Investigating the Effects of AI-Supported Instructional Design on Early Childhood Language Development Through AI Modeling

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ABSTRACT: *With the rapid development of artificial intelligence (AI) technology, AI-assisted educational tools are gradually being applied in the field of early childhood education. However, significant untapped research potential remains regarding Instructional Design, selection issues, and activity-related problems in education (Research Background and Motivation). In light of this, the present research focuses on utilizing AI technology to assist education, aiming to explore the impact of AI-assisted Instructional Design on children's language development through modeling and analysis of relevant data using AI models. The specific research process involves verifying the effectiveness and feasibility of the Instructional Design through AI modeling analysis and providing new ideas and methods for early childhood education practice (Research Method, Research Goals, Research Process). During the course design phase, the researchers design curricula for children in different regions of the world, using CE1 and CE2 data-sets to assess students' acceptance of the curriculum. Finally, the research uses the Conti-Ramsden data-set to conduct targeted education comparisons for children with language impairments (Core Experiment). The overall research findings provide a reference for future early education curricula and offer guiding recommendations (Research Results, Research Significance, Research Contribution).*

KEYWORDS -*: Educational Technology; Assisted Instruction; Early Childhood Language Education; Instructional Design.*

I. INTRODUCTION

The rapid development of artificial intelligence (AI) has significantly transformed early childhood education, providing opportunities to enhance learning experiences, particularly in language development. Traditional methods, though effective to some extent, face limitations in personalization and interactivity. AI-powered tools, such as interactive robots and digital platforms, address these limitations by offering personalized instruction, real-time feedback, and interactive engagement. These tools help improve young learners' vocabulary, comprehension, narrative abilities, and overall cognitive and emotional development. AI-assisted educational tools, utilizing technologies like speech recognition and natural language processing, provide real-time interactions that strengthen children's language comprehension, listening, and expression skills. Through immediate feedback on pronunciation, grammar, and vocabulary, AI enables continuous language improvement. This research not only investigates the impact of AI on young children's language development but also evaluates its role in increasing classroom engagement and fostering enthusiasm for learning. By analyzing participation in AI-enhanced environments, the research aims to propose effective AI-based language teaching strategies that support educators in creating more interactive and personalized learning experiences, promoting holistic language development (Chen, 2024; Nyenooke & Omoruyi, 2023; Nasution, 2023).

II. LITERATURE REVIEW

In recent years, the application of artificial intelligence (AI) technology in education has garnered widespread attention. The potential of AI as an educational tool primarily manifests in its interactivity, personalized learning capabilities, and real-time feedback mechanisms. To gain a more comprehensive understanding of AI's role in early childhood language development, this section will review relevant research across several domains, including the application of AI in education, practical implementations of AI-assisted language learning, theoretical foundations of early childhood language development, and instructional design methodologies based on Ralph Tyler's Instructional Design.

This literature review will systematically examine how AI technologies are being embedded into educational settings, with particular emphasis on their effectiveness in supporting young learners' linguistic growth. By synthesizing empirical studies and theoretical perspectives, we aim to establish a robust framework for evaluating AI's impact on language acquisition during this critical developmental stage. The analysis will also explore how Tyler's principles of Instructional Design (objectives, experiences, organization, and evaluation) can inform the development of AI-enhanced language learning interventions tailored to preschool-aged children.

Through this multi-dimensional review, we seek to identify both the transformative potential and practical limitations of AI in early language education, while providing evidence-based insights for educators and policymakers navigating this emerging technological landscape.

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2.1 Current status of AI applications in early childhood education

Currently, AI applications in early childhood education mainly target language development, math readiness, and scientific thinking. Research indicates that integrating digital technologies enhances children's motivation, participation, and expressive abilities (Fernández-Montoro et al., 2025). Interactive, game-based learning supported by AI helps expand vocabulary and cognitive skills (Catalano et al., 2025).

Some systems use voice interaction and storytelling to guide children in applying new words in narrative contexts. These AI-driven approaches offer adaptive, personalized learning experiences that maintain engagement and support foundational development (Kaya & Ünsal, 2025).

In 2018, Luckin et al. found that in practical applications, AI technology had already been widely implemented across educational settings for different age groups, ranging from adaptive learning systems to intelligent tutoring systems. Based on research results, they discovered that AI can effectively enhance learners' learning experiences and outcomes (Luckin et al., 2018).

In the same year, Belpaeme et al. reported that the use of AI technology could enhance young children's understanding of language through voice interaction and non-verbal communication, such as gestures and facial expressions (Belpaeme et al., 2018).

In 2019, Kory-Westlund and others conducted research in early childhood education using intelligent dialogue systems (chatbots), educational technologies, and personalized learning platforms. For example, AI assistants based on Natural Language Processing (NLP) could help children with vocabulary learning and speech training (Kory-Westlund & Breazeal, 2019).

In 2020, Belpaeme et al. carried out in-depth research on preschool children. The results showed that compared to traditional teacher-led instruction, the interactive learning experiences provided by AI technology were more effective in stimulating children's learning interest and engagement (Gordon et al., 2020).

In 2022, Educational Benefits Skill Development: AI applications have been linked to improvements in creativity, emotional control, and computational thinking among young learners(Su & Yang, 2022).

In 2024, Social Robots: AI-based robots will be utilized to improve social interactions, particularly for children with autism spectrum disorders, enhancing their communication skills(Honghu et al., 2024).

In 2024, Interactive Learning Tools: Tools that promote hands-on exploration have been shown to effectively teach AI concepts to young children, fostering engagement and understanding(Rai et al., 2024).

In 2024, Activity-Based Learning: Research indicates that activity-based learning methods are more effective than traditional approaches in teaching AI concepts(Rai et al., 2024).

