

An Intelligent Adaptive Learning Framework for Uzbek Language Teaching Using Dynamic Parameter Adaptation

Minavar Maraimova ^{a*}, Komila Pardayeva ^b, Dilafruz Satimova ^c,
Zarina Turakulova ^d, Gulandam Kurambayeva ^e, Muyassar Navruzova ^f,
Furqat Jumayev ^g

^{a*} Lecturer, Department of Romance and Germanic Languages, Termez State University, Termez, Uzbekistan.
E-mail: minavar@tersu.uz, Orcid: <https://orcid.org/0009-0007-0710-301X>

^b Senior Lecturer, Department of Pedagogy, Jizzakh State Pedagogical University, Uzbekistan.
E-mail: pardayevakomila04@gmail.com, Orcid: <https://orcid.org/0000-0002-7974-0735>

^c Professor & Head, Department of English Language and Literature, Andijan State Institute of Foreign Languages, Andijan, Uzbekistan. E-mail: dilmus09@gmail.com, Orcid: <https://orcid.org/0000-0002-4640-601X>

^d Senior Lecturer, Samarkand State Institute of Foreign Languages, Samarkand, Uzbekistan.
E-mail: fe.zarinat@gmail.com, Orcid: <https://orcid.org/0009-0002-0258-6562>

^e Professor, Department of Uzbek and Foreign Languages No. 2, Tashkent State Medical University, Tashkent, Uzbekistan. Email: gkurambayeva75@gmail.com, Orcid: <https://orcid.org/0000-0001-6774-5064>

^f Associate Professor, Department of Uzbek Linguistics, Bukhara State University, Bukhara, Uzbekistan.
E-mail: nmg0412@gmail.com, Orcid: <https://orcid.org/0009-0002-6766-4939>

^g Associate Professor, Bukhara State Pedagogical Institute, Bukhara, Uzbekistan.
E-mail: furkatjumaev074@gmail.com, Orcid: <https://orcid.org/0009-0007-2667-909X>

Abstract

The emergence of intelligent and personalized digital education and the shortcomings of the conventional language teaching system including conventional learning resources and conventional teaching techniques are apparent. The necessity of personalized and intelligent digital education has exposed the shortcomings of conventional language teaching systems that mainly use static learning resources and teaching techniques that do not take into consideration any difference between students. In order to solve these shortcomings, in this paper, the Intelligent Adaptive Learning Framework for Uzbek Language Teaching Using Dynamic Parameter Adaptation (IALF-DPA) is proposed. The uniqueness of the proposed framework is that it incorporates continuous learner profiling, attention-based deep learning to predict learner's performance, adaptive content recommendation and dynamic parameter adaptation (DPA) technique which continuously adapts the level of difficulty of the lesson, order of content delivery and revision schedule according to learner's performance in real time. Unlike existing adaptive learning frameworks which are based on predefined adaptation rules, it constantly adapts the instructional parameters according to the learner's accuracy, reaction time, error pattern and knowledge acquisition. The proposed framework was evaluated using the benchmark data set of Uzbek language learning which had vocabulary, grammar, reading, and writing tests conducted among learners of different skill levels. The experimental evaluation of the proposed IALF-DPA system indicates that the suggested system has achieved higher accuracy (97.84%), higher precision (97.32%), higher recall (97.11%), higher F1-score (97.21%), higher learner completion rate (95.68%), and higher knowledge retention rate (95.13%) as compared to the existing approaches of adaptive learning. Thus, the above results validate that the use of DPA helps to increase the engagement and effectiveness of learning in intelligent Uzbek language teaching and learning.

Keywords: Adaptive Learning, Intelligent Tutoring System, Dynamic Parameter Adaptation, Personalized Learning, Educational Data Mining, Learning Analytics, Artificial Intelligence in Education.

