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Design an adaptive e-learning environment based on personalized factors and its impact on the development of students' metacognitive thinking skills

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Introduction: Modern e-learning platforms are increasingly using personalized elements to better address diverse learners and enhance learning outcomes. To investigate the effects on the development of students' metacognitive thinking, this study develops an adaptive e-learning environment based on two personalized factors: learning styles and knowledge levels.
Methods: The study, which used a quasi-experimental design with undergraduate students, revealed that there was no obvious effect on metacognitive growth when content was personalized for learning styles.
Results: This reflects the increasing concern among academics about the usefulness of learning styles in personalized learning. On the other hand, metacognitive engagement was found to be strongly influenced by prior knowledge.
Discussion: The findings imply a shift to evidence-based adaptive design, arguing that to successfully promote higher-order cognitive abilities, e-learning environments should give priority to empirically verified factors like knowledge expertise.

KEYWORDS

adaptive learning, e-learning, learning styles, metacognitive thinking, personalized learning

1 Introduction

Adaptive e-learning has emerged as a response to the limitations of one-size-fits-all instruction, aiming to accommodate the heterogeneity of learners' needs, preferences, interests, and pacing. Contemporary systems increasingly allow students to shape their own learning trajectories, and empirical work reports that such adaptive online environments can improve performance and overall learning effectiveness when they meaningfully tailor experiences to individual learners (Abbasi et al., 2021; El-Sabagh, 2021; Wu, 2022). Yet, a critical reading of the literature reveals that much of this work operationalizes personalization primarily at the cognitive level—adjusting content difficulty, sequencing, or modality—while giving comparatively less systematic attention to learners' metacognitive profiles and the intentional cultivation of metacognitive thinking skills (Andrini, 2023; Burin et al., 2020; Saadati et al., 2023).

Although adaptive e-learning is recognized as a scalable and economical method of improving learning, some students experience environments that are not in accordance with their needs—either too challenging or too simple; this leads to less than optimal engagement and advancement (Charbonneau-Gowdy et al., 2023; Ismailoff, 2023; Ou, 2024; Schlagheck and Schewe, 2023). Research consistently indicates motivation and engagement increase when adaptive systems more closely reflect learners' characteristics. This indicates that personalization can support learning if its underlying design is theoretically sound and carefully executed (Alam, 2021; El-Sabagh, 2021; Gligorea et al., 2023). However, cognitive matching continues to be prioritized over systematic assistance for metacognitive development in many published implementations.

In the meantime, research on higher education indicate that in increasingly complex, technologically advanced academic environments, metacognitive skills—the ability to plan, monitoring, and assessing one's own learning—are becoming essential (Alias and Sulaiman, 2017; Rhodes, 2019). Many universities are responding to the correlation between the development of metacognitive thinking and observable improvements in academic performance by integrating formative assessment and online learning into their courses (Amin et al., 2020; Llacuna, 2023; Nusantari et al., 2021). According to El-Sabagh (2021), Gligorea et al. (2023), and Raj and Renumol (2022), adaptive e-learning environments that track learners' behaviors and integrate individual characteristics are therefore well-positioned to do more than just react to actions; if metacognition is treated as a central design target rather than a secondary by-product, they can be designed to purposefully foster self-regulation and personalized learning skills.

Within this broader context, personalization is often framed around learning styles and learner requirements, reflecting the view that students enrolled in the same course may still need different content formats, supports, and pacing (Grubišić et al., 2015). Adaptive learning environments—often implemented via learning management systems and related tools—are intended to move beyond static content delivery by dynamically adjusting instruction based on learner preferences or styles. Yet, reviews note that current systems tend to exploit communication technologies effectively for distributing materials but less effectively for responding intelligently to individual actions and perceived needs (Shemshack and Spector, 2021). Moreover, the concept of personalized learning itself remains under-defined; it frequently functions as an umbrella label for diverse strategies that seek to respect individual abilities, prior knowledge, and needs, without a consistent theoretical or operational core (Schmid and Petko, 2019). This lack of conceptual clarity contributes to fragmented practices and makes it harder to design and evaluate interventions that robustly integrate cognitive and metacognitive dimensions.

However, research on metacognition indicates a substantial research gap. Conceptual frameworks and empirical research on learners' metacognition in technology-enhanced environments are still comparatively weak, even though metacognition is widely recognized as essential for effective teaching and learning, particularly through intentional and reflective thinking (Haukås et al., 2018). Although adaptive systems have advanced technically, theory-driven research on how these systems might methodically foster metacognitive abilities has lagged practice. Instead of supposing that personalization will automatically promote metacognition, this gap indicates an opportunity—and a need—for research that clearly links personalization mechanisms (such as adaptation to learning styles and prior knowledge) with metacognitive results.

Considering this, the present study sets itself in the framework of metacognitive skills, personalized learning factors, and adaptive e-learning. It addresses the following question: How do students' metacognitive skills grow in an adaptive learning environment that is built around individual criteria like learning styles and knowledge levels? Two sub-research questions were generated from this main question as follow.

RQ1: What instructional design framework can be developed for an adaptive learning environment that incorporates personalization factors (learning styles and knowledge levels) to enhance students' metacognitive skills?

RQ2: What is the impact of implementing such an adaptive learning environment on the development of students' metacognitive skills?

Research Hypotheses:

The research aims to verify the validity of the following hypotheses:

H1: An adaptive e-learning environment incorporating personalized factors (learning styles) will have a positive impact on the development of metacognitive thinking skills among students.

H2: An adaptive e-learning environment incorporating personalized factors (knowledge levels) will have a positive impact on the development of metacognitive thinking skills among students.

To address the research problem, the current research compares the impact of an adaptive e-learning environment based on knowledge levels to another based on learning styles to examine how students' metacognitive thinking skills are developed. Consequently, the study thus aims both to design and develop an adaptive e-learning environment targeted at metacognitive skill development and to explore how prior knowledge and learning style parameters interact within that environment to outline learners' metacognitive skills.

2 Literature review

The growing body of research on adaptive e-learning environments highlights the significance of personalization based on learner characteristics that are empirically supported. Prior knowledge and self-regulated learning behaviors are examples of further evidence-based variables that are stronger predictors of learning success than traditional personalization models, which have frequently depended on learning styles.

2.1 Adaptive e-learning environments

According to the literature, adaptive e-learning environments comprise intricate digital systems that apply technological pedagogical content knowledge by combining learner monitoring, assessment, feedback, and content management to provide personalized instruction (Kem, 2022; Martin et al., 2020; Muñoz et al., 2022). These environments, as compared to providing static materials, continuously collect and analyse learner data to optimize the type, difficulty, and sequencing of content (El-Sabagh, 2021; Gligorea et al., 2023; Kaouni et al., 2023). From a theoretical view, this reveals adaptive e-learning as a practical representation of personalized learning: an active attempt to create educational experiences that are sensitive to each learner's needs rather than depending on standardized instruction (Aggarwal, 2023; Sibley et al., 2024).

According to Essa et al. (2023) and Gligorea et al. (2023), the theoretical basis of these systems typically belongs within personalized e-learning, where learner characteristics—such as cognitive skills, learning preferences, and motivation—serve as essential criteria for adaptation. Previous research emphasizes that students actively develop comprehension by their own thinking, reflection, and regulation rather than just receiving information, emphasizing metacognition as a key concept. Instructors can create assignments and resources that support the adaptive system to better outfit each student's needs when they have knowledge about their cognitive and metacognitive profiles (Hasanuddin, 2021; Ramírez-Montoya et al., 2021; Schipper et al., 2020).

Personalized learning and instructor replacement are clearly defined in this literature. While instructors are still in charge of planning lessons, and offering psychological support, adaptive e-learning serves as a further mechanism that helps lead students toward autonomy by creating personalized pathways and feedback (El-Sabagh, 2021; Kem, 2022). To maintain motivation, many systems modify learning settings by continuously evaluating performance.

The variety of personalization elements employed in adaptive systems is the subject of a further significant body of research. In addition to performance data, research indicates that factors that affect how learners process information and feel cognitive load include learning style, prior knowledge, cognitive learning style, motivation, and emotional assessment styles (Shemshack and Kinshuk, 2021; Alamri et al., 2020). This theoretical framework presents flexible learning styles as tools for controlling perceived challenges and cognitive load (Darling-Aduana et al., 2022; Ji et al., 2022). According to a variety of practical research, learning style assessments are used by adaptive platforms to guide content modification and to promote engagement and achievement (Graf et al., 2010).

