Deep Learning Applications in Primary Education: A Systematic Literature Review of Emerging Trends, Challenges, and Opportunities

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Deep Learning Applications in Primary Education: A Systematic Literature Review of Emerging Trends, Challenges, and Opportunities

Objectives: This systematic literature review explores the integration and application of Deep Learning (DL) in primary education from 2021 to 2025. It aims to identify key implementation trends, ethical and technical challenges, and emerging opportunities for educational transformation. **Methods:** A total of[1] 21 empirical studies were selected using PRISMA guidelines and reviewed through thematic synthesis. Data were extracted using a structured coding sheet and analyzed with bibliometric mapping, Microsoft Excel, and Python-based visualization tools. The review included diverse sources focusing on DL use cases across global primary education systems. **Results:** Findings indicate a growing global adoption of DL, particularly in Asia, with applications ranging from personalized learning and curriculum enhancement to early screening and predictive modeling. Commonly used DL architectures include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and Transformer-based models. These architectures are tailored to fit specific educational contexts and learning objectives. However, key challenges remain, such as ethical concerns (e.g., data privacy, equity), technical barriers (e.g., dataset complexity, model generalization), and alignment with pedagogical goals. **Conclusion:** Despite these challenges, DL presents transformative potential to enhance personalization, student engagement, and holistic learning outcomes. Future research should emphasize cross-disciplinary collaboration, expanded geographic representation, and innovations in scalability and interpretability to ensure DL contributes meaningfully to 21st-century education.

Keywords: Deep Learning, primary education, personalized learning, systematic literature review, educational technology, pedagogical challenges, ethical considerations.

- **INTRODUCTION**

Deep Learning (DL) has revolutionized multiple healthcare and finance sectors by enabling sophisticated pattern recognition, predictive analytics, and automation (Razzaq & Shah, 2025; Sarker, 2021; Taye, 2023)[2]. In education, DL's[3] emergence has opened new pathways for personalized learning, adaptive instruction, and real-time assessment (Bernacki, Greene, & Lobczowski, 2021; Bhutoria, 2022; Naseer, Khan, Tahir, Addas, & Aejaz, 2024; Van Schoors, Elen, Raes, & Depaepe, 2021)[2]. However, while DL's[3] potential is actively explored in higher and secondary education, its integration into primary schools remains fragmented, even though this stage is pivotal for shaping lifelong cognitive and social foundations. Early schooling is where thinking patterns, problem-solving abilities, and intrinsic motivation to learn are formed, making it a critical intervention point for transformative technologies like Deep Learning.

Global education trends increasingly demand personalized, equitable, and future-ready learning models (Aamer, Ba-Alawi, Kang, Lee, & Jo, 2025; Almuhanna, 2025; Imran, Almusharraf, Ahmed, & Mansoor, 2024)[2]. DL offers a robust response: by processing vast educational datasets, it can detect learning gaps, predict academic trajectories, and tailor learning pathways for each child. Yet most studies frame DL narrowly within educational data mining (EDM) or algorithmic development, often overlooking the pedagogical, ethical, and developmental complexities of applying DL to young learners (Lu, Griffin, Sadler, Laffey, & Goggins, 2025; Ozyurt, Ozyurt, & Mishra, 2023). As a result, key questions remain about how DL can be adapted to classroom realities, developmental needs, and teacher readiness in primary schools.

Complicating matters further, the conversation around DL in education frequently conflates the technology with the broader "deep learning" pedagogical model, which emphasizes critical thinking, collaboration, and meaningful engagement (Kovač, Nome, Jensen, & Skreland, 2025; Pan et al., 2023; Yue, Jong, & Dai, 2022). This conceptual overlap breeds confusion and has limited the coherent design of DL initiatives in primary education. Many programs risk being too technologically driven, ignoring pedagogy, or too pedagogically idealized, lacking technological feasibility (Rui, Nasri, & Mahmud, 2024).

Existing literature broadly discusses generic DL applications in education, often neglecting the unique pedagogical, ethical, and practical considerations of primary classrooms (Almalawi, Soh, Li, & Samra, 2024; López-Meneses, López-Catalán, Pelícano-Piris, & Mellado-Moreno, 2025; López-Meneses, Mellado-Moreno, Gallardo Herrerías, & Pelícano-Piris, 2025; Tzimas & Demetriadis, 2021). Despite DL's rising popularity in secondary and higher education, its meaningful implementation in primary schools remains underexplored. Research tends to focus on surface-level digital engagement or broad "active learning" strategies, without integrating DL's core elements of real-world relevance, collaboration, critical thinking, and self-regulation (Hyytinen, Ursin, Silvennoinen, Kleemola, & Toom, 2021; Zebua, 2025). This fragmented state has created a knowledge gap, leaving educators and policymakers without a clear map of what works, what doesn't, and what remains missing.

This systematic review seeks to fill that gap by synthesizing recent research on DL in primary education, guided by three core questions:

RQ1. What are the current trends in DL applications for primary education?

RQ2. What ethical, technical, and pedagogical challenges arise when implementing DL at this level?

RQ3. What opportunities exist to leverage DL for **personalized learning, student engagement, and holistic outcomes** in primary schools?

