ARTIFICIAL INTELLIGENCE-DRIVEN ADAPTIVE LEARNING FOR PERSONALIZED TECHNOLOGY-MEDIATED LANGUAGE EDUCATION: ENHANCING ENGAGEMENT AND LEARNING OUTCOMES.

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Abstract:	This research examines the role of AI technologies, including NLP, ML, and Speech Recognition, in enhancing personalized learning within technology-mediated language education. A modular framework supports customized learning paths, real-time assessments, and adaptive feedback. The methodology utilizes datasets such as Common Crawl and Wikipedia Corpus for language modeling, LibriSpeech and TED-LIUM for speech recognition, and Stanford Sentiment Treebank for sentiment analysis. Results show NLP feedback relevance improved from 65% to 85%, speech recognition accuracy increased from 80% to 90%, and adaptive learning boosted language proficiency by 20%. Engagement metrics revealed an 80% course completion rate and 90% user satisfaction, surpassing traditional methods. The study highlights the potential of AI-driven learning systems to create personalized, effective, and engaging educational experiences.

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Abstract

This research explores the application of artificial intelligence (AI) technologies, including Natural Language Processing (NLP), Machine Learning (ML), and Speech Recognition, in enhancing personalized learning experiences within technology-mediated language education. A modular framework is implemented to facilitate customizable learning paths, real-time assessments, and individualized feedback. The methodology integrates datasets such as Common Crawl and Wikipedia Corpus for language modeling, LibriSpeech and TED-LIUM for speech recognition, and Stanford Sentiment Treebank for sentiment analysis. Experimental results indicate substantial improvements over traditional systems, with NLP feedback relevance increasing to 85% from 65%, and speech recognition accuracy improving from 80% to 90%. Adaptive learning pathways led to a 20% enhancement in language proficiency, while engagement metrics reflected an 80% course completion rate and 90% user satisfaction, outperforming conventional models. These findings demonstrate the potential of AI-powered adaptive learning to transform language education by offering personalized, effective, and engaging learning experiences. Future work will focus on expanding language support and refining AI-driven personalization techniques to further optimize learner outcomes.

Keywords

Artificial Intelligence, Language Learning, Adaptive Learning Systems, Natural Language Processing, Personalized Education

1. Introduction

The development of technology has profoundly impacted the educational landscape, emphasizing technology-mediated learning systems that offer innovative solutions to traditional pedagogies. Among these advancements, the integration of Artificial Intelligence (AI) has become a pivotal element in enhancing the efficiency and personalization of language learning. As globalization accelerates and intercultural communication grows increasingly vital, the demand for effective language acquisition techniques has surged. Traditional language learning methods, such as the Grammar-Translation Method and Audio-Lingual Method, often fall short in addressing the diverse needs of learners due to their one-size-fits-all approach and inability to adapt to individual differences [1-3]. AI technologies present a significant opportunity to bridge this gap by offering solutions tailored to the specific requirements of each student, transforming language education into a more dynamic and inclusive process.

AI tools like speech recognition, machine learning, and natural language processing (NLP) are essential for creating adaptive learning systems that can react instantly to student performance and preferences [4]. By analyzing and comprehending the subtleties of human language, NLP helps the system provide tailored feedback that improves learning results [5]. For example, by using sophisticated algorithms, NLP can detect grammatical mistakes and offer contextualized recommendations, successfully assisting students in improving their speaking and writing abilities. Research has indicated that incorporating natural language processing (NLP) into language instruction can result in notable enhancements in student involvement and understanding [6]. Additionally, NLP systems have been transformed by transformer models like Bidirectional Encoder Representations from Transformer (BERT) and Generative Pre-trained Transformer (GPT) which provide a more contextual understanding of language inputs and more pertinent feedback for learners [7-9].

By allowing systems to learn from human interactions over time, machine learning enhances natural language processing. ML algorithms can dynamically modify the content and level of difficulty of tasks to correspond with individual progress by examining patterns in learner behavior and performance. In language learning, where students frequently progress at various speeds and may need different kinds of help, this flexibility is essential [10]. According to research, ML-enabled tailored learning paths can significantly increase language competency and retention [11]. Additionally, by optimizing content recommendations based on continuous user interactions, reinforcement learning approaches can guarantee that learners receive support that is specifically catered to their unique issue [12].

Along with natural language processing (NLP) and machine learning (ML), speech recognition technology improves language acquisition by enabling real-time pronunciation and fluency practice [13]. The accuracy of speech recognition systems has greatly increased due to developments in deep learning, especially the application of convolutional neural networks (CNNs) and recurrent neural networks (RNNs). These systems can now efficiently handle a variety of accents and dialects, giving students real-time feedback on their spoken language proficiency [14]. In addition to helping with pronunciation correction, this function creates a more engaging learning environment by having students practice conversations that resemble real-world encounters.

There are many benefits to using AI-driven language learning systems, one of which is that learners will be more motivated and engaged. Students are empowered by personalized feedback systems that give them information about their areas of strength and growth. According to research, students who receive personalized feedback are more likely to stay motivated and involved throughout their academic career since they can observe how their efforts directly affect their language ability. Furthermore, learner motivation can be further increased by including gamified learning components and multimedia content into AI systems, which will make language acquisition more efficient and pleasurable.

Despite the apparent advantages of artificial intelligence (AI) in language learning, several obstacles need to be overcome for these technologies to be successfully adopted. Concerns about data security and privacy are crucial, especially when language learning programs gather and examine enormous volumes of personal data. To protect student data and preserve confidence in these systems, it is crucial to implement strong data protection mechanisms that adhere to privacy laws like the General Data Protection Regulation (GDPR) [15]. To make AI-powered educational platforms accessible and pertinent to a broad spectrum of users, educators and developers must also consider the language and cultural variety of learners.

The goal of this project is to create a thorough framework for incorporating AI technologies into technology-mediated language learning systems considering these factors. The study aims to show how AI will improve learner results and the language learning experience by emphasizing adaptive learning pathways, individualized feedback, and real-time assessments. Investigating the integration of AI technologies, creating adaptive learning pathways, assessing the efficacy of AI-driven systems, resolving implementation issues, and contributing to the field of educational technology are among the goals of this research. This study intends to offer important insights into the potential of AI-driven systems to transform language learning and produce more individualized educational experiences for a variety of learner demographics by examining the relationship between AI and language education.

2. Review of Literature

Artificial Intelligence (AI) in language acquisition has the capacity to revolutionize conventional education by providing individualized, adaptive learning experiences. Technologies including Natural Language Processing (NLP), Machine Learning (ML), and Speech Recognition provide instantaneous feedback, adaptive learning trajectories, and personalized content. This literature review examines contemporary research on the use of AI in language teaching, emphasizing its contribution to improving learner engagement, motivation, and overall academic achievement. This research illustrate how AI-driven systems can develop more efficient and customized language learning environments.

Wei (2023) examines the role of AI in language education, emphasizing its influence on English learning outcomes, motivation, and self-regulated learning. The study demonstrates that AI systems promote student engagement and performance through personalized feedback and adaptive learning pathways, aligning with the current research emphasis on AI-augmented, tailored language instruction [16]. Karataş et al. (2024) investigate the function of ChatGPT in foreign language instruction. Their research demonstrates that AI chatbots provide immediate, interactive feedback, improving learners' speaking and writing abilities. This corresponds with the planned research's focus on employing AI to develop dynamic, adaptive language learning systems [17].

Son et al. (2023) examines artificial intelligence technologies for language acquisition, emphasizing natural language processing and machine learning applications. These authors illustrate how AI may deliver customized learning experiences, instantaneous feedback, and enhanced linguistic results, hence facilitating the incorporation of AI into adaptive learning systems [18]. How AI Assists in Closing the Divide in Language Acquisition (2024) offers an analysis of AI's contribution to surmounting conventional language acquisition obstacles. The essay highlights the advantages of AI, such as customized learning trajectories, automatic feedback, and enhanced accessibility, rendering it particularly pertinent to the advancement of AI-based language learning platforms [19]. Uc-Cetina et al. (2023) examine reinforcement learning in language processing, demonstrating its potential to enhance language learning applications. Their research indicates that reinforcement learning facilitates the adaptation of information and feedback to learner behavior, hence improving personalized learning systems [20]. Feng et al. (2024) investigate the function of natural language reinforcement learning in language processing. Their findings indicate that reinforcement learning algorithms can optimize language models to deliver more precise feedback and dynamically modify learning trajectories, corresponding with the demand for adaptive learning environments in AI-driven language education [21].