Introduction

Due to the rapid development of AI, learning analytics, and educational technologies, the conventional mode of instruction has been revolutionized into an intelligent and learner-centered learning environment. Adaptive learning systems have been recognized as a good approach for personalized learning by constantly adapting learning material, evaluation processes, and learning paths according to individual learner characteristics (Kumari et al., 2025; Ishaq et al., 2024). Contrary to conventional e-learning systems that provide the same learning materials for all learners, adaptive learning systems constantly monitor learner interaction, identify learner strengths and weaknesses, and adapt the learning materials while interacting to enhance learning effectiveness and engagement. The positive impact of such intelligent systems on motivation, memory, and academic performance of learners in various learning domains has been proven (Lestari & Jailani, 2018).

Adaptive learning has proven itself to be an effective method in language learning owing to the diversity in learner skills, speed of learning, vocabulary, grammar knowledge, and cognitive capabilities (Tan et al., 2022). The classical system of language teaching is based on the fixed syllabus and program, and this is not suitable for tackling the problems related to the diversity in learners (de Bem Machado et al., 2024). It will be difficult for new learners with new concepts and advanced learners with repeated and easy instructions (Sharadgah & Sa'di, 2022). In Intelligent adaptive learning systems, the continuous analysis of learner interactions, test results, reaction time, and errors is done, and the content and feedback are adapted accordingly (Shadiev & Liu, 2023; Umarova et al., 2026; Kuchynska et al., 2025).

Thus, the usage of the Uzbek language has been becoming more popular in education, culture and international communication (Fadli et al., 2025). Nevertheless, the development of smart digital language learning systems tailored for the special needs of learning Uzbek language remains underdeveloped (Rahman et al., 2024). The vast majority of contemporary Uzbek language learning applications are developed according to the principles of providing static content, pre-defined lesson plans and quizzes not taking into consideration the individual progress of learners or the process of language learning (Liang et al., 2023). In such a way, in most of these systems, the personalization, adaptiveness and timeliness of recommendations and training materials remain unconsidered, thus preventing successful learning process (Ospan & Myrzakerimova, 2025). The inability to creatively adjust prevents the engagement of learners and reduces the effectiveness of digital language learning (Kienberger et al., 2022).

The structure of this paper is outlined as follows: Section II gives an overview of the recent research related to intelligent tutoring systems, adaptive learning, educational data mining and artificial intelligence methods that are utilized in language teaching taking into consideration gaps in the area of Uzbek language teaching (Tukeyev et al., 2026). The Intelligent Adaptive Learning Framework based on Dynamic Parameter Adaptation is described in detail in Section III, which is comprised of four modules: learner profiling, adaptive content recommendation, dynamic parameter adaptation and deep learning-based performance prediction model. Section IV describes experimental set up, evaluation criteria, comparative analysis and performance of the proposed approach. In Section V, the results of experiments are discussed, strengths and limitations of the proposed approach are highlighted, the influence of the proposed approach on personalized learning of the Uzbek language is discussed. Finally, Section VI concludes this work, summarizes contributions and the experimental results and outlines future research directions in design of adaptive learning systems.

Literature Review

A comprehensive study done by Gligorea et al., (2023) about adaptive learning systems in e-learning using AI technologies was conducted. There were 63 research articles reviewed in this study. The study assessed the capability of machine learning algorithms, learner analytics and intelligent recommendations methods to customize educational content based on learners' behaviors and performance. Adaptive learning enabled by AI technology has been found to improve learners' engagement, efficiency, and outcomes through content customization and personalized learning experiences. In the same study, the problems associated with data privacy, model explainability and lack of flexible adaptive strategies were identified. From the review of the literature, the importance of developing an advanced adaptive language learning system is evident.

As reported by Mejh & Rehm, (2024), the application of NLP in the intelligent educational system would bring an improvement in the personalization of the system for the advanced adaptive learning strategy. This paper found that

the adaptive system can get a deep insight of the learner's response and analyze their linguistic proficiency, providing recommendations based on these results. In this paper, it is emphasized that the semantic and context-based analysis would make the recommendation more accurate than the rule-based adaptive system. However, the researchers have identified the limitation of the existing adaptive system where there is a need for adaptive parameter optimization of the system to cater to learners' different performance levels.