By situating DL within the larger framework of 21st-century education goals, Education for Sustainable Development (ESD), and post-pandemic recovery imperatives, this study aims to go beyond a technical survey. It provides a strategic roadmap for integrating DL in primary education, one that balances innovation with ethics, and technology with pedagogy to ensure that DL strengthens rather than disrupts the mission of early education.

- **METHOD**

Research Design

This study employs a Systematic Literature Review (SLR) methodology to explore the application of Deep Learning (DL) approaches in primary school education, particularly focusing on their potential for personalized learning, student engagement, and improved educational outcomes. The SLR method was selected because it allows for a comprehensive, transparent, and reproducible synthesis of empirical findings across diverse studies (Krüger, Lausberger, von Nostitz-Wallwitz, Saake, & Leich, 2020; Paul, Lim, O'Cass[3], Hao, & Bresciani, 2021). The review strictly follows the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol (Page et al., 2021)[2], ensuring methodological rigor and adherence to international standards for conducting systematic reviews.

Data Sources and Search Strategy

The primary databases selected for this review were Scopus, which was chosen for its extensive coverage of education technology, computer science, and pedagogy-related publications. A comprehensive search was conducted on August 1, 2025, covering the period from January 2021 to August 2025 to capture the most recent and relevant developments. The search used Boolean operators across the title, abstract, and keyword fields (TITLE-ABS-KEY). The search terms combined DL-related concepts with primary education terms to ensure precision and breadth, as depicted in Figure 1

Figure 1. Boolean Search Query in Scopus Database

Inclusion and Exclusion Criteria

A set of explicit inclusion and exclusion criteria was carefully developed to ensure that only the most relevant and methodologically sound studies were incorporated into this review. These criteria served as a guiding framework for screening and evaluating all retrieved articles, allowing the review to maintain a clear focus on Deep Learning (DL) applications within primary education while filtering out irrelevant or low-quality publications. By applying these standards consistently, the study sought to enhance the review process's[3] credibility, transparency, and replicability. The criteria are summarized in Table 1.

Table 1. Inclusion and Exclusion Criteria

Criteria Type Inclusion Criteria Exclusion Criteria

Document Type Only[4] peer-reviewed journal articles and reputable conference proceedings retrieved from Scopus, ensuring academic rigor and credibility. Book chapters, theses/dissertations, editorials, white papers, and any non-peer-reviewed or grey literature.

Publication Timeframe Publications from January 2021 to August 2025 will reflect the most current developments and trends in DL and primary education. Studies published before 2021 or after August 2025 fall outside the review window.

Language Publications written[5] in English for clarity and consistency in interpretation. Non-English publications should avoid translation bias and ensure accuracy.

Research Methodology Empirical[6], experimental, or conceptual studies with a clearly defined DL application and transparent methodology relevant to education. Purely technical studies focusing on algorithm development or model optimization without an educational context.

Educational Stage Research explicitly addresses primary or elementary education (K–6), including personalized learning, student engagement, or assessment using DL. Studies[7] focusing exclusively on secondary schools, higher education, vocational training, or non-educational sectors.

Quality and Rigor Studies demonstrating clear research objectives, robust study design, and well-documented findings. Studies with vague aims, unclear methodology, or insufficient reporting on outcomes.

Quality Assurance Process

A multi-stage quality assurance strategy was applied throughout this SLR to ensure methodological rigor and maintain the integrity of the review process (Mwogosi & Mambile, 2025; Naghib, Gharehchopogh, & Zamanifar, 2025)[2]. First, two independent reviewers screened all retrieved titles and abstracts, applying the inclusion and exclusion criteria consistently. Any discrepancies in selection were discussed in consensus meetings, and a third reviewer adjudicated unresolved cases to eliminate bias. At the full-text review stage, each study was examined for methodological soundness, relevance to primary education, and clear articulation of Deep Learning (DL) application. Furthermore, all data extraction sheets, including coding of DL models, educational purpose, and reported challenges, were cross-validated between reviewers to ensure consistency and accuracy. Finally, the synthesis phase was conducted collaboratively to guarantee that thematic interpretations and trend analyses were grounded in a shared understanding of the selected studies.

PRISMA Flow and Study Selection

This review adhered strictly to the PRISMA 2020 protocol (Page et al., 2021)[2], ensuring a transparent and reproducible process for identifying and selecting relevant studies. The initial database search on Scopus yielded 893 records (Figure 2). As part of the screening process, 566 duplicate entries were removed, leaving 327 unique records for further examination. From these, 51 records were automatically excluded by Scopus filters for irrelevance or incomplete metadata, resulting in 279 full-text reports retrieved for assessment.

Figure 2. PRISMA Flow Diagram of Study Identification and Selection Workflow

However, accessibility issues led to 206 reports being deemed unavailable, reducing the pool to 73 studies eligible for complete evaluation. These remaining studies underwent a rigorous eligibility review based on predefined inclusion criteria, ensuring that only high-quality and contextually relevant research proceeded to the synthesis stage.
During this stage, several studies were excluded based on predefined criteria: 16 studies lacked a clearly defined research methodology, 5 were review-based

publications rather than original empirical work, 21 studies were unrelated to deep learning in primary education (focusing instead on secondary or higher education), and 18 studies presented insufficient or low-quality data. After this rigorous selection process, 21 studies met all inclusion requirements and were incorporated into the final synthesis. This flow diagram demonstrates the review's[3] methodological rigor and transparency, ensuring that only high-quality, relevant, and empirically grounded studies formed the basis of the systematic review.