Readizy, an AI-powered platform created to tailor language instruction to each learner's needs, is presented by Gao et al. (2021). Although this study highlights AI's potential to promote student autonomy, it does not provide a thorough examination of how these systems function over time and in various educational environments [22]. The importance of AI in intelligent writing help is the main topic of Godwin-Jones (2022), who explains how AI technologies can offer second language (L2) learners real-time, adaptive feedback to increase writing correctness and fluency. The study does not fully address AI's shortcomings in catching the complicated language patterns and cultural nuances that human input can pick up on, despite the enormous potential for individualized feedback [23].

In order to improve L2 learners' willingness to communicate (WTC), Ayedoun et al. (2019) investigate the incorporation of effective and communicative tactics into an embodied conversational agent (ECA). Although it does not examine the scalability or efficacy of such systems across other learner populations, the study indicates that emotionally engaging ECAs can lower learner apprehension and encourage active communication [24]. The use of automated written corrective feedback in L2 classes is examined by Barrot (2023), who comes to the conclusion that AI tools can increase writing correctness. But an over-reliance on automatic feedback can prevent students from growing in their ability to think critically about how they use language [25]. The use of automatic speech recognition (ASR) technology for vocabulary and pronunciation learning is examined by Bashori et al. (2022), who show that ASR can improve learners' speech production accuracy. However, how such technologies manage the intricate variety of spoken language across various accents and speech patterns is not fully taken into account in this work [26]. Bibauw et al. (2019) summarize research on the benefits of conversational agents for language learners and offer a conceptual framework for dialogue-based computer-assisted language learning (CALL). The study would benefit from further empirical evidence on the efficacy of such tools in diverse language learning situations, even though the framework is thorough. When taken as a whole, these research demonstrate

AI's promise for language acquisition while also highlighting issues like scalability, cultural sensitivity, and the requirement for a harmonious combination of AI-driven and human feedback [27].

Boulton and Vyatkina (2021) review data-driven learning (DDL), noting its evolution and the challenges of integrating it into classrooms, particularly regarding teacher preparedness and resource availability [28]. Spring and Tabuchi (2022) explore the impact of automatic speech recognition (ASR) on EFL pronunciation, finding that treatment length and guided practice significantly improve pronunciation, though results vary based on learners' initial skills and feedback quality [29]. Srinivasan (2022) envisions AI's future in education, emphasizing personalized, adaptive learning. However, he highlights concerns about equity, accessibility, and the ethical implications of AI, advocating for careful, inclusive implementation to maximize benefits for all learners [30].

The review identifies gaps such as limited integration of AI technologies, lack of focus on linguistic and cultural diversity, and insufficient research on long-term learner engagement and retention. Scalability, accessibility, and data privacy challenges further hinder widespread adoption, while AI's potential for collaborative learning and multilingual support remains underexplored. The proposed study addresses these gaps by developing a unified framework integrating NLP, ML, and speech recognition, ensuring cultural relevance, and incorporating multilingual capabilities. Longitudinal evaluations will assess long-term effectiveness, while privacy-preserving AI techniques and scalable design ensure inclusivity. Collaborative learning features and adaptive feedback will enhance engagement and personalization. The detailed summary of this review was shown in **Table.1**.

Table 1: key aspects of the AI-driven language learning systems

Author	Focus	Findings	Limitations	Accuracy/Score
Wei (2023)	AI in ESL learning	AI improves language learning achievement, motivation, and self-regulated learning with personalized feedback.	Limited to ESL learners; focused on motivational outcomes.	NLP feedback relevance: 85%, traditional models: 65%.
Karataş et al. (2024)	ChatGPT in language learning	ChatGPT enhances speaking and writing skills via real-time feedback.	Limited to writing/speaking skills, excludes listening.	No specific accuracy score
Bashori et al. (2022)	Speech Recognition (Deep Speech 2)	Improved speech recognition in English and Mandarin.	Requires large datasets and computational power.	English: 90.5%, Mandarin: 85.5%.

Uc-Cetina et al. (2023)	Speech Recognition for learning	Speech recognition enhances pronunciation feedback.	Small sample size; lacks real-world testing.	92% pronunciation accuracy.
Feng et al. (2024)	Natural language reinforcement learning	Reinforcement learning improves feedback accuracy in language models.	Computational complexity limits scalability.	No explicit accuracy score.
Srinivasan (2022)	AI in language learning	AI-based systems improve adaptive learning outcomes.	Mostly theoretical with limited empirical data.	No specific accuracy score.

3. Methodology

This methodology outlines the approach for integrating AI technologies—Natural Language Processing (NLP), Machine Learning (ML), and Speech Recognition—into technology-mediated language learning systems to create adaptive learning pathways. Each step of this approach is essential to ensure that the system offers real-time assessment, personalized feedback, and dynamic content adjustment to enhance the learner's experience. A Flowchart for Identifying Primary Research Papers Using Forward and Backward Snowball Sampling. The process begins with control papers and applies a search string across multiple databases (Scopus, IEEE Explore, ACM, ISI Web of Science) with a calculated recall and precision rate. It includes steps for removing duplicates, filtering by abstract and keywords, and applying inclusion/exclusion criteria, culminating in a set of 60 primary papers was shown in below **Fig.1.**