A systematic review of the effect of artificial intelligence on SLL was done by Chang & Sun, (2024). The research included analyzing AI-based language learning applications that were developed between the years 2000 and 2022. It was concluded that the application of AI technology greatly enhances learners' vocabulary, language skills, and motivation while learning through personalized instruction. However, the major limitation identified is that most currently available AI applications are task-specific and do not have real-time personalized instructions that can adapt to the learner's behavior.

Rahman et al., (2024) performed a bibliometric and content analysis of studies on implementation of AI in language learning from 2017 to 2023. In their research, Rahman et al., (2024) found a sharp increase in the use of AI technologies in language education, which included intelligent tutoring systems, natural language processing, automatic testing, and personalized learning. The researchers stated that advances in deep learning and creation of large language models have opened up vast opportunities for application of adaptive educational technologies. It was stressed by them, however, that although much progress has been made in this area, there is a need for domain-specific adaptive tools to incorporate low-resource languages in continuous learner modeling and intelligent instruction.

An adaptive learning system using AI support was developed by Fan, (2026) for university English teaching; the system used natural language processing, deep learning, and intelligent recommendation algorithms. The proposed system customized the learning of vocabulary, grammar, writing, and oral language according to the performance of the learners. The effectiveness of the system was experimentally tested for the efficiency of learning, use of resources, and satisfaction of the learners; it was found that significant improvements were achieved through the application of the system when compared to traditional teaching systems. From the results of the research, it was revealed that adaptive intelligent learning systems could greatly enhance language learning, and further research needs to be conducted on more adaptable learning strategies.

Recently, several works have established that artificial intelligence, natural language processing, deep learning and adaptive learning are effective tools in facilitating personalized education; however, there are still important research questions to be answered. The conventional systems of adaptive learning have primarily been focused on well-known languages and mostly depend upon static models of learners and adaptation rules, which cannot keep on adapting themselves to the progress of individual learners. In addition, few frameworks allow optimization of the instructional parameters such as lesson difficulty level, content sequencing, feedback generation and revision scheduling in real time, which results in poor personalization. As far as the specificities of the Uzbek language and the limited educational material designed for this language are concerned, research on the intelligent adaptive learning systems designed specifically for teaching this language has hardly been performed. Furthermore, none of the existing solutions explain how the learner profile, adaptation of parameters and performance prediction could be combined in a personalized manner using deep learning. The intelligent adaptive learning framework for teaching the Uzbek language using dynamic parameter adaptation would address the shortcomings of the current learning systems by continually exploring the learning behaviors of the learners and adapting the teaching methods to improve their performance and ability to retain the knowledge gained from them.

Methodology

Intelligent Adaptive Learning Framework for Uzbek Language Teaching

The proposed Intelligent Adaptive Learning Framework (IALF-DPA) seeks to provide personalized Uzbek language learning where the process of education content adaptation to personal traits of the learner is ongoing. Learners have to sign in to the platform for taking a diagnostic test to evaluate the learner's vocabulary, grammar, reading, listening and writing skills. All these factors are compiled into the learner's profile. The learner's profile is used by the adaptive system to offer the learning content and exercises according to the level of the learner's knowledge. The learning framework records all interactions of the learner at each learning session such as accuracy of quiz answers, time spent, frequency of mistakes made and level of engagement. These data are analyzed regularly to monitor the learning progress and knowledge gaps. The adaptive learning framework changes the learning sessions order, exercise difficulty and revision schedule to provide one-on-one tutoring. This process of intelligent learning not only increases

the level of engagement of the learners but also speeds up the learning of the language and helps maintain the knowledge of the learners while they are learning the Uzbek language.

