

AI-Based Personalized Learning Models for English Language Acquisition

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Abstract: Historically, traditional English language education has adhered to standardized models and approaches based on the premise that a uniform approach will be able to cater to different learners from different backgrounds, irrespective of their level of language learning, speed of language acquisition, and different cognitive styles, which leads to disengagement and unequal results. This paper presents a personalized learning model for acquisition of English as a second language that consists of four interconnected components: learner profiling component, adaptive content generator, skill-specific feedback component, and progress tracking component. The proposed model comprises a multi-layer architecture that contains a data layer, intelligence layer, and interaction layer and will be developed through a fourth phase methodology. The proposed model stands out from previous attempts of dealing with the problems of pronunciation tutoring, writing assistance, listening support, and learner-style predicting as it represents the harmony of the previous attempts in one continuously changing model that is specifically designed for English language learners. The discussion touches the expected advantages of the use of the model, including lower level of disengagement of learners and increased speed of corrective cycles, but also raises the issues related to the privacy of data, dependence on technological infrastructure and algorithmic discrimination. The proposed model offers a practical foundation for future empirical validation and real-world deployment in English language learning contexts.

Key Words: artificial intelligence, personalized learning, english language acquisition, adaptive learning systems, learner profiling, intelligent tutoring systems, natural language processing

(Received: 17 March 2023; Revised: 28 April 2023; Accepted: 26 May 2023; Published: 30 June 2023)

Introduction

The acquisition of English as a second or foreign language has been influenced for many years by the constraints of the "one-size-fits-all" instructional model, with instruction based on similar materials and methods regardless of the level of language proficiency, learning speed, and cognitive style of learners (Kuddus, 2022). Artificial Intelligence has appeared in education as a revolutionary phenomenon that provides an opportunity to move from standard education to personalized one (Chen et al., 2021). AI technology is becoming increasingly reliable in analyzing the behavior of learners, forecasting gaps in knowledge, and modifying the process of learning in accordance with the individual needs of learners (Mitra & Banerjee, 2022).

It is noted that pronunciation error detection based on Big Data analytics has contributed significantly to English proficiency improvement through the use of personalized feedback (Liu & Quan, 2022). A comparative analysis of various educational systems in the USA, China, and India has proved that AI technologies based on human-in-the-loop approach can be adapted to different cultural and educational backgrounds without losing their personalization (Bhutoria, 2022). AI technology in the field of learning environments provides evidence that language acquisition is far more effective in the process of continuous learning than in separate classes (Jia et al., 2022).

An innovative platform which has been developed for teaching listening in English education at the level of college education provides a considerable boost to learner autonomy (Zhou, 2020). The main issues and problems of AI-based platforms have been identified, along with solutions to address the problems connected with data privacy, algorithmic bias, and scalability (Murtaza et al., 2022). Predictive modeling is nowadays the basis of personalized education, as predictive models based on artificial intelligence successfully predict academic performance of learners and change the process of education accordingly (Gupta et al., 2022).

Learning styles prediction systems based on AI technology demonstrate how early determination of learning styles could result in effective personalization for years (Pardamean et al., 2022). AI technologies are actively applied in improving personalized education and skill development in professional settings (Umutlu & Gursay, 2022), while research on AI recommender systems shows the connection between personalized education and labor market demands in terms of future employability of learners (Tavakoli et al., 2022).

This research proposes a comprehensive AI-driven framework for the personalization of language learning processes that integrates pronunciation analysis, listening comprehension assistance, adaptive content ordering, and learning style classification into a singular platform tailored to English language learning. This contribution is essential because the aforementioned types of integrations are not present in previous studies on the field. The paper discusses an innovative integrated AI-based personalized learning approach comprising the modules of pronunciation analysis, listening comprehension support, content sequencing and learner style predictions, which are not covered by other works in the area. The organization of the paper is as follows. Section II reviews some of the previous AI-based language learning systems and indicates the gaps in the existing studies. Section III describes the components of the personalized learning system. Section IV characterizes the system under consideration and how it was developed. Section V presents the evaluation plan of the authors' model. Section VI provides the pros and cons of the system proposed. Finally, the conclusions and some perspectives for further research are given in Section VII.