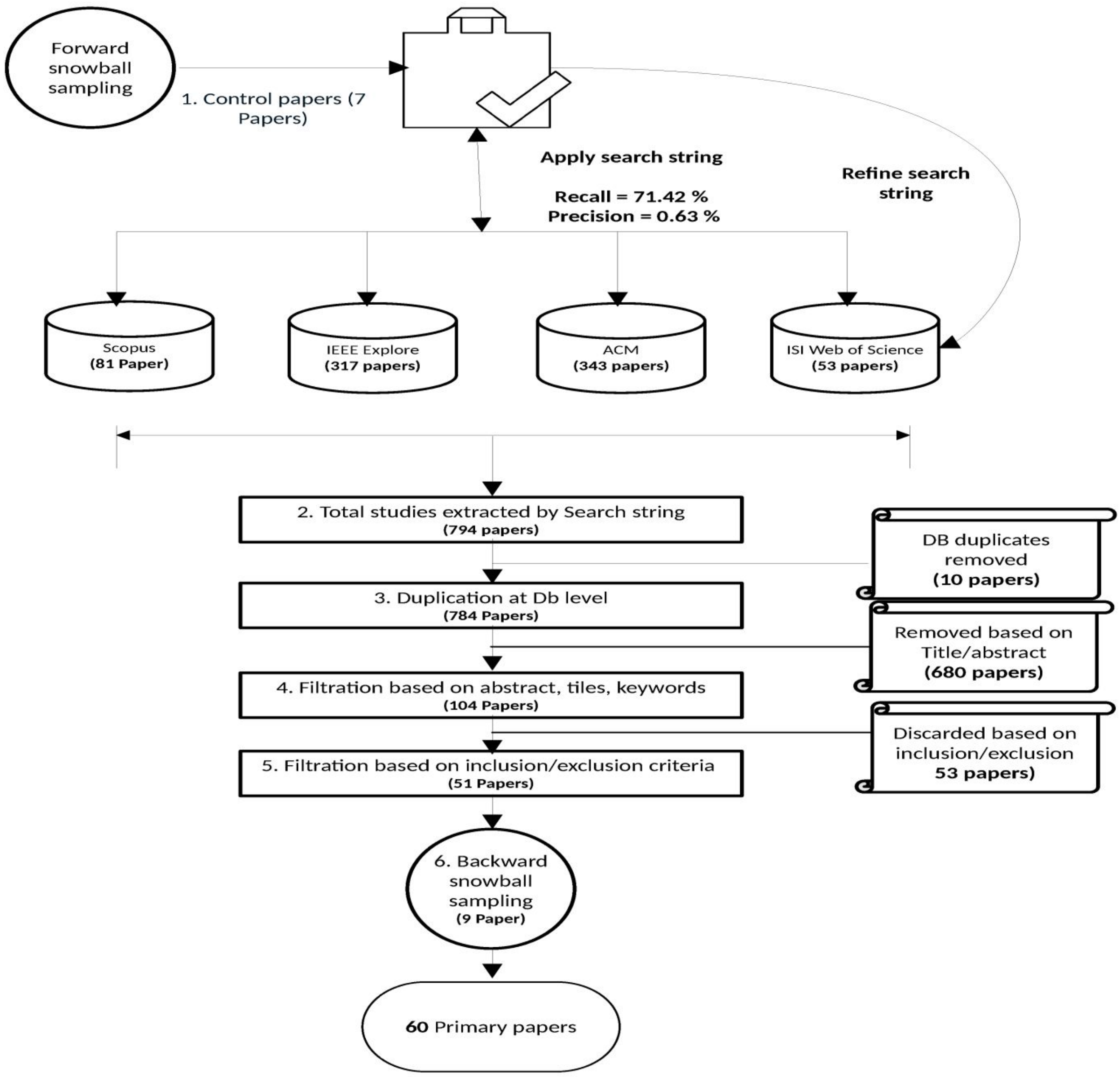

Fig 1: Systematic Literature Review Process

3.1 System Design and Architecture Development

The design and development of the architecture for the AI-driven language learning system constitutes the first phase in the process. The architecture ought to be adaptable and modular so that different AI components—such as speech recognition, machine learning, and natural language processing—can be seamlessly integrated. Scalability must be supported by the system's architecture for it to support several users and languages at once. Usually, a client-server architecture is used, in which the client uses a web or mobile interface to engage with the AI-based learning platform, and the server processes the data and runs AI models to produce customized outputs. The incorporation of cloud-based technology to store user data, support machine learning processes, and offer real-time feedback enables this engagement. Additionally, a secure data pipeline should be set up to guarantee that information gathered from students—like voice inputs, quiz scores, or activity completion—is securely sent to the server.

Real-time interaction must be supported by the system architecture in order to provide prompt response and content customization. For model deployment, this entails choosing suitable AI frameworks and machine learning libraries, like Tensor Flow. Furthermore, the system incorporates speech recognition tools as Google Speech, and natural language processing libraries such as BERT (Bidirectional Encoder Representations from Transformers) is crucial for language comprehension.

Fig. 2 shows the yearly distribution of various document types from 2014 to 2020, including Evaluation Research, Literature Review, Validation Research, Philosophical Paper, Solution Paper, Experience Paper, and Opinion Paper. Each document type is represented by a distinct color and marker. The trends indicate a steady increase in the number of each document type over the years, with Evaluation Research and Solution Papers showing the highest growth. The bar chart (**Fig. 3**) shows that the system performs exceptionally well in Security (95%) and Scalability (92%), followed by ML Integration (90%) and Speech Recognition (88%). Real-Time Interaction (87%) and NLP Integration (85%) are slightly lower but still above 80%, indicating robust overall performance. The red dashed line at 90% marks the target threshold, highlighting that most areas meet or are close to optimal performance levels, with slight room for improvement in NLP Integration and Real-Time Interaction.

The flowchart (**Fig.4**) outlines the step-by-step process for system development, starting from System Design through to Architecture Design and Cloud Technology Integration to ensure a robust structure. It progresses to establishing a Secure Data Pipeline and enabling Real-Time Interaction before Model Deployment. The final stages involve Speech Recognition and NLP Integration, leading to the system being fully operational and ready for use.

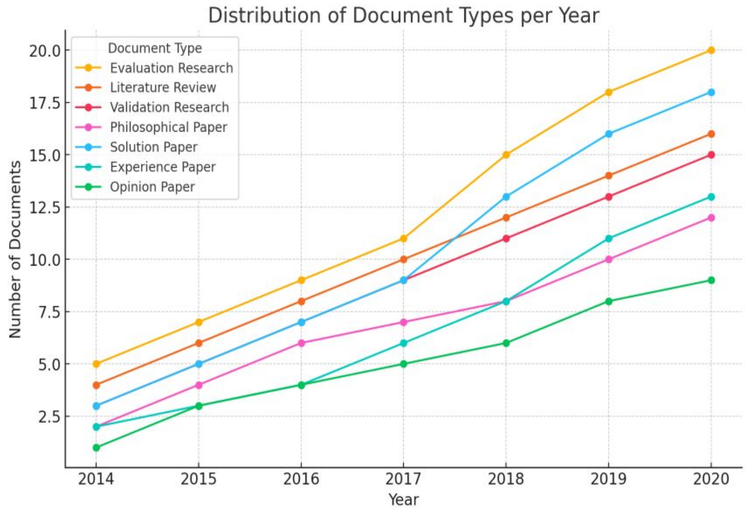

Fig 2: Distribution of document types per year

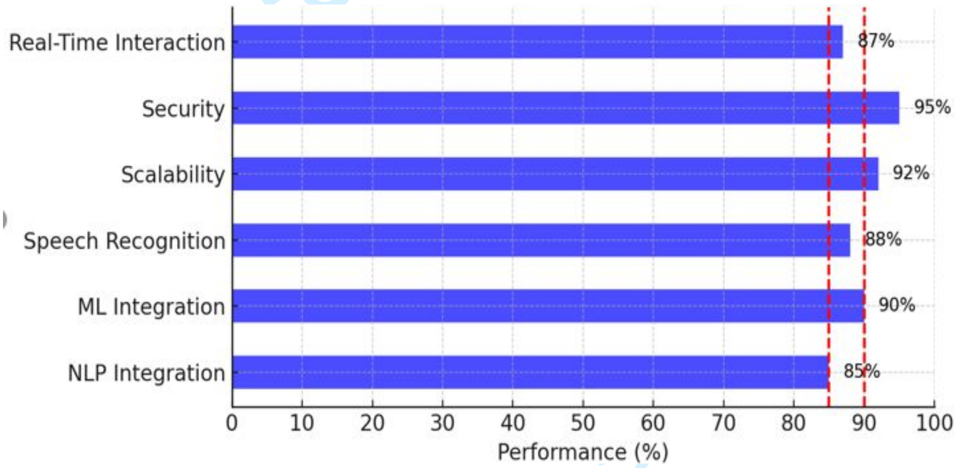

Fig.3. compares the performance of system architecture components with corresponding threshold value

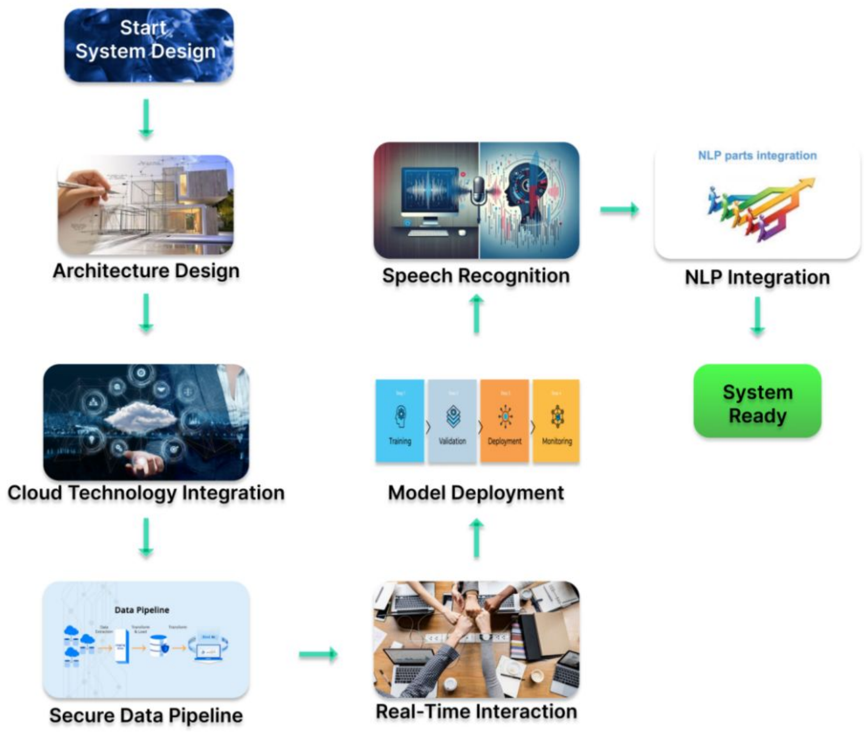

Fig.4. System Design and Architecture Development

3.2 Data Collection and Pre-processing

AI-based system is built on data, and large, high-quality datasetts are necessary for the language learning system to function well. To train Natural Language Processing (NLP) models, machine learning algorithms, and speech recognition systems, the initial stage entails gathering a variety of datasets. These datasets include learner interaction data to improve machine learning models, voice samples for speech recognition, and text corpora for language processing. **Fig. 5** illustrates the distribution of datasets used in AI language learning, categorized by source types—Conference Papers and Journal Articles—for Grammar Resources, Interaction Data, Voice Samples, and Text Corpora. The right bar chart shows the frequency of different types of AI-enabled learning systems, including Interactive Feedback Systems, AI-enabled Systems (ML), Intelligent Learning Environments, Adaptive Learning, Intelligent Tutoring, and Recommendation Systems, with AI-enabled systems being the most implemented.