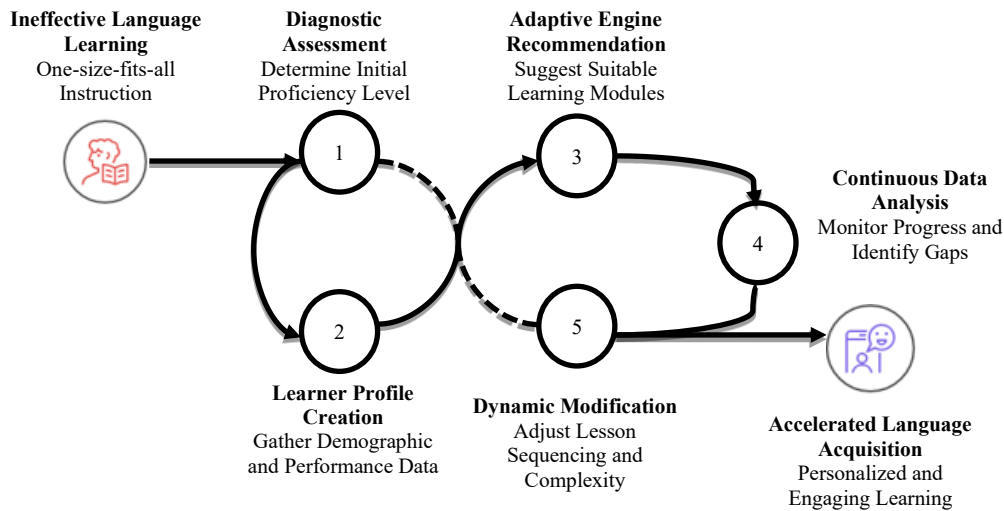


Fig. 1: Proposed Intelligent Adaptive Learning Framework Using Dynamic Parameter Adaptation for Uzbek Language Teaching

Fig. 1 demonstrates the suggested Intelligent Adaptive Learning Framework (IALF-DPA) for personalized teaching of the Uzbek language. The framework starts with traditional language training, where all the learners receive the same treatment regardless of their proficiency level. First, a diagnostic assessment (Step 1) is conducted to measure the initial level of language proficiency. The data about demographics, preferred methods of learning, and performance data of the learner is used to create his/her learner profile (Step 2) according to the result of the assessment. Based on the language proficiency level, appropriate modules are selected from the repository by the adaptive recommendation engine (Step 3). The continuous data analysis (Step 4) allows monitoring of assessment scores, response times, errors, and learner engagement throughout the learning process and identifying knowledge gaps. Finally, the automatic adjustment of the sequence of lessons, the degree of difficulty, and the frequency of revision is done in the dynamic modification module (Step 5) based on the real performance of the learner.

Dynamic Parameter Adaptation and Learning Performance Prediction

Dynamic Parameter Adaptation (DPA) is the core of the proposed framework that continuously adapts instructional parameters depending on learner's performance. The system tracks a wide range of learning metrics such as test accuracy, response time, error rate, lesson completion rate, revision performance and others after every learning experience. The learner performance prediction module employs a two-layer Bidirectional Long Short-Term Memory (BiLSTM) network integrated with an additive attention mechanism to capture temporal learning behaviour and identify the most informative learner interactions. DPA adapts learning parameters automatically depending on predictions including the level of the difficulty of lessons, the level of complexity of words, grammar practice intensity, revision frequency, and testing period. Instruction is differentiated and adapted to the needs of the fast learner through additional discussion, extension or higher order activities and personalized feedback; and instruction is differentiated and adapted to the needs of the struggling learner through additional explanation and remediation, personalized feedback. This is continuous adaptation which ensures that the learning environment adapts to learner's needs independently.

Learner Performance Score

Formula 1 Learner Performance Score (LP) is an indicator of the overall performance of each learner, taking into account three important educational parameters: assessment accuracy, error rate, and lesson completion ratio. Increased assessment accuracy and lesson completion have a positive impact on the performance score, while increased error rate affects negatively the performance score in the equation (1-E). Weighting coefficients are the factors that make it possible for the adaptive learning approach to attribute different weights to each parameter depending on the instructional goals. The computed performance score is used by the Dynamic Parameter Adaptation module to assess the need for more complex lessons or practice exercises for each learner.