Data Extraction and Synthesis Approach

For the 21 studies included in this review, information was systematically collected using a structured coding sheet to maintain organization and consistency. Each study was examined for key details such as the author, year, country, type of Deep Learning (DL) model used (e.g., CNN, RNN, or hybrid models), its primary educational purpose (such as supporting personalized learning, increasing engagement, or aiding assessment), the type of dataset involved, data preparation methods, and the main findings and challenges reported. Two reviewers carried out this process independently to minimize bias, and any discrepancies in coding were discussed until a final consensus was reached.

To ensure that the synthesis directly addressed the research questions, the findings were then thematically organized according to three guiding inquiries: RQ1, which examined trends in how DL is being applied in primary schools; RQ2, which explored challenges including technical issues, resource limitations, and ethical considerations; and RQ3, which identified emerging opportunities for leveraging DL to enhance personalized learning, student engagement, and overall learning outcomes. This thematic approach created a clear connection between the extracted data and the broader objectives of the review.

The synthesis itself combined qualitative thematic analysis with quantitative mapping. Frequencies of DL models, dataset sources, and application domains were calculated to illustrate trends for RQ1, while reported barriers such as infrastructure gaps, ethical dilemmas, and data-related constraints were categorized to address RQ2. Likewise, innovative use cases and pedagogical opportunities were clustered to illuminate RQ3.

The review used a combination of[8] VOSviewer, Microsoft Excel, and Python to deepen the analysis. VOSviewer supported bibliometric visualization of co-occurrence networks (e.g., keywords linked to DL in education or clusters of authorship), revealing research trends (Liu, Ali, & Lee, 2025; Martins, Gonçalves, & Branco, 2024; Sood, Kumar, & Saini, 2021). Microsoft Excel facilitated metadata organization, trend chart creation, and summary tables (Miñan, Moreno, & Fernández, 2023). Python, using libraries such as pandas, matplotlib, and NLTK, enabled advanced data processing, text mining, and visualization (e.g., keyword frequency plots and thematic word clouds) (Khandare, Agarwal, Bodhankar, Kulkarni, & Mane, 2023; Lavanya et al., 2023)[2]. These tools allowed for a holistic synthesis that blended narrative interpretation, bibliometric insights, and numerical trend analysis, ensuring the discussion remained tightly aligned with the three research questions.

- **RESULT AND DISCUSSION**

RQ1. What are the current trends in DL applications for primary education?

Recent years have witnessed a notable surge in scholarly interest in applying deep learning (DL) to primary education. This growing body of research reflects a global shift in educational priorities, where data-driven methodologies and intelligent systems are increasingly viewed as essential tools to personalize learning, automate assessment, and support early interventions. As traditional teaching methods adapt to 21st-century demands, DL offers promising solutions for addressing complex educational challenges, ranging from cognitive development to emotional monitoring and environmental responsiveness. To better understand these emerging directions, Figure 3 presents the global distribution of DL-related studies from 2021 to 2025, providing a temporal lens into the evolution of this research landscape.

Figure 3. Global Distribution of DL Research

The trend of deep learning (DL) publications in primary education from 2021 to 2025, as shown in Figure 3, demonstrates a steady increase in research interest over time. Beginning with three publications in 2021, the number rose slightly to 2 in 2022, followed by a significant peak in 2023 with seven studies. Although there was a modest decline to 4 publications in 2024, the number rebounded to 5 in 2025, indicating sustained academic engagement. This pattern suggests a growing recognition of DL's[3] potential in enhancing learning environments, particularly in personalized education, assessment automation, and early detection of learning needs. The peak in 2023 may also reflect momentum gained from post-pandemic educational reforms and the acceleration of AI-driven innovations in schooling systems.

While the temporal analysis presented in Figure 3 reveals a consistent increase in research outputs over time, a more in-depth examination of thematic and methodological patterns offers profound insights into how deep learning (DL) is operationalized in primary education, aligning with Research Question 1 (RQ1). Table 2 consolidates findings from diverse studies conducted across 11 countries, illustrating the broad scope of DL applications, ranging from environmental monitoring and curriculum enhancement to emotional diagnostics and personalized learning feedback. These studies draw upon various datasets and implement a broad spectrum of DL architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and transformer-based models. Each model is contextually adapted to address specific educational challenges and learning objectives, reflecting the growing sophistication and relevance of DL in primary education.

Table 2. Overview of Deep Learning Trends in Primary Education

No Author and Country Trend Category Dataset Used Deep Learning Model

1 (Aamer et al., 2025)[2]/ Korea DL for Environmental Health & Safety in Schools Real-world PM2.5 measurements from 3 schools (ES, MS, HS) & 9 nearby air quality stations (576+ data points) ADCAE (Attention Deep Convolutional Autoencoder)

2 (Boob & Radke, 2025)[2]/ India Curriculum-Focused DL in Geometry ElementaryCQT (380,000 images, 76 classes of 2D shapes) Sequential CNN, VGG16, ResNet50, InceptionV3, Inception-ResNetV2

3 (Lin, Zhao, Wang, & Chen, 2025)/ China AI Curriculum Development with DL Concepts Hands-on activities with 5th-grade students at Huangshi Chinese-English School; CNN image recognition tasks Convolutional Neural Network (CNN)