The empirical foundations of learning style-based customization are explicitly challenged by more current and critical studies. The importance of learning styles in adaptive design is called into question by reviews by Pashler et al. (2008) and Coffield et al. (2004), which emphasize the lack of evidence that matching instructional strategies with assessed learning styles consistently improves learning outcomes. Learning styles are now viewed as one of several potentially helpful indicators of learner variability rather than the main factor influencing adaptation because of this criticism.

Adaptive systems based on models such as Kolb and Felder-Silverman revealed that personalization is both pedagogically promising and technically possible, particularly when it comes to user satisfaction (Graf et al., 2010). However, the matching hypothesis's weak empirical support suggests that depending on learning styles increases the risk of oversimplifying learner diversity like prior knowledge and metacognitive regulation (Pashler et al., 2008; Coffield et al., 2004).

Future research and development on adaptive e-learning should (a) provide empirical and theoretical reasoning for the personalization variables selection; (b) treat learning styles as a supplement rather than a main factor; and (c) test how combinations of variables, such as prior knowledge and the use of metacognitive strategies, affect learning outcomes. This approach maintains the subtle nature of learner diversity, takes adaptive e-learning closer to evidence-based practice, and presents personalization as diverse.

2.2 Personalized learning factors

According to the research, there is still insufficient consensus on the implementation models of personalized learning in e-learning (Abhirami and Devi, 2022; Bennani et al., 2020; Mustafa, 2021). According to Behera et al. (2020), Ghanim (2024), and Omopariola et al. (2023), personalization is generally defined as the methodical adaptation of content, sequencing, and pedagogical strategies to align with the characteristics of an individual learner rather than applying a uniform instructional pathway to all students. In technology-enhanced environments, personalization is positioned as both a design principle and an ongoing decision-making process. This usually entails diagnostic procedures—such as profiling learner attributes or needs—as well as the creation of customized programs, feedback, and recommendations (Behera et al., 2020; Omopariola et al., 2023). However, certain researchers argue that while personalization has emerged as an important concept in discussion and technology design, it received relatively little empirical attention in educational research, leading to confusion about concepts across research (FitzGerald et al., 2018).

A more consistent conceptual basis is provided by several works that specifically connect customized learning elements to well-established learning theories as shown in Table 1. Constructivist perspectives, for instance, stress that knowledge is actively created through experience interaction. According to this perspective, prior knowledge becomes a crucial personalization factor since it serves as the foundation for new learning, directing how adaptive systems determine readiness and distinguish between different levels of content difficulty (Cheung et al., 2021; Tapalova et al., 2022). The design of diverse learning paths and activities that appeal to various ways of engaging with experience is supported by the experiential learning theory, which emphasizes learning as a cycle of experience and reflection. In the same way, metacognitive theory emphasizes students' knowledge of and control over their own thought processes, suggesting that adaptive systems can and need to include elements that encourage introspection, self-evaluation, and tactical modification. When combined, these theoretical perspectives imply that personalized e-learning elements—like prior experience, metacognitive skills, and self-control—are based

TABLE 1 Linking personalized factors to learning theories.

Theory	Key concept	Relevance to personalized factors
Constructivism (Piaget, Vygotsky)	Knowledge is constructed through experience and social interaction	Prior knowledge forms a scaffold for adaptive learning
Experiential Learning Theory (Kolb)	Learning through experience and reflection	Informs the design of varied learning paths
Self-Regulated Learning Theory (Zimmerman)	Learners monitor and control their learning processes	Directly connects to metacognitive skill development
Metacognitive Theory (Flavell)	Awareness and regulation of one's own thinking	Adaptive systems can promote reflection and self-monitoring

on strong theories of how learning occurs rather than being random variables.

Based on these theoretical foundations, recent research emphasizes that while developing individualized educational paths, effective customization necessitates careful evaluation of learners' strengths, limitations, skills, and preferences (Cheung et al., 2021; Tapalova et al., 2022). Meaningful adaptive design is based on personal needs rather than just demographic or performance data, according to empirical data from online surveys of e-learning consumers (Arsovic and Stefanovic, 2020; El-Sabagh, 2021; Gligorea et al., 2023). Personality traits, learning preferences as well as styles, self-assessed competency, study habits, and expectations about the course and institution are all considered "personal needs" in this context. According to the literature, learners are better able to interact with personalized approaches and understand adaptive feedback when they are assisted in expressing their requirements.

Another popular argument is that determining one's own learning needs can act as a metacognitive intervention. According to Arsovic and Stefanovic (2020) and Madden et al. (2020), informal self-assessment tools—such as reflective questionnaires, checklists, or self-rating scales—are techniques that assist students in developing self-awareness about how they learn, what they find challenging, and what they anticipate from instruction. These resources are linked to the development of reflective learning, which are seen by educators as essential characteristics of successful students. From a critical perspective, this presents personalization as a learner-cantered process where students co-create their learning profiles through reflection and self-report, rather than just an external system function.

Additionally, the literature argues for a deeper and comprehensive understanding of personalization that overcomes a limited emphasis on learner characteristics or surface content modification. Personalized e-learning environments should be conceptualized along several axes, according to several authors (Shemshack and Spector, 2020; Walkington and Bernacki, 2020). These axes include: (a) learner characteristics (e.g., prior knowledge, motivation, preferences); (b) learning processes (e.g., self-regulation, metacognitive monitoring); (c) educational objectives (e.g., conceptual understanding, skill acquisition, metacognitive development); and (d) features of the instructional content (e.g., complexity, modality, authenticity). According to this framework, personalization is a set of design choices and system behaviors that should be aligned with clear learning goals rather than just one approach.

The present body of research on personalized learning elements has both strengths and shortcomings when these contributions are critically synthesized. Certainly, there is increasing agreement that personalization should emphasize learner activity and metacognition rather than treating students as passive recipients of personalized content and should be theoretically grounded, especially in constructivist, experiential, and self-regulated learning frameworks (Cheung et al., 2021; Madden et al., 2020; Shemshack and Spector, 2020). A change from entirely system-driven adaptation to more participatory models of personalization, where students actively decide their learning paths, is reflected in the emphasis on needs assessment and self-reflection (Arsovic and Stefanovic, 2020; Gligorea et al., 2023). However, the literature also highlights several shortcomings. First, empirical research on the real effects of various personalized factors—like learning style, personality, or emotional tendencies—on learning outcomes is still inconsistent, with some variables having stronger support than others, despite policy enthusiasm and design innovations (Abhirami and Devi, 2022; FitzGerald et al., 2018). Second, rather than looking at how personalization elements interact (e.g., how prior knowledge and self-regulation together influence the efficiency of adaptive pathways), many studies consider personalization factors separately. Third, there is still no agreement on how to implement important concepts (such as "personal needs" or "reflective learner") in ways that are both practically and theoretically feasible in adaptive systems.

Future research on personalized learning factors should shift toward integrated, theory-informed models that incorporate many learner characteristics and processes. According to Shemshack and Spector (2020) and Walkington and Bernacki (2020), such models would provide a more cohesive basis for creating and assessing customized e-learning environments by ideally aligning diagnostic processes, system modifications, and metacognitive supports with clearly stated learning theories and objectives.

2.3 Metacognitive thinking skills

The literature generally describes metacognitive thinking skills as higher order processes that go beyond basic cognition, which concentrates on learning through thinking and experience, and allow students to supervise, direct, and improve their own learning (Negi et al., 2022). To choose, modify, or give up strategies as necessary, metacognition includes active awareness of one's own mental processes, active monitoring of comprehension and performance, and evaluation of cognitive activity (Negi et al., 2022). The concept that metacognition serves as a mediating mechanism between instructional design, adaptive responses, and knowledge acquisition is supported by empirical research that highlights the role of metacognitive strategies, and cognitive engagement as strong predictors of academic achievement (Hayat et al., 2020; Yelgeç and Dagyar, 2020).

According to this perspective, metacognitive experiences are instances when students become aware of their cognitive states while solving problems or completing assignments, whereas metacognitive knowledge consists of beliefs about other learners, comprehension of tasks and strategies, and insight into how these components interact to shape learning outcomes (Flavell, 1979). Much of the current research on metacognitive instruction is based on the early work of Flavell (1979), which argued that more systematic efforts were required to teach metacognitive knowledge and monitoring skills and to explain the sometimes-unexpected developmental patterns observed in this domain.

Further research highlights individual perceptions of and reflections on their own mental processes, further refining metacognition as a "feeling of cognition" (Drigas and Mitsea, 2020; Fleur et al., 2021; Wu, 2022). According to this perspective, metacognitive learners are those who approach learning with complete responsibility and perception; they realize their schemes while learning in response to feedback from their own performance (Drigas and Mitsea, 2020; Fleur et al., 2021; Hamzah et al., 2022).

