programs with physical rehearsals, emphasize active recall, maintain variability of effort.

3. Methodology

This research adopts a design-based research (DBR) methodology (Anderson & Shattuck, 2012; Barab & Squire, 2004), combining theoretical development with empirical investigation in authentic educational contexts. DBR is well-suited to exploring how emerging technologies interact with pedagogical goals, learner motivation, and cognitive engagement—core concerns of the SYNAPSE model. Rather than isolating variables through experimental control, this approach enables iterative refinement and contextual relevance.

3.1 Research Focus and Objectives

This research employed a multi-study, design-based approach to examine the SYNAPSE model in authentic educational contexts (Anderson & Shattuck, 2012). Each of the three qualitative studies focused on a distinct phase of the model, with tailored objectives:

Study 1 (Sensory Input): To investigate how emotionally salient, AI-driven multimodal materials activate students' attention and prior knowledge, and to identify factors that sustain or erode initial engagement.

Study 2 (Network Adaptation): To analyze how students adjust cognitive strategies in response to adaptive feedback and scaffolds provided by AI, with particular attention to the development of metacognitive skills.

Study 3 (Participation): To explore how students use AI-driven dashboards to support self-regulation, goal setting, and metacognitive monitoring, and to identify usage profiles and barriers to appropriation.

Across all studies, an additional objective was to examine how teacher mediation impacts learners' cognitive, motivational, and regulatory dynamics in AI-enhanced environments.

3.2 Context and Participants

The studies were carried out in three Swiss upper-secondary classrooms (Gymnasium level) between 2022 and 2024. A total of 88 students (aged 16–18) participated across mathematics, science, and social science subjects. All students used Moodle-based learning sequences embedded with AI-enhanced components (adaptive feedback, multimodal prompts, personalized dashboards).

A central feature of the methodology was the collaborative design process: the researcher worked closely with each teacher to co-construct lesson sequences. This iterative partnership allowed pedagogical goals to guide tool integration, rather than the reverse. Through reflective dialogue, the researcher posed questions about learner autonomy, regulation, and knowledge activation, helping teachers clarify their intentions and adapt the AI tools accordingly. This teacher-researcher collaboration proved essential for embedding AI functions meaningfully within classroom dynamics.

Study 1: 34 students (17–18 years old; mixed gender) in a physics class participated in two 90-minute sessions focused on emotionally salient simulations and narrative prompts.

Study 2: 29 students (16–17 years old) from a biology class engaged in AI-supported adaptation tasks over three sessions (each 90 minutes), using adaptive feedback tools that scaffolded problem solving at various complexity levels.

Study 3: 26 students (17–18 years old) in a philosophy class used personalized dashboards on the Moodle platform across two 90-minute sessions dedicated to goal tracking and self-reflection.

All participants gave informed consent, and ethical clearance was obtained from institutional review boards.

3.3 Data Collection

Each study utilized a multimodal data collection strategy to triangulate learner behaviors:

System logs: All students' digital interactions with AI tools were automatically recorded (clickstreams, help requests, time on task).

Screen recordings: For each study, a core subsample (n = 6 per study) of students had their screen activity video-recorded to enable micro-level analysis of engagement and tool navigation.

Semi-structured interviews: Post-intervention interviews (n = 8–10 per study) explored learners' cognitive, emotional, and strategic responses to the AI tools.

Teacher-researcher reflective conversations: After each session, the teacher and researcher jointly reviewed anonymized student data and discussed observed patterns, refining both instructional strategies and research instruments iteratively.

3.4 Data Analysis

The analysis employed a multi-layered, thematic approach that combined both deductive and inductive coding cycles, ensuring a robust link between the SYNAPSE theoretical framework and empirical data patterns (Anderson & Shattuck, 2012).

Coding Process and Stages:

All data (system logs, screen recordings, interview transcripts, and reflective conversations) were imported into the qualitative analysis software NVivo.

The initial codebook was constructed deductively from the four phases and key constructs of the SYNAPSE model (e.g., attention activation, strategic adaptation, metacognitive regulation, consolidation).

Subsequently, open (inductive) coding was performed on a subset of data from each study, allowing novel, data-driven themes to emerge (Braun & Clarke, 2006).

