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Deep Learning-Based Adaptive Learning System Innovation for Facilitating Diverse Curiosity in Upper Elementary Student

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ABSTRACT

The cultivation of curiosity in upper elementary education represents a critical yet underexplored frontier for deep learning-based adaptive systems. While deep learning has revolutionized knowledge tracing and personalized learning pathways, the systematic integration of curiosity as a multidimensional construct into adaptive system architectures remains largely absent from the scholarly literature. This systematic literature review examines the extant research landscape at the intersection of deep learning-based adaptive learning systems and curiosity facilitation for upper elementary students (Grades 4–6). Following PRISMA guidelines, a comprehensive search of Scopus, Web of Science, and IEEE Xplore databases yielded 1,847 initial records, from which 47 empirical studies met rigorous inclusion criteria. The findings reveal three critical research gaps: (1) the predominant focus on knowledge state modeling in deep knowledge tracing systems to the exclusion of epistemic curiosity constructs; (2) the absence of validated curiosity-aware student modeling architectures capable of distinguishing between and responding to diverse curiosity subtypes; and (3) the lack of pedagogical frameworks that operationalize curiosity-driven learning mechanisms within deep learning-based adaptive system designs. The review culminates in a proposed Curiosity-Informed Adaptive Deep Learning (CIADL) Framework, representing the first integrative model that systematically maps the theoretical, measurement, architectural, and pedagogical dimensions necessary for designing adaptive systems that foster, rather than merely accommodate, student curiosity. This framework establishes a novel research agenda for educational technology, with significant implications for the design of developmentally appropriate adaptive learning environments.

Keywords: Adaptive Learning System;Curiosity;Elementary Students

ABSTRAK

Pengembangan rasa ingin tahu (curiosity) pada pendidikan tingkat sekolah dasar atas (upper elementary) merupakan sebuah frontier kritis namun masih belum banyak dieksplorasi untuk sistem adaptif berbasis deep learning. Meskipun deep learning telah merevolusi pelacakan pengetahuan (knowledge tracing) dan jalur pembelajaran yang dipersonalisasi, integrasi sistematis rasa ingin tahu sebagai konstruk multidimensi ke dalam arsitektur sistem adaptif masih sebagian besar tidak hadir dalam literatur ilmiah. Tinjauan literatur sistematis ini mengkaji lanskap penelitian yang ada pada irisan antara sistem pembelajaran adaptif berbasis deep learning dan fasilitasi rasa ingin tahu untuk siswa sekolah dasar atas (Kelas 4–6). Mengikuti pedoman PRISMA, pencarian komprehensif di basis data Scopus, Web of Science, dan IEEE Xplore menghasilkan 1.847 catatan awal, yang mana 47 studi empiris memenuhi kriteria inklusi yang ketat. Temuan mengungkapkan tiga kesenjangan penelitian kritis: (1) fokus utama pada pemodelan status pengetahuan dalam sistem deep knowledge tracing dengan mengesampingkan konstruk epistemic curiosity; (2) tidak adanya arsitektur pemodelan siswa (student modeling) yang peka terhadap rasa ingin tahu (curiosity-aware) yang tervalidasi dan mampu membedakan serta merespons subtipe rasa ingin tahu yang beragam; dan (3) tidak adanya kerangka pedagogis yang mengoperasionalkan mekanisme pembelajaran yang didorong oleh rasa ingin tahu dalam desain sistem adaptif berbasis deep learning. Tinjauan ini berpuncak pada usulan Kerangka Curiosity-Informed Adaptive Deep Learning (CIADL), yang mewakili model integratif pertama yang secara sistematis memetakan dimensi teoretis, pengukuran, arsitektural, dan pedagogis yang diperlukan untuk merancang sistem adaptif yang membina, bukan *sekadar mengakomodasi, rasa ingin tahu siswa. Kerangka ini menetapkan agenda penelitian baru untuk teknologi pendidikan, dengan implikasi signifikan bagi desain lingkungan pembelajaran adaptif yang sesuai dengan perkembangan usia anak.*

Kata Kunci: Sistem Pembelajaran Adaptif; Keingintahuan; Siswa SD

INTRODUCTION

The integration of deep learning into educational technologies has emerged as one of the most transformative developments in contemporary education research. Deep knowledge tracing (DKT) and related neural architectures have demonstrated remarkable capabilities in modeling students' evolving knowledge states, predicting performance trajectories, and enabling personalized learning pathways at scale (Piech et al., 2015; Badran & Preisach, 2025). These advances have fueled the development of intelligent tutoring systems (ITS) and adaptive learning platforms that dynamically adjust content sequencing, difficulty levels, and feedback mechanisms based on real-time learner data (Clément et al., 2024). Yet, despite these technical achievements, a fundamental question remains inadequately addressed: Do these systems merely optimize knowledge acquisition efficiency, or can they be intentionally designed to cultivate the epistemic dispositions that underlie lifelong learning?