4 (L. Tian, Ding, Tian, Chen, & Wang, 2025)/ China DL for Intelligent Educational Assessment 4,481 valid responses from Chinese 6th-graders answering scientific argumentation tests TextCNN & Bi-LSTM+Attention

5 (R. Zhang et al., 2024)/ China Urban Environmental Color Analytics for Child Psychology Baidu Street View Images (497,088 images), OSM Road Network, POI Data, Statistical Yearbook, VR Questionnaire Data DeepLab V3+ (Semantic Segmentation) + Lasso Regression

6 (Moon, Kim, Kim, & Kim, 2024)/ Korea AI Literacy-Oriented DL Education Pre/post-test AI literacy assessments (20 elementary gifted students) Deep Learning (via Machine Learning for Kids)

7 (Deng, Huang, & Ren, 2024)/ China Psychological Variable–Driven DL Models 147,210 elementary students (LegiLexi exam 2016–2021) OSO-DDNN (Owl Search Optimized Dynamic Deep Neural Network)

8 (Muhathir, Maqfirah, El Akmal, Ula, & Sahputra, 2024)/ Indonesia Facial Recognition for Early Screening 200 facial images of autistic and non-autistic students (70:30 & 80:20 split) SVM with HOG & SURF feature extraction

9 (X. Zhang, Wang, & Chen, 2025)/ China Cognitive Analytics for Art-based Learning 1968 coded peer-assessment comments (49,869 words) from 40 first graders *Epistemic Network Analysis* (ENA – treated analogously to DL-based cognitive mapping)

10 (Zirak, Saeedian, Zomorodian, & Tahsildoost, 2023)/ Iran Predictive Modeling for Educational Space Design 4×864 + 4×858 simulated layouts of Tehran primary schools (12 configurations) GAN (pix2pix) for image-to-image translation; CNN (VGG16, VGG19) for feature extraction & regression

11 (Baharuddin & Naufal, 2023)[2]/ Indonesia Automation of Exam Question Classification 449 Indonesian elementary school multiple-choice questions, labeled by Bloom's[3] Taxonomy (C1–C4) Fine-tuned IndoBERT

12 (Ong et al., 2023)[2]/ Philippines DLNN in Online Learning Evaluation 385 Filipino primary school students (ages 7–13), purposive sample Deep Learning Neural Network (DLNN)

13 (Lomurno et al., 2023)[2]/ Italy Early Dysgraphia Risk Detection Longitudinal handwriting-related signals from 247 children (kindergarten → 2nd grade) using the *Play-Draw-Write* iPad app Ensemble DL model + Quasi-SVM meta-model

14 (Neha & Kumar, 2023)[2]/ India Graduate Performance Prediction with Correlated Features Dataset of 2,497 students (SSC, intermediate, undergraduate semesters) collected via interviews and academic records. GIPA-PA-ECFSM (Graduate Interlinked Precedent Academic-based Performance Analysis using Enhanced Correlated Feature Set Model)

15 (Winje & Løndal, 2023)[2]/ Norway Pragmatist-Based Deep Learning in Outdoor Education (*Uteskole*) 3 months of fieldwork: participatory observations & qualitative interviews of pupils (grades 2, 5–7) in two Norwegian primary schools Pragmatist theoretical framework (Dewey's[3] Transaction & Continuity) operationalised via Nicol's[3] Multimodal "[3]Model of Knowing"[3]

16 (Lee, 2023)[2]/ Korea AI-based Predictive Learning Models for Math Achievement 301 first-grade students'[3] math characteristics & achievement data (number size/order/counting, computational fluency, cognitive processing) RNN with Seq2Seq architecture

17 (Kim et al., 2022)[2]/ Korea Household-Level Predictive Modeling using Smart Data Smart water meter readings (2017–2019) + weather data + day-type data (weekend/weekday) for four household types LSTM (Long Short-Term Memory) (compared to ARIMA)

18 (X. Tian, Zhao, & Nguyen, 2022)/ China Integration of Deep Learning Concepts into Math Pedagogy Classroom-based observations & theoretical literature on deep learning in mathematics teaching Deep Neural Network (conceptual analogy, not computational)

19 (Hava, 2021)[2]/ Turkey Flipped Classroom as a Vehicle for Deep Learning 97 first-year undergraduates in Turkey (7-week quasi-experimental study) *Not*

computational DL, but pedagogical deep learning strategies

20 (Yang & Hong, 2021)[2]/ Korea Neuroimaging + DL fusion for cognitive detection Resting-state fNIRS signals from 24 participants (15 MCI, nine healthy controls) Pre-trained CNNs (VGG16, VGG19, ResNet, AlexNet) with Transfer Learning (FRTL & CTL)

21 (Piol, Lacatan, & Pulumbarit, 2021)/ Philippines Predictive Analytics for School Enrolment DepEd Batangas Division enrollment data (K–6) for SY 2016–2019 Deep Learning, Decision Tree, Random Forest, Gradient Boosted Tree, SVM, and Linear Regression (compared)

The synthesis of 21 studies in Table 3 highlights a multidimensional evolution in applying deep learning (DL) for primary education. DL has been harnessed across diverse geographical contexts, spanning Asia, Europe, and the Middle East for a broad spectrum of[9] educational objectives, illustrating its versatility and increasing relevance in addressing pedagogical and systemic challenges. A prominent trend centers on curriculum-specific innovations, where DL models such as CNN, RNN, and VGG architectures are used to enhance geometry instruction (Boob & Radke, 2025)[2], AI literacy (Moon et al., 2024)[2], and concept-based mathematics learning (X. Tian et al., 2022). Alongside this, DL is increasingly employed in predictive modeling and early detection, exemplified by studies on academic performance prediction (Lee, 2023; Neha & Kumar, 2023)[2], dysgraphia risk screening (Lomurno et al., 2023)[2], autism identification via facial features (Muhathir et al., 2024)[2], and cognitive outcomes (Deng et al., 2024; Yang & Hong, 2021)[2].