Related Work on AI-Driven Personalized English Language Learning Systems

A broad discussion of artificial intelligence (AI) technologies applied in English teaching reveals that automated feedback systems, intelligent tutoring and speech recognition programs are increasingly superseding traditional, teacher-centered practices in the context of additional education (Fitria, 2021). AI systems for generating avatars of conversational agents reveal that affective and motivational aspects are as significant for preserving engagement in language learning as cognitive components are (Pataranutaporn et al., 2021).

AI-based framework for evaluating the efficiency of self-study of English provides empirical proof that personalization parameters should be adjusted continually as the language proficiency of the students' changes (Shu & Xu, 2022). The use of AI-based technological platforms in conjunction with flipped classroom learning models indicates that AI personalization shows its best results when applied together with pedagogical innovations instead of being treated as an additional service only (Li & Peng, 2022).

AI-based Arabic language tutor demonstrates the crucial design principles of speech-driven personal tutoring programs that can be effectively implemented in English pronunciation and conversation lessons (Shao et al., 2022). An innovative project aiming to create personal education and learning system for chemistry education utilizing the Internet of Things (IoT) technology together with clustering techniques

has justified the practicality of adopting the learner grouping strategy for developing language proficiency clustering techniques (Wang & Lv, 2022).

X5Learn, a personal learning assistant that combines AI with interaction of users with computers, illustrates that interface design features and user trust are vital factors determining whether users will use AI personalization (Perez-Ortiz et al., 2021). In the context of English language studies, AI-based writing assistant is capable of improving the accuracy of the text written and students' confidence in the writing process (Gayed et al., 2022).

An overview of the current situation in AI-based adaptive education identifies the algorithms used in the process of adapting learning programs, including Bayesian knowledge tracing, reinforcement learning and rule-based engines (Ezzaim et al., 2022). Theoretical ideas about AI-infused education explore the nature of the relationship between human and artificial intelligence in the process of acquisition of knowledge, noting that effective implementation of AI requires balancing technology and expertise of teachers (Meng et al., 2022). This issue is studied within the context of landmarks of technology development, considering interaction of 5G and artificial intelligence in English language teaching, especially in terms of providing students with personal feedback (Yu & Nazir, 2021).

AI language models used in specific spheres like drug development reveal the universality of the language model architecture and prove that under proper consideration, the same models used for personal education can be used for general applications as well (Liu et al., 2021).

The reviewed studies collectively indicate that the development of AI-supported personalization in language education is mature along different trajectories, such as speech and pronunciation training, writing aid, listening help, prediction of learner style, and interface creation. Nonetheless, those trajectories appear to have developed separately from one another. It is well established that motivational as well as emotional factors influence sustained motivation as strongly as educational efficiency, while choices regarding the provided platform influence tremendously how fast a personalized resource responds. What has not been created so far is a unifying framework bringing together these different strands into one comprehensive and continuously updated model designed specifically for the needs of English learners, which is the gap this paper is aiming to fill.

Proposed AI-Based Personalized Learning Framework

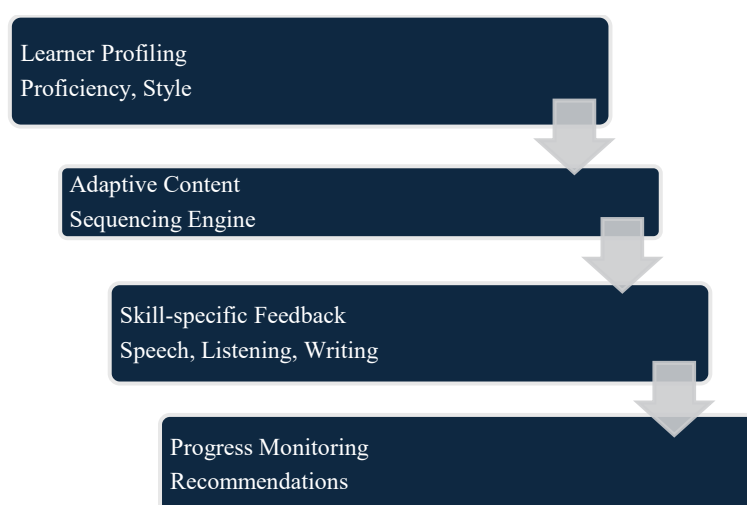


Figure 1: Conceptual Framework for the Proposed AI-Based Personalized Learning Model