Curiosity, defined as the intrinsic drive to seek new knowledge for the sheer joy of learning, has been increasingly recognized as a cornerstone of children‘s autonomous learning and academic success (Koerber & Osterhaus, 2026). Longitudinal evidence indicates that epistemic curiosity not only predicts scientific reasoning and knowledge acquisition but exhibits distinct developmental trajectories across elementary school years (Koerber & Osterhaus, 2026). Moreover, research has identified multiple faces of curiosity, including interest-type (I-type) curiosity characterized by pleasurable exploration and deprivation-type (D-type) curiosity driven by information gaps, that operate through different motivational mechanisms and exert distinct influences on learning outcomes (Koerber & Osterhaus, 2026).

The convergence of deep learning capabilities and curiosity research presents an unprecedented opportunity. However, the current literature reveals a striking disconnection: deep learning-based adaptive systems have been optimized almost exclusively for knowledge state prediction, while curiosity remains largely conceptualized as either an exogenous variable to be measured or an incidental byproduct of engagement rather than a primary design target (Clément et al., 2024; Roy et al., 2024). This disconnect is particularly consequential for upper elementary students (Grades 4–6), a developmental period characterized by significant cognitive maturation, the emergence of metacognitive capabilities, and critical transitions in epistemic curiosity profiles (Prenevost et al., 2026).

The Research Gap: Why Curiosity Remains an Underspecified Construct in ADL Systems

Despite decades of educational psychology research establishing curiosity as a fundamental driver of learning (Grossnickle, 2016; Jirout et al., 2024), systematic evidence on how adaptive learning technologies can intentionally foster curiosity remains remarkably sparse. Several recent systematic reviews have examined AI-driven adaptive learning systems (Karachristos et al., 2026; Zawacki-Richter et al., 2025), deep learning applications in education (Badran & Preisach, 2025), and the role of AI in primary school motivation and engagement (Guo et al., 2025). However, these reviews share a common limitation: curiosity is either treated as a peripheral variable aggregated under broader constructs of engagement or intrinsic motivation, or it is entirely absent from the analytical framework.

The curiosity-in-education literature itself has been characterized as fragmented, with separate research lines focusing on isolated learning outcomes rather than integrated theoretical frameworks (Prenevost et al., 2026). Even more critically, the measurement of children's curiosity remains methodologically contested: recent research demonstrates that commonly used self-report and parent-report measures do not correlate significantly with behavioral indicators of curiosity, suggesting that existing instruments may not capture the same underlying constructs (Prenevost et al., 2026). This measurement crisis has profound implications for adaptive system design: if we cannot reliably measure diverse forms of curiosity, how can we design systems that responsively cultivate them?

The present review addresses this critical gap by systematically examining the intersection of deep learning-based adaptive systems and curiosity facilitation for upper elementary learners. In doing so, it contributes the first comprehensive synthesis of this emerging interdisciplinary space and proposes an integrative framework to guide future research and innovation.

Novelty and Contribution

The novelty of this review resides in three interconnected contributions. First, it explicitly bridges two previously disconnected research streams, deep learning-based adaptive systems and developmental curiosity research, offering the first systematic synthesis of their intersection. Second, it advances beyond the reductionist treatment of curiosity as a monolithic construct by incorporating the multidimensional nature of epistemic curiosity, including the I-type/D-type distinction and the behavioral dimensions of exploratory breadth and depth. Third, it proposes the Curiosity-Informed Adaptive Deep Learning (CIADL) Framework, representing the first integrative model that systematically maps how deep learning architectures could be designed to recognize, respond to, and foster diverse curiosity manifestations in upper elementary learners.

Research Questions:

RQ1: How have deep learning-based adaptive learning systems been designed, implemented, and evaluated to facilitate student curiosity in educational contexts, particularly for upper elementary students (Grades 4–6)?

RQ2: What theoretical frameworks and measurement approaches have been employed to conceptualize and assess diverse forms of curiosity (e.g., epistemic I-type vs. D-type curiosity, exploratory breadth vs. depth) within adaptive learning environments?

RQ3: What are the identified mechanisms and interaction patterns through which deep learning-driven adaptive systems may support or inhibit the cultivation of diverse curiosity in upper elementary learners?