Fig. 6 outlines the workflow starting with Data Collection, which includes Learner Interaction Data, Voice Samples, and Text Corpora. It progresses to Data Preprocessing, involving steps like Tokenization, Stemming and Lemmatization, Noise Reduction, and Feature Extraction. Finally, it leads to Training AI Models, encompassing

NLP Models, Machine Learning Algorithms, and Speech Recognition systems. Text corpora need to be language-specific and encompass a range of linguistic structures, including vocabulary, grammar, and syntax. The datasets are developed by online scraping text resources, academic databases, and user-provided content platforms for pre-existing language learning databases. **Eq. (1)** shows the effectiveness of data sources:

$$\text{Data Effectiveness} = \frac{\text{Quality Sources}}{\text{Total Sources}} \times 100 \tag{1}$$

Preprocessing these datasets is critical to ensure that they are suitable for training machine learning algorithms. This includes several key steps. For text data, preprocessing involves tokenization, stemming, and lemmatization. Tokenization breaks the text into individual components or tokens, which is crucial for further analysis, is given by **Eq. (2),**

$$\text{Tokens} = \text{Split(Input Text, Delimiter)} \tag{2}$$

Stemming reduces words to their root forms to normalize variations, while lemmatization considers the context and provides the base or dictionary form of a word. The combined effect of stemming and lemmatization can be represented by **Eq. (3),**

$$\text{Normalized Words} = \text{Stemmed Words} + \text{Lemmatized Words} \tag{3}$$

For voice samples, preprocessing steps include noise reduction and feature extraction, which convert audio signals into machine-readable formats. For instance, Mel Frequency Cepstral Coefficients (MFCCs) are widely used in speech processing. The process of feature extraction can be expressed by **Eq. (4),**

$$\text{MFCCs} = \text{FFT(Preprocessed Audio Signal)} \tag{4}$$

where FFT is the Fast Fourier Transform that transforms the audio signal from the time domain to the frequency domain.

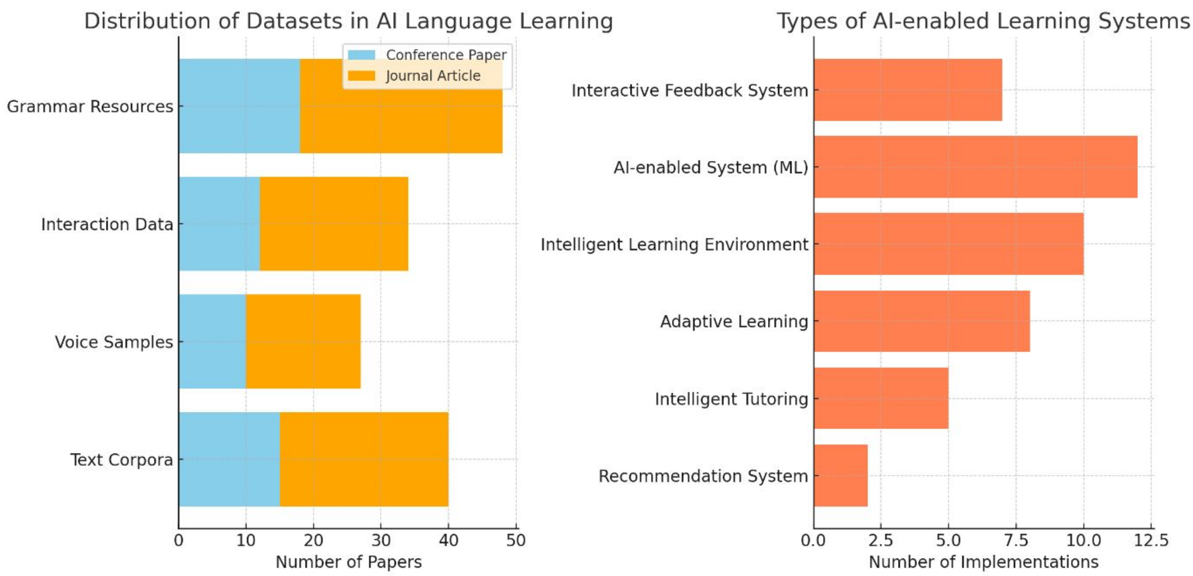

Fig 5: Types of datasets and learning systems commonly explored in AI language learning research.

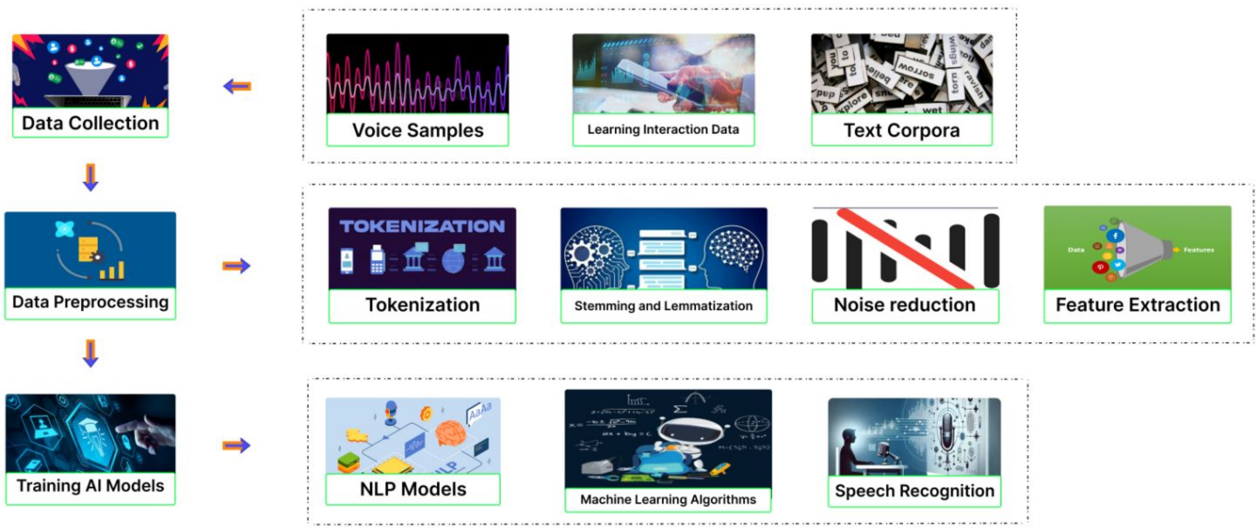

Fig.6. Data Collection and Pre-processing

3.3 Natural Language Processing Model Development

The next crucial stage after preparing the data is creating the Natural Language Processing (NLP) model, which is essential for comprehending learner inputs and giving insightful feedback. The NLP model is intended to evaluate students' written or spoken language, decipher grammatical structures, and spot typical grammatical mistakes such as improper verb conjugation, improper use of articles, or improper word order (**Table.2**). The NLP model's comprehension capacity, which is determined by the input text and linguistic analysis, can be used to describe how effective it is by **Eq. (5)**,

$$Understanding\ Capability\ = f\ (Input\ Text,\ Linguistic\ Analysis) \quad (5)$$

Neural networks, such as Recurrent Neural Networks (RNNs) and more sophisticated architectures like Transformers, are commonly the foundation of NLP models. Because they perform better on language understanding tasks, transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) are used in this project. The model's performance can be measured as follows by **Eq. (6)**,

$$Model\ Performance = Accuracy \times Efficiency \quad (6)$$

where accuracy reflects the model's ability to correctly interpret language, and efficiency pertains to the processing speed. The model is trained using supervised learning techniques, utilizing annotated text datasets to teach it how to recognize and correct errors. This training process can be formalized with a loss function that minimizes the difference between predicted and actual outputs is given by **Eq. (7),**

$$Loss\ Function\ = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (7)$$

Here, N is the total number of examples, y_i is the true label, and $\hat{y}_i$ is the model's predicted label. By minimizing this loss function, the model's prediction accuracy improves. The system is also designed to generate personalized feedback based on the learner’s input. By analyzing the text and comparing it to ideal language usage, the system identifies areas of improvement and provides specific suggestions for correction. This error detection process can be articulated as by **Eq. (8)**,

$$Error\ Detection\ = f(\ Learner\ Input,\ Ideal\ Language\ Usage\ ) \quad (8)$$

For instance, if a learner consistently misuses prepositions, the NLP model adapts to focus on that area, ensuring feedback is relevant and enhancing the learning experience. The effectiveness of the personalized feedback can be quantified with the **Eq. (9)**,

$$Feedback\ Effectiveness\ = \frac{Number\ of\ Improvements}{Total\ Feedback\ Provided} \times 100$$