Table 1 : Current status of AI applications in early childhood education

Time Author	***Research Topic***	***Research Method***	***Research Results***	***Research Purpose***
Fernández-Montoro et al. (2025)	*ICT training models for early educators teaching children with functional diversity*	*Questionnaire + Structural Equation Modeling (254 teachers)*	*Positive attitudes increased ICT use; age negatively impacted use*	*To improve ICT training and resource support for early educators*
Catalano et al. (2025)	*Predictive role of reading, writing, and math readiness in children's school transition*	*Questionnaire + Focus groups + Regression analysis*	*Math readiness had the strongest impact on transition success*	*To guide teaching focus during preschool-to-school transition*
Kaya & Ünsal (2025)	*Impact of the "Children Learning the Language of Nature" project on skills and environmental awareness*	*Field-based activities + Rating scales + Wilcoxon test*	*Significant gains in core skills and environmental attitudes*	*To explore the benefits of nature-based education in early childhood*
Luckin et al. (2018)	*AI technology in Education*	*Literature review and case analysis*	*Challenges of AI-assisted learning*	*Discussion on the application prospects of AI in education*
Belpaeme et al. (2018)	*Social robots assist in teaching.*	*Literature review analysis*	*Multimodal communication helps in understanding*	*Exploring the potential of robot education*
Kory-Westlund, J. M., & Breazeal, C. (2019).	*Children interacting with social robots.*	*Long-term experimental observation*	*Robots promote vocabulary learning*	*Exploring the mechanism of language acquisition*
Gordon et al., 2020	*The impact of AI interactive learning on preschool children*	*In-depth analysis and comparison of AI and traditional teaching.*	*AI interaction increases interest and engagement.*	*Assessing the impact of AI on children's motivation to learn.*
(Su & Yang, 2022)	*The application of AI tools in preschool education.*	*A review of 17 studies from 1995 to 2021.*	*AI improves children's understanding and multiple skills.*	*Literature evaluating the impact of AI on early childhood education.*

(Rai et al., 2024)	*Applications and challenges of AI in preschool education.*	*Evaluating research designs and educational methods.*	*Active learning improves AI literacy, and tools need to be enriched.*	*Explore AI tools and promote AI literacy among children.*
(Honghu et al., 2024)	*The application of AI in early childhood education and the improvement of social interactions in autism.*	*Literature review and analysis of existing research.*	*AI technology is effective in improving children's social interaction and reducing autism.*	*Explore the potential and challenges of AI technology in early childhood education.*

2.2 Application of Ralph Taylor's Instructional Design in Preschool Education

Since its inception, the Ralph Tyler Instructional Design has been widely applied across the field of education. Originating from Taylorism principles in the early 20th century, this model was initially designed to standardize and optimize educational processes by emphasizing efficiency (Au, 2011). Over nearly a century of development, the Tyler Model has established a goal-oriented framework, ensuring curriculum effectiveness and quality through four systematic stages: defining educational objectives, selecting and organizing content, implementing instructional activities, and evaluating outcomes.

Throughout more than 100 years of practical application, this model has been extensively utilized at various educational levels and across diverse educational contexts, providing a scientific structure and methodology for Instructional Design. In particular, it enables educators to design curricula systematically and coherently, thereby enhancing the scientific rigor and effectiveness of instruction.

In recent years, the rapid advancement of artificial intelligence (AI) technologies has brought new opportunities for enhancing the Tyler Instructional Design. Research increasingly demonstrates that integrating AI with the Tyler framework can significantly improve educational practices. Clearly defined objectives, supported by AI analytics, can offer precise guidance for instructional planning and help educators formulate targeted and adaptive teaching strategies. The selection of appropriate learning experiences, aided by AI-driven personalization, can foster greater student engagement and motivation, promoting holistic development.

Moreover, intelligent organization of curriculum content through AI can enhance knowledge systematization, coherence, and student-centered learning experiences. AI tools can make learning content more dynamic, interactive, and tailored to individual needs. Scientific evaluation processes, when combined with AI-driven assessment technologies, can improve the accuracy and efficiency of measuring student progress, offering timely feedback for both learners and instructors. In doing so, AI supports continuous improvement in Instructional Design and implementation, ultimately enhancing the overall quality of education.

Since the early 2000s, scholars have reexamined Taylorism's relevance in the context of digital transformation in education. Duggal et al. (2023) noted that educational reforms aiming to enhance efficiency have centered on standardizing curricula and applying performance metrics. With the rise of online learning platforms, traditional instructional models have increasingly merged with technology-enhanced approaches to optimize teaching processes. Subsequently, Au (2011) noted that the rise of high-stakes testing had triggered a revival of "New Taylorism," where educational practices were increasingly determined by standardized assessments. Critics of this trend emphasized that over-standardization could undermine students' holistic development, advocating instead for a balanced approach that incorporates flexibility and innovation into Instructional Design (Au, 2011). While Stolovitch and Keeps (2008) did not address the Ralph Tyler Instructional Design specifically, their work on the Professional Development Curriculum (PDC) model in business and industry highlighted a convergence strategy for aligning needs with existing resources, which shares some conceptual similarities with goal-oriented Instructional Design. In recent years, the adaptability of Taylorism has been demonstrated in new contexts. Lin et al. (2024) showed that in Technical and Vocational Education and Training (TVET), Taylorism has been ensemble with connectivism principles to enhance operational skills, demonstrating its continued relevance in contemporary educational environments. Similarly, a 2022 case study emphasized the importance of continuous curriculum monitoring and adjustment to meet national standards, further validating the Tyler Model's significance in ensuring educational quality ("Evaluation of Higher Education Curricula: Application Experience," 2022).

Alongside curriculum theory developments, recent research has explored the integration of artificial intelligence (AI) technologies in education. Chen et al. (2024) demonstrated that AI-driven storytelling techniques, through interactive and personalized experiences, can effectively enhance students' vocabulary acquisition and comprehension skills. In another Research, Avan and Kalenderoglu (2024) ensemble augmented reality (AR) with AI to support the development of listening skills, finding that these technologies significantly improved students' attention and engagement in language learning. Furthermore, Masturoh et al. (2024) investigated the role of AI in enriching children's gaming and learning experiences through real-time activity monitoring, showing that AI-enhanced games can effectively promote learning outcomes. Their additional research confirmed that incorporating AI into games can improve operational efficiency and support complex decision-making within educational contexts (Masturoh et al., 2024). Together, these studies suggest that combining AI with established Instructional Designs like Taylor's can offer promising pathways for modernizing educational practices and improving student learning experiences.