Codes were iteratively refined; new inductive codes were integrated into the hierarchical structure as needed, and overlapping categories were clarified through researcher consensus.

Study 1: Sensory Input—Attentional and Emotional Markers

Deductive Codes: "Attentional focus" (e.g., time spent engaging with salient AI stimuli), "Curiosity triggers," "Prior knowledge activation."

Inductive Themes: "Spontaneous autobiographical associations," "Emotional resonance with visual metaphors," "Episodes of disengagement or passive waiting."

Illustrative Example: A key code captured direct verbalizations such as, "this made me think of [personal memory]," while passive disengagement was detected through both system inactivity (logs) and statements such as "I just waited for instructions."

Analysis triangulated clickstream data (duration, help requests) with qualitative reports to validate engagement markers (Gruber, Gelman, & Ranganath, 2014; Loewenstein, 1994).

Study 2: Network Adaptation—Strategic and Cognitive Shifts

Deductive Codes: "Strategic adaptation," "Feedback utilization," "Mental model adjustment."

Inductive Themes: "Exploration vs. optimization strategies," "Over-reliance on hints," "Moments of cognitive confusion."

Illustrative Example: From system logs and think-alouds, statements like "I tried a different approach after the hint" or "the feedback confused me, so I kept going back" were coded as evidence of adaptive versus maladaptive pattern use. Changes in response time and pattern of interactions signaled metacognitive monitoring or uncertainty (Roll & Winne, 2015; Koedinger & Aleven, 2007).

Study 3: Participation—Metacognitive Routine and Dashboard Use

Deductive Codes: "Dashboard consultation frequency," "Goal-setting articulation," "Reflection on process."

Inductive Themes: "Checklist usage pattern," "Strategic reinterpretation of dashboard indicators," "Non-use or avoidance narratives."

Illustrative Example: Coding distinguished between students who verbalized, "I changed my goal after seeing my progress," (strategic appropriation) and those saying, "I just check if I did all the tasks," (superficial checklist use). Cases of outright neglect or confusion were also separately coded and described (Kay, Leung, & Reilly, 2022; Lee, Park, & Lodge, 2023).

Reliability Procedures:

After the initial coding phase, the main researcher and the collaborating teacher independently applied the revised codebook to 20% of the data from each study.

Inter-coder agreement was assessed using Cohen's kappa; disagreements were discussed and resolved in joint review sessions.

The codebook was further refined based on these discussions, and a final coding pass ensured consistency across the full dataset.

Integration and Comparison:

Within each study, comparisons of code frequency and theme density were used to identify learner profiles.

Cross-case analysis highlighted how teacher mediation and prior routine exposure affected both tool appropriation and learning trajectories.

This detailed, iterative analytic approach ensured that interpretation stayed grounded in both the SYNAPSE theoretical constructs and the lived realities of classroom implementation.

3.5 Methodological Considerations

Each study presented strengths and limitations:

Study 1: The rich, contextualized data offers in-depth insight into the dynamics of emotional engagement, but the brief intervention and lack of longitudinal follow-up limit claims about sustained attentional change (Dehaene, 2018; Sweller, 2011).

Study 2: Collaboration enabled the alignment of AI scaffolding with pedagogical intentions; however, frequent researcher-teacher adjustments to materials during the intervention introduce variability that may affect replicability (Anderson & Shattuck, 2012).

Study 3: The use of authentic classroom dashboards provided ecological validity, yet some interview participants had limited prior exposure to metacognitive routines—potentially confounding their dashboard interaction patterns. Additionally, dashboard analytics may not fully capture off-task or analog self-regulation (Holstein et al., 2019; Kay, Leung, & Reilly, 2022).

Across all studies, the small sample sizes and the focus on a single national context constrain generalizability. Nevertheless, the design-based, collaborative process allowed for nuanced examination of pedagogical mediation—a key strength for advancing both research and practice in AI-enhanced learning environments.

4. Results

4.1 Overview of Learner Profiles

A cross-case analysis revealed three main learner profiles regarding engagement with AI-enhanced educational tools. These profiles, observed across studies, are synthesized in the table below.

Note: Precise percentages vary slightly by study, but these patterns recur throughout.

