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The Role of Artificial Intelligence (AI) in Early Childhood Education Learning Evaluation

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ABSTRACT

This qualitative study examines the role of Artificial Intelligence (AI) in early childhood education learning evaluation. Data were obtained through a review of recent literature and interviews with 10 purposively selected teachers, lecturers, and educational technology practitioners. The findings indicate that AI can support adaptive and personalised assessment, provide timely feedback, integrate data across learning environments, and facilitate the early identification of children's needs. However, its implementation is constrained by limited teacher digital competency, unequal technological infrastructure, and concerns about children's data privacy. AI should therefore complement, rather than replace, teachers and be introduced gradually through educator training, infrastructure development, appropriate policies, and robust data protection.

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INTRODUCTION

This research topic is the role of Artificial Intelligence (AI) in Early Childhood Education (PAUD) learning evaluation. Early childhood learning evaluation is a fundamental aspect for understanding children's cognitive, social, emotional, and motor development. However, conventional evaluation practices are often generic, less adaptive, and unable to capture the dynamics of child development holistically. The presence of AI offers a new approach that is more adaptive, personalised, and data-driven, making it relevant for research in the context of early childhood education. The significance of this research lies in its contribution to addressing the need for a more contextual and evidence-based evaluation system. By utilising AI, teachers and parents can obtain a real-time picture of children's development, while simultaneously strengthening educational transparency and accountability. This research is also important because it highlights the challenges of AI implementation, such as the limitations of educators' digital competencies, technological infrastructure, and ethical issues regarding the use of children's data.

The research questions posed are (1) What is the role of AI in supporting adaptive and personalised evaluation in PAUD?, (2) How does AI function as a contextual and evidence-based evaluation tool?, (3) What are the challenges and implications of implementing AI in PAUD evaluation?. Theories considered include the Zone of Proximal Development (Vygotsky, 1978), Piaget's constructivism (1972), Bronfenbrenner's ecological theory (1979), Gardner's multiple intelligences (1993), and Rogers' diffusion of innovation (2003). These theories provide a conceptual framework for understanding how AI can support adaptive, contextual, and inclusive evaluation. The hypothesis proposed is that AI contributes significantly to improving the quality of PAUD evaluation through personalisation, cross-environment data integration, and early detection of children's special needs, although its implementation faces challenges in teacher competency, infrastructure, and data ethics.

The operational definitions in this study are (1) Artificial Intelligence (AI), an intelligent computing system capable of automatically processing child development data and providing real-time feedback, (2) Adaptive evaluation, an assessment that adjusts indicators based on the child's individual responses and needs. (3) Contextual evaluation, an assessment that takes into account the child's cultural, social, and environmental background, (4) Personalization, the ability of the AI system to adjust evaluation content according to the child's learning style and multiple intelligences, (5) Child data ethics, the principles of privacy protection, security, and parental consent in the use of child development data. Historically, previous studies have shown that AI can strengthen data-based evaluation and improve learning effectiveness. However, other studies emphasise the need for educator readiness and ethical regulations. By referring to these studies, this study is directed at providing a comprehensive understanding of the potential, challenges, and implications of using AI in PAUD evaluation.

METHODS

This research employed qualitative methods, incorporating a literature review approach combined with exploratory interviews. This approach was chosen because the research aimed to deeply understand the role of Artificial Intelligence (AI) in early childhood education evaluation, rather than simply measuring variables quantitatively.

Empirical data were obtained from 10 purposively selected informants. They included early childhood education teachers, early childhood education lecturers, and educational technology practitioners. Their real identities are not disclosed; pseudonyms are used to maintain confidentiality.

Participant Code	Age (years)	Profession/Role	Length of Experience	Socioeconomic Background	Work/Study Context
R1 – R3	28–32	Early Childhood Education Teacher	5–7 years	Intermediate	Local PAUD institutions
R4 – R6	33–38	AUD Lecturer	8–12 years	Intermediate	College
R7 – R10	39–45	Educational Technology Practitioner	10–15 years	Intermediate	Community/Educational Institution

Table 1. Characteristics of Research Participants
Note: The name of the institution is not mentioned to maintain anonymity.