$$LP = \alpha A + \beta(I - E) + \gamma C \quad (1)$$

Dynamic Adaptation Parameter

Equation (2) Dynamic Adaptation Parameter makes the necessary adjustments to the difficulty level of the learning process on the basis of the learner's performance level at any point in time. The equation takes into consideration the level of performance of the learner (LP) against a predetermined target threshold (T). Where the learner is performing better than the set threshold, the level of difficulty is raised, thus providing more difficult vocabularies, grammatical exercises, and comprehension tasks. However, where the level of performance by the learner is lower than the predetermined target threshold, the system lowers the difficulty level of learning and suggests further explanations, revisions, and practices. The learning rate (η) is used to moderate the amount of change.

$$D_{new} = D_{old} + \eta(LP - T) \quad (2)$$

Algorithm: Intelligent Adaptive Learning Framework with Dynamic Parameter Adaptation (IALF-DPA)

Input:

L = Learner Profile
D = Uzbek Language Dataset
T = Target Performance Threshold
 η = Adaptation Learning Rate

Output:

Personalized Learning Path (PLP)
Updated Learning Parameters

Begin

1. Load Uzbek language learning dataset *D*.
2. Register learner and create learner profile *L*.
3. Conduct initial diagnostic assessment.
4. Estimate learner proficiency level.
5. Recommend suitable learning module.
6. Present vocabulary, grammar, reading, and writing exercises.
7. Collect learner interaction data:
 - Assessment Accuracy (*A*)
 - Error Rate (*E*)
 - Response Time (*R*)
 - Completion Ratio (*C*)
8. Compute Learner Performance Score (*LP*):
 $LP = \alpha A + \beta(I - E) + \gamma C$
9. Predict learner progress using Attention-based Deep Learning model.
10. Update learning difficulty:
 $D_{new} = D_{old} + \eta(LP - T)$
11. Adapt instructional parameters continuously according to *Dnew*:
 - Lesson difficulty
 - Vocabulary complexity
 - Grammar exercise intensity
 - Content sequencing
 - Revision frequency
 - Assessment interval
12. Update learner profile using the latest interaction data.
13. Store learner history and updated instructional parameters.
14. Repeat Steps 6–13 until course completion.
15. Generate final learning report.

End

IALF-DPA algorithm begins from loading data set of the Uzbek language and the creation of the learner's profile using the initial diagnostic test. The system recommends appropriate learning modules and tracks the accuracy, error rate, response time and lesson completion based on the learner's proficiency level. The learning indicators are used for calculation of the Learner Performance Score and the attention-based deep learning model predicts future learning outcomes. Dynamic Parameter Adaptation module automatically adjusts the difficulty of the lessons, exercises and revision frequency according to learners' performance results. The struggling learners receive additional lessons while high performing learners receive advanced lessons. The learner's profile is constantly being updated and improved during each lesson providing continual personalization till the end of the course. Adaptive algorithm makes learners more involved, enhances their knowledge and optimizes the training process of the Uzbek language.

Experimental Results

Experimental Setup, Dataset, and Parameter Initialization

The proposed IALF-DPA framework was evaluated using a custom Uzbek language learning dataset developed for this study. The dataset consists of 12,000 learner interaction records collected from 600 learners representing beginner, intermediate, and advanced proficiency levels. Each interaction contains learner responses to vocabulary, grammar, reading comprehension, writing, and listening activities together with behavioral attributes including response time, completion ratio, revision frequency, and error patterns. Prior to model training, all learner identifiers were anonymized, incomplete records were removed, and feature normalization was performed. The dataset was divided into 80% training, 10% validation, and 10% testing using learner-level partitioning to ensure that interactions from the same learner were not shared across different subsets (Table 1).