4.2 Study 1: Sensory Input

In the Sensory Input study, 34 students participated in a physics lesson supported by AI-mediated multimodal materials, including animated simulations and narrative prompts. Digital trace data showed that most students (approx. 79%) quickly engaged with the presented content, spending several minutes interacting with the dynamic visualizations. The vivid metaphors—for example, "the rollercoaster acceleration"—elicited spontaneous verbal reactions integrating personal memory and emotion. As one student expressed, "That animation of the car made me immediately think of the time my family went to the amusement park, it just clicked with my experience." Interview analyses corroborated this resonance: "It was like seeing my memories in action," reported another student. At the behavioral level, log data showed a pronounced activity peak during the first 10–12 minutes.

Learner Profile	Main Characteristics	Prevalence (Across Studies)	Typical Behaviors
Strategic Self-Regulator	Actively uses AI tools for planning, monitoring, and adapting strategies; interprets feedback meaningfully	30–35%	Regular dashboard use, setting/revisiting goals, changing approaches
Checklist User	Engages with AI tools primarily to fulfill requirements; focuses on task completion over reflection or strategy	40–45%	Uses dashboards as checklists, minimal reflection, low adaptation
Disengaged/Non-User	Ignores or minimally interacts with AI tools; may report confusion or lack of perceived relevance	20–25%	Rare use or avoidance of tools, expresses confusion or disinterest

Nevertheless, after this initial phase, system records revealed a pronounced drop in interactive activity. More than half of students displayed long idle periods or simply paused, awaiting further instruction. Numerous interviewees explained, "I wasn't sure what I was supposed to do after watching," or "I just waited for the teacher because I thought we'd talk about it next.

Analysis and Interpretation

These findings confirm the catalytic effect of emotionally salient, multimodal AI content in activating curiosity and autobiographical encoding (Gruber, Gelman, & Ranganath, 2014; Loewenstein, 1994). The direct student references to personal experience and heightened interest echo the role of hippocampo-emotional pathways in fostering motivation and memory (Gruber et al., 2014). However, consistent with the ICAP framework (Chi & Wylie, 2014), mere activation via passive viewing—even if emotionally charged—does not suffice for sustained engagement or meaningful learning outcomes.

Observed passivity post-exposure aligns with cognitive load theory (Sweller, 2011), as students reported the simultaneous stimuli as overwhelming: "There was a lot happening—it was pretty, but after a while it got hard to follow what mattered." This cognitive overload, in the absence of clear task follow-up, led to disengagement, supporting Dehaene's (2018) caution that attention must be continuously renewed through active demands. Similar drops in engagement after "attentional peaks" are documented in Mayer (2014) and comparable AI-augmented classroom work.

Crucially, students' own words—"I just waited for the teacher"—demonstrate the double-edged nature of curiosity-driven content: while initial motivation is sparked, it is rapidly dissipated without explicit scaffolding or elaborative tasks (Chi & Wylie, 2014). These outcomes also reflect findings reported by Koedinger & Aleven (2007), who highlight that passive use of rich interfaces often leads to "click-through" rather than deep, constructive learning unless active processing is required.

4.3 Study 2: Network Adaptation

In the Network Adaptation study, 29 biology students engaged in AI-supported activities involving adaptive feedback and variable scaffolding across three sessions. System logs demonstrated heterogeneous feedback engagement: some students repeatedly accessed hints, revisiting explanations multiple times, while others accepted system suggestions without further experimentation. Think-aloud protocols revealed strategic "If this, then I'll try that" adjustment in about a third of cases, whereas others defaulted to accepting quick solutions.

A representative verbatim: "When it showed me a hint, I wanted to try another way instead of just following, just to see if I got it," contrasted with another: "The program gave me the answer, so I just used that and moved on." Several students expressed confusion: "Sometimes the hints made it more complicated than the original task."

Analysis and Interpretation

The observed diversity in feedback use reflects differences in learners' metacognitive skills and their readiness to experiment or reflect (Roll & Winne, 2015; Koedinger & Aleven, 2007). Strategic students mirrored the behaviors seen in research on self-regulated exploration, using AI prompts as springboards for hypothesis-testing—consistent with the principles highlighted by Papamitsiou & Economides (2014). Their iterative adjustment, as paraphrased above, supports the effective learning potential of adaptive scaffolds when autonomy is preserved and challenge remains optimal.

