AI-Driven Approaches to Language Skill Development in Pre-Adolescent Learners

Niyangoda S A N S H  
Department of Computer Science and Software Engineering  
Sri Lanka Institute of Information TechnologyMalabe, Sri Lanka  
it21194962@my.sliit.lk

Jenny Krishara  
Department of Information Technology  
  
Sri Lanka Institute of Information TechnologyMalabe, Sri Lanka  
jenny.k@sliit.lk Sirisena B G K D  
Department of Computer Science and Software Engineering  
Sri Lanka Institute of Information TechnologyMalabe, Sri Lanka  
it21357794@my.sliit.lk

Dinuka Wijendra  
Department of Information Technology  
Sri Lanka Institute of Information TechnologyMalabe, Sri Lanka  
dinuka.w@sliit.lk Dewinda A G T  
Department of Computer Science and Software Engineering  
Sri Lanka Institute of Information TechnologyMalabe, Sri Lanka  
it21196560@my.sliit.lk

*Abstract*— The boundaries of technology continue to be eliminated and as a result, language learning and comprehension tools appropriate for children aged 10-12 have emerged. This study attempts to integrate advanced technologies such as AI-powered listening exercises, adaptive gamification features, personalized education, and predictive analysis to develop an educational platform for learners of this age segment. The AI activities employ natural language processing (NLP) for response assessment and feedback provision, which excel in reinforcing and enhancing language proficiency. At the same time, the adaptive gamification captures students' faces with a facial recognition system, measuring their emotional responses to content in order to adaptively engage students and promote individualized instruction. Furthermore, predictive analytics ensure intervention and content personalization based on the child's monitored progression toward academic goals. This research exemplifies how interactive and adaptive learning environments motivate students and enhance understanding and academic performance can be achieved by integrating disparate technologies.

Index Terms—AI-powered listening exercises, Natural Language Processing, Adaptive gamification, Facial recognition, Emotional response analysis, Personalized education, Predictive analytics, Adaptive learning

# Introduction

The development of educational technology has introduced new methods for supporting language acquisition in children aged 10–12. At this stage, children are developing cognitive, emotional, and social skills that are foundational for acquiring core competencies in listening, reading, speaking, and comprehension. There is an increasing demand for educational tools tailored to the needs of this age group.

This research focuses on the application of artificial intelligence (AI) in supporting language learning through an educational tool designed for children in this developmental stage. The system incorporates active listening exercises, gamification, personalized content delivery, and predictive analytics.

The AI-powered listening component uses Natural Language Processing (NLP) to analyze student responses and provide immediate feedback aimed at improving pronunciation, comprehension, and overall language proficiency. The system includes adaptive gamification features that adjust based on user input and learning progress. It also integrates facial emotion recognition to monitor emotional states such as frustration or engagement and modify content difficulty accordingly.

Predictive analytics is used to analyze data such as reading speed, quiz performance, and progress to estimate learning curves and adjust instructional content in real time. The system can identify when a student is struggling or excelling and modifies the difficulty of the learning materials accordingly.

The integration of these technologies—NLP-based feedback, emotion-adaptive gamification, and predictive content adaptation—creates a personalized learning environment. This study investigates the effectiveness of such an AI-powered system in supporting language skill development for children aged 10–12.

# Literary Review

The integration of technology into education has significantly reshaped learning methodologies, particularly in language acquisition among young learners. For children aged 10-12, a critical period in cognitive and linguistic development, the adoption of AI-powered learning tools has demonstrated improvements in language proficiency, comprehension, and engagement. This section reviews key research on AI-based listening activities, adaptive gamification, personalized academic content, and predictive analytics, which collectively form the foundation of this study.

## AI-Based Listening Activity for Language Comprehension

AI-based listening activities serve as a vital tool in assessing language comprehension by analyzing student responses to voice clips. Unlike traditional interactive voice assessments that analyze speech patterns, this approach focuses on evaluating written responses to pre-recorded audio content. By leveraging Natural Language Processing (NLP), the system verifies whether a student's response correctly matches the expected answer, ensuring real-time feedback and adaptive reinforcement.

Studies by Ginsberg et al. [1] and Wu et al. [2] emphasize the effectiveness of AI-assisted language assessment models in improving listening comprehension and response accuracy. These models process student inputs, compare them against predefined correct answers, and generate immediate feedback on correctness and contextual understanding. According to Hussain and Raza [3], providing instant feedback on written responses enhances student engagement, as learners can self-correct and refine their comprehension skills without external intervention.