Table 2: Application of Ralph Taylor's Instructional Design in Preschool Education

Time Author	Research Topic	Research Method	Research Results	Research Purpose
(Pérez, Fernández, González, & de la Torre Domingo, 2006)	*Transformation and integration of the Taylorism teaching model to the e-learning model*	*Content analysis, questionnaires, interviews, observations; triangulation of data*	*Explore how to integrate traditional models with innovation in the era of digital teaching*	*The teaching model is flexible and phased, combining traditional efficiency tools with digital teaching*
(Stolovitch & Keeps, 2008)	*Educational resource needs and responses*	*Focus on the PDC Model*	*Constructing a coherent curriculum relevant to career development, an evolving practical model applicable to any industry.*	*Developed a Professional Development Course (PDC) model for businesses and successfully applied it to General Motors.*
(Au, 2011)	*Discuss New Taylorism & Standardized Teaching and Testing.*	*Critique of the impact of high-stakes testing on teaching and learning* *Examining the historical*	*High-stakes testing standardizes instruction in America's schools and undermines teachers'*	*Analyze the changes that high-stakes testing has on teaching* *The argument that high-stakes testing is the "new Taylorism" in education*

		context of scientific management in education	*decision-making power.*	
(Lin et al., 2024)	*Taylorism combined with TVET courses.*	*Taylorism and connectionism combined in Instructional Design and innovative framework implementation.*	*The new curriculum significantly improves escalator troubleshooting skills and promotes collaborative learning.*	*Integrate Taylorism and Connectivism into TVET courses to improve escalator troubleshooting skills.*
(Chen, 2024)	*The impact of AI storytelling applications on language learning*	*Systematic literature review and key features analysis.*	*AI storytelling app promotes language acquisition and literacy.*	*Explore the role of AI in language learning and literacy development.*
(Masturoh et al., 2024)	*Games and play applications of AI in early childhood education.*	*Qualitative research and literature data collection.*	*AI improves gaming experience and real-time monitoring effects.*	*Promote the application of AI in early childhood educational games.*
(Avan & Kalenderoğlu, 2024)	*AI and AR for improving listening skills in early childhood education.*	*Analysis of interactive stories and multisensory learning applications.*	*AR and AI technologies improve children's hearing and concentration.*	*Enhance children's listening skills and language development.*

Overall, research indicates that the application of AI technology in designing targeted curricula for future children's education remains at a preliminary stage. This suggests that while there is immense potential for future research, there are also significant challenges and shortcomings, including a lack of long-term studies and the absence of an ensemble framework for the incorporation of AI into early childhood education (Chen, 2024).

In summary, the Ralph Tyler Instructional Design provides a foundational framework for efficiency and accountability in education. Rooted in the principles of scientific management, the model has undergone significant development over more than a century, particularly in response to technological advancements and evolving societal needs. At present, integrating AI technology into the traditional model enhances its emphasis on efficiency, standardization, and measurable outcomes, making it more meaningful and better suited to today's learning environments. This integration not only helps optimize educational processes but also fosters students' creativity and adaptability to the demands of the AI era.

2.3 Research on the AI model of early childhood language development

2.3.1 The importance of AI in language development

Early childhood is a critical period for the development of language skills. Language development during this stage is essential for future effective communication with others. Through language development, young children learn to accurately express their thoughts and emotions. Beginning with basic motor skills and vocalizations and progressing to complex language abilities, these developments are crucial for social interaction and fulfilling their needs (Gooden & Kearns, 2013). Moreover, if children can skillfully use language to express their unique thoughts and needs during early childhood, it not only promotes their social skills in future interactions but also plays a pivotal role in academic participation, ultimately influencing their overall lifelong development (Gooden & Kearns, 2013).

Research on children's language development is often grounded in Piaget's cognitive development theory and Vygotsky's sociocultural theory. Piaget (1970) proposed that children's cognitive development occurs through four stages, with the preoperational stage (ages 2–7) marking a period of rapid growth in language and symbolic thinking. During this stage, children primarily learn language through imitation and interaction, and AI technologies can serve as effective interactive partners, facilitating a cycle of language input and output. On the other hand, Vygotsky's (1978) concept of the "Zone of Proximal Development" (ZPD) highlights the critical role of social interaction in children's language development.

The stages of language development involve multiple aspects, including vocabulary, grammar, semantics, and pragmatics. Children progress through different stages—from pre-conceptual communication to single-word use, two-word combinations, and eventually short sentences—each reflecting increasing linguistic complexity that is essential for effective communication (Zahra & Sit, 2024). Early language development is vital because it lays the foundation for effective communication, cognitive growth, and social interaction. Early language skills are strongly linked to later academic success and social competence. Various factors influence language development, including the home environment, parental involvement, and educational approaches.

A rich language environment and educational interventions can significantly enhance language development in young children. During the language development stage, improved language abilities help children better understand and express their surrounding world. A positive home environment can notably enhance language skills, leading to better peer interactions and fewer behavioral problems (Chang & Sung, 2015).

For example, exposure to rich language environments, diverse learning activities, and positive interactive experiences can enhance children's expressive and cognitive abilities. Interaction with caregivers and exposure to rich language experiences are crucial for stimulating language growth during early childhood ("Language Development," 2022). Techniques such as the question-and-answer method have been proven effective in improving children's language abilities, enabling them to construct sentences more confidently and express their thoughts (Solihin & Maesaroh, 2024).In summary, research on early childhood language development shows that the improvement of language skills not only affects children's social and cognitive abilities but is also closely related to future academic success. The theories of Piaget and Vygotsky provide an important framework for understanding the process of children's language learning, while a good family environment and educational intervention can significantly promote early childhood language development. The application of AI technology also provides new possibilities and support for facilitating this process.

2.3.2 A review of relevant literature on AI models

Although the emphasis on structured language development is essential, some studies suggest that an overreliance on traditional formal education methods may inhibit children's natural language acquisition. Therefore, achieving a balance between guided instruction and opportunities for free expression is critical for optimal development (Chang & Sung, 2015). In today's AI-driven society, scholars advocate for shifting from conventional one-size-fits-all approaches to more personalized education programs tailored to children's individual needs (Halkiopoulos & Gkintoni, 2024).