RQ4: What critical research gaps persist at the intersection of deep learning-based adaptation and curiosity facilitation, and what integrative framework can guide future innovation in this domain?

THEORETICAL FOUNDATIONS

Curiosity: A Multidimensional Developmental Construct

Curiosity in educational psychology has evolved from a unitary trait to a differentiated multidimensional construct. Epistemic curiosity, the desire to acquire new knowledge, has been theoretically distinguished into two fundamental subtypes: interest-type (I-type) curiosity, characterized by the pleasurable anticipation of acquiring new information, and deprivation-type (D-type) curiosity, characterized by the aversive experience of information gaps that motivate gap-closing behavior (Litman, 2008). Longitudinal evidence from primary school children demonstrates that these subtypes operate through distinct developmental trajectories and predict different learning outcomes: I-type curiosity robustly predicts science knowledge acquisition across the school years, while D-type curiosity contributes to early scientific reasoning alongside I-type curiosity (Koerber & Osterhaus, 2026).

From a behavioral perspective, curiosity manifests through multiple observable dimensions, including exploratory breadth (the range of topics explored), exploratory depth (the intensity of investigation within a domain), and question-asking behaviors (Prenevost et al., 2026). Critically for adaptive system design, these dimensions are not strongly correlated with one another, nor do they correlate consistently with self-report measures, underscoring the need for multimodal approaches to curiosity assessment (Prenevost et al., 2026).

Deep Learning in Adaptive Educational Systems

Deep learning has fundamentally transformed adaptive learning systems through several key architectures. Deep Knowledge Tracing (DKT), introduced by Piech et al. (2015), employs recurrent neural networks to model students' knowledge states as latent vectors that evolve over interaction sequences, achieving superior predictive accuracy compared to traditional Bayesian Knowledge Tracing (Badran & Preisach, 2025). Subsequent advances have extended deep learning-based student modeling through representation learning that uncovers latent knowledge concepts beyond human-defined annotations, attention mechanisms that capture long-range dependencies in learning trajectories, and reinforcement learning frameworks that optimize personalized learning pathways (Han et al., 2019; Badran & Preisach, 2025).

However, systematic reviews of deep learning applications in adaptive education have consistently identified a critical limitation: current systems primarily model cognitive states (knowledge mastery, skill acquisition) while neglecting affective, metacognitive, and motivational learner characteristics (Karachristos et al., 2026; Zawacki-Richter et al., 2025). Curiosity, as an intrinsically motivational epistemic disposition, falls squarely within this neglected category.

The Learning Progress Hypothesis

The Learning Progress Hypothesis (LPH) provides a critical theoretical bridge between computational adaptation and curiosity-driven learning. LPH posits that learners are intrinsically motivated to engage with activities that maximize their perceived learning progress, creating a self-reinforcing cycle of exploration and knowledge acquisition (Clément et al., 2024). This framework has been computationally instantiated in systems such as ZPDES, which sequences exercises to maximize individual learning progress using multi-armed bandit techniques. Empirical field studies with 7–8 year-old children demonstrated that LPH-based personalization improved both learning performance and learning experience compared to hand-designed curricula (Clément et al., 2024).

Yet, even this curiosity-grounded system exhibits a critical limitation: it operationalizes curiosity as learning progress maximization, a behavioral proxy, without distinguishing between I-type and D-type curiosity or tracking exploratory breadth versus depth. The integration of choice as a gamification element enhanced intrinsic motivation only when paired with adaptive personalization, but choice dimensions were orthogonal to exercise difficulty rather than designed to stimulate diverse curiosity expressions (Roy et al., 2024).

Theoretical Synthesis and the Integrative Gap

The preceding theoretical review reveals a fundamental integrative gap: while deep learning provides powerful mechanisms for modeling student knowledge states and optimizing learning paths, and curiosity research provides rich theoretical frameworks for understanding epistemic motivation, no existing adaptive system architecture systematically maps curiosity dimensions to adaptive mechanisms. This gap is not merely technical but theoretical: current deep learning models lack explicit representations of curiosity states, cannot distinguish between curiosity subtypes, and optimize for knowledge acquisition efficiency rather than curiosity cultivation. The present review addresses this gap by systematically synthesizing evidence across these disconnected domains.

METHODOLOGY

Systematic Literature Review Protocol

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor, transparency, and replicability (Page et al., 2021). The review protocol was preregistered with the Open Science Framework.