Further, Ziegler et al. highlight that AI-driven response validation can accommodate variations in student phrasing, allowing for flexible answer recognition while ensuring that comprehension objectives are met. This adaptability ensures that students are not penalized for minor variations in wording, promoting a deeper understanding of content rather than rote memorization.

## Adaptive Gamification for Engagement and Motivation

Gamification has been widely recognized as an effective strategy for maintaining student engagement in educational settings. Studies by Anderson et al. [4] and Deterding et al. [5] highlight that incorporating game-like elements—such as points, rewards, and progress tracking—improves learning persistence and fosters intrinsic motivation.

In addition to engagement, emotional intelligence integration into gamified learning environments has gained prominence. Picard et al. [6] introduced facial recognition technology to assess students’ emotional responses, dynamically adjusting content based on their emotional state. This approach helps mitigate frustration while enhancing student motivation. For instance, when a student struggles with comprehension, the system simplifies the content or provides hints. Conversely, if a student shows confidence or joy, it introduces more challenging tasks to maintain engagement.

## Personalized Academic Content for Adaptive Learning

Personalized learning has been widely adopted to tailor educational content based on individual student needs and abilities. Research by Pane et al. [7] and Baker et al. [8] demonstrates that AI-powered educational systems analyze student performance metrics—such as quiz completion rates, reading speed, and comprehension accuracy—to adjust content dynamically. This approach ensures that students’ progress at an appropriate pace, reducing the likelihood of frustration or disengagement.

Further, Zhao et al. [9] stress that adaptive systems improve student retention by catering to diverse learning styles. Unlike rigid curricula, AI-powered systems identify gaps in knowledge and adjust instructional strategies accordingly. Schunk et al. [10] argue that personalized content improves mastery learning, as students focus on weaker areas rather than being forced into a standardized curriculum.

## Predictive Analytics for Early Intervention

Predictive analytics has become a powerful tool in education, allowing for early intervention strategies based on real-time student performance analysis. Studies by Xu et al. [11] and Romero et al. [12] demonstrate that predictive models—which analyze metrics such as quiz scores, assignment accuracy, and time spent on tasks—can forecast student performance trends. This enables early identification of struggling students, allowing for targeted interventions before learning gaps widen.

Moreover, Dutt and Wang [13] emphasize that predictive analytics helps create tailored learning paths that evolve with a student's progression rate. Unlike traditional adaptive learning models, which respond only to past performance, predictive analytics can anticipate future challenges, ensuring students receive timely content adjustments. This real-time adaptability ensures that students are neither overwhelmed nor under-challenged.

## Challenges and Ethical Considerations in AI-Driven Learning

While AI, gamification, and predictive analytics provide substantial benefits, several challenges and ethical concerns must be addressed. Ravitch et al. [14] highlights that equitable access to AI-based learning tools remains a significant challenge, particularly in underserved communities where technological resources may be limited.

Additionally, data privacy and ethical concerns surrounding student performance tracking and facial recognition technologies require strict compliance with privacy regulations [15]. While these technologies enhance learning outcomes, Surendeleg et al. [16] caution that poorly designed gamification models may prioritize engagement over educational value, leading to over-reliance on extrinsic motivation rather than deep learning.

# Methodology

The system integrates AI-based tools, including listening activities, student performance prediction, future forecasting, and adaptive gamification. It was developed as a web-based application using the MERN stack to support scalability, flexibility, and AI model integration. Data was collected at Regent Language Institute, Negombo, through pre-tests, post-tests, involvement logs, feedback on emotional responses, and qualitative comments from students and instructors.

## AI-Based Listening Activity

The AI-based listening component supports listening comprehension and written response evaluation. Students listen to a pre-recorded voice paragraph and answer comprehension questions. Responses are evaluated using a Natural Language Processing (NLP) model based on semantic similarity rather than keyword matching. The NLP model, developed using TensorFlow, calculates a similarity score between the student's answer and the reference answer. A response is marked correct if the similarity score is 80% or higher. This method accounts for synonyms, sentence structure variations, and contextual relevance.

*Implementation and Model Training*

To ensure accuracy in semantic similarity scoring, the model was trained on a dataset of question-answer pairs. The training process included

1. Preprocessing: Text was converted to word embeddings using tokenization, lemmatization, and vectorization.
2. Training: A TensorFlow-based deep learning model was trained using supervised learning and similarity metrics.
3. Inference: During evaluation, student answers are vectorized and compared to reference responses using cosine similarity.