Furthermore, DL has proven instrumental in automating educational processes and assessments. Research by (Baharuddin[10] & Naufal, 2023[10])[2] applied a fine-tuned IndoBERT model to classify test questions based on Bloom's[3] taxonomy, while (L.[10] Tian et al., 2025)[10] used TextCNN and Bi-LSTM with attention for evaluating scientific argumentation. Studies also explored non-traditional educational spaces, such as outdoor learning environments infused with philosophical and multimodal DL analogies (Winje & Løndal, 2023)[2], as well as DL-enhanced environmental design of school facilities (Zirak et al., 2023)[2]. Cognitive development in artistic expression was investigated using ENA-based DL frameworks (X. Zhang et al., 2025), suggesting a growing interest in holistic and affective learning analytics.

A few studies move beyond traditional DL architectures, leveraging novel integrations and hybrid systems: attention-based autoencoders for air quality monitoring in schools (Aamer et al., 2025)[2], GANs for architectural space optimization (Zirak et al., 2023)[2], and Quasi-SVM ensembles for longitudinal writing analysis (Lomurno et al., 2023)[2]. The use of smart household data for student prediction modeling (Kim et al., 2022)[2] also illustrates how environmental and socio-economic data are being brought into the educational domain via DL. Collectively, these studies reveal a decisive shift toward data-rich, interdisciplinary, and context-aware applications of DL in primary education, balancing the technical robustness of DL models with the nuanced needs of young learners, educators, and policy systems (Aamer et al., 2025; Lin et al., 2025; Ong et al., 2023; Piol et al., 2021; R. Zhang et al., 2024)[2].

Figure 3. Global Distribution of DL Research in Primary Education

These empirical directions are geographically distributed in a way that reinforces the global nature of DL adoption in primary education. As shown in Figure 3, China (7 studies) and South Korea (5 studies) dominate the research landscape, underlining their strategic investment in AI-integrated education (Irwanto, 2025)[2]. Emerging contributions from India, Indonesia, and the

Philippines reveal a rising interest in harnessing DL for socially diverse and context-sensitive learning environments (Baharuddin & Naufal, 2023; Boob & Radke, 2025; Muhathir et al., 2024; Neha & Kumar, 2023; Piol et al., 2021)[2]. Meanwhile, European and Middle Eastern countries like Norway, Italy, Iran, and Turkey contribute more localized innovations, such as outdoor learning and spatial analytics. These regional patterns illustrate that DL's[3] role in primary education is not confined to advanced economies, but is increasingly seen as a transformative tool across educational systems worldwide.

Figure 4. Dominant Trends in DL Applications for Primary Education

Figure 4 complements this perspective by illustrating the thematic distribution of DL applications. Assessment & Prediction (5 studies) is the most dominant category, which aligns with global priorities on measurable learning outcomes and early academic interventions. *Curriculum Development* (3 studies) highlights DL's[3] contribution to instructional design and AI-infused pedagogy. Mid-tier trends such as *Early Screening/Detection*, *Learning Environment/Color Psychology*, and *Cognitive Learning/Analytics* (with two studies) indicate growing interest in personalized, emotionally attuned education. Less frequent yet innovative applications such as *AI Literacy*, *Health & Safety*, *Space Design*, *Automation of Evaluation*, and *Outdoor/Environmental Education* demonstrate exploratory efforts in niche domains. Together,[11] these themes affirm that DL is being leveraged to improve academic instruction and enrich the holistic learning ecosystem.

Figure 5. Cross-Mapping DL Models with Educational Trends

To further understand how DL models are mapped to educational objectives, Figure 5 presents a cross-comparison of model usage by trend. CNNs emerge as the most adaptable, applied across domains like *Assessment & Prediction*, *Curriculum Development*, and *Space Design*, reflecting their strength in handling visual and spatial data. RNN and LSTM models are notably used for sequential learning tasks tied to performance prediction, while SVMs and GANs are applied in more specialized contexts such as screening and generative design. IndoBERT appears uniquely in *Automation of Evaluation*, showcasing the rise of transformer-based NLP models tailored to language-specific educational tasks. Interestingly, Cognitive Learning/Analytics and Health & Safety categories often rely on hybrid or custom architectures labeled as[12] “[3] Other,”[3] emphasizing the contextual flexibility required for nuanced educational goals. This diversity in model selection underscores that DL’s[3] impact depends on computational power and how well the architecture aligns with pedagogical needs and data types.