Metacognition has been identified as an essential feature of successful learners in evolving knowledge societies where individuals cannot predict which content will be important in the future because it is closely related to learning how to learn and to the development of self-awareness (Drigas and Mitsea, 2020; Negi et al., 2022). Highly significant higher order skills that influence how students tackle challenging tasks are metacognitive thinking, regulation, and evaluation (Hamzah et al., 2022; Llacuna, 2023; Mohseni et al., 2020). Because it enables instructors to create learning activities that specifically target planning, monitoring, and reflection rather than just content recall, fostering a deeper understanding of the principles and processes of metacognitive thinking is seen as a foundation for developing higher order instructional methods (Hamzah et al., 2022; Llacuna, 2023).

Since digital platforms can incorporate tools, and analytics that encourage learners to control their cognitive processes, assess their strategies, and regulate their efforts, an increasing body of research suggests that e-learning environments are particularly appropriate contexts for developing metacognitive skills (Elekaei et al., 2020; Gupta and Bamel, 2023; Mardiah, 2022). As students progressively accept on greater responsibility for organizing and directing their own learning, metacognitive activities—such as self-evaluation, goal setting, or reflection on progress—are also associated with the development of self-directed learning in personalized e-learning environments (Gupta and Bamel, 2023; Mardiah, 2022). The claim that metacognition enhances learning efficiency and positively impacts learning paths is supported by empirical research, but it also emphasizes that these advantages are subject upon learners having knowledge about their own cognitive processes (Antonio and Prudente, 2022; Schneider et al., 2022). However, other researchers point out that even as they interact in practice, many metacognitive elements—such as information, experiences, and regulating processes—can be analytically differentiated and may function rather independently (Ramadhanti and Yanda, 2021).

The literature argues that metacognition must be carefully defined as a cognitive process connected to learning, to create and validate models that specifically foster metacognitive thinking skills (Lumpkin, 2020; Rivas et al., 2022). According to this perspective, effective problem solving requires both metacognitive control and cognitive knowledge (Lumpkin, 2020; Rivas et al., 2022). Mastering metacognitive tasks facilitates learners' initial comprehension of task needs, and as they gain experience, they become more capable (Rivas et al., 2022; Lumpkin, 2020).

Several significant issues belong to the literature. First, given the variability of future knowledge demands, metacognition is not just an abstract theoretical construct; it is closely related to practical skills of planning, monitoring, evaluation, and regulation that can and should be taught (Drigas and Mitsea, 2020; Negi et al., 2022). Second, it is becoming more widely accepted that metacognitive training works effectively in technology-rich, individualized e-learning settings where digital tools may support self-directed learning, scaffold awareness, and offer feedback (Elekaei et al., 2020; Gupta and Bamel, 2023; Mardiah, 2022).Third, research indicates that effective models should treat metacognitive regulation (the continuous control of cognitive activity) and metacognitive knowledge (about tasks, strategies, and self) as separate but related targets for intervention (Ramadhanti and Yanda, 2021; Rivas et al., 2022).

In conclusion, the review suggests that future research should keep improving strategies for developing metacognitive skills directly, incorporating them systematically into curricula and e-learning designs, and analyzing how they interact with other important factors like motivation, prior knowledge, and self-efficacy to influence learning outcomes (Antonio and Prudente, 2022; Schneider et al., 2022).

2.4 Learning theories of adaptive e-learning environments

Learning theories that highlight the limitations of human cognition and the necessity of matching instructional design to learners' processing capacities serve as the foundation for adaptive e-learning environments. The key concept here is cognitive load theory (CLT), which makes a difference between extraneous load (unnecessary requirements imposed by presentation), and intrinsic load (inherent task difficulty). Minimum cognitive levels of entry (MCLEs), which indicate a learner's baseline ability to access and benefit from content, and cognitive accessibility profiles, which capture how challenging specific training materials may be for various learners, are concepts introduced by CLT-based research in e-learning (Klepsch and Seufert, 2020; Skulmowski and Xu, 2022). Adaptive design within this framework requires careful adjustment of instructional pace and content flow. Instructors and system designers must continuously assess the cognitive demands placed on students, which struggles that how information is presented can either help learning (Buchner et al., 2022; Szulewski et al., 2021). Materials that are too complicated causing cognitive overload, which reduces engagement. Therefore, reliable diagnostic evaluations of learner performance, and prior knowledge are regarded as necessary conditions for successfully controlling cognitive load. These diagnostics let adaptive e-learning make decisions on how to organize modules such that relevant load is promoted and intrinsic load is manageable, as well as when to enhance challenge and simplify content.

By emphasizing how students actively create knowledge through mental activity and interaction with content, constructivist theory offers a complementary foundation. According to this viewpoint, adaptive systems are more than just ways to provide content; they are settings where students can create their own unique knowledge. Key instructional decisions, such as what is taught, how it is presented, at which pace, and how learning is assessed, can be largely delegated to interactive systems due to the development of adaptive e-learning (El-Sabagh, 2021; Gligorea et al., 2023; Liu and Yu, 2023). The delivery of personalized content that reflects learners' unique characteristics, such as learning levels, learning styles, and pace of progress, is one of the main driving forces behind e-learning research, according to a regular theme in the literature (Mishra, 2023; Suhendi et al., 2021; Zajda, 2021). According to Abhirami and Devi (2022) and Arsovic and Stefanovic (2020), these systems integrate formative evaluation to personalization by using diagnostic data about each student's skills and development as the foundation for both adaptation and assessment.

Practical design strategies for adaptive e-learning are also influenced by cognitive load theory. Designing learning modules in accordance with several load types (intrinsic, extraneous, and germane) and creating materials with adaptable presentation options that may be tailored to learner needs are two crucial tasks that are emphasized (Ginting et al., 2021; Sweller, 2020). In terms of cognition, the system must consider the working memory's limited capacity, which consists of the visual and auditory subsystems, and organize data so that it may be processed and encoded into long-term memory without overloading either channel. A flexible e-learning system is one that can modify settings to suit individual cognitive profiles, maintaining effective learning experiences and preventing decreases in learning rate or outcome quality when materials are too inflexible (Abbasi et al., 2021). According to the literature, providing various learners differentiated content, pacing, or representational formats integrates cognitive flexibility in practice and aids in bridging the gap between learning loads and working memory limitations.

Subsequently, it integrates theoretical insights from constructivism and instructional design with the practical goal of improving learners' capacity to manage their cognitive resources, examining how adaptive e-learning environments impact metacognitive skills and how various learner profiles interact with these designs is regarded as a relevant and essential research direction.

3 Platform architecture overview

The Adaptive E-Learning Environment (ALEE) employs a modular, layered architecture designed to deliver personalized instruction based on learners' knowledge levels and learning styles, with the explicit goal of fostering metacognitive thinking skills in knowledge recognition, organization, and processing. This integrated system comprises four interdependent layers—User Interaction, Adaptive Learning Engine, Learning Analytics and Data Management, and Content and Resource Repository—that work continuously to diagnose learner needs, adapt instructional content and feedback, capture behavioral data, and maintain a dynamic knowledge base accessible across devices.

At the learner interface level, the platform provides intuitive dashboards that display individualized learning objectives, real-time progress indicators, and adaptive feedback alongside profile management tools that store pre-assessment results, VAK learning style preferences (visual, auditory, and kinesthetic), and interaction histories. Instructors access a dedicated console for monitoring cohort progress, reviewing metacognitive development analytics, and adjusting system parameters, ensuring that human oversight complements automated adaptation while maintaining accessibility through responsive design.

The system's intelligence resides in the Adaptive Learning Engine, which processes learner profiles and performance data to personalize content delivery and feedback. This engine cross-references knowledge levels—established through initial metacognitive scale assessments—with VAK style preferences to recommend appropriate learning objects (videos, text, quizzes) and complexity levels via rule-based adaptation algorithms. Real-time monitoring of interaction patterns triggers dynamic feedback mechanisms that deliver customized remediation for struggling learners or enrichment for advanced ones, with messaging explicitly designed to prompt metacognitive reflection on strategy use and progress. A content recommendation subsystem then generates sequenced learning paths by matching learner attributes against repository metadata, optimizing cognitive engagement and self-regulation throughout the process.