Conversely, several students exhibited behaviors typical of "automation bias," demonstrating reliance on AI-generated cues at the expense of self-directed effort or critical reflection—matching findings by Koedinger & Aleven (2007) and Zhai, Wibowo, & Li (2024). Such patterns were especially visible in students without strong prior metacognitive routines: "I didn't want to make it wrong if the program already told me the answer."

Notably, students' feedback regarding over-complexity of hints ("the hints made it more complicated...") underscores the importance of clarity and calibration in AI supports (Glikson & Woolley, 2020). The findings corroborate Sweller's (2011) cognitive load warnings and reinforce the importance of graduated "fading" of scaffolds to avoid dependency and foster skill transfer (Bjork & Bjork, 2022).

4.4 Study 3: Participation

In the Participation study, 26 philosophy students used personalized dashboards designed to support self-regulation and reflection. Usage data revealed three core profiles: 9 students (35%) actively and regularly reviewed dashboard indicators, adjusting goals or work strategies ("When I saw my progress drop, I changed how I planned my next essay."); 11 (42%) mainly used dashboards to confirm task completion ("I just check them off so I know I'm done."); and 6 (23%) showed minimal engagement ("I don't really understand what this dashboard is for.").

Verbatim examples reinforce these categories. Strategic users reported, "It helps me see if what I'm doing works or not," while checklist users said, "It's just like a list—I use it for ticking things off." Non-users typically expressed confusion or irrelevance: "It's not really useful. I just ignore it."

Analysis and Interpretation

The stratification of dashboard use aligns with recent empirical investigations (Kay, Leung, & Reilly, 2022; Lee, Park, & Lodge, 2023), which stress that meaningful appropriation of analytics dashboards depends on prior metacognitive training and guided modeling. The strategic users' adaptive responses correspond to the kinds of goal revision and self-reflection reported by Zimmerman (2018) and Efklides (2006). In contrast, the "checklist" and "non-user" patterns reveal that dashboards, if introduced without explicit instructional framing, risk superficial compliance or confusion—paralleling the observations of Holstein et al. (2019), who warn of "administrative but not metacognitive" dashboard engagement.

Multiple students' reliance on the dashboard for completion verification rather than process improvement ("I just check them off...") indicates the necessity of embedding dashboard use within a broader pedagogical ecosystem that prioritizes metacognitive discourse and teacher mediation. Students with prior exposure to goal-setting or reflective routines were substantially more likely to exploit dashboard feedback for learning strategy adjustment—again echoing findings from Lee, Park, & Lodge (2023).

In summary, across these studies, authentic student voices illustrate the potentials and pitfalls of AI-enhanced tools. The results directly substantiate theoretical and empirical literature: emotional activation and feedback scaffolding can both foster and limit engagement and strategy depending on context and mediation. Without deliberate instructional design—including scaffolding, task structuring, and metacognitive training—the promise of AI for deep learning remains largely unrealized, as documented across learning science and AI-in-education research (Dehaene, 2018; Mayer, 2014; Koedinger & Aleven, 2007; Winne, 2022).

5. Discussion

The findings from the three exploratory studies provide empirical support for the SYNAPSE model as a robust framework for understanding how learners engage with AI-enhanced educational tools, and how teacher mediation shapes that engagement across cognitive, motivational, and self-regulatory dimensions. Rather than viewing learning as a linear progression, the SYNAPSE model conceptualizes it as a dynamic interplay of attentional activation, strategic adjustment, reflective regulation, and memory consolidation. The empirical observations across phases confirm this non-linear, interdependent architecture and highlight several key contributions to the science of learning, teacher education, and the ethical design of educational AI.

From a learning sciences perspective, the results reinforce long-standing theoretical principles while offering novel insights into their phase-specific application in AI-mediated contexts. The short-lived attentional responses observed in the activation phase underscore that emotional salience alone does not suffice to sustain engagement. Without a task structure or elaboration demand, even the most compelling stimuli lose their pedagogical power (Dehaene, 2018; Mayer, 2014). This confirms that attention is necessary but not sufficient for meaningful learning and must be converted into cognitive effort through task design and teacher orchestration.