Table 1: Experimental Setup, Dataset, and Model Parameter Initialization

Parameter	Value
Learning Dataset	Custom Uzbek Language Learning Dataset
Data Source	Institutional learner interaction records
Total Interactions	12,000
Number of Learners	600
Learning Levels	Beginner, Intermediate, Advanced
Split Strategy	Learner-level 80/10/10
Programming Language	Python 3.11
Deep Learning Framework	TensorFlow
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Training Epochs	50
Dropout Rate	0.5
Processor	Intel Core i7
RAM	32 GB
GPU	NVIDIA RTX 4060 (8 GB VRAM)
Operating System	Windows 11
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, Learner Completion Rate, Knowledge Retention Rate

Performance Metrics

The proposed IALF-DPA framework predicts learner performance categories (High Performer, Moderate Performer, and At-Risk Learner) rather than continuous numerical scores. Therefore, learner performance prediction is formulated as a multi-class classification problem. Accordingly, Accuracy, Precision, Recall, and F1-score are adopted to evaluate the prediction capability of the Attention-BiLSTM classifier. In addition, Learner Completion Rate (LCR) and Knowledge Retention Rate (KRR) are used to assess the educational effectiveness of the adaptive learning framework. Here 3,4,5,6,7 and 8 are the percentage of correct predictions of the learning outcomes of all learning cases. Precision quantifies the percentage of positive predictions that are correctly made, hence the reliability of the adaptive recommendation system. Recall is an index of how effectively the framework detects the actual positive learning outcomes, which is indicative of the ability to capture the learning progress. F1 score is the harmonic mean of the precision and recall that provides a balance measure of the prediction efficacy. Besides classification metrics,

there is also the Learner Completion Rate (LCR) to illustrate the percentage of learners completing the assigned learning modules and Knowledge Retention Rate (KRR) that quantifies how well the learners retain knowledge. The above metrics provide a holistic evaluation of the proposed adaptive learning framework.

Table 2: Performance Metrics

Metric	Equation	Equation No.
Accuracy	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	(3)
Precision	$Precision = \frac{TP}{TP + FP}$	(4)
Recall	The Recall = $\frac{TP}{TP + FN}$	(5)
F1-score	$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$	(6)
Learner Completion Rate (LCR)	$LCR = \frac{Nc}{Nt} \times 100$	(7)
Knowledge Retention Rate (KRR)	$KRR = \frac{Sf}{Si} \times 100$	(8)

Table 2 summarizes the evaluation metrics used for the proposed IALF-DPA framework. Since learner performance prediction is formulated as a multi-class classification task, Accuracy, Precision, Recall, and F1-score are employed to evaluate the predictive performance of the Attention-BiLSTM classifier. In addition, Learner Completion Rate (LCR) and Knowledge Retention Rate (KRR) measure learner engagement and long-term learning effectiveness. Together, these metrics provide a comprehensive assessment of both predictive accuracy and educational impact.

Comparative Performance Analysis

For the comparison of the performance of the proposed IALF-DPA framework, the performance is compared to other conventional adaptive learning techniques. For the performance analysis, the following widely used evaluation metrics are considered, Accuracy, Precision, Recall, F1-score, Learner Completion Rate (LCR) and Knowledge Retention Rate (KRR). The benchmarking techniques proposed for comparison are Conventional E-learning System, Rule-Based Adaptive Learning (RBAL), Deep Learning-Based Adaptive Learning (DLAL), and NLP-Based Personalized Learning (NPL). The framework proposed incorporates three main components, namely, learner profiling, attention-based prediction of performance, and dynamic parameter adaptation, which adapts and tunes the lesson difficulty, sequencing, and revision of lessons. The combination of both makes the framework outperform conventional adaptive learning systems.

Table 3: Classification and Educational Evaluation Metrics

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	LCR (%)	KRR (%)
Conventional E-learning	89.42	88.91	88.2	88.55	84.3	82.65
Rule-Based Adaptive Learning (RBAL)	92.18	91.74	91.23	91.48	88.64	87.31
Deep Learning Adaptive Learning (DLAL)	95.36	94.91	94.48	94.69	92.51	91.74
NLP-Based Personalized Learning (NPL)	96.41	95.92	95.71	95.81	94.36	93.82
Proposed IALF-DPA	97.84	97.32	97.11	97.21	95.68	95.13