Supporting continuous adaptation, the Learning Analytics and Data Management layer captures comprehensive behavioral data—login frequency, quiz attempts, time-on-task, and navigation patterns—which the analytics engine processes to identify engagement trends, learning trajectories, and metacognitive growth patterns across knowledge recognition, organization, and processing dimensions. Automated dashboards visualize individual learner progress for self-monitoring, while detailed instructor reports enable formative assessment and targeted interventions, creating a feedback loop that informs both system adaptation and pedagogical decision-making.

The Content and Resource Repository serve as the foundational knowledge base, contain diverse learning objects (videos, interactive modules, textual resources, quizzes, reflection prompts) exactly tagged with metadata aligned to adaptive parameters, including learning outcomes, difficulty levels, media types, and specific metacognitive skill targets. A content management system empowers instructors to upload, update, and map these resources to modules or learner pathways, ensuring the repository remains current and directly responsive to personalization requirements. Figure 1 illustrates this integrated architecture, while Figure 2 details the repository structure, demonstrating how metadata-driven organization enables precise content retrieval and adaptation.

A closed-loop system that regularly enhances learning experiences to promote metacognitive development is created by

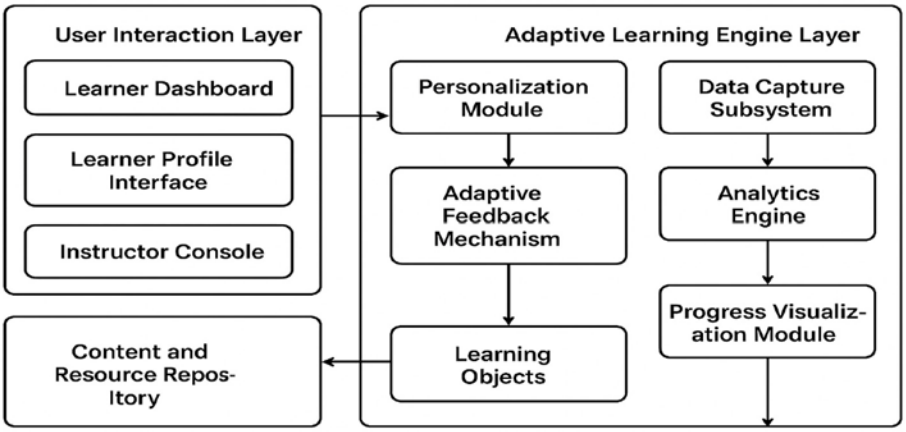

FIGURE 1
Platform architecture of adaptive e-learning environment.

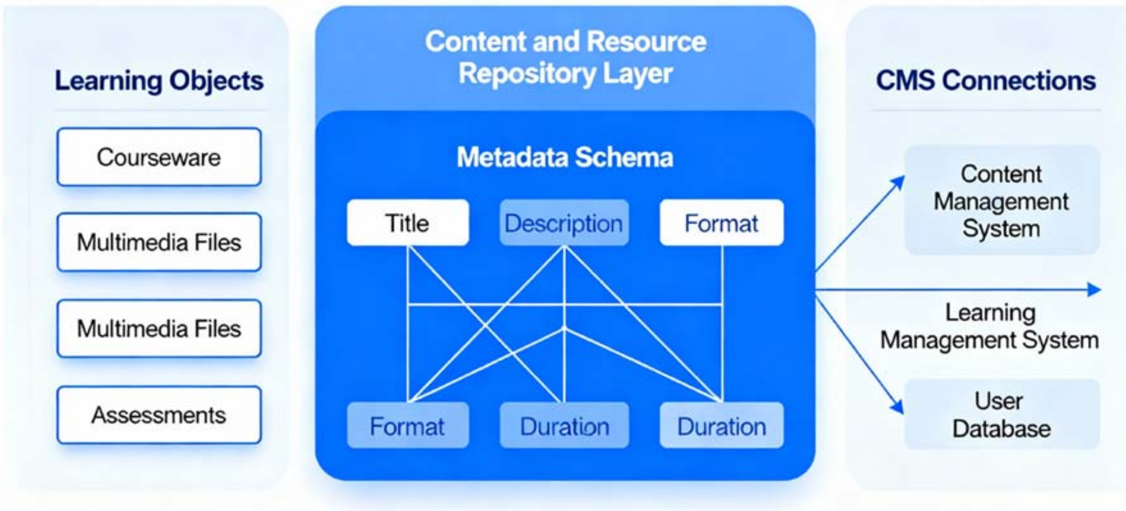

FIGURE 2
Content and resource repository layer diagram.

this integrated architecture, which guarantees smooth data flow from learner interactions through analytics and adaptation back to personalized material delivery.

4 Research methodology

4.1 Research design

This study utilized a quasi-experimental design with pre- and post-test measures to evaluate the impact of the Adaptive E-Learning Environment (ALEE) on students' metacognitive thinking skills as outlined in Table 2.

In the first experimental group (EX. G. 1), the platform dynamically adjusted learning pathways according to participants' learning styles, identified through a VAK questionnaire that recommended content formats such as visual diagrams, auditory lectures, or kinaesthetic activities. The second experimental group (EX. G. 2) received adaptation based on prior knowledge levels, determined by pre-test performance, which dictated material difficulty and instructional sequencing.

As outlined in Table 3, participants comprised 64 undergraduate students (32 male, 32 female), aged 18–19 years, randomly selected from the Multimedia and Graphics Design Program at the Applied College, Prince Sattam bin Abdulaziz University. After pre-testing with the metacognitive skills scale, participants were randomly assigned to the two experimental groups ($n = 32$ each), ensuring equivalent baseline metacognitive abilities across conditions.

TABLE 2 Research design.

Groups	Pre-measurement	Experimental treatment	Post-measurement
EX. G. 1	Metacognitive skills scale	Adaptive learning environment based on learning styles (Visual, auditory, and Kinesthetic)	Metacognitive skills scale
EX. G. 2	Metacognitive skills scale	Adaptive learning environment based on knowledge levels (low, high)	Metacognitive skills scale

TABLE 3 Sample demographic data.

Characteristic	EX. G. 1 (learning styles)	EX. G. 2 (knowledge level)	Total
Gender			
Male	16 (50%)	16 (50%)	32 (50%)
Female	16 (50%)	16 (50%)	32 (50%)
Prior knowledge			
Low	18 (56%)	18 (56%)	36 (56%)
High	14 (44%)	14 (44%)	28 (44%)
Learning styles			
Visual	9 (28%)	9 (28%)	18 (28%)
Auditory	9 (28%)	9 (28%)	18 (28%)
Kinesthetic	14 (44%)	14 (44%)	28 (44%)
Age	18–19 years	18–19 years	18–19 years

4.2 Research tools

4.2.1 The metacognitive thinking scale

The metacognitive thinking scale was systematically developed to measure three core dimensions—knowledge recognition (10 items), knowledge organization (11 items), and knowledge processing (9 items)—aligned with higher-order levels of Bloom's revised taxonomy (Appendix 1). Development began with establishing clear measurement objectives targeting cognitive aspects of metacognition, followed by creating 30 items with multiple-choice formats (A, B, C, D) arranged hierarchically from general to specific, ensuring clarity, ease of comprehension, and comprehensive coverage across Bloom's taxonomy levels. A correction key was prepared together with item formulation to standardize scoring. Content validity was established through expert review, where a group of educational technology specialists evaluated item clarity and instructional alignment, resulting in targeted revisions to phrasing and the exclusion of unclear items.

The scale demonstrated strong psychometric properties. Internal consistency reliability was confirmed with Cronbach's $\alpha = 0.893$, indicating excellent measurement stability. Item-level analysis via Pearson correlations ($n = 30$) revealed robust relationships between individual items and total scores, ranging from 0.407 to 0.904 across all dimensions (medium to large effects), with skill-specific correlations showing knowledge recognition items at 0.502–0.843, knowledge organization at 0.528–0.779, and knowledge processing at 0.632–0.900 (Table 4).

On the other hand, Inter-skill correlations with the overall scale score were closely perfect: knowledge recognition ($r = 0.961$), knowledge organization ($r = 0.922$), and knowledge processing ($r = 0.934$), confirming high construct validity per Guilford's (1956) criteria where coefficients $\geq$0.9 indicate near-perfect relationships (Table 5).