Research has demonstrated that the integration of AI technologies into children's language learning can produce significant positive effects (Su & Zhong, 2022). By offering engaging, adaptive, and personalized learning experiences, AI tools enhance language acquisition outcomes and improve learner engagement (Halkiopoulos & Gkintoni, 2024). These tools leverage methods such as interactive storytelling, real-time feedback, and customized learning pathways to meet the needs of diverse learners, including children with disabilities (Chen, 2024a).

The following sections will outline key aspects of AI's role in supporting early language education (Su & Yang, 2022a; Yi, Liu, & Lan, 2023).AI approaches that can estimate and regulate learners' emotional states can favorably impact language learning by tailoring instruction to individual emotional and cognitive profiles(Halkiopoulos & Gkintoni, 2024). Tools like the SpeakDif project utilize natural language processing to create interactive environments that support language development for intellectually disabled children(Al-Qahtani, 2024).

Enhancing Listening and Speaking Skills: Augmented reality (AR) and AI applications improve listening skills by providing multisensory experiences that capture children's attention and foster active participation(Avan & Kalenderoğlu, 2024).AI storytelling applications help children focus on details and extract meaning, crucial for language comprehension(Avan & Kalenderoğlu, 2024).

Motivation and Engagement: AI tools, such as interactive pens, increase intrinsic motivation by offering enjoyable and effective learning experiences, contrasting with traditional methods. Features like audio readings and graded difficulty levels make language learning more accessible and engaging for children(Ma, 2024).

AI technologies, such as chatbots and automatic speech recognition (ASR), support children's language learning by providing instant feedback, reducing anxiety, and allowing personalized practice. These tools enhance engagement and facilitate language acquisition in a supportive, interactive environment (Son et al., 2023).

AI technology in children's language learning enhances vocabulary, comprehension, and narrative skills through interactive and personalized storytelling applications. These tools utilize voice recognition and adaptive algorithms, promoting cognitive and emotional development, particularly in bilingual and diverse educational settings(Chen, 2024).

AI technology enhances children's language learning by utilizing annotated data for effective reading materials, employing natural language processing, and generating self-learning data-sets through machine learning. This approach fosters independent learning and improves students' reading abilities in Chinese(Huang & Kong, 2021).

AI technology in children's language learning personalizes experiences through adaptive learning systems, immediate feedback, and gamification. It creates individualized learning paths, enhances engagement, and provides real-time assessments, making language acquisition interactive and tailored to each child's unique needs and pace(Chen, 2024)

Table 3 A review of relevant literature on AI models

Time Author	***Research Topic***	***Research Method***	***Research Results***	***Research Purpose***
(Huang & Kong, 2021)	*Children's language learning ability*	*Generative learning methods*	*Improve students' independent learning and reading ability*	*Analyze the application of AI in children's Chinese reading services.Improve students' independent Chinese learning ability through AI*
(Qiu & Ke, 2023)	*AI facial recognition helps language learning*	*AI analyzes social emotions* *Face recognition assists language education4o*	*Strengthening early childhood language education provides reference for early childhood education*	*Analyze early childhood social emotions.* *Use artificial intelligence technology to enhance language education.*
(Son et al., 2023)	*AI technology helps language learning, providing feedback and practice.*	*AI technology: writing assessment, dynamic assessment, and speech recognition*	*AI continues to be ensemble into language education, affecting learning and teaching*	*Research trends and discoveries in AI in language education. Promote the application*

				and understanding of AI in language learning
(Chen, 2024)	*AI personalized learning improves the interactivity of language learning。*	*Adaptive learning, intelligent tutoring, natural language processing tools* *AI-driven language learning applications*	*AI improves personalized language learning experience and transforms teaching methods.*	*Research the application of AI in language learning methods and explore the personalized learning experience brought by AI technology*
(Al-Qahtani, 2024)	*AI improves language and social skills of children with special needs*	*Natural language processing enables personalized learning; machine learning promotes language development*	*AI improves language skills and helps communication and integration*	*AI optimizes the environment to improve the language ability of children with special needs*
(Avan & Kalenderoğlu, 2024)	*AI storytelling app improves hearing and cognitive development*	*AR multi-sensory learning, AI stories improve listening comprehension*	*AR and AI improve listening, increase focus and engagement*	*Researching the impact of AR and AI on listening skills* *Exploring children's engagement and attention span*
(Ma, 2024)	*AI technologies such as the AI Pen enhance language learning, stimulate interest and promote vocabulary acquisition*	*Research on the application of AI tools such as caterpillar pen in language learning* *Combining AI tools with traditional teaching methods*	*AI tools stimulate intrinsic motivation for language learning and combine with traditional methods to improve learning outcomes*	*Research the impact of AI tools on children's language learning motivation* *Explore the effectiveness of AI pens in improving language education participation*

2.4 Research Gaps

Existing studies highlight the potential of AI in enhancing personalized learning and student engagement in early childhood education (ECE). AI tools such as interactive storytelling, vocabulary-building tasks, and gamified activities can boost children's participation, imagination, and language skills. However, research directly examining the impact of AI-assisted education on Chinese children's language development remains limited.

While AI integration is transforming ECE by improving teaching, promoting AI literacy, and supporting diverse learners, challenges persist, including inadequate research, limited instructional design, and low AI literacy among educators (Wu, 2024; Su & Yang, 2022). Studies combining AI with instructional models like Ralph Tyler's are especially scarce.

Additionally, frameworks for AI-supported personalized education remain underdeveloped, and applications beyond STEAM fields—particularly in language learning—require further exploration (Masturoh et al., 2024). Equipping educators with AI competencies is also under-addressed (Rai et al., 2024).

Although AI shows promise in enhancing vocabulary acquisition, its long-term impact on children's motivation and grammar learning is unclear (Kennedy et al., 2016). Balancing AI with traditional methods is essential to achieve effective outcomes. In response, this study adopts the Ralph Tyler instructional model to construct a structured AI-assisted language learning framework for young children.

III. Methodology

3.1 Define Objectives

This study began with an analysis of global educational disparities using a data-set containing key indicators such as dropout rates, literacy, and enrollment in primary and higher education. These insights informed the instructional design goals.

Based on Ralph Tyler's instructional design model and AI technologies, the research aimed to support children's language development by enhancing vocabulary, expression, and comprehension skills. The design also considered learners' backgrounds, cognitive abilities, and local cultural contexts to stimulate interest and promote self-directed learning.