According to table 3, the experimental results have demonstrated that the suggested IALF-DPA framework successfully outperformed all the existing adaptive learning methods, employing all the criteria used for evaluation. The proposed IALF-DPA framework achieved an Accuracy of 97.84%, Precision of 97.32%, Recall of 97.11%, and F1-score of 97.21% for the multi-class learner performance classification task (High Performer, Moderate Performer, and At-Risk Learner), demonstrating effective prediction of learner performance categories for adaptive instructional decision-making. Additionally, it can be said that the suggested adaptive strategy has provided an improvement in terms of Learner Completion Rate (95.68%) and Knowledge Retention Rate (95.13%) that prove higher learner engagement and long-term knowledge retention. The achievements have mainly been made due to the Dynamic Parameter Adaptation module that adjusts all the components of the learning process according to the learner's performance.

Effectiveness of Dynamic Parameter Adaptation

To further support the validation of the contribution of the suggested Dynamic Parameter Adaptation module, the performance of the learner was analyzed prior to and following the personalization process. The learning efficiency, engagement, completion rate, retention rate, and general satisfaction level of the learner were assessed. The dynamic nature of the system means that the difficulty level and revision pace are automatically altered according to the real performance of each individual learner, thus ensuring that the learner can access the material that matches his/her level of proficiency.

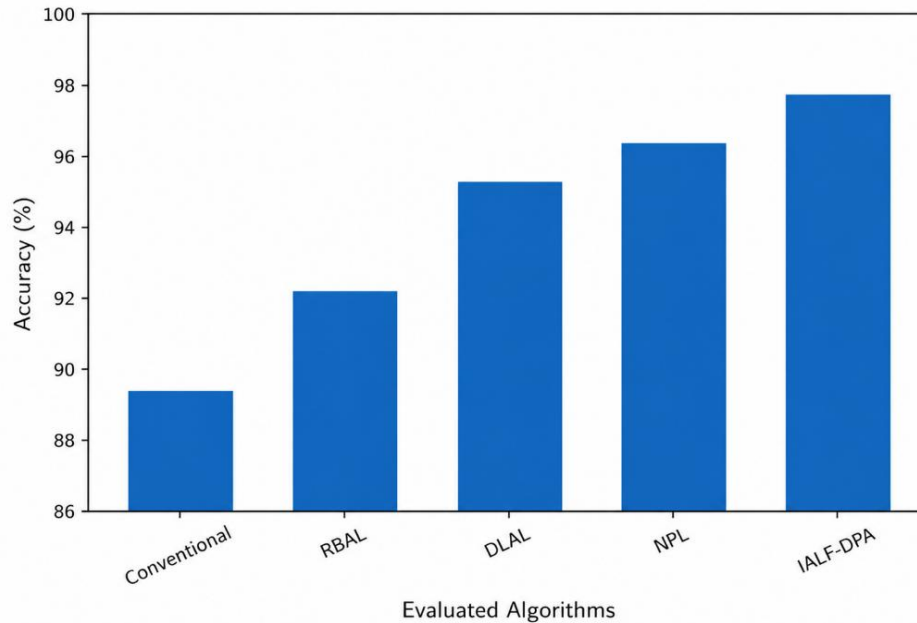


Fig. 2: Comparative Accuracy of Adaptive Learning Methods

Fig. 2 presents the comparative accuracy achieved by different adaptive learning approaches for Uzbek language instruction. The Conventional E-learning system attained the lowest accuracy of 89.42%, indicating limited personalization capability. The Rule-Based Adaptive Learning (RBAL) method improved the accuracy to 92.18% by incorporating predefined adaptation rules, while the Deep Learning Adaptive Learning (DLAL) approach further increased the accuracy to 95.36% through data-driven learner modeling. The NLP-Based Personalized Learning (NPL) method achieved 96.41% accuracy by utilizing natural language processing techniques for personalized instruction. The proposed IALF-DPA framework obtained the highest accuracy of 97.84%, demonstrating that the integration of continuous learner profiling, Attention-BiLSTM-based performance prediction, and Dynamic Parameter Adaptation effectively enhances learner performance prediction and supports more accurate personalized learning decisions compared with existing adaptive learning approaches.