The adaptation phase revealed that adaptive feedback can support metacognitive growth, but only if learners are explicitly trained to interpret and act upon it. These findings align with research on formative feedback (Aleven et al., 2016; Koedinger & Aleven, 2007) and confirm that AI feedback systems must be situated within instructional strategies that promote strategic reflection. Similarly, the participation phase demonstrated that dashboards and metacognitive tools are most effective when learners are already familiar with goal-setting, planning, and reflective practices (Kay et al., 2022; Winne & Hadwin, 2008). This reinforces the idea that technological tools can amplify—but do not originate—regulatory capacities.

The studies also confirmed the diversity of learner profiles, even within relatively homogeneous classroom settings. Some students adopted exploratory, self-regulated approaches, while others relied passively on system prompts or dismissed the tools altogether. These differences appear to be shaped less by the technical quality of the AI tools and more by learners' prior experience with autonomy, feedback, and reflection, as well as the pedagogical framing offered by the teacher. This finding supports motivation theory, particularly Self-Determination Theory (Deci & Ryan, 2000), which emphasizes the interplay between competence, autonomy, and relatedness as drivers of engagement and persistence.

For teacher education, these findings carry urgent implications. Current professional development often focuses on digital literacy or tool mastery, yet neglects the deeper pedagogical and motivational orchestration required for AI to truly enhance learning (Dogan et al., 2025; Fu & Weng, 2024). The SYNAPSE model offers a structure for phase-specific teacher training, where educators learn to diagnose where learners are in the cognitive process, select or adapt tools accordingly, and scaffold their use through modeling, questioning, and ethical reflection.

For example, in the activation phase, teachers can learn to combine emotionally salient stimuli with guided inquiry or prediction tasks, transforming initial curiosity into cognitive exploration. During strategic adaptation, they can model how to read and respond to feedback by verbalizing thinking processes, encouraging hypothesis testing, and gradually removing supports. In the participation phase, teachers can integrate dashboards into goal-setting routines, linking indicators to strategy revision and metacognitive prompts. Rather than using AI tools in isolation, educators trained through the SYNAPSE framework become orchestrators of a co-regulated learning ecology, where tools, students, and pedagogical intentions are aligned.

Finally, the studies highlight the ethical stakes of AI integration. In each phase, the risk of over-automation emerged as a recurrent theme. Whether through uncritical acceptance of algorithmic suggestions, dependence on hints, or instrumental dashboard use, learners showed a tendency to outsource cognitive effort when the technology allowed it. These patterns underscore the need for ethical safeguards in AI design, such as transparent feedback explanations (Holstein et al., 2019), intelligent fading of scaffolds (Roll & Winne, 2015), and personalized levels of tool autonomy. Educational technologies must be designed not only for effectiveness, but also for cognitive emancipation, preserving learners' capacity for judgment, reflection, and agency.

The SYNAPSE model thus contributes to the ongoing discourse on human-centered AI in education by offering both a theoretical architecture and a practical framework for design and implementation. By articulating learning in phases linked to cognitive functions, motivational drivers, and self-regulatory practices, the model enables a more granular, developmentally sensitive use of technology. It shifts the conversation from whether AI works to how, when, and for whom it works—and under what pedagogical and ethical conditions it should be deployed.

In doing so, SYNAPSE positions AI not as an autonomous accelerator of learning, but as a reflexive partner—an artifact to be interpreted, mediated, and integrated into meaningful educational practice.

6. Practical Implications and Recommendations

The SYNAPSE model offers more than a descriptive framework for understanding learning in AI-enhanced contexts; it also serves as a practical guide for educators, developers, and policymakers seeking to align technological integration with cognitive and motivational principles. The results of the three exploratory studies provide phase-specific insights into how tools can support— or undermine—learning processes, depending on how they are designed and mediated.

This study underscores three central contributions to the field of teacher education in the era of AI-enhanced learning: (1) the necessity of pedagogical mediation, (2) the critical importance of scaffolding learners' metacognition and autonomy, and (3) the role of collaborative, design-based approaches in sustaining responsible, context-sensitive AI integration.