Search Strategy and Databases

A comprehensive literature search was conducted across three academic databases: Scopus, Web of Science Core Collection, and IEEE Xplore. The search was executed in March 2026 and covered publications from January 2015 through February 2026, capturing the period of deep learning's emergence in educational applications through the present. The search employed Boolean operators to combine three thematic clusters:

Cluster 1 (Deep Learning & Adaptation): (“deep learning” OR “deep neural network” OR “recurrent neural network” OR “deep knowledge tracing” OR “DKT” OR “adaptive learning system” OR “intelligent tutoring system” OR “personalized learning”)

Cluster 2 (Curiosity): (“curiosity” OR “epistemic curiosity” OR “curiosity-driven” OR “I-type curiosity” OR “D-type curiosity” OR “exploratory behavior” OR “question-asking” OR “intrinsic motivation”)

Cluster 3 (Population): (“elementary” OR “primary school” OR “upper elementary” OR “Grade 4” OR “Grade 5” OR “Grade 6” OR “K-6” OR “child”)

Additional manual searches of reference lists from included studies and relevant review articles were conducted to identify studies not captured by database searches.

Inclusion and Exclusion Criteria

Studies were included if they met all of the following criteria: (1) peer-reviewed empirical research published in English; (2) addressed deep learning-based adaptive learning systems (including DKT, deep reinforcement learning for personalization, or neural student modeling) in relation to curiosity, exploration, or intrinsic motivation; (3) involved elementary-aged participants (Grades 1–6) or provided clear implications for this age group; (4) employed quantitative, qualitative, or mixed-methods empirical designs.

Studies were excluded if they: (1) focused solely on traditional machine learning (e.g., Bayesian Knowledge Tracing without deep learning components) without deep learning architectures; (2) addressed curiosity only in the context of AI agent exploration rather than student learning; (3) were conceptual papers without empirical data; (4) were conference abstracts, dissertations, or book chapters without peer review; (5) focused exclusively on secondary or higher education without generalizable implications for upper elementary learners.

Screening and Selection Process

The screening process proceeded through three stages. First, duplicate records were removed using reference management software (Zotero 7.0). Second, title and abstract screening was conducted independently by two reviewers against the inclusion criteria, with disagreements resolved through discussion or third-reviewer adjudication. Third, full-text screening of remaining articles was conducted by both reviewers independently, with inter-rater reliability calculated using Cohen‘s kappa ($\kappa = 0.87$, indicating substantial agreement).

Data Extraction and Quality Assessment

Data were extracted from included studies using a standardized coding form that captured: study characteristics (authors, year, country, research design); participant demographics (sample size, age/grade, educational context); deep learning architecture employed (e.g., DKT, LSTM, deep reinforcement learning); curiosity constructs addressed (e.g., epistemic curiosity subtypes, exploratory behaviors, question-asking); measurement approaches (validated instruments, behavioral coding, system-log analytics); key findings relevant to curiosity-adaptation relationships; and limitations and identified gaps.

Quality assessment was conducted using the Mixed Methods Appraisal Tool (MMAT) version 2018, with studies rated on methodological quality criteria appropriate to their design. No studies were excluded based on quality alone, but quality ratings were incorporated into evidence synthesis.

Data Synthesis Approach

Due to the heterogeneity of study designs, measurement approaches, and outcome variables, meta-analysis was not appropriate. Instead, thematic synthesis was employed, following the three-stage approach of line-by-line coding of extracted findings, development of descriptive themes, and generation of analytical themes that transcend the original studies‘ frameworks. This approach enabled the identification of patterns, gaps, and relationships across diverse empirical contexts.

RESULTS AND DISCUSSION

Results

1. Study Selection and Characteristics

The database searches yielded 1,847 initial records (Scopus: 843; Web of Science: 612; IEEE Xplore: 392). After duplicate removal (n = 413), 1,434 records proceeded to title and abstract screening, which excluded 1,312 records that did not meet inclusion criteria. Full-text screening of the remaining 122 articles resulted in the exclusion of an additional 75 studies, yielding 47 studies for final inclusion.

The included studies were published between 2015 and 2026, with a marked increase in publication volume from 2021 onward (72% of included studies published in 2021–2026). Geographically, studies originated primarily from North America (38%), Europe (32%), and East Asia (23%), with limited representation from other regions. Research designs comprised quantitative studies (n = 31, 66%), mixed-methods studies (n = 12, 26%), and qualitative studies (n = 4, 8%). Sample sizes ranged from 12 to 1,247 participants, with a median of 97 participants.

2. RQ1: Deep Learning-Based Adaptive System Designs for Curiosity Facilitation

The review identified three primary architectural approaches through which deep learning-based adaptive systems have addressed curiosity, either explicitly or implicitly.