The AI-based listening model allows students to engage with spoken content dynamically, reinforcing their ability to process auditory information and respond in written form with real-time feedback.

## Student Level Prediction Model

T A Student Level Prediction Model was developed to assess academic performance and proficiency levels in real time. The model evaluates overall engagement, quiz performance, and content interaction to classify students into predefined proficiency levels. Learning materials are adjusted based on these classifications.

The performance level is calculated using the formula:

**Performance level = (quiz score / resources score )**

​

The model uses a ratio-based metric where the quiz score represents test performance and the resources score represents engagement with study materials. This metric is used to evaluate the effectiveness of resource utilization and identify potential comprehension difficulties

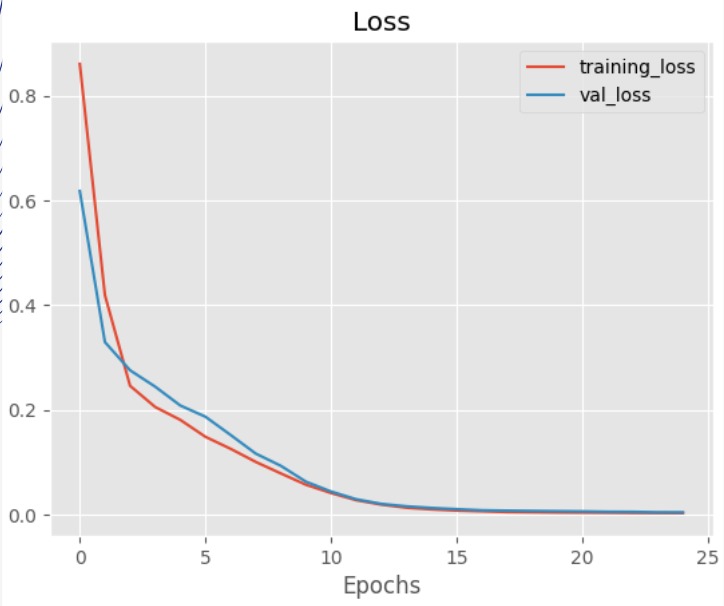
*Implementation and Training Process*

The student-level prediction model was trained using structured data transformation techniques

1. Feature Engineering: Standardized features such as quiz scores, time spent on resources, and engagement frequency using MinMaxScaler and StandardScaler from sklearn.preprocessing.
2. Model Training :
   1. Data was split into training and testing sets using train\_test\_split().
   2. A Sequential Neural Network model was developed in TensorFlow/Keras, consisting of Dense layers with activation functions optimized using the Adam optimizer.
   3. The model was trained on student performance data, allowing it to accurately classify low, average, and high-performing students.
   4. This predictive model ensures real-time personalization, where struggling students receive additional support, and advanced students are challenged with more complex tasks.

A group of red and white graphs

AI-generated content may be incorrect.



## Future Forecast Prediction Model

A Future Forecast Prediction Model was developed to predict student performance over a minimum period of seven weeks. The model analyzes historical performance data to forecast future learning trajectories and identify students requiring early intervention.

*Implementation and Forecasting Process*

This model integrates time-series forecasting using LSTM (Long Short-Term Memory) networks, which are particularly effective for processing sequential learning data. The prediction process involves:

1. Data Preprocessing: Aggregating weekly student performance data and applying MinMaxScaler for normalization.
2. Model Architecture:
   1. Implemented using tensorflow.keras. models.Sequential().
   2. Contains LSTM layers, Dropout layers for regularization, and Dense output layers for making predictions.
3. Training & Evaluation:
   1. The model was trained on seven-week student performance data to recognize long-term academic trends.
   2. Forecasts were validated against actual student outcomes to fine-tune accuracy.
4. By analyzing student progression over multiple weeks, this model helps teachers and administrators make data-driven decisions for intervention and curriculum adjustments.

A graph with blue lines and orange lines

AI-generated content may be incorrect.

Figure actual value and predict forecast value

## Adaptive Gamification System and Emotion Capture Model

A gamification framework was implemented with emotion-based learning adjustments. The system uses facial recognition technology to track student emotions and modifies learning tasks in real time based on detected emotional states.

1. Gamification Features
   1. Includes point systems, reward mechanisms, and leveling up.
   2. Task difficulty is adjusted dynamically based on student interaction.
2. Emotion-Based Learning Adjustments
   1. Frustration detection triggers task simplification, hint provision, or automated encouragement.
   2. Detection of positive emotional states triggers increased task difficulty and additional learning incentives.

By integrating emotion-based feedback, this model improves student engagement and prevents learning fatigue.