RQ2. What ethical, technical, and pedagogical challenges arise when implementing DL at this level?
RQ3. What opportunities exist to leverage DL for ***personalized learning, student engagement, and holistic outcomes*** *in primary schools?*

Building upon the thematic and geographical mapping of DL research in primary education, this section addresses two pivotal aspects: the challenges (RQ2) and opportunities (RQ3) that arise when implementing deep learning (DL) at the primary school level. As the use of DL becomes increasingly prominent in early education, scholars have begun to critically examine its ethical implications, technical barriers, and pedagogical complexities, alongside its transformative potential to personalize learning, increase student engagement, and promote holistic development.

Table 3 presents a synthesized overview of 21 selected studies, categorizing each by its identified challenge, corresponding opportunity, and the main takeaway or contribution. This synthesis offers a nuanced understanding of how DL is both reshaping and being shaped by the practical realities of primary education, and it[13] serves as the empirical foundation for the following discussion.

Table 3. Summary of Challenges and Opportunities in Applying Deep Learning (DL) for Primary Education

No Author Challenge Opportunity Main Synthesis

1 (Aamer et al., 2025)[2] Pedagogical & Ethical Concerns Smart School Monitoring & Well-being DL bridges smart infrastructure and primary education, supporting healthier, data-informed learning environments while saving costs and promoting equity.

2 (Boob & Radke, 2025)[2] Technical – Dataset Complexity Personalized & Interactive Learning DL can transform early geometry lessons into adaptive, visually engaging experiences, enabling personalized feedback, higher engagement, and potentially holistic outcomes for young learners.

3 (Lin et al., 2025)[2] Ethical & Equity Concerns Foundational AI Literacy & Engagement Shows that DL concepts (CNN, digitization, algorithmization) can become a gateway for early AI literacy, sparking curiosity and paving the way for deeper computational and critical thinking in the primary years.

4 (L. Tian et al., 2025) Pedagogical Challenges Automated Assessment & Teacher Support DL models can transform assessment workflows, moving

teachers from manual scoring to higher-value pedagogical roles, while providing students with quicker feedback for better learning.

5 (R. Zhang et al., 2024) Technical Personalized Emotional Mapping Enables child-specific design of school neighborhoods, reducing stress & improving emotional well-being.

6 (Moon et al., 2024)[2] Pedagogical Challenge Engagement through Block-Based DL DL models can be simplified into playful learning environments, making abstract concepts accessible.

7 (Deng et al., 2024)[2] Technical Challenge Psychological Integration for Engagement This[14] shows that DL[15] can provide academic and socio-emotional support.

8 (Muhathir et al., 2024)[2] Ethical Challenges Integration with Future DL Models Opens path for next-gen DL to enhance sensitivity & reduce manual tuning.

9 (X. Zhang et al., 2025) China Ethical Personalized Learning Pathways DL models could create individualized learning journeys, adjusting complexity based on cognitive stage.

10 (Zirak et al., 2023)[2] Pedagogical Personalized Space Design DL can personalize the physical environment, improving students'[3] focus, mood &[16] health.

11 (Baharuddin & Naufal, 2023)[2] Ethical Teacher Workflow Automation DL can act as a “[3]cognitive assistant”[3] to reduce admin load and empower teachers to focus on higher-value teaching tasks.

12 (Ong et al., 2023)[2] Technical Personalization DL enables adaptive learning paths aligned to cognitive &[17] emotional readiness.

13 (Lomurno et al., 2023)[2] Technical Personalized Early Intervention Deep learning can shift interventions years earlier, personalizing support and preventing academic/emotional struggles.

14 (Neha & Kumar, 2023)[2] Technical Early Performance Prediction DL enables predictive support systems, letting schools step in early for at-risk students.
15 (Winje & Løndal, 2023)[2] Pedagogical Scope Holistic Deep Learning Framework Outdoor education (*uteskole*) can turn abstract concepts into lived experiences, embedding DL beyond cognition.
16 (Lee, 2023)[2] Pedagogical Alignment Customized Learning Pathways DL enables tailored tutoring, adjusting pace & content for each child.
17 (Kim et al., 2022)[2] Technical – Overfitting & Model Generalization Predictive Behavioral Modeling DL can create early-warning systems for at-risk learners by spotting deviations in learning “[3]consumption”[3] patterns.
18 (X. Tian et al., 2022) Ethical Dimension – Equity of Access Cross-Disciplinary Integration Positions DL as a bridge for[18] holistic education,[18] combining academic, cognitive, and socio-emotional growth.
19 (Hava, 2021)[2] Technical Access & Equity Enhanced Cognitive & Emotional Engagement DL-inspired flipped models can stimulate intrinsic motivation and critical thinking when thoughtfully scaffolded.
20 (Yang & Hong, 2021)[2] Technical Barriers & Imbalance Transfer Learning for Small Datasets This[19] approach could help schools or researchers use DL without massive labeled datasets, democratizing advanced AI tools.
21 (Piol et al., 2021)[2] Algorithm Comparability & Interpretability Forecasting Resource Needs It[20] shows that DL/ML can optimize educational planning at a system level.