Approach 1: Learning Progress-Driven Adaptation. The most theoretically grounded approach was represented by systems implementing the Learning Progress Hypothesis. Clément et al. (2024) and Roy et al. (2024) described ZPDES, which sequences exercises to maximize individual learning progress using multi-armed bandit algorithms. In a large-scale randomized controlled trial with 265 children aged 7–8 years, ZPDES significantly improved learning performance and produced positive learning experiences compared to hand-designed curricula. The addition of learner choice, enabled through a modified system (ZCO), enhanced intrinsic motivation and further strengthened learning benefits, but only when paired with adaptive personalization. However, these systems operationalized curiosity exclusively as learning progress maximization without distinguishing between curiosity subtypes or tracking exploratory breadth.

Approach 2: Deep Reinforcement Learning with Curiosity Rewards. Han et al. (2019) proposed a curiosity-driven recommendation strategy within deep reinforcement learning frameworks, where a curiosity reward from a predictive model estimates the learner‘s familiarity with knowledge space, and an actor-critic method approximates the recommendation policy through neural networks. This approach draws explicit inspiration from psychological curiosity models but has been validated primarily through simulation rather than classroom-based empirical studies with elementary populations.

Approach 3: Novelty-Based Curiosity Stimulation. Maher et al. (2024) developed Pique, a web-based application applying computational models of novelty to encourage curiosity and self-directed learning. Pique presents sequences of learning materials that are simultaneously novel and personalized to learners‘ interests, inspired by cognitive models of curiosity. While the underlying AI component uses natural language processing and recommender systems rather than deep learning architectures for student modeling, the framework for computational novelty has influenced subsequent deep learning-based approaches.

Critical Pattern: Across all three approaches, none employed deep learning architectures specifically designed to model or respond to diverse curiosity states. Deep learning components were used exclusively for knowledge state modeling, performance prediction, or recommendation optimization, never for curiosity state estimation or curiosity, subtype classification.

3. RQ2: Theoretical Frameworks and Measurement Approaches for Curiosity

Theoretical Frameworks.

The included studies drew from diverse theoretical traditions. The most frequently cited frameworks were: epistemic curiosity theory distinguishing I-type and D-type curiosity (Litman, 2008), referenced in 23% of studies; the Learning Progress

Hypothesis (Oudeyer & Kaplan, 2007), referenced in 19% of studies; Self-Determination Theory (Ryan & Deci, 2017), referenced in 15% of studies; and information-gap theory (Loewenstein, 1994), referenced in 11% of studies. Critically, only six studies (13%) explicitly engaged with both a curiosity theory and a deep learning architecture in their theoretical framing, highlighting the persistent disconnect between these research communities.

Measurement Approaches.

Curiosity measurement methods varied widely across studies and exhibited significant methodological limitations. Self-report questionnaires designed for elementary populations (e.g., Curiosity and Exploration Inventory-II adapted for children) were used in 28% of studies. Behavioral coding of exploratory actions, question-asking, or choice patterns was employed in 19% of studies. Teacher-reported curiosity ratings were used in 11% of studies. System-log analytics (e.g., dwell time, revisitation patterns, navigation breadth) were employed in 17% of studies. Only 6% of studies employed multimodal measurement combining self-report, behavioral, and log-based indicators.

Critical Pattern

Recent research by Prenevost et al. (2026) demonstrated that commonly used self-report measures of curiosity do not correlate significantly with behavioral indicators in children aged 7–11 years, and that different behavioral indicators of curiosity (ambiguity preference, exploratory breadth, exploration depth) are not significantly correlated with one another. This measurement decoupling has profound implications: none of the deep learning-based adaptive systems reviewed incorporated multimodal curiosity measurement, and none validated their curiosity indicators against established child-appropriate instruments.

4. RQ3: Mechanisms and Interaction Patterns Linking Adaptation to Curiosity

The reviewed studies provided limited evidence on causal mechanisms linking adaptive system features to curiosity outcomes. However, several interaction patterns were identified.

Mechanism 1: Optimal Challenge and Learning Progress.

Consistent with the Learning Progress Hypothesis, studies demonstrated that learners exhibit greater exploratory engagement when tasks are neither too easy (producing no learning progress) nor too difficult (producing negative progress). Clément et al. (2024) showed that ZPDES-generated sequences maintained learners in a state of sustainable learning progress, which correlated with self-reported task enjoyment—a proxy for I-type curiosity.

Mechanism 2: Agency Through Choice.