4.3 Research procedures

The research procedures followed a systematic sequence: first, metacognitive skills and educational standards were identified to inform platform design using established instructional models where The three aspects—knowledge recognition, knowledge organization, and knowledge processing—were derived from the metacognitive knowledge component of Flavell's (1979) and Anderson and Krathwohl's (2001) revised Bloom's taxonomy; second, research instruments—including the metacognitive skills scale and VAK questionnaire—were developed and validated for reliability and content validity, to verify the accuracy and appropriateness of the proposed standards, the authors developed a preliminary questionnaire and submitted it to a panel of experts in educational technology. Their feedback was used to confirm the validity of the standards. The reliability of the list was assessed using Cooper's agreement equation (Cooper, 1998). The resulting Cooper coefficient was 88.3%, indicating a high level of reliability for this type of measurement; third, the experiment was conducted over six weeks with pre/post assessments and platform usage tracking; and finally, data were analyzed using appropriate statistical techniques, including t-tests, ANOVA, and effect size calculations to determine group differences and treatment effects.

4.3.1 Design an adaptive e-learning environment based on personalized factors

The design of this adaptive e-learning environment reflects a considered shift from traditional preference-based personalization toward an evidence-based approach grounded in empirical research. While comprehensive adaptive models typically require deep analysis of learners' styles, interests, prior knowledge, and motivations to balance instructional challenge with appropriate support (Anoir et al., 2022; Amin et al., 2023; Arsovic and Stefanovic, 2020; Kaouni et al., 2023), this study prioritized prior knowledge over learning styles following critical reviews that found insufficient evidence for stylistic matching benefits (Pashler et al., 2008; Coffield et al., 2004). Recognizing the expertise reversal effect—where scaffolds beneficial for novices become counterproductive for experts—the platform used knowledge levels as the primary adaptation variable while incorporating learning styles as secondary personalization to address learners' actual cognitive capacities rather than perceived preferences, thereby fostering self-regulation, deeper comprehension, and content

TABLE 4 Pearson correlation coefficients between the score of each question, the total score of the test, and the total score of each skill of the scale ($n = 30$).

Knowledge recognition			Knowledge organization			Knowledge processing		
No.	Skill correlation	Correlation with the overall score	No.	Skill correlation	Correlation with the overall score	No.	Skill correlation	Correlation with the overall score
1	0.637	0.678	10	0.744	0.642	21	0.851	0.824
2	0.658	0.678	11	0.763	0.761	22	0.900	0.904
3	0.617	0.514	12	0.744	0.761	23	0.825	0.803
4	0.843	0.795	13	0.672	0.706	24	0.764	0.746
5	0.672	0.654	14	0.743	0.786	25	0.706	0.683
6	0.593	0.546	15	0.724	0.738	26	0.681	0.546
7	0.730	0.620	16	0.779	0.730	27	0.658	0.678
8	0.502	0.505	17	0.528	0.407	28	0.763	0.761
9	0.683	0.627	18	0.785	0.741	29	0.724	0.738
			19	0.726	0.690	30	0.632	0.554
			20	0.744	0.642			

TABLE 5 Pearson correlation coefficients between the total score for each major skill and the total score for the scale ($n = 30$).

Scale skills	Questions no.	Total degree	Correlation coefficient
Knowledge recognition	9	9	0.961
Knowledge organization	11	11	0.922
Knowledge processing	10	10	0.934

relevance through continuous evaluation and dynamic feedback mechanisms (Al-Chalabi and Hussein, 2020; Gligorea et al., 2023).

This instructional design followed the ADDIE framework through five integrated phases personalized to the Games Programming Design course within Prince Sattam bin Abdulaziz University's Multimedia and Graphics Design program, selected for students' technological proficiency and device access. The analysis phase established foundational requirements by profiling learners' characteristics, identifying metacognitive development needs from the literature review, and evaluating resource constraints favoring online delivery with modern pedagogical frameworks. Learning objectives targeted higher-order cognitive skills (analysis, synthesis, evaluation) from Anderson and Krathwohl's (2001) revised Bloom's taxonomy, aligned with course syllabi and module plans (Figure 3).

During the design phase, SMART objectives (Specific, Measurable, Achievable, Relevant, Time-bound) structured module content across three adaptive paths—learning models, processes, and evaluation—supported by detailed event boards mapping system activities, learning scenarios, objectives, materials, and experiences into operational sequences for electronic implementation (Figure 4). The production phase created multimedia assets, including content guides, custom images, audio clips, video resources, and interactive modules programmed to support metacognitive skill development through personalized data tracking.

Implementation involved professional accreditation of instructional materials through expert validation of modules, syllabi consistency, student activities, implementation skills, responses, and adaptive feedback mechanisms, with real-time behavioral modifications based on self-knowledge to optimize navigation, error correction, and learning processes (Figure 5). The evaluation phase comprised expert design review to confirm standards compliance and an exploratory experiment with 20 students to establish instrument validity and reliability coefficients prior to full deployment.

To optimize metacognitive development and engagement, this systematic, evidence-based design produced a dynamic platform that supported student independence through pace control, path investigation, and personalized experiences that relied upon prior knowledge.

4.3.2 Research experiment

The main experiment involved 64 undergraduate students who were randomly assigned to two experimental conditions after successful exploratory testing. Experimental Group 1 ($n = 32$) received adaptation based on prior knowledge levels (low/high thresholds derived from pre-tests dictating content difficulty and sequencing), while Experimental Group 2 ($n = 32$) received VAK learning style personalization (visual, auditory, kinesthetic content). Using SPSS v.22 to confirm pre-experiment equivalency, it was found that there were no significant baseline differences on the metacognitive skills scale between groups ($t = 2.259$, $p > 0.05$, Table 6: Group 1 M = 16.04, SD = 2.732; Group 2 M = 14.16, SD = 7.217), attributing subsequent performance changes to treatment effects.

During the first semester of the 2022–2023 academic year, the 6-week intervention began on October 16, 2023. Participants utilized their course on Games Programming Design to access

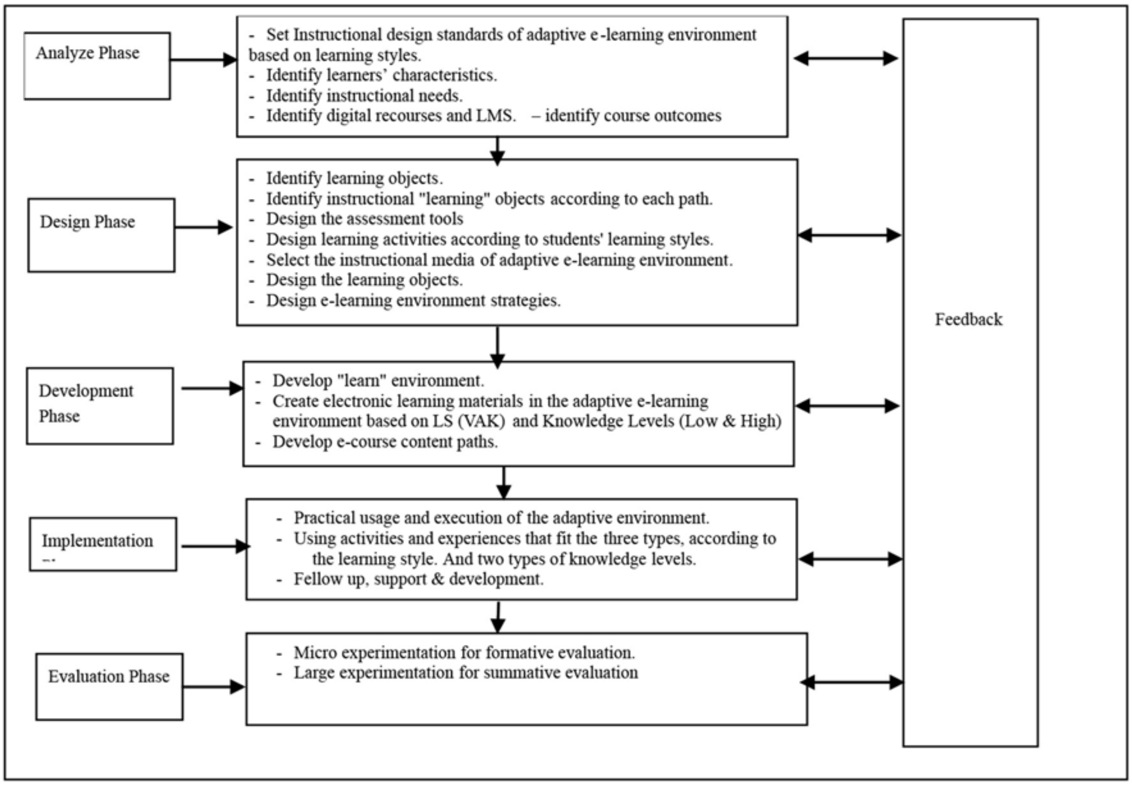

FIGURE 3
The ID (model) of the adaptive e-learning environment based on personalized factors.

the Adaptive E-Learning Environment (ALEE). To measure the development of metacognitive skills in both situations, a post-test was administered right after the intervention completed, and the experimental groups were continuously personalized during platform interactions, automatically gathered for behavioral analytics. In the environment, this measured sequence preserved validity for the environment while guaranteeing academic accuracy.