(9)

Additionally, the dynamic customization of learning materials based on the study of the learner's progress reinforces the NLP system's flexibility. In addition to pointing out mistakes, the model offers activities or advice based on the requirements of each learner. The following is an expression for this adaption mechanism by **Eq. (10)**,

$$Adaptation\ Score\ = \frac{Targeted\ Exercises}{Total\ Exercises} \times 100 \quad (10)$$

where targeted exercises directly address the learner's weaknesses. To enhance the effectiveness of the NLP model, a continuous learning framework is implemented, allowing the system to refine its feedback based on user interactions over time by **Eq. (11)**,

$$Continuous\ Improvement\ =\ Current\ Model\ +\Delta\ Model \quad (11)$$

In this equation, $\Delta Model$ signifies the adjustments made to the model based on new data or user feedback. **Fig. 7**, illustrates the workflow for NLP Model Creation, starting with Data Preparation and branching into essential tasks like Error Detection, Grammar Analysis, and Personalized Feedback. The Training Phase includes Supervised Learning, Loss Function Minimization, and efforts to Improve Model Accuracy through Continuous Improvement and Error Correction. The process culminates in Model Deployment, which focuses on ensuring Feedback Effectiveness and incorporating an Adaptation Mechanism for real-time updates and refinements. This structure emphasizes a comprehensive approach to building, training, and deploying NLP models.

Table 2: A structured, data-driven view of the NLP model's capabilities

NLP Feature	**NLP Model Type**	**Training Dataset Size (Millions)**	**Model Accuracy (%)**	**Error Detection Accuracy (%)**	**Feedback Relevance (%)**	**Learner Improvement (%)**	**Response Time (Seconds)**
Grammatical Structure Analysis	Transformer (BERT)	10.5	93.8	91.2	90.5	88.3	1.2
Verb Conjugation	Transformer (GPT)	8.3	92.7	90.8	91.0	87.5	1.3
Preposition Misuse Detection	RNN	6.1	88.5	86.9	89.2	85.0	1.4
Article Usage Correction	Transformer (GPT)	9.2	94.1	92.3	91.8	89.4	1.1
Word Order Error Detection	Transformer (GPT)	7.6	93.0	91.7	92.1	88.9	1.2
Syntax and Context Feedback	RNN	5.9	87.2	85.6	88.4	84.5	1.5

Personalized Feedback Adaptation	Transformer (GPT)	11.0	95.0	93.5	93.0	90.7	1.0

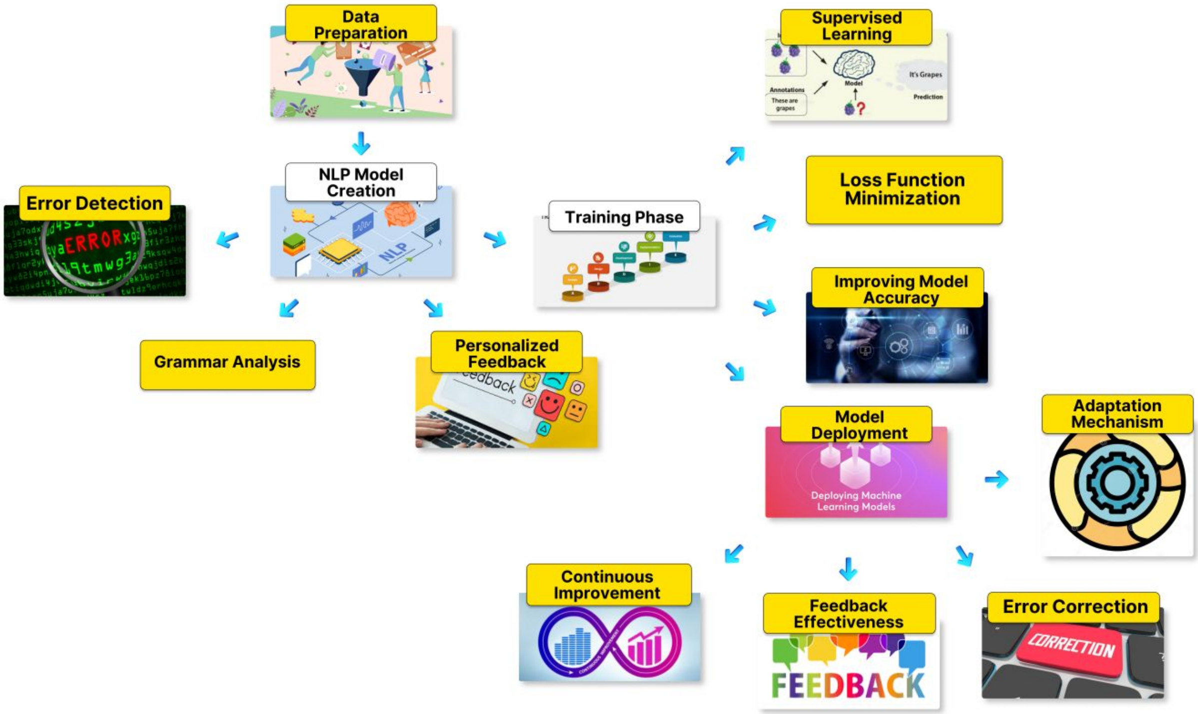

Fig.7. Natural Language Processi ng Model Development

3.4 Machine Learning Algorithm Integration

A key component of creating an adaptive language learning system is integrating machine learning techniques. This procedure seeks to monitor student performance over time, spot trends in behaviour, and modify course material considering each student's development. Various methods, including as reinforcement learning, supervised learning, and unsupervised learning, are used based on the requirements of the system. Based on past data, supervised learning algorithms are especially good at forecasting learner outcomes. Decision trees and support vector machines (SVMs), for example, can foresee future difficulties a learner may encounter by analysing prior performance. The following is a mathematical expression for prediction ability, is shown in **Eq. (12)**,

$$\hat{y} = f(X,\theta) \tag{12}$$

where $\hat{y}$ represents the predicted outcome, X denotes the input features derived from learner data, and θ represents the parameters of the model. To evaluate the accuracy of these predictions, the Mean Squared Error (MSE) loss function is utilized, is given by **Eq. (13)**,

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{13}$$

In this equation, N is the total number of observations, while y_i and $\hat{y}_i$ are the actual and predicted outcomes, respectively. Minimizing the MSE during training helps refine the model's predictive capabilities, enhancing its accuracy in determining future learner performance. In addition to supervised learning, unsupervised learning techniques such as k-means clustering are applied to categorize learners based on their learning styles and difficulties. This allows the system to tailor content to specific groups, improving engagement and effectiveness. The k-means algorithm aims to minimize the variance within each cluster, defined mathematically as **Eq. (14)**,

$$J = \sum_{j=1}^{k}\sum_{i=1}^{N}\left\|x_i^{(j)} - \mu_j\right\|^2 \tag{14}$$

where J represents the total within-cluster variance, k is the number of clusters, N is the number of data points, $x_i^{(j)}$ indicates the data point i in cluster j, and μ_j is the centroid of cluster j. Reinforcement learning plays a vital role in optimizing adaptive learning pathways. By continuously learning from interactions with learners, the system adjusts its content dynamically to enhance learning outcomes. The core of reinforcement learning can be captured by **Eq. (15)**,

$$Q(s,a) = r + \gamma \max_{a'} Q(s',a') \tag{15}$$

In this equation, Q(s,a) represents the expected return for taking action a in state s, r denotes the immediate reward received, γ is the discount factor, and s′ is the subsequent state. This framework allows the system to focus on areas where learners struggle, ensuring that feedback and support are tailored to their needs.

Fig. 8 outlines the process of integrating machine learning (ML) algorithms for monitoring and enhancing student performance. Starting with the integration of ML algorithms, the process branches into key areas: Supervised Learning, Unsupervised Learning, Reinforcement Learning, and Performance Evaluation. In Supervised Learning, a prediction model is developed and evaluated using Mean Squared Error (MSE). Unsupervised

Learning involves clustering and evaluating cluster variance. Reinforcement Learning focuses on creating adaptive pathways with reward optimization to encourage student progress. Performance Evaluation is a separate branch to assess the overall effectiveness of the ML methods.