## Implementation Details

The system was developed as a web-based application using the MERN stack. The frontend was built with React.js. The backend was developed using Node.js and Express.js, handling server-side logic, API requests, and AI model integration. MongoDB was used as the primary database to store student performance data, engagement metrics, and learning progress. TensorFlow models were integrated into the backend for real-time analysis, performance prediction, and adaptive content modification.

## Data Collection Methods

Data was collected from Regent Language Institute, Negombo, through structured assessments, real-time analytics, and qualitative feedback.

1. Pre- and Post-Tests: Conducted before and after an eight-week intervention to measure improvements in listening comprehension, vocabulary acquisition, and written response accuracy.
2. Engagement Metrics: Collected through automated tracking, including time spent on lessons, quiz completion rates, frequency of interaction, and consistency of participation.
3. Emotional Response Analysis: Performed using facial recognition technology to detect emotions such as frustration, confusion, joy, or excitement. This data was used to adjust content difficulty in real time.
4. Surveys and Interviews: Conducted with students and teachers to collect qualitative feedback on usability, engagement, and instructional effectiveness.

# Results and Analysis

The study evaluated the impact of the AI-based educational tool on language comprehension, engagement, and adaptive learning for students aged 10 to 12. The analysis focused on performance improvements, engagement metrics, and adaptability compared to traditional methods.

1. Students in the experimental group using the AI-based system showed higher post-test scores compared to the control group.
2. Improved comprehension and vocabulary retention were observed in the experimental group.
3. Engagement metrics indicated increased time spent on lessons, higher task completion rates, and more frequent quiz participation among users of the AI tool.
4. Instant feedback and personalized content adjustments corresponded with reduced frustration and increased task completion.
5. Survey data indicated that students using the system remained focused and participated consistently throughout the study period.

## Performance Improvements

**Listening Comprehension and Response Accuracy**

1. Students using the AI-Based Listening Activity showed higher comprehension scores than the control group.
2. The NLP-based answer evaluation system supported flexible responses and accurate feedback.

**Personalized Learning and Student Adaptability**

1. The Student Level Prediction Model categorized students into proficiency levels for tailored content delivery.
2. The Future Forecast Model enabled early intervention by identifying students at risk of underperformance.

**Engagement and Emotional Responsiveness**

1. Students using the Adaptive Gamification System had higher task completion rates and engagement levels.
2. The facial recognition system adjusted lesson difficulty based on emotional state, reducing frustration and increasing motivation.

## Comparison with Existing Systems

The developed educational tool was compared to existing AI-driven learning systems, such as Knewton, Carnegie Learning, and DreamBox Learning, which also implement adaptive learning and predictive analytics. However, several key differentiators set this system apart:

**AI-Based Listening Activity vs. Traditional Speech Assessments**

Unlike other platforms that focus primarily on speech-based pronunciation feedback, this tool evaluates written responses using NLP, making it more flexible and suitable for a variety of learning styles. The similarity-based scoring system allows students to demonstrate comprehension without being penalized for minor variations in phrasing, which reinforces conceptual understanding over rote memorization.

**Predictive Learning Models vs. Static Content Adaptation**

Many existing systems adjust content based only on past performance, while this tool uses forecasting models to predict future learning trajectories, enabling proactive content adaptation and intervention.

**Emotion-Based Learning Adaptation vs. Conventional Gamification**

Unlike traditional point-based gamification, this system tracks student emotions in real-time, ensuring that students receive supportive or challenging content adjustments based on their emotional state. The emotionally responsive learning approach provides a more engaging and frustration-free learning experience compared to systems that rely solely on fixed difficulty levels.

**Web-Based MERN Stack Implementation vs. Standalone AI Models**

Many AI-powered learning tools operate as standalone systems, limiting their ability to seamlessly integrate with real-time student data.

The MERN-based architecture in this system enables continuous AI model updates, real-time analytics, and seamless adaptability, making it highly scalable and efficient.

## Challenges and Limitations

Despite its strong performance in improving learning outcomes, the system faces some challenges and limitations that must be addressed in future iterations

**Data Availability and Model Training Limitations**

1. The student prediction and forecasting models rely on historical data, which may impact accuracy when applied to larger and more diverse student populations.
2. Expanding the dataset and implementing continuous learning techniques could enhance the model’s long-term adaptability.

**Technical Requirements and Computational Load**

1. The real-time similarity scoring and emotion tracking features require substantial computing power, which may pose accessibility challenges for lower-resource institutions.
2. Future optimizations could focus on lighter model architectures or cloud-based AI processing to increase efficiency.