The data collection instruments consisted of semi-structured interview guidelines and an open-ended questionnaire. The data collection procedure was carried out in four stages:

Stage	Activity	Instrument	Duration
1	Identify sources	Purposive sampling list	-
2	Online/offline interviews	Semi-structured interview guidelines	45–60 minutes
3	Documentation of results	Audio recordings, field notes	-
4	Triangulation with literature	Open questionnaire, document analysis	-

Table 2. Data Collection Procedures

The data were analysed using qualitative thematic analysis. The analysis process included: (a) Initial coding, marking themes from interview transcripts, (b) Categorisation, grouping codes into categories such as “evaluation adaptivity,” “technological challenges,” and “children’s data ethics.” (c) Interpretation, connecting empirical findings with relevant theories (Vygotsky, Piaget, Bronfenbrenner, Gardner, Rogers). Thematic analysis was chosen because it is able to capture patterns and meanings in qualitative data, thus aligning with the research objectives that emphasise in-depth understanding.

RESULTS AND DISCUSSION

Results

Analysis from 10 sources revealed three main focuses: adaptive and personalised evaluation, contextual and evidence-based evaluation, and challenges of AI implementation. Regarding Adaptive and Personal Evaluation, Early Childhood Education (R1–R3) teachers observed that AI helps adjust the difficulty of evaluations to suit the child's abilities.

> *"I saw that children who typically struggled with motor skills no longer felt stressed because the AI system provided incremental training tailored to their abilities. (R1 transcript)."* This supports the hypothesis that AI enhances personalised learning.

In addition, in the aspects of Contextual and Evidence-Based Evaluation, educational technology practitioners (R7–R10) emphasise the integration of data across environments.

> *"AI reports aren't just numbers, but also include developmental charts and activity recommendations. This makes it easier for parents to understand their child's condition. (transcript R8)."* This finding aligns with Bronfenbrenner's ecological theory, which emphasises the influence of the micro and macro environment.

Meanwhile, in terms of Implementation Challenges, most of the speakers highlighted the limitations of teachers' digital competencies and data ethics issues.

> *"Teachers often only use basic features, even though more detailed data analysis is available. This is due to a lack of training. " (R4 transcript)*

> *"Children's data privacy must be protected. Without clear regulations, AI could cause problems. (R9 transcript)"*

Summary of findings can be seen in Table 3 below with explanations provided.

Focus of Findings	**Resource Person Observation**	**Transcript Example**	**Brief Explanation**
Adaptive & personal evaluation	AI adjusts the difficulty level according to the child's ability.	R1: “Children with motor difficulties are no longer stressed, because of the gradual training.”	AI supports personalisation of learning, reducing evaluative pressure
Contextual evaluation & evidence	AI integrates home–school data to produce holistic reports	R8: “AI reports are not just numbers, but graphs and activity recommendations.”	AI reports are more comprehensive, making it easier for teachers and parents to understand progress.
Implementation challenges	Limited teacher competency, infrastructure, and child data privacy issues	R4: “Teachers only use basic features.” R9: “Children’s data privacy must be maintained.”	The main barriers are digital literacy, access to technology, and child data protection.

Table 3. Summary of Findings

Discussion

The results of the study showed that AI was able to adjust evaluation indicators according to children's abilities in real time. Early childhood education teacher informants (R1–R3) observed that children with motor difficulties no longer felt stressed because the AI system provided step-by-step exercises. This supports the hypothesis that AI enhances personalised learning. This finding is consistent with the Zone of Proximal Development theory (Vygotsky, 1978), which emphasises the importance of support according to a child's developmental level. Furthermore, Gardner's (1993) theory of multiple intelligences is relevant because AI can adjust evaluations based on a child's learning style (visual, auditory, kinesthetic). Thus, AI acts as a facilitator, making evaluations more humane and responsive.