6.1 The Centrality of Pedagogical Mediation

The findings consistently highlight that the effectiveness of AI tools depends less on their technological sophistication than on the quality and intentionality of their pedagogical orchestration. Teachers shape the purposes, boundaries, and instructional framing that turn AI from a passive content provider into an active catalyst for deep learning (Holstein et al., 2019; Luckin, 2018). For instance, throughout the three studies, sustained learner engagement and meaningful use of dashboards or feedback systems were only observed in classrooms where teachers explicitly modeled strategic tool use, posed metacognitive questions, and provided opportunities for dialogue around the technology's role in learning.
Teacher preparation programs should prioritize the development of skills for designing, mediating, and critically evaluating AI technologies—not merely operating them. This extends to modeling adaptive tool use, fostering reflective classroom dialogues about AI's strengths and limitations, and developing routines for integrating digital feedback into ongoing formative assessment (Koedinger & Aleven, 2007; Dehaene, 2018).

6.2 Scaffolding for Metacognition and Learner Autonomy

The SYNAPSE study demonstrates that meaningful appropriation of AI requires students to have internalized metacognitive routines—such as goal setting, self-monitoring, and strategy revision—that cannot be left to digital systems alone (Zimmerman, 2018; Efklides, 2006). Teachers' roles in explicitly teaching, modeling, and scaffolding these routines emerged as decisive for fostering strategic, reflective tool use and for preventing superficial or "checklist" engagement, as mirrored in dashboard and feedback studies (Kay, Leung, & Reilly, 2022; Lee, Park, & Lodge, 2023).

Professional development should provide educators with concrete frameworks (such as SYNAPSE) and practical examples for teaching metacognitive strategies in tandem with AI integration. Furthermore, PD should support teachers in designing scaffolded "fading" plans so that digital supports decrease as students gain confidence—a key for building autonomy and avoiding automation bias (Bjork & Bjork, 2022; Roll & Winne, 2015).

6.3 Collaborative, Context-Sensitive AI Integration

Finally, the co-design model adopted in this research, characterized by iterative teacher–researcher partnership, proved fundamental for tailoring AI tools to real classroom needs and for aligning technological affordances with learning goals (Anderson & Shattuck, 2012). This approach echoes calls in the literature for design-based research as a means to bridge the perennial gap between emerging technologies and classroom realities (Barab & Squire, 2004; Design-Based Research Collective, 2003).

Continuous professional development—embedded within professional learning communities and supported by ongoing collaboration with researchers or digital learning specialists—should become the norm. Teacher education programs should also offer opportunities for pre-service and in-service teachers to engage in co-design cycles, develop digital agency, and cultivate an ethical, critical stance towards AI adoption (Glikson & Woolley, 2020; Fu & Weng, 2024).

In summary, the SYNAPSE model equips teacher education programs with a dual roadmap: first, as a diagnostic tool for critically analyzing learners' digital practices; second, as a prescriptive guide for embedding metacognitive, ethical, and motivational principles in technology-enhanced instruction. To realize the true promise of AI in education, teacher professional development must go beyond technical training to foster pedagogical expertise, reflective judgment, and a collaborative ethic that keeps human learning and motivation at the center of innovation1.

This synthesis (Figure 2) retains your core findings and amplifies them per internationally recognized best practices for scientific publication. If you wish to enrich further with case examples, rubrics for teacher training, or policy recommendations, these can be added.

Figure 6 Teachers Practices

SYNAPSE Phase	Objective of teacher training	Suggested practices
Phase 1 **Sensory Input**	Learn to design multimodal prompts and experiences that arouse emotion and curiosity.	Use surprise, questions or contrast to arouse attention; Co-create opening scenarios with students; Introduce emotional relevance from the outset.
Phase 2 **Network Adaptation**	Guide learners in interpreting feedback and adjusting strategies.	Model scaffolding erasure; Create reflective routines (*What would you try next?*); Encourage Creativity *(Try it differently)* Practice, practice, practice…
Phase 3 **Participation**	Encourage goal-setting, monitoring and dashboard awareness.	Train students to formulate SMART goals; Interpret trend graphs; Encourage verbalization of strategy changes, of choices, of planification… Design weekly metacognitive checks.
Phase 4 **Storage &** **Embodiment**	Promote long-term retention and meaningful application.	Program spaced retrieval; Combine digital recall with physical rehearsal or creative expression; Encourage transfer tasks.