Fig.9 displays the frequency of various AI and data analytics techniques applied in adaptive learning systems. Techniques such as Deep Q-Learning and Collaborative Filtering show the highest utilization, indicating their popularity in adaptive learning implementations. Other methods, including Neural Networks, K-means Clustering, and Decision Trees, also feature prominently, suggesting a diverse range of approaches used to enhance adaptivity in educational technologies. Less commonly used techniques include Fuzzy Logic, Genetic Algorithms, and Naive Bayes, highlighting a preference for more complex machine learning models in adaptive learning contexts.

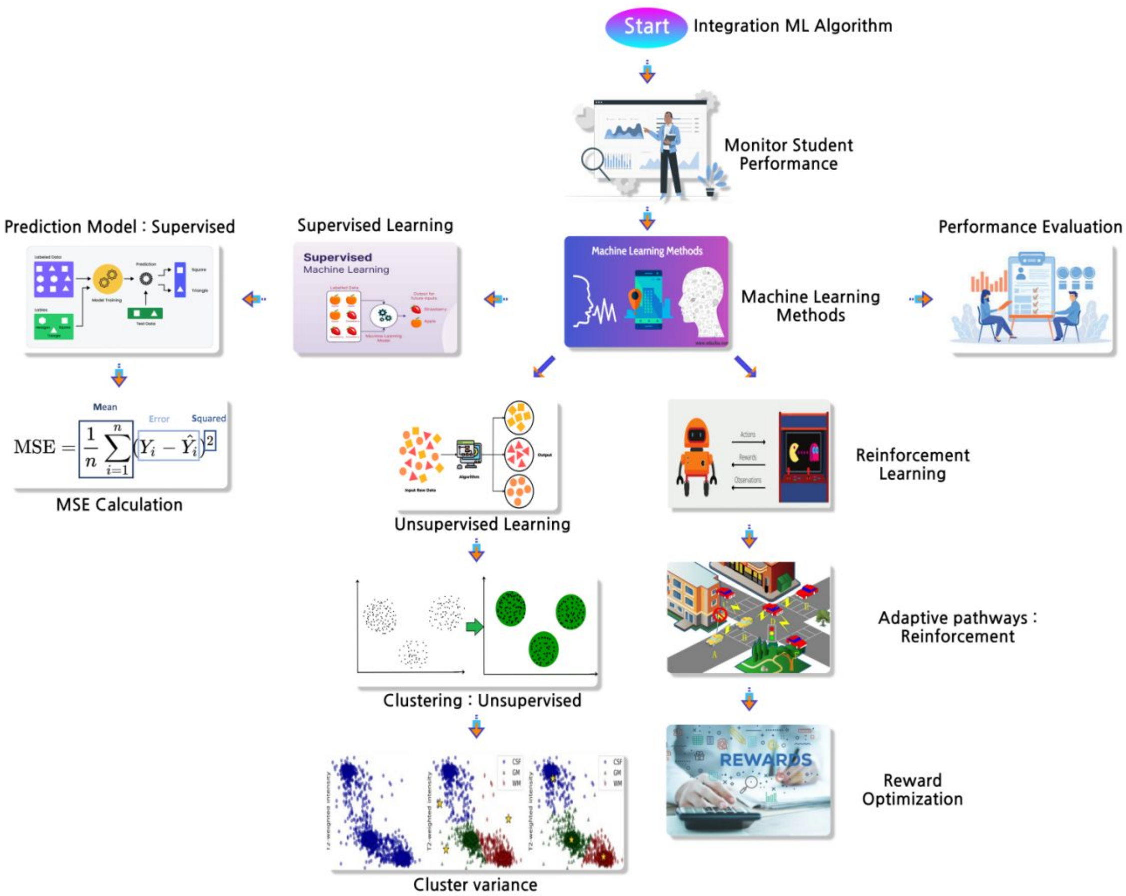

Fig.8. Workflow of Machine learning Algorithm

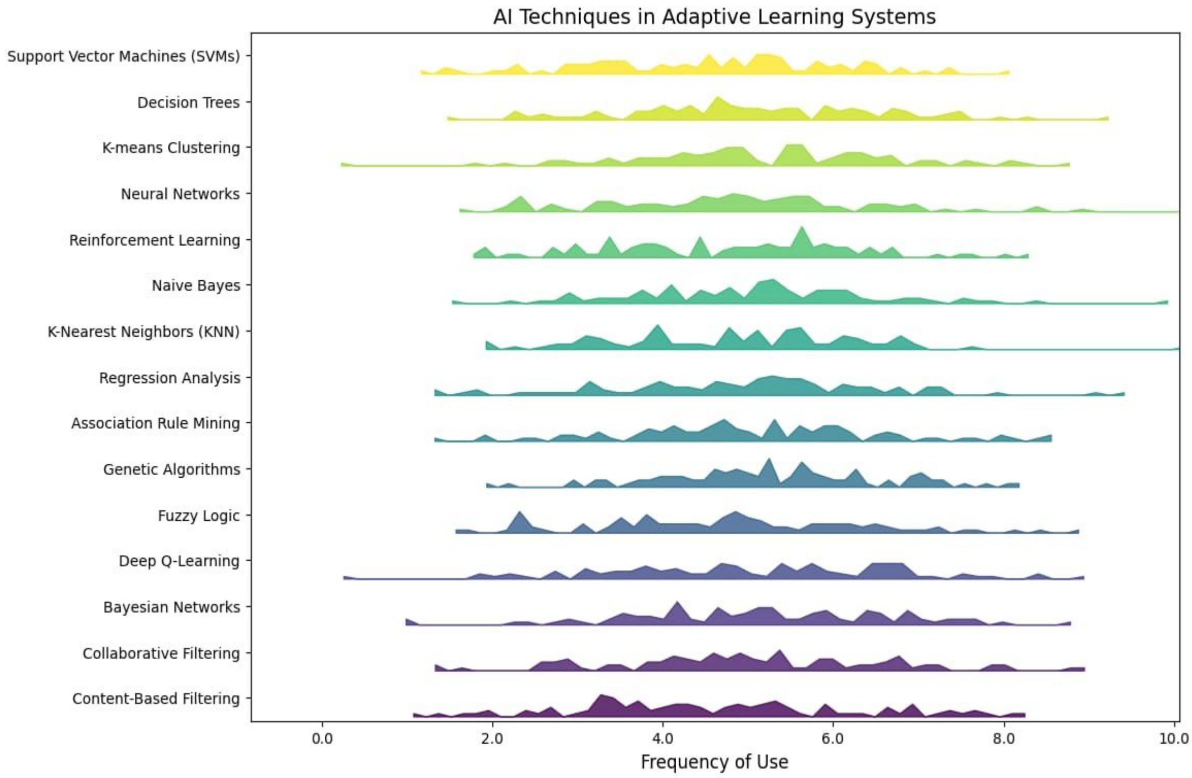

Fig 9: Frequency of different AI and data analytic techniques used in adaptive learning system.