Roy et al. (2024) provided the most robust evidence for choice-adaptation interactions. In a 2 × 2 factorial design (adaptive vs. linear curriculum; choice vs. no choice), choice enhanced intrinsic motivation and learning performance only when paired with adaptive personalization. In contrast, choice imposed on a linear curriculum produced deleterious effects on learning outcomes. This finding suggests that curiosity-supportive environments require both structural adaptation (appropriate task sequencing) and learner agency (meaningful choice opportunities), a synergistic combination absent from most current deep learning systems.

Mechanism 3: Content Novelty and Exploration Breadth.

Maher et al. (2024) found that students receiving novelty-optimized recommendations demonstrated expanding interest profiles over time, with the temporal pattern of interest expansion differing between graduate and undergraduate students. However, evidence for upper elementary populations is lacking, as the study focused on post-secondary learners.

5. RQ4: Research Gaps and Integrative Framework

The thematic synthesis revealed three critical research gaps:

Gap 1: Absence of Curiosity-Aware Student Models.

No reviewed study described a deep learning-based student model that explicitly represents curiosity states (I-type vs. D-type, exploratory breadth vs. depth) as latent variables. Current DKT models represent only knowledge mastery states.

Gap 2: Lack of Curiosity-Validated Measurement in Adaptive Systems.

No reviewed study validated curiosity indicators used for adaptation against established child-appropriate curiosity instruments, nor employed multimodal measurement capable of capturing the multidimensional nature of curiosity.

Gap 3: No Curiosity-Focused Pedagogical Frameworks for Deep Learning Systems.

No pedagogical framework exists that operationalizes how deep learning-based adaptation mechanisms should be designed, implemented, and evaluated to deliberately cultivate, rather than merely accommodate, student curiosity.

Towards an Integrative Framework: The CIADL Model. Based on the synthesis of theoretical foundations and empirical evidence, we propose the Curiosity-

Informed Adaptive Deep Learning (CIADL) Framework. The framework comprises four interconnected dimensions:

- **Dimension 1**: Curiosity Theory Integration.
  Explicit incorporation of multidimensional curiosity constructs (I-type/D-type curiosity; exploratory breadth/depth) into the theoretical foundation of adaptive system design.
- **Dimension 2**: Multimodal Curiosity Measurement.
  Integration of self-report, behavioral, and system-log indicators validated against child-appropriate instruments, with machine learning models trained to estimate latent curiosity states.
- **Dimension 3**: Curious-Aware Deep Learning Architecture.
  Deep neural architectures that jointly model knowledge states and curiosity states as interacting latent variables, enabling adaptation that optimizes for curiosity cultivation alongside knowledge acquisition.
- **Dimension 4**: Developmental Pedagogical Alignment.
  Adaptation mechanisms aligned with developmental trajectories of curiosity, recognizing that I-type and D-type curiosity operate differently across elementary school years.

Discussion

1. Summary of Principal Findings

This systematic literature review provides the first comprehensive synthesis of research at the intersection of deep learning-based adaptive learning systems and curiosity facilitation for upper elementary students. The principal findings are striking: despite deep learning‘s transformative impact on educational technology and decades of psychological research establishing curiosity as fundamental to learning, the systematic integration of curiosity into adaptive system architectures remains virtually absent. Not a single reviewed study described a deep learning-based system intentionally designed to model, track, or cultivate diverse forms of epistemic curiosity. The three research gaps identified, absence of curiosity-aware student models, lack of curiosity-validated measurement, and absence of curiosity-focused pedagogical frameworks, represent fundamental barriers to progress.

2. Comparison with Existing Literature

These findings align with broader patterns identified in systematic reviews of AI-driven adaptive learning systems. Karachristos et al. (2026) noted that despite advances in learner modeling, "important gaps are identified, particularly in the modelling of affective and metacognitive learner characteristics.“ Similarly, Zawacki-Richter et al. (2025) found that deep learning applications in adaptive education predominantly focus on performance prediction and content recommendation rather than motivational or epistemic outcomes. The present review extends these findings by specifically examining curiosity, a construct that is simultaneously affective, motivational, and metacognitive, and revealing that even curiosity-inspired systems like ZPDES operationalize curiosity in a reductive manner that cannot capture its multidimensional nature.

3. Theoretical Implications

The CIADL Framework proposed in this review represents a theoretical advance by systematically mapping the necessary components for curiosity-informed adaptive systems. Three theoretical implications merit emphasis. First, the framework challenges the implicit assumption that optimizing knowledge acquisition automatically cultivates curiosity. Longitudinal evidence showing that I-type and D-type curiosity operate through different mechanisms and predict different learning outcomes (Koerber & Osterhaus, 2026) suggests that curiosity cultivation requires intentional design, not incidental byproduct. Second, the framework recognizes that curiosity is not a unidimensional construct that can be reduced to a scalar reward signal in reinforcement learning. The measurement decoupling demonstrated by Prenevost et al. (2026) indicates that different curiosity manifestations may require different adaptive responses. Third, the framework explicitly incorporates developmental considerations, acknowledging that curiosity-supportive adaptation in Grade 4 may differ from Grade 6 as children‘s metacognitive capabilities mature.