AI technologies enable real-time evaluation of learners' needs across regions and allow for dynamic adjustments to instructional goals and pathways. AI-powered tools, such as learning robots or assistants, further support individualized learning and engagement.

3.2 Select Learning Experiences

Many countries, especially developing ones, face serious educational challenges. For example, in Cameroon, nearly 77% of primary school students cannot read, due to factors such as conflict, overcrowded classrooms, and lack of infrastructure.

To address this, the study developed targeted curriculum content using data from the Cameroon Government, UNICEF, and CAYSTI. The focus was on second-grade students, a critical stage in their development.

Curriculum materials were aligned with children's cognitive levels and included gamified content from CAYSTI. Activities ranged from shape recognition and number operations to vocabulary building and sentence construction. AI-powered tools like translation, speech recognition, and interactive videos provided multimodal learning experiences that improved understanding and engagement.

3.3 Organize Learning Experiences

Based on the defined goals and selected content, instructional activities were designed to match young children's developmental stages. Interactive teaching methods and AI-driven feedback supported real-time instructional adjustments.

Activities such as AI-based role-playing and group cognitive games promoted collaboration and motivation. The study also used CHILDES data-sets focusing on 5-year-olds with language impairments. These data-sets revealed that around 7% of children experience language difficulties without other disabilities.

Using AI technologies like speech recognition and NLP, the study designed targeted language interventions. Virtual characters interacted with children and provided real-time feedback on pronunciation, grammar, and vocabulary. This approach helped improve language skills in natural dialogue settings.

3.4 Evaluate Learning Outcomes

To ensure the effectiveness of the AI-assisted Instructional Design, a rigorous curriculum evaluation system will be established. Evaluation will encompass multiple dimensions, including children's learning performance, language development, cognitive growth, learning engagement, and attitudes across diverse global regions. A mixed-methods approach—combining observational techniques and standardized assessments—will be adopted to provide a comprehensive and objective evaluation of outcomes.

AI technologies will play a pivotal role in supporting data-driven evaluation, enhancing both objectivity and breadth.

Real-time learning analytics will be utilized to continuously capture key indicators such as Research duration, error rates, and response times, creating individualized learning profiles to monitor developmental trajectories.

In addition to traditional assessment scores, AI-enabled multidimensional data collection will allow for a more holistic analysis, including children's participation levels, emotional responses, and language fluency.

Automated data analysis and reporting will further assist educators in identifying learning needs with greater precision, enabling timely pedagogical adjustments and personalized support.

IV. AI MODEL

4.1 Data Collection

Firstly, during the data collection phase for determining the course objectives, in-depth analysis and research were conducted on key indicators from over 200 countries worldwide, including 29 different data attributes such as dropout rates, completion rates, proficiency levels, literacy rates, birth rates, and enrollment statistics for both primary and higher education. Secondly, during the course development phase, data sets for CE1 and CE2 students from coastal and eastern regions were used to analyze academic performance during the first two semesters. Additionally, a comparative experimental setup was used, comparing the data from schools that did not benefit from these interventions. Lastly, for children under the age of five with language impairments, three data sets with a sample size of 1,163 were used for research.

The specific details of the data sets are as follows: the first data set includes samples from British adolescents, the second data set includes samples from Canadian children aged 4 to 9, and the third data set includes samples from American children aged 4 to 12. Conti-Ramsden 4：The Conti-Ramsden 4 data-set was collected to assess the effectiveness of narrative tests in adolescents. It includes samples from 99 typically developing (TD) children and 19 children with specific language impairment (SLI), aged between 13.10 and 15.90 years.

ENNI：

The ENNI data-set was collected during a Research that aimed to identify children with SLI through a storytelling ability index based on a story grammar model. The corpus includes a sample of 300 typically developing (TD) and 77 children with specific language impairment (SLI), aged between 4 and 9 years. Each child was presented with two wordless picture stories, one of which was more complex than the other. Unlike Conti-Ramsden 4, the examiner held the book and turned the page after the child seemed to have finished telling the story for a certain picture. The children were also allowed to practice a training story, during which the examiner gave the child more explicit prompts.

Gillam：

The Gillam dataset is based on another tool for narrative assessment called the Test of Narrative Language (TNL). It includes 250 children with language impairment and 520 controls, aged between 5 and 12 years old. Detailed descriptions about each participant do not exist. TNL includes four storytelling tasks, the first is recalling a story based on a script, and the rest are wordless picture books. The first set of pictures depicts a story in which the main character attempts a goal several times, and the rest are single-picture stories. Single-picture stories require more input from the children and are therefore more suitable for older children. TNL seems to be between ENNI in terms of difficulty.

4.2 Data Processing

In the data preprocessing stage, it is possible to effectively process and accurately analyze the data. Through the data preprocessing process, irrelevant information can be deleted, and effective features can be retained for learning.

The first step in data preprocessing is data cleaning, which reduces the accuracy of model fitting by removing unnecessary information to reduce erroneous data. Common methods for numerical data include a median filling method, a mode filling method, etc. The specific formula is as follows:

Median filled Method: $x_i{}^\wedge = \frac{1}{n} \Sigma_{j=1}^{n} x_j$ (1)

Mode filled method: $\mathrm{mode}(\mathrm{x}) = argmax_{c \in C} P(x = c)$ (2)

In the feature extraction phase, thresholds are set for specific sparse data and unimportant data features are removed. This process extracts data with higher relevance to the results, ensuring that the model learns effective information and produces more accurate outcomes. Traditional feature extraction methods include PCA, which reduces data dimensionality by decomposing the variance matrix and retaining the direction with the highest variance. The specific mathematical formulas for PCA are as follows:

$$\mathrm{W} = \arg\max tr(W^T XX^T W)_W \;\; s.t. W^T W = I \; (3)$$

Finally, standardize the data by processing the dimensions and differences of the data, making the numerical values more normalized. Traditional data preprocessing methods include Z-Score normalization and Max-Min normalization. The specific formulas are as follows:

$$\text{Z-Score normalization: } x^{'} = \frac{x-\mu}{\sigma} \quad (4)$$

The data as a whole follows a normal distribution.

$$\text{Max-Min normalization: } x^{'} = \frac{x-x_{min}}{x_{max}-x_{min}} \; (5)$$

All data will be within the range of [0, 1] after Max-Min normalization preprocessing.