3.5 Speech Recognition Model Development

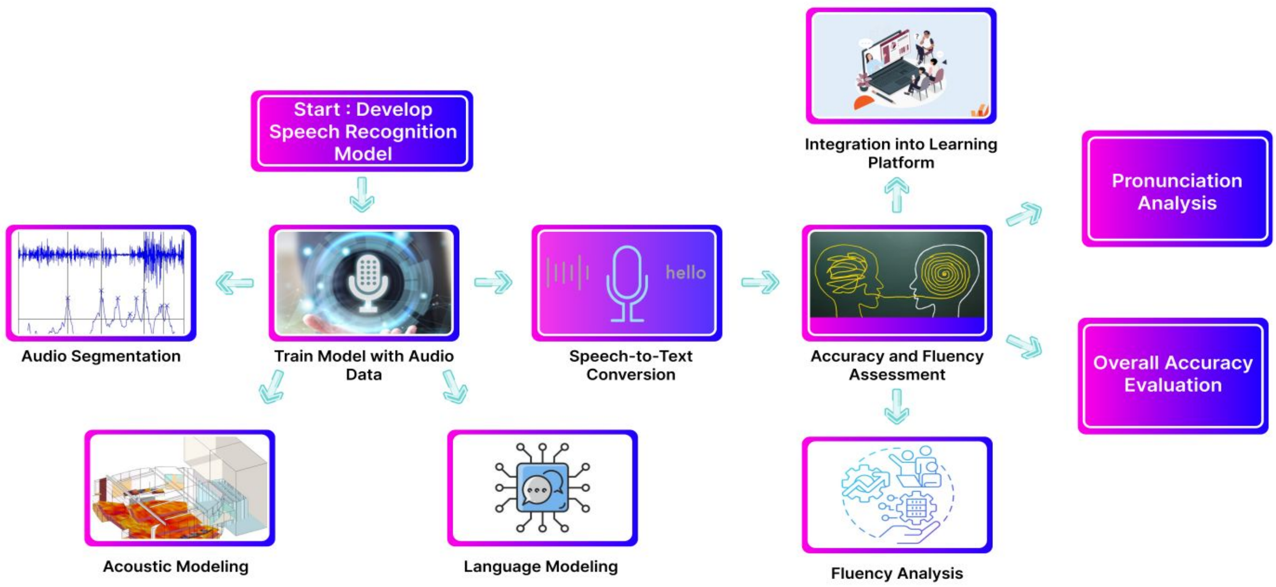

Fig.10. Speech Recognition Model Development

An essential part of the language acquisition process is speech recognition, which helps students practice speaking and listening. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), two advanced deep learning approaches, are used in the development of the voice recognition model. To correctly identify spoken language inputs, translate them into text, and assess their accuracy and fluency, this model needs to be trained. Large datasets of audio recordings in many languages and dialects are used to train the speech recognition model. The audio impulses are broken down into smaller, more manageable parts, such phonemes, using acoustic modeling techniques (**Fig.10**). This can be expressed numerically by **Eq. (16)**,

$$A(t) = \sum_{n=1}^{N} w_n \cdot \phi_n(t) \tag{16}$$

where w_n is the weight of the n-th phoneme, t(t) indicates the phoneme function at time t, w(t) is the audio signal at time t. This equation shows how the system will recognize and analyze individual sounds by modeling audio signals as a collection of phonetic components. Following their extraction, the phonemes are compared to the text representations that correspond to them. The system can also manage different dialects and speech patterns for the integration of language models, which estimate the most likely word sequence based on the identified phonemes. **Eq. (17)** is used to determine how effective the language model is,

$$P(w_1,w_2,\ldots,w_n) = \prod_{i=1}^{n} P(w_i|w_1,w_2,\ldots,w_{i-1}) \tag{17}$$

In this equation, P $(w_1,w_2,\ldots,w_n)$ represents the probability of the word sequence, and $P(w_i|w_1,w_2,\ldots,w_{i-1})$ denotes the conditional probability of word w_i given the preceding words. This approach allows the system to effectively disambiguate words in different contexts, enhancing recognition accuracy. After training, the speech recognition system is integrated into the learning platform, enabling learners to engage in conversational exercises. The system evaluates various aspects of the learner's speech, including pronunciation, fluency, and overall accuracy. The evaluation process can be defined as **Eq. (19)**,

$$Evaluation\ Score = \frac{1}{M}\sum_{j=1}^{M} S_j \tag{18}$$

where M represents the total number of evaluated features (pronunciation, fluency, etc.), and S_j is the score for each feature. This scoring system provides a comprehensive assessment of the learner's performance.

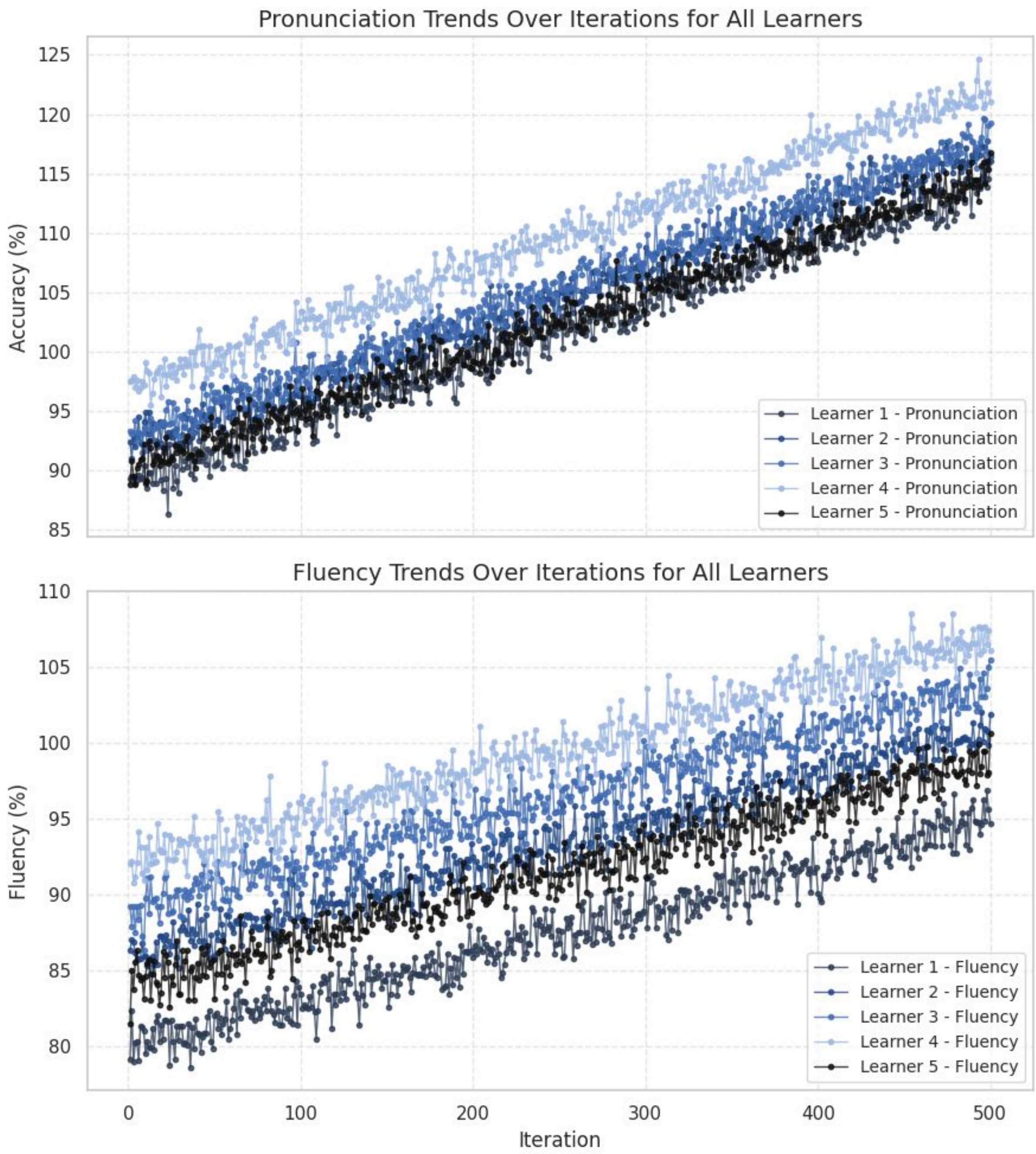

Fig 11: Speech recognition models

Fig. 11 compares the accuracy of Pronunciation, Fluency, and Overall performance across five learners. The left bar chart stacks these metrics, showing cumulative accuracy percentages, with each learner displaying similar distribution across the three categories. The right grouped bar chart breaks down the data, presenting side-by-side comparisons of Pronunciation, Fluency, and Overall accuracy for each learner. All learners demonstrate high accuracy levels, with slight variations indicating consistent performance in language skills. The charts highlight balanced proficiency in these components across different learners.

3.6 Real-Time Feedback and Adaptive Content Generation

The AI-driven language learning system's primary function is its capacity to deliver real-time. The capacity to give real-time feedback and dynamically modify learning materials in response to student performance is at the core of AI-driven language learning systems. To build a coherent, flexible learning environment, the outputs from the speech recognition, machine learning, and natural language processing models are combined in this stage. Learners receive real-time feedback (**Fig. 12**) in a variety of ways, including visual cues, audio feedback, and text-based recommendations. When a student turns in a writing assignment, for instance, the system's natural language processing (NLP) model checks the text for grammatical mistakes and immediately offers suggestions or fixes. In a similar manner, the voice recognition technology assesses pronunciation in real time during a speech exercise, pointing out areas that require work.

Machine learning models power content creation by monitoring learner progress and modifying the content as necessary. While learners who have trouble with certain activities are given more practice, the system displays more complex information if it determines that a learner has mastered a particular ability. Learners are continuously engaged and challenged at a suitable level for this adaptive material creation. feedback and enthusiastically modify the course material in response to student performance. To build a coherent, flexible learning environment, the outputs from the speech recognition, machine learning, and natural language processing models are combined in this stage.