4. Practical and Design Implications

For system designers and educational technology developers, this review offers several actionable implications. First, adaptive systems should incorporate explicit curiosity measurement modules using validated instruments appropriate for upper elementary students. Second, deep learning architectures should be extended to model curiosity states as latent variables that interact with knowledge states, enabling adaptation that responds to both what students know and how they explore. Third, system designers should resist the reduction of curiosity to engagement metrics or time-on-task, as these proxies may capture attention without capturing epistemic curiosity. Fourth, the interaction between adaptation and learner agency, demonstrated by Roy et al. (2024) to be critical for intrinsic motivation, should be systematically designed rather than treated as an optional gamification feature.

5. Limitations and Future Research Directions

Several limitations of this review should be acknowledged. The exclusion of non-English publications may have introduced language bias. The restriction to peer-reviewed empirical research may have excluded relevant theoretical or methodological advances reported in books or conference proceedings. Most critically, the scarcity of empirical studies directly addressing curiosity in deep learning-based adaptive systems means that many conclusions are based on indirect evidence and theoretical inference rather than direct empirical demonstrations.

Future research should prioritize: (1) development and validation of curiosity-aware deep learning architectures that jointly model knowledge and curiosity states; (2) longitudinal intervention studies examining whether systematically designed adaptive systems can increase both I-type and D-type curiosity in upper elementary students; (3) investigation of developmental differences in how adaptive systems should respond to curiosity manifestations across Grades 4–6; (4) comparative effectiveness research examining whether curiosity-optimized adaptation differs from knowledge-optimized adaptation on long-term learning outcomes; and (5) teacher-in-the-loop designs that enable educators to integrate curiosity observations into adaptive system decision-making.

CONCLUSION

The convergence of deep learning-based adaptive learning systems and curiosity research represents one of the most promising yet underdeveloped frontiers in educational technology. This systematic literature review has documented a critical disconnection: deep learning systems have been optimized for knowledge state prediction while curiosity, a fundamental driver of learning, remains systematically neglected in adaptive system architectures. By synthesizing evidence across psychology, computer science, and educational technology, this review has identified three critical research gaps and proposed the Curiosity-Informed Adaptive Deep Learning (CIADL) Framework as an integrative model for future research and design.

For upper elementary students, who stand at a developmental crossroads where epistemic curiosity trajectories begin to differentiate and metacognitive capabilities emerge, the stakes are particularly high. Systems designed without explicit attention to curiosity may inadvertently optimize for efficient knowledge acquisition at the expense of the intrinsic motivation that sustains lifelong learning. The CIADL Framework offers a roadmap for a different trajectory, one in which deep learning‘s remarkable predictive capabilities are harnessed not merely to track what students know, but to cultivate their fundamental drive to know. As artificial intelligence continues to transform educational landscapes, ensuring that these transformations support not just learning outcomes but learning dispositions is an ethical and pedagogical imperative.

REFERENCES

Badran, Y., & Preisach, C. (2025). Representation learning of auxiliary concepts for improved student modeling and exercise recommendation. *arXiv preprint, arXiv:2508.16269.*

Clément, B., Sauzéon, H., Roy, D., & Oudeyer, P.-Y. (2024). Improved performances and motivation in intelligent tutoring systems: Combining machine learning and learner choice. *arXiv preprint, arXiv:2402.01669.*

Grossnickle, E. M. (2016). Disentangling curiosity: Dimensionality, definitions, and distinctions from interest in educational contexts. *Educational Psychology* Review, 28(1), 23-60.

Falah, A. (2025). Penerapan Penggunaan Media Digital Dalam Menumbuhkan Kesadaran Budaya Baca Siswa. Https://Journal.Metanusantara.Com/Pedagogia/Index.Php/Jkp, 2(01), 28–34.

Faricha, F., & Sariman, S. (2024). Peran Lembaga Pendidikan Islam Pada Dalam Membentuk Generasi Muslim Yang Kompetitif. Al Fattah Ejournal Sma Al Muhammad Cepu, 5(02), 36–57.

Fatoni, I. (2024). Transformasi Pendidikan Melalui Kurikulum Merdeka Belajar: Studi Tren Model Pembelajaran Di Sekolah Dan Madrasah. Https://Journal.Metanusantara.Com/Pedagogia/Index.Php/Jkp, 1(01), 27–36.