7. Conclusion and Future Research

This study has introduced and empirically validated the SYNAPSE model, a four-phase framework guiding the integration of artificial intelligence (AI) into education while respecting cognitive, motivational, and ethical imperatives. The evidence from three qualitative studies demonstrates that the impact of AI in learning environments depends fundamentally on the pedagogical orchestration provided by teachers, the scaffolding of metacognitive skills, and the creation of collaborative partnerships. However, these results also reveal that the rise of AI presents educators with unfamiliar challenges and opportunities—demanding not just technical skills, but the development of new professional competences.

7.1 Key contributions and implications

For educators, the SYNAPSE model is both a practical analytic lens and a curriculum design guide. Yet, the findings make clear that meaningful use of AI tools requires much more than surface-level familiarity: teachers need explicit guidance and sustained, context-sensitive training to adopt new pedagogical routines and mindsets. The advent of AI is transforming teaching into a new profession—one where the educator must master not only subject matter and generic pedagogy, but also the mediation, ethical evaluation, and critical use of digital technologies.

Contemporary teachers become "AI-enhanced learning orchestrators," blending technological fluency with reflective judgment and ethical stewardship. This necessitates continual professional development formats that go beyond one-off workshops, integrating mentoring, co-design, and communities of practice.

For developers, the research substantiates the need to co-design AI solutions with educators and to create intuitive, transparent interfaces that support—not supplant—professional agency. Tools should include built-in guidance and support for both teachers and students, embodying scaffolds that can be gradually faded to promote autonomy and skill transfer.

For policymakers, the SYNAPSE model offers both an evaluative and developmental toolkit, highlighting the urgent need for investment in teacher preparedness. This includes recognizing and supporting the emergence of new teaching roles at the crossroads of pedagogy and technology, and enshrining teacher voice and leadership in all stages of AI adoption.

7.2 Concrete Recommendations

For Research:

Future work should investigate longitudinal teacher development trajectories in AI-rich environments, examining how professional identity and practices evolve as teachers acquire new digital mediation skills.

Research should develop and evaluate model-based training pathways that help teachers integrate metacognitive and ethical competences into their instructional repertoire.

Comparative studies across educational systems should analyze how local contexts shape the recognition and support of this new profession.

For Practice:

Teacher education programs should embed modules specifically focused on AI literacy, digital ethics, and orchestration strategies, supported by mentorship and peer feedback.

School leadership should facilitate continuous, collaborative professional learning communities, where teachers co-develop lesson sequences with technologists and researchers, and are recognized as expert designers of AI-enhanced pedagogy.

Development and sharing of toolkits, reflective protocols, and case studies enable teachers to document, analyze, and refine their practices as "AI educators."

For Policy:

Policy frameworks should valorize the teaching profession's new competences by updating standards of digital proficiency, including curricular requirements for AI mediation, metacognitive scaffolding, and ethical reasoning.

Investment should prioritize scalable, context-adaptive professional development schemes that are iterative and co-constructed—not transactional or top-down.

Policies must ensure that the voice of educators is central in procurement, evaluation, and scaling decisions related to AI tools in education.

7.3 Methodological Directions for Future Studies

To further operationalize these recommendations, future research should:

- Utilize mixed-methods and participatory approaches to capture shifts in teachers' professional self-perception and instructional design practices over time.
- Experiment with design-based interventions pairing novice and expert teachers as co-learners and co-researchers in AI-rich settings.
- Evaluate not just student outcomes, but also teachers' sense of efficacy, ethical comfort, and perceived agency as key metrics of successful AI integration.
- Foster international collaborations to adapt training and policy frameworks to diverse cultural and institutional realities.

In conclusion, integrating AI into education is transforming the teaching profession itself. The SYNAPSE model calls not just for new tools, but for a systemic reimagining of teacher preparation, professional development, and policy support. Empowering educators to become confident, reflective, and ethical orchestrators of AI-enhanced learning is not optional, but essential, if the transformative promise of AI is to be realized in ways that amplify—and never diminish—the human core of education.

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APPENDIX A :

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