4.3 Model

4.3.1 Logistics Regression

In this research, during the modeling analysis process, we first used logistic regression to conduct an in-depth analysis of preschool children with language disorders. Logistic regression is a classification algorithm based on probability theory, used to solve binary or multi-classification problems. Its fundamental idea is to fit data onto an S-shaped function (sigmoid function), transforming the results of linear regression into probabilities, thereby converting continuous numerical outputs into discrete classification values. The specific mathematical formula is as follows:

Mathematical function of the Sigmoid:$\mathrm{P(y = 1 \mid x)} = \frac{1}{1+ e^{-(W^T x+b)}}$ (6)

The mathematical loss function:$\mathrm{J(W)} = -\Sigma_{i=1}^{n}[y_i \log p_i + (1 - y_i) \log 1 - p_i]$ (7)

This research also takes into account that logistic regression is prone to over-fitting. Therefore, during this research process, we optimized the logistic regression model by employing some appropriate strategies such as adding regularization and modifying the loss function to reduce over-fitting, thereby improving the model's generalization ability and accuracy. Specific optimization methods include L1 regularization and L2 regularization. In logistic regression, regularization is used to penalize model complexity by adding a regularization term to the loss function. This term is typically the sum of the squares or absolute values of the model parameters, which encourages the model to select smaller weight parameters during optimization.

L1 regularization refers to the sum of the absolute values of the elements in the weight vector w, typically represented as ||W||1. This results in a sparse matrix because many features have a negligible impact on the outcome, or are nearly zero. Consequently, in the correlation matrix representation, these features are represented as 0. If most variables are 0, then the elements of the matrix are 0, and the entire matrix becomes a sparse matrix. The specific mathematical formula is as follows:

L1 regularization: $\lambda \sum_{j=1}^{m} |W_j|$ (8)

L2 regularization refers to the square root of the sum of the squares of each element in the weight vector w (as seen in the L2 regularization term of Ridge regression, which includes a squared symbol). It is typically represented as ||w||2. The idea behind regularization is still to seek the minimization of the cost function. The specific mathematical formula is as follows:

L2 regularization: $\lambda \sum_{j=1}^{m} {W_j}^2$ (9)

Regularization is the implementation of the strategy for minimizing structural risk, which involves adding a regularization term or penalty term to the empirical risk. This allows the model to tend towards selecting simpler parameter combinations, thereby reducing the risk of over-fitting and enhancing the model's generalization ability. The regularization term is typically a monotonically increasing function of model complexity; the more complex the model, the larger the regularization term. If over-fitting occurs, using a penalty function can reduce the occurrence of over-fitting. If over-fitting is observed, employing a penalty term can effectively mitigate the occurrence of over-fitting.

4.3.2 Ensemble Algorithm

The ensemble algorithms used in this research mainly fall into three different categories: random deep forest models based on tree structures, Ada-Boost models, and Boosting models.

Bagging (Bootstrap Aggregation) is an ensemble learning method based on bootstrap sampling. It generates multiple training sets of equal size by randomly sampling (with repetition) from the original training set. Then, each training set is used to train a base classifier, and these classifiers are combined through voting or other methods to form a more powerful classifier.

"Random Forest" is an ensemble learning algorithm based on decision trees, an extension of the bagging algorithm. Unlike traditional decision trees, random forests not only randomly select samples from the training data but also randomly select a portion of features for splitting at each node, thereby generating multiple slightly different decision trees. Classification is performed through the voting of these decision trees.

The core idea of bagging is to increase sample diversity through multiple random samplings and reduce the variance of a single base classifier, thereby improving the accuracy and stability of the overall classification.

The specific mathematical formulas are as follows:

Tree splitting criterion formula: $\text{Gini(D)} = 1 - \sum_{k=1}^{K} p_k^2$ (10)

Split gain calculation formula: $\Delta Gini = Gini(\text{D}) - \frac{|D_L|}{|D|} Gini(D_L) - \frac{|D_R|}{|D|} Gini(D_R)$ (11)

In the random forest algorithm, each base decision tree is built through random sampling and random feature selection, and these decision trees are referred to as weak classifiers. By combining multiple weak classifiers, the random forest algorithm can produce a more accurate and stable strong classifier.

Ada-Boost is an ensemble method. Its core idea is to apply a weighted strategy to the samples that were previously misclassified, so that the new classifier pays more attention to the mislabeled samples, thereby effectively solving the problem of data imbalance. It also utilizes its advantages and compensates for the deficiencies to enhance the algorithm performance. In each iteration, Ada-Boost selects a new weak classifier and increases the weight of the samples that were misclassified in the previous round, while reducing the weight of the correctly classified samples. After completing the iterations, Ada-Boost combines the classification results of all weak classifiers through weighted summation to obtain the final classification result.

GBDT (Gradient Boosting Decision Tree) evolved from the boosting tree. The key feature of GBDT lies in using the negative gradient of the loss function to simulate (replace) the residuals, so for a general loss function, they only need to be first-order differentiable. The goal of the GBDT algorithm is to construct a classifier for regression or classification by integrating multiple decision trees. The GBDT algorithm improves the prediction accuracy of the entire model by combining previous decision trees and adopting an iterative residual learning process, while avoiding some problems of the gradient descent algorithm, such as getting stuck in a local optimal solution. In the data fitting process of the GBDT algorithm, each decision tree is regarded as a basic learner, and each basic learner will learn the residual fitting result of the previous decision tree.

Through iterative processes, the final model obtained is a linear combination of multiple base learners. GBDT optimizes iteratively through an additive model, and the specific mathematical formula for the model prediction at step t is as follows:

$F_t(x) = F_{t-1}(x) + \eta \, . \, h_t(x)$ (12)$F_{t-1}(x)$

epresents the prediction from the previous tree t-1， $h_t(x)$is the output of the Tree， η is the learning rate.