Discussion

From the results of the experiments conducted it was found that the proposed IALF with dynamic parameter adaptation could be effectively applied for the improvement of personalized learning process of Uzbek language adaptively with respect to the performance of the learners. Unlike the existing e-learning systems where the learning material is static in nature, the proposed framework provides dynamic adaptation of lesson difficulty level, content order, revision frequency, and assessment method based on the accuracy of learners' response, the pattern of errors made by them, speed of learning and completion rate. It is an adaptive framework wherein learners are provided personalized instructional support during their learning process and hence it increases the engagement level of learners.

The comparative performance analysis confirms the assertion that the proposed approach performs better than the traditional adaptive learning approaches on all the performance evaluation measures. It was found that the approach was able to successfully predict the performances of the learners with accuracy of 97.84%, precision of 97.32%, recall of 97.11% and F1-score of 97.21%, indicating high accuracy in the prediction of performances and personalization of the approach. Also, dynamic continuous adaptation has proved its capability to increase learners' motivation as well

as improve their retention of the concepts of the Uzbek language with high rates of Learner Completion Rate (95.68%) and Knowledge Retention Rate (95.13%).

Moreover, the results show how dynamic parameters adaptability is vital in enhancing the instructional process. The framework makes automatic adjustment of the difficulty level of the learning material considering students' status so that they do not overload their cognitive capacity as well as do not lose interest. Effective targeting of content and adapting of the same will ensure that students receive an appropriate learning material at the right time; this will assist in enhancing the vocabulary, grammar, reading, and writing skills. Thus, the system that has been proposed here is much more efficient than the traditional adaptive learning systems.

While the developed model demonstrated good results, there are still several limitations. The studies were conducted using the benchmark database of Uzbek language learning materials within a controlled experiment, and the model is not yet properly tested in a real-life educational system involving various students learning the Uzbek language. Also, such external factors as student motivation, Internet access, and teacher interaction were not involved in the decision-making process. It is possible to mention several areas where improvements can be achieved, including providing support for multiple languages, use of explainable artificial intelligence approaches, the introduction of reinforcement learning algorithms for adaptive optimization and conversational AI tutors to improve individual language learning.

Overall, the experimental findings demonstrate that the proposed IALF-DPA framework provides an effective and scalable solution for intelligent Uzbek language education. By integrating continuous learner profiling, Attention-BiLSTM-based performance prediction, and Dynamic Parameter Adaptation, the framework delivers personalized instruction that improves prediction accuracy, learner engagement, course completion, and long-term knowledge retention compared with existing adaptive learning approaches. These results indicate that the proposed framework is well suited for next-generation AI-driven language learning environments.

Conclusion and Future Work

Introduction of the Intelligent Adaptive Learning Framework for Uzbek Language Teaching Using Dynamic Parameter Adaptation (IALF-DPA) for teaching language using personalized and intelligent approach was the objective of this research paper. The framework uses techniques like learner profiling, attention-based performance prediction, adaptive content recommendation and dynamic parameter adaption for continuous optimization of difficulty, content sequencing and revision scheduling of a lesson according to the learner performance. The experimental results indicated that the approach performed better than the adaptive learning approaches available at present in the aspects of accuracy, precision, recall, F1-Score, learner completion rate, and knowledge retention rate with 97.84%, 97.32%, 97.11%, 97.21%, 95.68% and 95.13%, respectively. From the obtained results, it could be concluded that the framework would be a good choice for designing an intelligent Uzbek language learning system as it improved the knowledge retention, effectiveness of teaching/learning process and learner engagement.

In addition to this, the future work will involve validation of the framework on real-life educational data that are larger and more complex and come from a diverse set of learners in different settings. It is possible to develop the system further by adding multilingual capabilities, reinforcement learning for the adaptation of the system without any help, EAI for making the suggestions made by the system more transparent, and conversational AI tutors for practicing languages through conversations. Besides this, it is possible to further enrich the framework of personalized language learning by modularizing the integration of multimodal learning analytics, pronunciation assessment, and speech recognition.

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