Figure 1 demonstrates the conceptual framework of an AI-based personal learning model. The first step is the creation of learner profiles to describe the levels of proficiency and styles of learning for every individual, followed by an adaptive sequence of content delivery that enables the provision of personalized teaching materials. After that, feedback through skills is produced for speech, listening, and writing, as well as continuous monitoring of progress is conducted to track improvement and provide recommendations for successful, personalized learning.

Learner Profile and Personalization Module

The Learner Profile Module collects basic information about the learner's competency level, method of learning, and language background through analysis tests and behavior monitoring. This module systematizes learners into active competency groups that are always changed instead of remaining unchanged after the learning process starts. The Adaptive Content Engine uses this module to organize the learning materials, such as words, grammatical constructions, and texts, according to the present profile and level of proficiency of the learner. The materials used are changed step-by-step because of the algorithm that is used in this module to avoid making students feel bored or stressed out.

Skill Particular Feedback Module

The Skill Particular Feedback Module consists of the components that help with pronunciation control, listening skills, and writing help. The speech is automatically processed to find out the mistakes in pronunciation, while the writing is analyzed depending on correctness, coherence, and vocabulary diversity in a real-time mode. Listening comprehension support checks the accuracy of hearing and adjusts the speed of playback and the richness of vocabulary according to it.

Progress Tracking and Suggestion Module

The Progress Tracking and Suggestion Module gets the indicators of performance from sessions and gives an analysis of progress from past results. This module helps to get motivation and involve students into the educational process by creating adaptive plans for learning.

System Architecture and Model Development Methodology

Architecture of the System

The presented system is based on a layered architecture including layers of data, intelligence, and interaction. The data layer combines learner information such as interaction records, assessment results, and written/spoken tasks into one database that would store information about all learners. The intelligence layer contains the most important AI models for processing the data. This includes the use of natural language processing techniques for grammar and writing analysis, speech recognition with pronunciation scoring models, and a recommendation engine based on content and collaborative filtering methods. The role of the interaction layer is to provide the users with appropriate content, feedback, and dashboards demonstrating their progress. The design of this layer promotes transparency and provides learners with insight why given content and recommendations are advised.

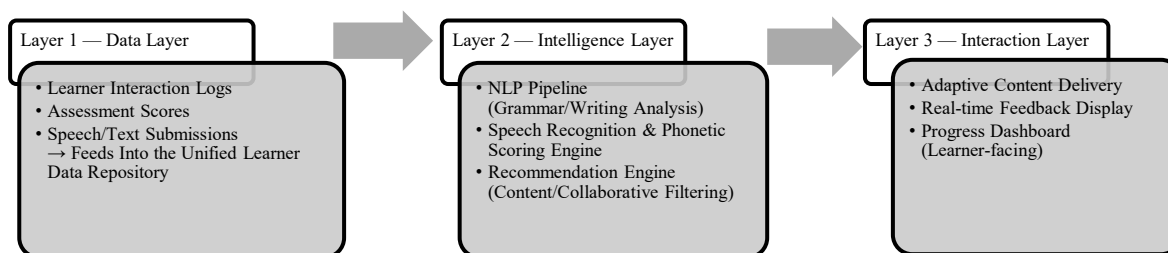


Figure 2: Layered System Architecture for the Proposed AI-Based Personalized Learning Model

The architecture of a personalized learning system proposed in this study is shown in figure 2. There are three layers in this architecture. The data layer gathers learner logs, scores, speech, and text entries to prepare a unique learner database. The intelligence layer uses natural language processing, speech recognition, and recommendation engines to analyze the learner's performance based on the data obtained in the previous layer. This way, the adaptive learning strategies are formed. Finally, in the interaction layer, the learner gets learning materials, feedback, and information about his or her progress in real time.