Educational technology practitioners (R7–R10) emphasised that AI can integrate data from home, school, and the community. AI reports not only include scores but also progress charts and activity recommendations. This strengthens the validity of evaluations and aligns with Bronfenbrenner's (1979) ecological theory, which emphasises the influence of micro and macro environments on child development. Studies by Marzano (2025) also support this finding, stating that evidence-based evaluations increase accountability and transparency. With AI, teachers and parents gain a more comprehensive picture of a child's development, enabling more appropriate interventions.

Most interviewees highlighted teachers' limited digital competency, unequal technological infrastructure, and ethical issues surrounding children's data privacy. Teachers (R4) stated that they often only use basic features due to a lack of understanding of available data analysis. Practitioners (R9) emphasised the importance of regulations to protect children's privacy. These findings align with Rogers' (2003) diffusion of innovation theory, which emphasises the need for socialisation, training, and policy support for the effective adoption of new technologies. Adams, C., Pente, P., Lemermeyer, G., & Rockwell, G. (2023) also emphasise that without an understanding of ethics, the use of AI risks data manipulation or privacy violations.

Focus of Findings	**Interviewee Observation (Verbal)**	**Supporting Theory**	**Scientific Interpretation**
Adaptive & personal evaluation	R1: “Children with motor difficulties are no longer stressed, because of the gradual training.”	*Vygotsky (ZPD), Gardner (MI)*	AI strengthens learning personalisation and supports targeted interventions.
Contextual evaluation & evidence	R8: “AI reports are not just numbers, but graphs and activity recommendations.”	*Bronfenbrenner (Ecology)*	AI improves the validity of evaluations by integrating data across environments.
Implementation challenges	R4: “Teachers only use basic features.” R9: “Children’s data privacy must be maintained.”	*Rogers (Diffusion of Innovation)*	The main barriers are digital literacy, access to technology, and child data protection.

Table 4. Relationship of Research Results with Theory and Hypothesis

This confirms that AI contributes significantly to improving the quality of early childhood education evaluations through adaptability, personalisation, and cross-environment data integration**.** However, successful implementation depends heavily on educator readiness, policy support, and ethical regulations. Therefore, AI is not a substitute for teachers, but rather a pedagogical partner that strengthens teachers' capacity to understand and respond to children's needs.

CONCLUSION

This study shows that AI can strengthen early childhood education evaluation by supporting adaptive and personalised assessment, integrating developmental data across learning environments, and providing more informative feedback to teachers and parents. However, its effective use depends on educators’ digital competence, adequate infrastructure, clear policies, and strong protection of children’s data. AI should therefore complement, rather than replace, teachers and be introduced gradually through appropriate training, resources, and ethical safeguards.

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REFERENCE

Adams, C., Pente, P., Lemermeyer, G., & Rockwell, G. (2023). *Ethical principles for artificial intelligence in K–12 education. Computers and Education: Artificial Intelligence, 4*, 100131. https://doi.org/10.1016/j.caeai.2023.100131

Bronfenbrenner, U. (1979). *The ecology of human development: Experiments by nature and design*. Harvard University Press.

Gardner, H. (1993). *Frames of mind: The theory of multiple intelligences* (2nd ed.). Basic Books.

Lee, H., Lee, J., & Lee, H. (2025). Developing ethical guidelines for generative AI for pre-service early childhood teachers. *International Journal of Early Childhood Education, 31*(2), 29–61. https://doi.org/10.18023/IJECE.2025.31.2.002

Marzano, D. (2025). *Generative artificial intelligence (GAI) in teaching and learning processes at the K–12 level: A systematic review*. *Technology, Knowledge and Learning*. Advance online publication. https://doi.org/10.1007/s10758-025-09853-7

Ministry of Education, Culture, Research, and Technology. (2022). *Independent curriculum for early childhood education (PAUD): Implementation guide*. Author.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.