The XGBoost algorithm uses gradient boosting (GBDT) to continuously add trees, aiming for the ensemble's predictions to closely match the true values. During each tree addition, XGBoost calculates the loss function using a second-order Taylor expansion approximation of the current data-set, determining each sample's leaf node score on the current tree based on gradients and second derivatives. A greedy algorithm is then used to select the optimal split point. The ensemble grows by continually splitting features, with each added tree learning a new function to fit the residuals from the previous prediction. After training k trees, predicting a sample's score involves finding the corresponding leaf node for that sample in each tree, where each leaf node corresponds to a score. Summing these scores gives the predicted value for the sample. Specifically, it optimizes the loss function during training, first determining the current tree's prediction on the current data-set, then training the next tree based on this, ultimately resulting in a model that sums all tree predictions weighted together.

The objective function of XGBoost includes the loss function and regularization term, with the specific mathematical formula as follows:

$$\mathrm{Obj} = \sum_{i=1}^{n} L\big(y_i, F(x_i)\big) + \sum_{t=1}^{T} \Omega(f_t) \quad (13)$$

$$\Omega(f_t) = \lambda T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \quad (14)$$

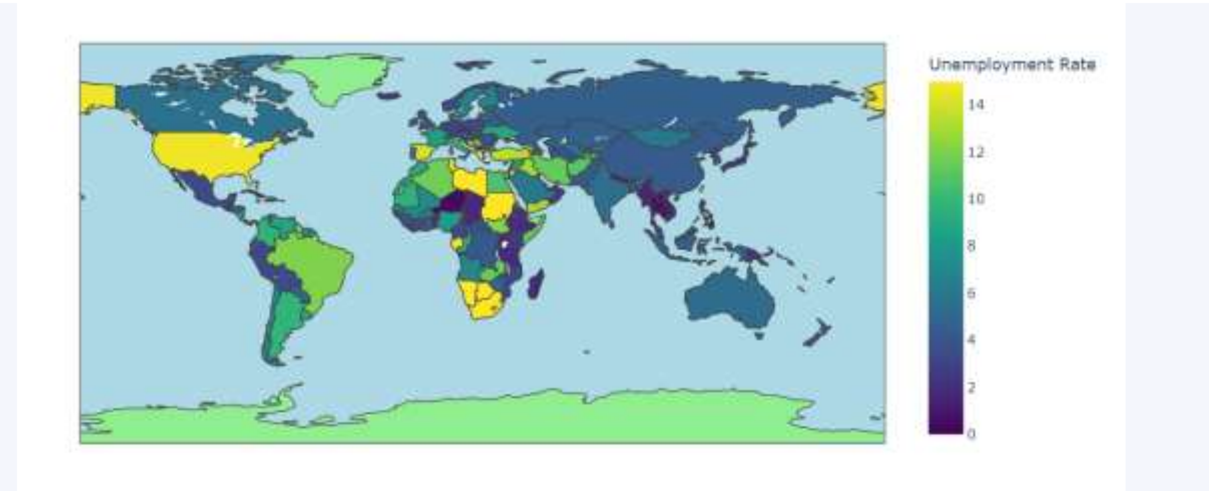
T is the number of leaf nodes in the tree， w_j^2 is the square value of the weight of the leaf node.， λ is the hyperparameter complexity。

Additionally, XGBoost employs techniques like parallel split point search, block data storage, and cache-aware processing to accelerate training. It also supports regularization to prevent over-fitting and handles missing values effectively. In summary, XGBoost's algorithmic approach involves continuously adding trees to approximate true values while employing techniques such as second-order Taylor expansion and parallelization to enhance model accuracy and efficiency.

V. RESULT & EVALUATION

5.1 Visualization results in different regions

First, in the course goal design stage, by analyzing the educational environment in different regions around the world, combined with factors such as geographic information, the following visualization chart is produced:



Through an in-depth analysis of the chart, we can see that early education has an important impact on a person's life. Even after completing the school exams, entering society also plays an important role in the salary level of society. Therefore, in the process of developing and designing the practical application of educational courses, it is of great research value to design different course objectives for children in different regions.

5.2 Language Development Test Results

By comparing and analyzing the pre-and post-test scores of the children in the experimental group and the control group, it was found that the children in the experimental group had significant improvements in language development and cognitive ability. In terms of vocabulary, language expression ability, language comprehension ability, etc., the test scores of the children in the experimental group were significantly higher than those of the control group; in terms of observation, attention, memory, and thinking ability, the children in the experimental group also showed certain advantages (Abdelhamid et al. 2023).

5.3 Model Evaluation

A confusion matrix is used for comprehensive evaluation during the evaluation phase of the model. The confusion matrix is a core tool for evaluating the performance of classification models. It comprehensively reflects the accuracy, error type, and distribution of the model by comparing the matching between the statistical model prediction results and the true labels.

The first-level evaluation indicators used to show the prediction performance of the classification model in each category are as follows. Taking the binary classification problem (positive class Positive, negative class Negative) of this Research as an example, the matrix structure is as follows:

True/Predicted	Predicted Positive Class	Predicted Negative Class
True positive	TP(True Positive)	FN(False Negative)
False positive	FP (False Positive)	TN(True Negative)

Table 4

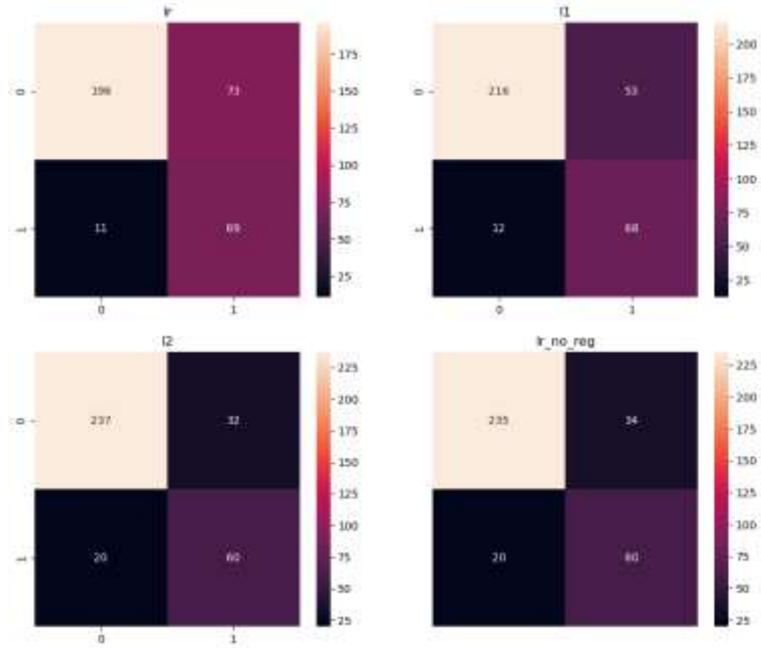
True Positive (TP): The number of samples correctly predicted as positive by the model (correct identification).