5 Results

Statistical analyses examined pre- and post-test performance across two important learner characteristics, learning styles and prior knowledge levels, to investigate variations in metacognitive thinking skills owing to adaptive e-learning customization. These analyses used extensive statistical testing and result interpretation to directly address the study objectives.

Hypothesis 1 Testing: "An adaptive e-learning environment incorporating personalized factors (learning styles) will have a positive impact on the development of knowledge organization skills among students" This hypothesis was tested by comparing pre- and post-test mean scores within the learning styles experimental group using the *Q*-value for related samples, which measures the significance of pre-post differences as outlined at Table 7.

When analyzing metacognitive thinking, the average scores for the Auditory, Kinaesthetic, and visual groups were 14.444, 14.429, and 13.444, respectively. The analysis of variance showed a value of (*P*) equal to 0.480, which indicates that there is no statistical significance for the differences between the different educational styles in this area.

In general, by analyzing the statistical values given in the table, not all the values of (*q*) reached the level of statistical significance required. This means that the learning style (whether visual, auditory, or kinaesthetic) does not significantly affect the levels of metacognitive thinking skills in the first group in the pre-measurement. Thus, it can be assumed that differences in learning styles do not lead to statistically significant differences in metacognitive thinking.

In general, by analyzing the statistical values given in the Table 8, the learning style significantly affects the skill of organizing knowledge and the overall degree of metacognitive thinking, as statistically significant differences were found in these two skills. In contrast, no statistically significant differences were found in knowledge skills over knowledge and knowledge processing skills. This suggests that the impact of learning style may be limited to some aspects of metacognitive thinking without others.

Overall, the analysis of the statistical values presented in the table indicates that learning style has a significant effect on both knowledge organization skills and the overall level of metacognitive thinking, as evidenced by the presence of statistically significant differences in these areas. In contrast, no significant differences were observed in knowledge recognition

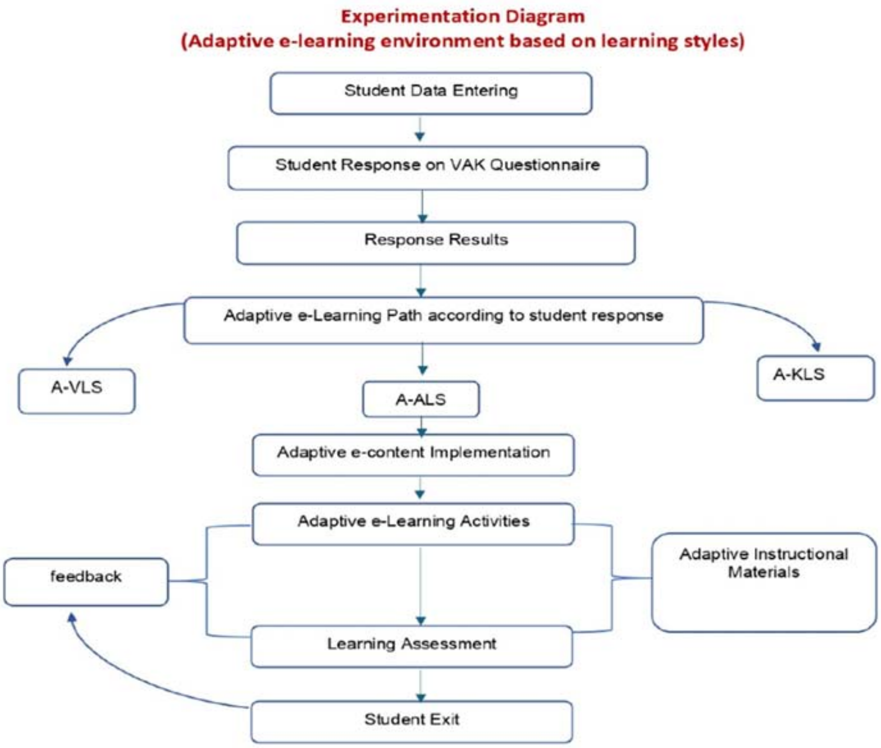

FIGURE 4
Event board for the development of the adaptive e-learning environment based on personalized factor.

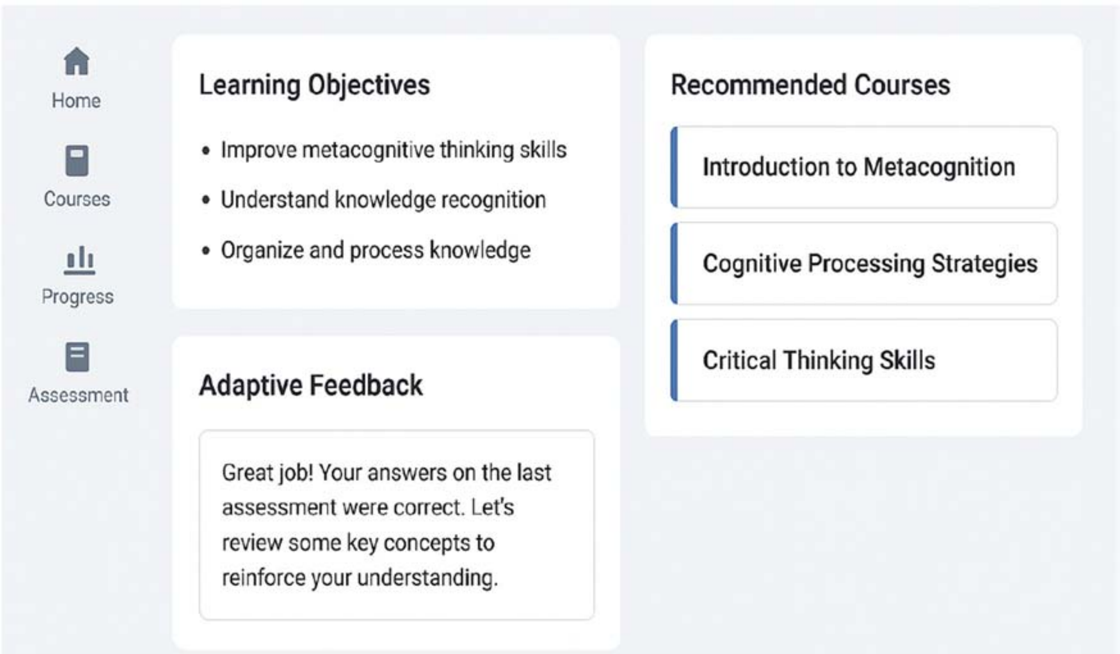

FIGURE 5
Student dashboard.

TABLE 6 Pre-application of research tools to measure group equivalence.

Application	Groups	Sample	Mean	St. dev.	T-value	Sig. level
Metacognitive skills scale	Ex. 1	32	14.16	2,259		Not sig.
	Ex. 2	32	16.04	2,732	7,217	

TABLE 7 The value of (q) to analyze the variance between the averages of the first group scores according to the learning style (visual, auditory, or kinesthetic) in the pre-measurement of metacognitive thinking.

Metacognitive skills and overall degree	Learning style	No.	Mean	Variance	Square sum	Square mean	Q	Significance
Knowledge recognition skill	Visual	9	4.222	Between groups	0.235	0.117	0.092	Not Sig.
	Auditory	9	4.333	Inside groups	36.984	1.275		
	Kinesthetic	14	4.429	Total	37.219			
Knowledge organization skill	Visual	9	5.000	Between groups	2.540	1.270	0.785	Not Sig.
	Auditory	9	5.667	Inside groups	46.929	1.618		
	Kinesthetic	14	5.071	Total	49.469			
Knowledge processing skill	Visual	9	4.222	Between groups	3.012	1.506	0.675	Not Sig.
	Auditory	9	4.444	Inside groups	64.706	2.231		
	Kinesthetic	14	4.929	Total	67.719			
Metacognitive skills	Visual	9	13.444	Between groups	6.346	3.173	0.480	Not Sig.
	Auditory	9	14.444	Inside groups	191.873	6.616		
	Kinesthetic	14	14.429	Total	198.219			

or knowledge processing skills. These findings suggest that the influence of learning style may be specific to certain dimensions of metacognitive thinking, rather than affecting all aspects equally.