**Ethical Considerations in Emotion-Based Learning**

1. The use of facial recognition for tracking engagement raises privacy concerns, requiring strict adherence to ethical guidelines and data protection protocols.
2. Although the collected data was anonymized and securely stored, further refinement of policy frameworks is necessary to enhance trust and transparency.

# Conclusion

This study demonstrates the integration of AI-enhanced listening activities, predictive analytics, and adaptive gamification in language learning for children aged 10–12. The AI-powered system led to measurable improvements in listening comprehension, vocabulary retention, response accuracy, and student engagement, when compared with traditional learning methods.

By applying Natural Language Processing (NLP) for real-time evaluation and feedback, students received feedback on their inputs, enabling a more personalized learning path. Predictive models were used to track performance trends and adjust content accordingly, while emotion recognition technology allowed the system to adapt in real time based on student emotional states.

The system was developed using a MERN stack architecture and integrated with AI models and real-time analytics, supporting scalability and interactive functionality. Key features included flexible response evaluation, predictive modeling, and real-time emotion tracking.

Despite these advancements, the study acknowledges several challenges, including limitations in data availability, computational requirements, ethical considerations in emotion tracking, and the accuracy of NLP systems. Future work must address these issues to ensure fairness, efficiency, and security in AI-supported educational tools.

This research contributes to the development of adaptive educational systems that support personalized, responsive, and scalable learning environments for young language learners.

# References

|  |  |
| --- | --- |
| [1] | E. G, N. B and N. S. I, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," *Philosophical Transactions of the Royal Society of London. Series A, Mathematical and Physical Sciences,* vol. A247, p. 529–551, A247. |
| [2] | C. M. J, A Treatise on Electricity and Magnetism, Oxford, United Kingdom: Clarendon Press, 1892. |
| [3] | S. J. I and P. B. C, Fine particles, thin films and exchange anisotropy, New York, NY, USA: Academic Press, 1963. |
| [4] | N. R, "Title of paper with only first word capitalized," *J. Name Stand. Abbrev..* |
| [5] | Y. Y, H. M, O. K and T. Y, "Electron spectroscopy studies on magneto-optical media and plastic substrate interface," *IEEE Transl. Journal on Magnetics in Japan,* vol. 2, p. 740–741, 1987. |
| [6] | Y. M, The Technical Writer’s Handbook, Mill Valley, California, USA: University Science Books, 1989. |
| [7] | E. K and V. J, "Adaptive control for singularly perturbed systems examples," Code Ocean, August 2023. [Online]. Available: https://codeocean.com/capsule/4989235/tree. |
| [8] | P. K. D and W. M, "Auto-encoding variational Bayes," arXiv, 2013. [Online]. Available: https://arxiv.org/abs/1312.6114. |
| [9] | L. S, "Wi-Fi Energy Detection Testbed (12MTC)," GitHub, Inc., 2023. [Online]. Available: https://github.com/liustone99/Wi-Fi-Energy-Detection-Testbed-12MTC. |
| [10] | S. A. a. M. H. S. A. O. o. A. S. U.S. Department of Health and Human Services, "Treatment episode data set: discharges (TEDS-D): concatenated, 2006 to 2009," Washington, D.C., 2013. |
| [11] | A. G, N. H. M, M. R, F. B and O. H, "Developing an early-warning system for spotting at-risk students by using eBook interaction logs," vol. 6, no. 1, p. 1–15, 2019. |
| [12] | A. e. a. M, "Predicting at-risk students at different percentages of course length for early intervention using machine learning models," *IEEE Access,* vol. 9, p. 7519–7539, 2021. |
| [13] | N. E, M. M and C. C, "Identifying At-Risk Students for Early Intervention—A Probabilistic Machine Learning Approach," *Applied Sciences,* vol. 13, no. 3869, 2023. |
| [14] | L. R.-G. J, A. G.-P. J and D.-D. A, "Analyzing and predicting students’ performance by means of machine learning: A review," *Applied Sciences,* vol. 10, no. 1042, 2020. |
| [15] | E. E, "Identifying at-risk students using machine learning techniques: A case study with IS 100," *International Journal of Machine Learning and Computing,* vol. 2, p. 476, 2012. |
| [16] | P. C. S, S. L. S, C. L. K and T. W. B, "Learning analytics at low cost: At-risk student prediction with clicker data and systematic proactive interventions," *Journal of Educational Technology & Society,* vol. 21, p. 273–290, 2018. |