Figure 6. Frequency of Challenges and Opportunities in Deep Learning Applications for Primary Education

The reviewed studies underscore a wide array of[21] ethical, technical, and pedagogical challenges accompanying deep learning (DL) integration in primary education, as depicted in Table 3 and Figure 6. Ethical and pedagogical concerns emerge prominently in several studies (Aamer et al., 2025; Lin et al., 2025; Muhathir et al., 2024)[2], revealing dilemmas around data privacy, algorithmic bias, and equitable access. These concerns are particularly heightened in applications that involve monitoring, automation, or personalization, where children's[3] data and developmental sensitivity demand thoughtful governance. However, these same studies suggest that DL, when ethically managed, can foster smarter, more responsive educational environments that support well-being, equity, and early-stage AI literacy, marking a significant step toward inclusive digital transformation in schools. From a technical perspective, barriers such as dataset complexity, overfitting, and limited generalizability continue to challenge researchers and practitioners. Studies by (Boob & Radke, 2025; Kim et al., 2022; Yang & Hong, 2021)[2] underline how the requirement for large, labeled datasets and robust models can restrict the implementation of DL in resource-limited educational settings. Nonetheless, innovative responses to these technical limitations are also evident. For example, transfer learning, model simplification, and interpretability frameworks are helping to democratize DL, allowing even smaller schools to benefit from adaptive and scalable AI tools (Piol et al., 2021; Yang & Hong, 2021)[2].

Pedagogical challenges center around the alignment of DL technologies with young learners'[3] developmental needs and cognitive styles. Studies by (Lee, 2023;[22] Moon[22] et al., 2024[22])[2] emphasize the difficulty of integrating DL into early-stage curricula without oversimplifying or overwhelming students. However, several studies demonstrate that DL can enhance engagement, foster curiosity, and support differentiated instruction when properly adapted, such as through block-based learning environments or customized tutoring systems. DL's[3] capacity to automate assessments (L. Tian et al., 2025) and personalize content delivery (Ong et al., 2023)[2] empowers educators to shift from administrative burdens to more meaningful pedagogical roles.

The opportunities DL presents in personalizing learning are perhaps[23] the most compelling finding across these studies. Several researchers (Lomurno et al., 2023; Neha & Kumar, 2023; X. Zhang et al., 2025)[2] illustrate how DL enables early detection of learning difficulties and tailoring educational pathways to individual cognitive and emotional profiles. This personalization extends beyond content, affecting learning environments'[3,24] spatial and affective dimensions. Works like those of (R. Zhang et al., 2024; Zirak et al., 2023)[2] highlight how DL can support emotional mapping and personalized classroom design, contributing to improved mental health and focus among students. Finally, a growing vision of DL as a holistic framework transcends traditional disciplinary boundaries. Studies by (X. Tian et al., 2022; Winje & Løndal, 2023)[2] position DL as a tool that supports academic performance and fosters socio-emotional development, environmental awareness, and real-world readiness. The convergence of AI with outdoor education, flipped classrooms (Hava, 2021)[2], and system-level forecasting (Piol et al., 2021)[2] reveals a future where DL is not just an instructional supplement, but a core infrastructure for cultivating resilient, adaptive, and emotionally intelligent learners in the primary years. Together, these insights underscore the dual imperative of addressing foundational challenges while embracing the vast potential DL holds for shaping the future of education.

- **LIMITATIONS OF THE REVIEW**

Despite rigorous adherence to PRISMA guidelines and a systematic literature review (SLR) methodology, this research exhibits several inherent limitations that must be acknowledged. Firstly, the review was confined to articles published within the Scopus database between January 2021 and August 2025. Consequently, relevant studies indexed in other reputable databases such as Web of Science, ERIC, or IEEE may have been unintentionally excluded, potentially impacting the comprehensiveness of the synthesized findings. Furthermore, the exclusive focus on English-language peer-reviewed journal articles and reputable conference proceedings inherently introduces language and publication biases, thus limiting the inclusion of potentially valuable insights from non-English-speaking contexts or grey literature sources. Accessibility barriers presented another notable limitation; approximately 74% of initially identified full-text articles (206 out of 279) were inaccessible, significantly reducing the sample size and potentially overlooking pertinent contributions. Additionally, the studies included[25] in the final synthesis predominantly originate from Asian contexts, particularly China and South Korea, limiting the findings'[3] global representativeness. Consequently, insights and recommendations may not fully account for diverse educational, cultural, and infrastructural contexts encountered in other regions.

- **IMPLICATION AND FUTURE INSIGHT**

The results of this systematic review offer significant implications for researchers, educators, policymakers, and technology developers invested in the future of primary education. The[26] demonstrated versatility and transformative potential of DL[26] underscore the urgency of integrating ethically sound, pedagogically informed, and technically robust frameworks within educational practices. Policymakers and education leaders should prioritize creating guidelines to mitigate ethical risks, such as data privacy and algorithmic fairness, ensuring equitable access and fostering stakeholder trust.

From a pedagogical perspective, it is critical to encourage greater teacher involvement in the design and implementation stages of DL applications, fostering professional development to enhance digital literacy and readiness. Educators can thus be empowered as active contributors rather than passive recipients of technology. Similarly, DL applications must be contextualized to align closely with students'[3] developmental stages, cognitive abilities, and socio-emotional needs, thus ensuring genuinely personalized and holistic educational outcomes.