In general, there are statistically significant differences between different learning styles in the skill of organizing knowledge and metacognitive thinking. The kinaesthetic style surpasses the audio and visual styles in both skills, and the auditory style surpasses the visual style in the skill of organizing knowledge and metacognitive thinking. On the other hand, there were no statistically significant differences between visual style and kinaesthetic learning style in the two skills.

The second hypothesis suggested that "An adaptive e-learning environment incorporating personalized factors (knowledge levels) will have a positive impact on the development of metacognitive skills among students." To verify the validity of the hypothesis, the average scores of the experimental group's pre- and post-evaluations on the metacognitive skills test were compared using the value of (Mann–Whitney U) for the related groups.

As revealed in Table 9, the low-level group had an average rank of 14.97, while the high-level group had an average rank of 18.46. The Mann–Whitney U-test revealed a U-value of 98.50 and a Z-value of 1.207, with a significance level of 0.227. Since this value is greater than 0.05, it indicates that there is no statistically significant difference between the two groups in terms of knowledge recognition skills.

Similarly, for knowledge organization skills, the low-level group recorded an average rank of 17.94, compared to 14.64 for the high-level group. The Mann–Whitney U-test produced a U-value of 100.00 and a Z-value of 1.031, with a significance level of 0.303. As this value also exceeds 0.05, it suggests that there is no statistically significant difference between the groups in their ability to organize knowledge. For knowledge processing skills, the low-level group had an average rank of 17.11, while the high-level group scored 15.71. The Mann–Whitney U-test results indicated a U-value of 115.00 and a Z-value of 0.437, with a significance level of 0.662. Since the significance level is greater than 0.05, this suggests that there is no statistically significant difference between the two groups regarding knowledge processing skills. Similarly, when analyzing overall metacognitive thinking, the low-level group had an average rank of 16.81, compared to 16.11 for the high-level group. The Mann–Whitney U-test produced a U-value of 120.50 and a Z-value of 0.211, with a significance level of 0.833. As this value exceeds 0.05, it can be concluded that there is no statistically significant difference between the two groups in metacognitive thinking.

Overall, the Mann–Whitney U analysis across different dimensions of metacognitive thinking indicates that there are no significant differences between students with low and high levels in the pre-measurement phase. This suggests that the varying levels do not have a substantial effect on students' degrees of metacognitive thinking within this sample.

TABLE 8 The value of (q) to analyze the variance between the averages of the first group scores according to the learning style (Visual, auditory, or Kinesthetic) in the post-measurement of metacognitive thinking.

Metacognitive skills and overall degree	Learning style	No.	Mean	Variance	Square sum	Square mean	Q	Significance
Knowledge recognition skill	Visual	9	5.7778	Between groups	3.556	1.778	1.075	Not Sig.
	Auditory	9	6.5000	Inside groups	47.944	1.653		
	Kinesthetic	14	5.8889	Total	51,500			
Knowledge organization skill	Visual	9	8.1111	Between groups	23.223	11.611	5.282	0.05
	Auditory	9	8.7143	Inside groups	63.746	2.198		
	Kinesthetic	14	6.6667	Total	86.969			
Knowledge processing skill	Visual	9	6.8889	Between groups	11.175	5.587	3.067	Not Sig.
	Auditory	9	6.8571	Inside groups	52.825	1.822		
	Kinesthetic	14	5.5556	Total	64.000			
Metacognitive skills	Visual	9	20.7778	Between groups	86.346	43.173	6.280	0.01
	Auditory	9	22.0714	Inside groups	199.373	6.616		
	Kinesthetic	14	18.111	Total	198.219			

TABLE 9 The value of (Mann–Whitney U) in terms of Z to calculate the difference between the average ranks of the second group scores according to the level of knowledge (low-high) in the pre-measurement of metacognitive thinking.

Metacognitive skills and overall degree	Knowledge level	No.	Average ranks	Total ranks	Mann–Whitney U	Z-value	Significance
Knowledge recognition skill	Low	18	14.97	269.50	98.50	1.207	0.227
	High	14	18.46	258.50			Not Sig.
Knowledge organization skill	Low	18	17.94	323.00	100.00	1.031	0.303
	High	14	14.64	205.00			Not Sig.
Knowledge processing skill	Low	18	17.11	308.00	115.00	0.437	0.662
	High	14	15.71	220.00			Not Sig.
Metacognitive skills	Low	18	16.81	302.50	115.00	0.211	0.833
	High	14	16.11	225.50			Not Sig.

By analyzing the data in Table 10, the following results can be concluded: when observing the results of the knowledge recognition skill, the average rank for the low-level group is 15.75, while the average rank for the high-level group is 17.46. The analysis of Mann–Whitney U showed that the value of U is 112.50, and the value of Z is 0.533 with a significance of 0.594. Since the significance value is greater than 0.05, this indicates that there is no statistically significant difference between low and high levels of knowledge recognition skill. In terms of knowledge organization skills, the average rank for the low-level group is 16.67, while the average rank for the high-level group is 16.29. The results of the Mann–Whitney U-test showed that the value of U is 123.00, and the value of Z is 0.117 with a significance of 0.907. This means that there is no statistically significant difference between the two groups in the skill of organizing knowledge, as the significance value is greater than 0.05.

For knowledge processing skills, the average rank for the low-level group is 18.39, while the average rank for the high-level group is 14.07. The results of Mann–Whitney's U analysis showed that the value of U is 92.00, and the value of Z is 1.333 with a significance of 0.182. Again, the significance value is greater than 0.05, indicating that there is no statistically significant difference between the two groups in knowledge processing skills.

When analyzing metacognitive thinking, we find that the average rank for the low-level group is 17.14, while the average rank for the high-level group is 15.68. The results of the Mann–Whitney U-test showed that the value of U is 114.50, and the value of Z is 0.441 with a significance of 0.659. Since the significance value is greater than 0.05, we can conclude that there is no statistically significant difference between the two groups in metacognitive thinking.

TABLE 10 The value of (Mann–Whitney *U*) in terms of *Z* to calculate the difference between the average ranks of the second group scores according to the level of knowledge (low-high) in the post-measurement of metacognitive thinking.

Metacognitive skills and overall degree	Knowledge level	No.	Average ranks	Total ranks	Mann–Whitney *U*	*Z*-value	Significance
Knowledge recognition skill	Low	18	15.75	283.50	112.50	0.533	0.594
	High	14	17.46	244.50			Not Sig.
Knowledge organization skill	Low	18	16.67	300.00	123.00	0.117	0.907
	High	14	16.29	228.00			Not Sig.
Knowledge processing skill	Low	18	18.39	331.00	92.00	1.333	0.182
	High	14	14.07	197.00			Not Sig.
Metacognitive skills	Low	18	17.14	308.50	114.50	0.441	0.659
	High	14	15.68	219.50			Not Sig.

6 Discussion

The primary objective of this study was to examine how an adaptive e-learning environment personalized through factors such as individualized learning paths impacts students' metacognitive thinking skills. To achieve this, a quantitative experimental design utilizing pre-test and post-test measures was employed. The findings indicated a positive relationship between adaptive learning design and the enhancement of metacognitive skills, demonstrating meaningful implications for both learning structures and processes. Furthermore, the results revealed that students with higher levels of metacognitive thinking were more actively engaged in the learning process compared to their peers, highlighting the critical role of metacognition in adaptive e-learning.

In summary, based on the results of Mann–Whitney *U*'s analysis of different metacognitive thinking skills, there are no statistically significant differences between low and high levels of these skills. This means that different levels do not significantly affect the degrees of metacognitive thinking in this group, suggesting that the effects that may be present are not large enough to be statistically significant. This finding aligned with Skulmowski and Xu (2022) and Klepsch and Seufert (2020), who emphasized that the minimum cognitive levels of entry (MCLEs) of students engaged in e-learning are unique to each student. These levels form cognitive accessibility profiles, or the degree students may have in reaching personalized content. Moreover, it is recommended that future studies be implemented to measure metacognitive thinking skills that were undertaken by learners and that there be more cognitive test results for comparison of the reframed results so that scholars may affirm whether the primary pre-test scores and post-test scores effects are quite reliable concerning the development of metacognitive thinking skills. In addition, the results align with providing personalized learning content based on the individual features of learners, which is one of the main motivations of e-learning research (Zajda, 2021; Suhendi et al., 2021; Mishra, 2023).

The findings of this study align with constructivist theory, which emphasizes knowledge construction through active mental engagement and has the potential to support the development of 21st-century learning skills. Constructivist principles suggest that learners create meaning through interaction and reflection, making adaptive e-learning systems a valuable tool for promoting personalized learning. Recent research highlights that providing customized learning content tailored to the unique characteristics of learners is a key motivation behind the design of e-learning environments (Zajda, 2021; Suhendi et al., 2021; Mishra, 2023). Recent research suggests learning styles should be used carefully, in combination with validated factors such as prior knowledge, motivation, and cognitive load (Kirschner and Van Merriënboer, 2013).