FN (False Negative): The number of positive samples incorrectly predicted as negative by the model (missed detection).

FP (False Positive): The number of negative samples incorrectly predicted as positive by the model (false alarm).

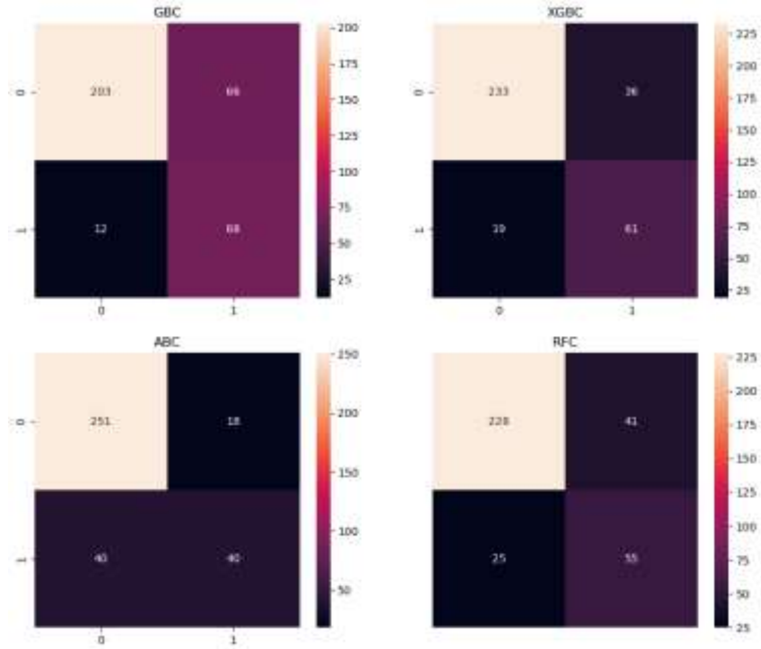
TN (True Negative): The number of samples correctly predicted as negative by the model (correct rejection).

Logistic Regression confusion matrix evaluation results are as follows:



From the results of the confusion matrix, we can see that the results of L1 and L2 regularization are indeed better than the evaluation results of the logistic regression model to a certain extent.

The results of the ensemble result confusion matrix evaluation analysis are as follows:



From the results of the confusion matrix, it can be seen that among the outcomes of fitting with the ensemble algorithm model, the XG Boost model has the most balanced performance, while the Ada-Boosting model provides the best prediction for true positives.

The secondary evaluation metrics of the confusion matrix reflect the model's performance across different dimensions, with the specific calculation formulas as follows:

Accuracy,:The overall proportion of correct predictions by the model:Accuracy:

$$\text{Accurcay} = \frac{TP + TN}{TP + TN + FP + FN} \quad (15)$$

Precision: The proportion of actual positives among samples predicted as positive

$$\text{Precision:Precision} = \frac{TP}{TP+FP} \quad (16)$$

Recall: The proportion of genuine samples correctly identified by the model

$$\text{Recall: Recall} = \frac{TP}{TP+FN} \quad (17)$$

F1-Score:Harmonic mean of precision and recall

$$\text{F1} = 2\,\frac{Precision\,.Recall}{Precision + Recall} \quad (18)$$

Advanced evaluation metrics for the confusion matrix of logistic regression are as follows:

	Lr	l1	l2	lr_no_reg
Precision	0.841199	0.859028	0.860287	0.856636
Recall	0.759312	0.813754	0.851003	0.845272
F1-score	0.777247	0.825067	0.854501	0.849430
Accuracy	0.759312	0.813754	0.851003	0.845272

Table 5

Advanced evaluation metrics for the confusion matrix of ensemble algorithms are as follows:

	GBC	XGBC	ABC	RFC
Accuracy	0.842128	0.844647	0.762011	0.836887
Precision	0.704318	0.758095	0.503881	0.756165
Recall	0.515741	0.546296	0.485158	0.463426
F1-score	0.572857	0.595509	0.474861	0.524936

Table 6

VI.Discussion

6.1 Effectiveness of AI Technology-Assisted Instructional Design

The research results show that the AI technology-assisted Instructional Design designed based on the Ralph Taylor Instructional Design, significantly promotes children's language development and cognitive ability. Through personalized teaching, interactive participation, and real-time feedback, the module meets children's learning needs, stimulates their learning interest and initiative, and thus improves their learning outcomes.

6.2 Research limitations

This Research has certain limitations. First, the number of experimental samples is limited, which may affect the universality and representativeness of the research results. Second, the experimental time is short, and it may not be possible to fully observe the long-term impact of the AI technology-assisted Instructional Design on children's language development and cognitive ability. In addition, there may be some uncontrollable factors in the research process, such as individual differences of children, family environment, etc., which will have a certain impact on the research results.

6.3 Future Research Directions

Future research can further expand the number of experimental samples, extend the experimental time, and deeply explore the long-term impact of AI technology-assisted Instructional Designs on children's language development and cognitive abilities. At the same time, it is possible to combine multidisciplinary research methods such as neuroscience and psychology to reveal the mechanism of action of AI technology-assisted education. In addition, it is also possible to explore how to combine AI technology-assisted education with other educational methods and means to provide children with more comprehensive and high-quality educational services.

VII. CONCLUSION

This Research designed an AI technology-assisted Instructional Design based on the Ralph Taylor Instructional Design and explored its impact on children's language development through practical application and experimental research. The results show that the design can effectively improve children's language development and stimulate their learning interest and initiative. Although the Research has certain limitations, it provides new ideas and methods for early childhood education practice. Future research can further improve and optimize the AI technology-assisted Instructional Design and promote the widespread application of artificial intelligence technology in the field of early childhood education.

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