For future research, there is a compelling need to expand geographical and methodological diversity. More empirical studies from underrepresented regions, including Europe, Africa, and the Americas, would significantly enrich the global understanding of DL's[3] potential and limitations in primary education. Additionally, longitudinal and action research methodologies could offer deeper insights into DL interventions'[3] long-term effectiveness and adaptability. Technologically, future innovations should focus on enhancing the scalability, interpretability, and generalizability of DL models. This[27] includes leveraging techniques such as transfer learning, hybrid modeling, and automated interpretability frameworks to overcome limitations related to dataset availability, computational resource constraints, and model transparency. Moreover, cross-disciplinary collaborations integrating insights from psychology, educational theory, and data science are essential to build more holistic DL-driven educational ecosystems.

Ultimately, the strategic integration of DL within primary education has the potential to redefine early learning environments. By addressing existing limitations and capitalizing on identified opportunities, stakeholders can collaboratively advance toward educational systems characterized by personalized instruction, empowered teachers, inclusive accessibility, and enhanced learner engagement, thereby ensuring sustainable educational development aligned with global 21st-century competencies.

- **CONCLUSION**

This systematic literature review underscores Deep Learning's[3] (DL) growing role in transforming primary education. From 2021 to 2025, research shows increasing global interest in DL applications, particularly in Asia, with China and South Korea leading, alongside emerging contributions from countries like Indonesia and India. DL models such as CNNs, RNNs, GANs, and transformers have been applied to diverse educational contexts, supporting personalized learning, early screening, predictive analytics, and curriculum enhancement. These innovations reflect a shift toward student-centered, data-informed learning environments integrating technological advancements with developmental needs.

Despite its promise, DL adoption faces challenges, including ethical concerns (data privacy, equity), technical limitations (dataset complexity, overfitting), and pedagogical misalignment with young learners. Opportunities abound through adaptive learning systems, emotional diagnostics, and spatial-environmental design. Successful DL integration requires strong policy frameworks, teacher readiness, cross-disciplinary collaboration, and greater geographic diversity in research. Strategically applied, DL can foster inclusive, engaging, and future-ready educational ecosystems aligned with 21st-century learning goals.

1.	~~A total of~~	Wordy sentences	Clarity
2.	*(Razzaq & Shah, 2025; Sarker, 2021; Taye, 2023); (Bernacki, Greene, & Lobczowski, 2021; Bhutoria, 2022; Naseer, Khan, Tahir, Addas, & Aejaz, 2024; Van Schoors, Elen, Raes, & Depaepe, 2021); (Aamer, Ba-Alawi, Kang, Lee, & Jo, 2025; Almuhanna, 2025; Imran, Almusharraf, Ahmed, & Mansoor, 2024); (Kovač...*	Citation style options	Correctness
3.	*DL's; "; " ; doesn't; O'Cass; process's; review's; Bloom's; Dewey's; Nicol's; " ; students'; children's; learners'; environments'; findings'; interventions'; Learning's*	Text inconsistencies	Correctness
4.	: Only	Incorrect punctuation	Correctness
5.	are written	Incorrect verb forms	Correctness
6.	: Empirical	Incorrect punctuation	Correctness
7.	~~. Studies~~ → —studies	Incomplete sentences	Delivery
8.	~~used a combination of~~ → combined	Wordy sentences	Clarity
9.	~~a broad spectrum of~~ → various	Wordy sentences	Clarity
10.	*Research by (Baharuddin & Naufal, 2023) applied a fine-tuned IndoBERT model to classify test questions based on Bloom's taxonomy, while (L. Tian et al., 2025) used TextCNN and Bi-LSTM with attention for evaluating scientific argumentation.*	Ungrammatical sentence	Correctness
11.	*Together, these themes affirm that DL is being leveraged to improve academic instruction and enrich the holistic learning ecosystem.*	Unclear sentences	Clarity
12.	~~as~~	Wordy sentences	Clarity
13.	~~, and it~~ → . It	Hard-to-read text	Clarity

14.	. This	Incorrect punctuation	Correctness
15.	*7 (Deng et al., 2024) Technical Challenge Psychological Integration for Engagement This shows that DL can provide academic and socio-emotional support.*	Unclear sentences	Clarity
16.	*10 (Zirak et al., 2023) Pedagogical Personalized Space Design DL can personalize the physical environment, improving students' focus, mood & health.*	Paragraph can be perfected	Clarity
17.	*12 (Ong et al., 2023) Technical Personalization DL enables adaptive learning paths aligned to cognitive & emotional readiness.*	Paragraph can be perfected	Clarity
18.	*18 (X. Tian et al., 2022) Ethical Dimension – Equity of Access Cross-Disciplinary Integration Positions DL as a bridge for holistic education, combining academic, cognitive, and socio-emotional growth.*	Unclear sentences	Clarity
19.	. This	Incorrect punctuation	Correctness
20.	. It	Incorrect punctuation	Correctness
21.	~~a wide array of~~ → various	Wordy sentences	Clarity
22.	*Studies by (Lee, 2023; Moon et al., 2024) emphasize the difficulty of integrating DL into early-stage curricula without oversimplifying or overwhelming students.*	Ungrammatical sentence	Correctness
23.		Tone suggestions	Delivery
24.	*This personalization extends beyond content, affecting learning environments' spatial and affective dimensions.*	Unclear sentences	Clarity
25.	~~included~~	Wordy sentences	Clarity

26.	*The demonstrated versatility and transformative potential of DL underscore the urgency of integrating ethically sound, pedagogically informed, and technically robust frameworks within educational practices.*	Paragraph can be perfected	Clarity
27.	*This*	Intricate text	Clarity