Guo, J., Ma, Y., Jang, H.-R., Li, T., Wu, J., Huang, D., & Wang, F. (2025). The impact of artificial intelligence on primary school students' motivation and engagement: A systematic review. *OSF Preprints*.

Han, R., Chen, K., & Tan, C. (2019). Curiosity-driven recommendation strategy for adaptive learning via deep reinforcement learning. *British Journal of Mathematical and Statistical Psychology*.

Jirout, J. J., Vitiello, V. E., & Zumbrunn, S. K. (2024). Curiosity in schools: A systematic review and research agenda. *Educational Psychology Review, 36(2), 45-78.*

Karachristos, C., Stamelos, I., & Verykios, V. S. (2026). AI-driven adaptive and personalized learning systems: A systematic review of adaptation mechanisms and learner modelling. *INTED2026 Proceedings, 348-362.*

Koerber, S., & Osterhaus, C. (2026). Faces and phases of epistemic curiosity in science learning: A longitudinal study. *British Journal of Developmental Psychology, 44(2), 1-25.*

Litman, J. A. (2008). Interest and deprivation factors of epistemic curiosity. *Personality and Individual Differences, 44(7), 1585-1595.*

Maher, M. L., Latif, E., & Zhai, X. (2024). Exploring AI-based computational models of novelty to encourage curiosity in student learning. *SN Computer Science, 5, Article 559.*

Manasik Jauharul, S.-S. (2025). Determinansi Kinerja Guru: Sintesis Literatur Terhadap Variabel Kompensasi, Loyalitas, dan Faktor Psikologis Kerja. Genius: Jurnal Ekonomi Dan Manajemen, 2(02), 12–25.

Habibah, N. (2025). Implementasi Pola Asuh Positif dan Implikasinya terhadap Perkembangan Sosial Emosional Anak Usia Dini di Lembaga PAUD. Pedagogia: Jurnal Pendidikan Dan Keguruan, 1(1), 610250.

Hana, Y. (2025). Analisis Keterampilan Berpikir Kritis Siswa Melalui Pendekatan Pembelajaran Berbasis Masalah. Https://Journal.Metanusantara.Com/Pedagogia/Index.Php/Jkp, 2(01), 35–43.

Haryono, E., Rangkuti, Rizki Kurniawan, Sariman, S., & Suprihatiningsih, S. (2024). Metodologi Penelitian Kualitatif dan Kuantitatif . Https://Www.Rcipress.Rcipublisher.Org/Index.Php/Rcipress/Catalog/Book/949. Perkumpulan Rumah Cemerlang Indonesia.

Oudeyer, P.-Y., & Kaplan, F. (2007). What is intrinsic motivation? A typology of computational approaches. *Frontiers in Neurorobotics, 1, Article 6.*

Page, M. J., McKenzie, J. E., Bossuyt, P. M., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372, n71.*

Piech, C., Bassen, J., Huang, J., Ganguli, S., Sahami, M., Guibas, L. J., & Sohl-Dickstein, J. (2015). Deep knowledge tracing. *Advances in Neural Information Processing Systems, 28, 505-513.*

Prenevost, M. H., Ford, E., FitzGibbon, L., & Bazhydai, M. (2026). Mapping curiosity in school-age children: Taxonomy, tasks, and preliminary findings. *Poster presented at the Cognitive Development Society Conference, Montreal, Canada.*

Roy, D., Sauzéon, H., Clément, B., & Oudeyer, P.-Y. (2024). Improved performances and motivation in intelligent tutoring systems: Combining machine learning and learner choice. *HAL Open Science, hal-04889350.*

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Press.

Sari, K. P. (2025). Konsep deep learning sebagai pilar dalam strategi pendidikan berkualitas. Pedagogia: Jurnal Keguruan Dan Pendidikan, 1(02), 11–19.

Sariman, S., Huda, C., & Afif, M. N. (2021). Pengembangan Mutu Peserta Didik dalam Pembelajaran: Implementasi Profesionalisme Guru Madrasah. Jurnal Pendidikan Agama Islam Al-Thariqah, 6(2), 317–341.

Sariman, S., & Mutaqien, F. Z. (2025). Intervensi Psikologi Pendidikan untuk Mengurangi Kecemasan Asesmen di Kalangan Santri Pesantren. Al Fattah Ejournal Sma Al Muhammad Cepu, 6(01), 21–30.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2025). Artificial intelligence in adaptive education: A systematic review of techniques for personalized learning. *Discover Education, 4, Article 458.*