Data Collection and Model Training Phases

Model creation process starts with the data collection that allows producing the learner interaction data using diagnostic tests, speech samples, and submitted written works. This phase is followed by the model training stage in which a supervised learning methodology is applied to the pronunciation error detection and writing feedback algorithms using error data produced by the learners.

Phases of Integration and Evaluation

During this stage, the trained models are installed in adaptive learning and serve as the feedback generator that impacts content sequencing instead of functioning on entirely diagnostic basis. Similarly, the evaluation phase comes when the feedback and recommendations produced by the system are reviewed and compared to the expert evaluation.

Proposed Evaluation Design and Anticipated Results

As this study presents a conceptual framework rather than a completed deployment, no empirical data has yet been collected; this section instead outlines the evaluation design intended to validate the model and the outcomes anticipated once it is implemented.

Evaluation Design

The proposed evaluation would involve two groups of English language learners of comparable initial proficiency: a control group receiving instruction through conventional, non-personalized materials, and an experimental group using the proposed AI-based personalized learning system. Both groups would be assessed at baseline and again after a defined instructional period using standardized pre- and post-tests covering vocabulary, grammar, listening comprehension, and speaking accuracy.

Evaluation Metrics

Effectiveness would be measured using four indicators: proficiency gain (difference between pre- and post-test scores), pronunciation error reduction rate (change in AI-detected pronunciation errors over time), engagement rate (frequency and duration of the learner's interaction with the system), and learner satisfaction (collected via post-study survey).

Anticipated Results

Based on the design principles established in Sections III and IV and the trends reported in related adaptive-learning studies, it is expected that the experimental group will show greater proficiency gain than the control group, because of continuous content adaptation and real-time skill-specific feedback. It is expected that pronunciation and writing error rates will decline more rapidly in the experimental group due to immediate corrective feedback, as compared to delayed feedback characteristic of conventional instruction. Engagement metrics are expected to be stronger in the experimental group due to motivational scaffolding contained in the progress monitoring module.

Expected Outcomes, Implications, and Limitations

It is anticipated that the designed model would bring about many favorable changes for learners of the English language. Continuous adaptive sequencing should reduce the cases of learner alienation due to a discrepancy between content difficulty and learners' competences, which is one of the issues with traditional static curricula. Real-time pronunciation and writing feedback should speed up error correction cycles so that learners can internalize corrections quicker than with the help of delayed teacher-mediated feedback. The use of motivational scaffolding within the module for progress monitoring will serve to improve retention of learners over the long periods of learning due to the addressing of the affective aspect of foreign language acquisition.

However, the efficient operation of the model will depend on the quality of the input data and the variability of the sample used for the training of its classifiers. Groups of learners having non-standard accents, dialects, or native languages will get less accurate feedback unless enough varied data is used for their training.

Several practical limitations should also be addressed. Data privacy is an issue to be taken into account, especially considering the fact that many learners are probably minors. The second limitation is the dependence on infrastructure, as the provision of real-time feedback requires permanent connection that may not be stable everywhere. Another problem is that too much dependence on computer systems deprives learners of opportunities to communicate with human beings, which is also significant for the development of pragmatic and sociolinguistic skills that computers are not able to generate.

Conclusion

In this paper, the creation of an AI-supported personalized learning approach for English language acquisition is demonstrated, bringing together a large piece of evidence from the adaptive learning, AI-supported feedback, and learner profiling literature. The proposed model encompasses a number of important components and combines these in one architecture to fill the current gap in literature which is a lack of comprehensive system integrating different aspects of learning process, such as pronunciation, writing, listening, and motivation. Although the model still has to face obstacles related to data safety, reliance on technology, and possible algorithmic bias, it still contributes to the development of practical foundation for further testing and using it for real language learning process. The suggested areas for future research include the implementation of the model on a pilot basis and its assessment in terms of achieving results.

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