Adaptive e-learning systems enhance flexibility in education by delivering learning materials that correspond to learners' styles, prior knowledge levels, and learning pace (El-Sabagh, 2021; Gligorea et al., 2023; Liu and Yu, 2023). Furthermore, the ability of these systems to diagnose individual learning abilities provides a strong foundation for assessing students' academic performance and tracking their progress (Abhirami and Devi, 2022; Arsovic and Stefanovic, 2020). This adaptability supports a more personalized and effective educational experience, fostering both learner engagement and achievement.

Moreover, the adaptive eLearning environment based on knowledge level factors is designed to focus on examining differences in the effects of learning paths resulting from the level of interactivity and the number of students' attempts in activities, instructional materials, and quizzes created with this knowledge. That way, differences should be related to learning paths and not depend upon the personal characteristics of the students. Since the other group were all similarly exposed to an adaptive scenario, based on knowledge levels, the differences obtained in the final scale may indicate how student preferences in the learning path tailored to them impact their motivation and engagement in the learning process, regardless of knowledge and skill levels. The effectiveness of personalized approaches in e-learning environments has been highlighted. Relevant literature containing similar approaches was also reviewed in the theoretical framework.

Adapting learning experiences to align with individual styles can foster greater self-regulation. For example, providing auditory learners with podcasts or audiobooks can help them manage their learning environment more effectively (El-Sabagh, 2021). On the other hand, encouraging all learners to engage in reflective practices that align with their preferred learning methods can enhance their self-regulatory capabilities. For instance, visual learners might benefit from drawings, while auditory learners may find it helpful to record audio reflections (Raiyn, 2016; Zens, 2021). Kinaesthetic Learners often thrive on experiential evaluation methods, such as performance tasks or simulations, where they can reflect on their actions and outcomes based on tangible experiences (Madhu and Bhattacharyya, 2023).

Based on the findings of this study, several practical implications can be drawn regarding the design of adaptive e-learning environments. The results revealed that personalization factors, particularly knowledge levels, significantly influenced the development of metacognitive thinking skills. Therefore, it is recommended that adaptive technologies be designed with a focus on personalized factors such as learners' prior knowledge, as these can positively impact learning outcomes. Designing adaptive e-learning systems that emphasize personalization may enhance the overall effectiveness of learning.

Moreover, educational designers and practitioners should account for individual differences when creating e-learning platforms and learning materials. Previous research has identified a variety of factors—including cognitive, affective, social, and environmental elements—that influence individual learning effectiveness (Schneider et al., 2022; Wang, 2022; Li et al., 2023). These differences may include variations in knowledge levels, intelligence, learning styles, motivation, and cognitive or metacognitive abilities, all of which serve as predictors of academic achievement. Consequently, in the context of metacognitive skill development through e-learning, personal learning styles and prior knowledge should be carefully considered. To address these variations, multiple forms of adaptive e-learning systems can be developed, as their effectiveness depends on learners' unique characteristics. Research also suggests that the integration of affective and cognitive computing at varying levels can further enhance personalization and support diverse learner needs.

Adaptive learning environments based on personalized factors aim to differentiate among students by accommodating variations in both learning styles and knowledge levels. Learning styles are typically described as the diverse ways in which individuals perceive, process, and evaluate information. Understanding students' learning styles is essential for the effective development of adaptive e-learning systems. Some e-learning platforms personalize the learning experience by using adaptive mechanisms that consider learners' knowledge levels, thereby fostering more engaging and meaningful learning experiences. Variations in learning styles can influence how students interact with and respond to these personalized learning paths, ultimately shaping their learning outcomes.

According to recent research, learning styles provide a "limited role" in successful personalized learning. According to an increasing amount of research, adaptive platforms should instead concentrate on cognitive factors, particularly prior domain knowledge, which affects how learners design tasks and set goals (Zhang et al., 2022). It has been demonstrated that the usage of Self-Regulated Learning (SRL) supports a beneficial effect by high levels of prior knowledge, making it a more dependable metric for instructional adaptation (Bach et al., 2025).

7 Conclusions and recommendations

This study reveals empirical evidence that the choice of personalization parameters has a significant impact on how effective adaptive e-learning environments are. Although integrating learning styles into instructional design is a widespread practice, the study we conducted indicates that it has little impact on the development of metacognitive thinking abilities, especially in high-complexity disciplines like games programming. However, prior knowledge was revealed to be the more powerful factor, providing an essential basis for students to develop their capacity to plan, track, and control their learning.

The study leads to the conclusion that for an adaptive system to be effectively "smart," dynamically assessed knowledge levels must be given priority. The environment establishes the cognitive space required for metacognitive development by matching instructional level to the learner's present expertise. For the next generation of e-learning systems, the shift from "preference-based" to "evidence-based" personalization is necessary.

This study demonstrates that adaptive e-learning environments can meaningfully enhance metacognitive thinking skills when personalization prioritizes evidence-based factors like prior knowledge over traditional learning styles. The finding that knowledge-adaptive pathways produced stronger effects ($\eta^2 = 0.21$) than style-based adaptation ($\eta^2 = 0.12$) provides instructors with actionable guidance: effective metacognitive support requires aligning instructional supports with learners' actual cognitive readiness rather than stylistic preferences alone. This nuanced understanding enables instructors to create more responsive digital learning environments that simultaneously advance engagement and self-regulated learning capacity.

This study offers meaningful insights into the transformative role of personalized factors within adaptive e-learning environments. The research sought to address gaps in the existing literature and contribute to ongoing discussions on effective adaptive e-learning strategies. Investigating the extent to which adaptive e-learning environments, designed around personalized factors, influence the development of students' metacognitive thinking skills remains a significant area of interest requiring systematic and scientific exploration.

Given the specific influence of learning styles on metacognitive dimensions such as knowledge recognition and knowledge organization, it is essential for instructors to adapt their teaching strategies to accommodate diverse learner needs. Recognizing the role of different personalized factors allows educators to design adaptive e-learning environments that foster greater engagement and improved learning outcomes. This nuanced perspective enhances the interpretation of the results and contributes to broader discussions on effective instructional practices. Overall, the findings enrich the current literature by offering new insights into factors that shape students' metacognitive development and highlight the potential benefits of adaptive e-learning environments tailored to individual differences.

Furthermore, this study lays the groundwork for connecting metacognition and adaptive e-learning environments with student learning success. It also provides valuable evidence for stakeholders, including teacher educators and policymakers, to develop frameworks and strategies for preparing future educators to integrate adaptive metacognition into teaching and learning. The implications of this research suggest promising directions for shaping evaluation practices in adaptive e-learning environments, particularly those designed to support metacognitive skills in higher education. Designing such systems requires careful attention to learners' characteristics, making the adaptive decision-making process a critical component. When defining adaptive parameters, it is necessary to consider learners' personal factors, as well as their metacognitive and situational factors, to ensure the environment meets individual needs.

Based on the findings, several practical recommendations were made. Future research should aim to replicate this study with larger and more diverse samples drawn from multiple colleges and academic programs to test the generalizability of the results. Expanding the participant pool will help determine whether the observed outcomes are consistent across different educational contexts and contribute to the development of more effective adaptive e-learning practices.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Scientific Deanship, Prince Sattam bin Abdulaziz University, Al-Khar, Saudi Arabia. The participants provided their written informed consent to participate in this study. This study was conducted in accordance with the ethical standards of the relevant institutional research committee and in line with established guidelines for research involving human participants. The participants were university students who voluntarily took part in the study after being informed of its purpose, procedures, and expected outcomes. Informed consent was obtained from all participants prior to data collection. The research involved the use of an adaptive e-learning environment, and the collected data were limited to learning activities, performance indicators, and responses related to metacognitive thinking skills. No sensitive personal data were collected. All data were anonymized and analyzed in aggregate form to ensure participant confidentiality and privacy. Participation or non-participation had no effect on students' academic evaluation, and participants were free to withdraw from the study at any time without penalty. The study did not involve any physical or psychological risk, and all procedures complied with institutional and ethical standards for educational research.

Author contributions

HE-S: Conceptualization, Formal analysis, Investigation, Methodology, Project Administration, Supervision, Software, Validation, Writing – original draft, Writing – review & editing. SA: Data curation, Methodology, Resources, Validation, Writing – original draft.

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Generative AI statement

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