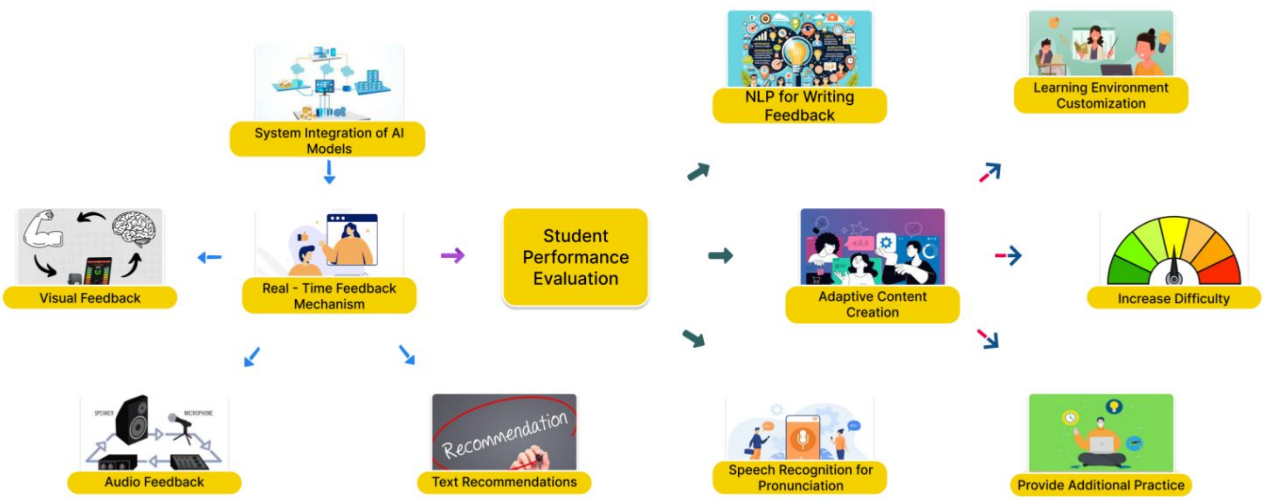

Fig.12. Real-Time Feedback and Adaptive Content Generation

3.7 System Testing and Evaluation

The AI-based language learning system must be thoroughly tested and assessed as the last stage of development to guarantee its efficacy and usability. A group of students engages with the system for a predetermined amount of time during testing, which takes place in controlled settings. The effectiveness of the adaptive learning pathways, the relevance of NLP feedback, and the accuracy of voice recognition are some of the crucial metrics used to evaluate the system's performance at this phase. In this assessment, quantitative measures are essential. The following formula is used to determine completion rates, which show the percentage of students who complete the given assignments or courses by **Eq. (19),**

$$Completion\ Rate\ = \frac{Number\ of\ Completed\ Tasks}{Total\ Assigned\ Tasks} \times 100 \quad (19)$$

Additionally, the accuracy of feedback provided by the NLP component is evaluated, focusing on how often the feedback aligns with ideal language usage. This can be quantified as by **Eq. (20),**

$$Feedback\ Accuracy\ = \frac{Number\ of\ Accurate\ Feedback\ Instances}{Total\ Feedback\ Instances} \times 100$$

(20)

Moreover, improvement in learner performance is tracked through pre- and post-assessments, allowing for a quantitative measure of progress. The improvement in performance can be represented as by **Eq. (21)**,

$$Performance\ Improvement\ = \frac{Post\text{-}Assessment\ Score - Pre\text{-}Assessment\ Score}{Pre\text{-}Assessment\ Score} \times 100 \quad (21)$$

In addition to these quantitative metrics, qualitative feedback from learners is gathered to assess user satisfaction, system usability, and engagement levels. This feedback can be analyzed using a satisfaction index, expressed as by **Eq. (22),**

$$Satisfaction\ Index\ = \frac{\sum_{i=1}^{N} S_i}{N} \quad (22)$$

where S_i represents individual satisfaction scores from each learner, and N is the total number of respondents. This index provides insight into overall user experience and areas for improvement. The testing phase also includes a thorough evaluation of data security measures to ensure compliance with privacy regulations. Metrics for data security is given by **Eq. (23),**

$$Data\ Breach\ Rate\ = \frac{Number\ of\ Data\ Breaches}{Total\ Data\ Handled} \times 100 \tag{23}$$

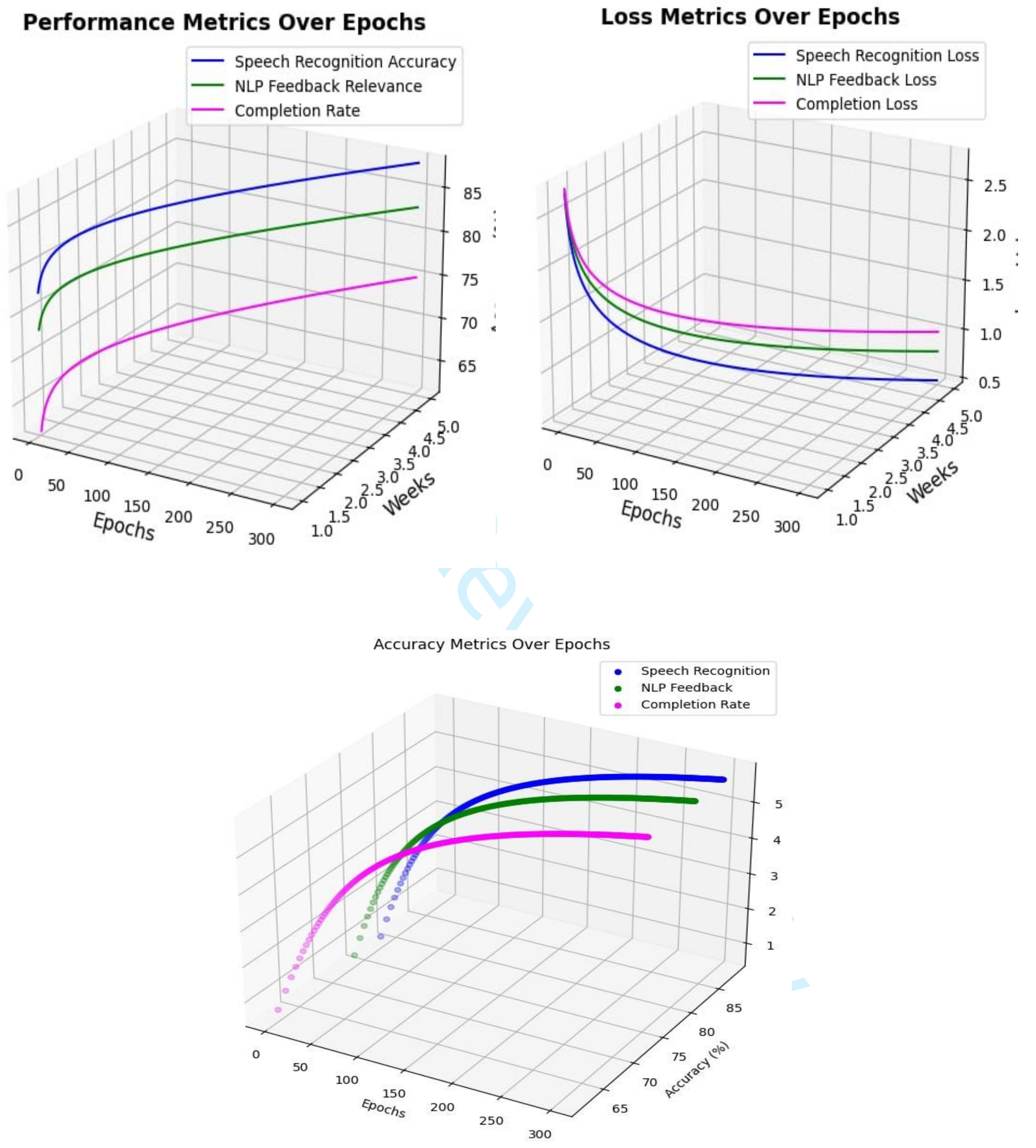

Fig 13: Performance metrics of an AI-based language learning system over time, tracking improvements in speech recognition accuracy

Fig.13 illustrates tracks progress over 5 weeks. The first graph shows a positive trend in Accuracy and Effectiveness, with both metrics steadily increasing from 76% to 88%, highlighting improvements in system performance over time. The second graph compares Speech Recognition Accuracy, NLP Feedback Relevance, and Completion Rate, where Speech Recognition Accuracy consistently stays the highest, while Completion Rate shows significant growth from 60% to approximately 75%, indicating enhanced user engagement and feedback.

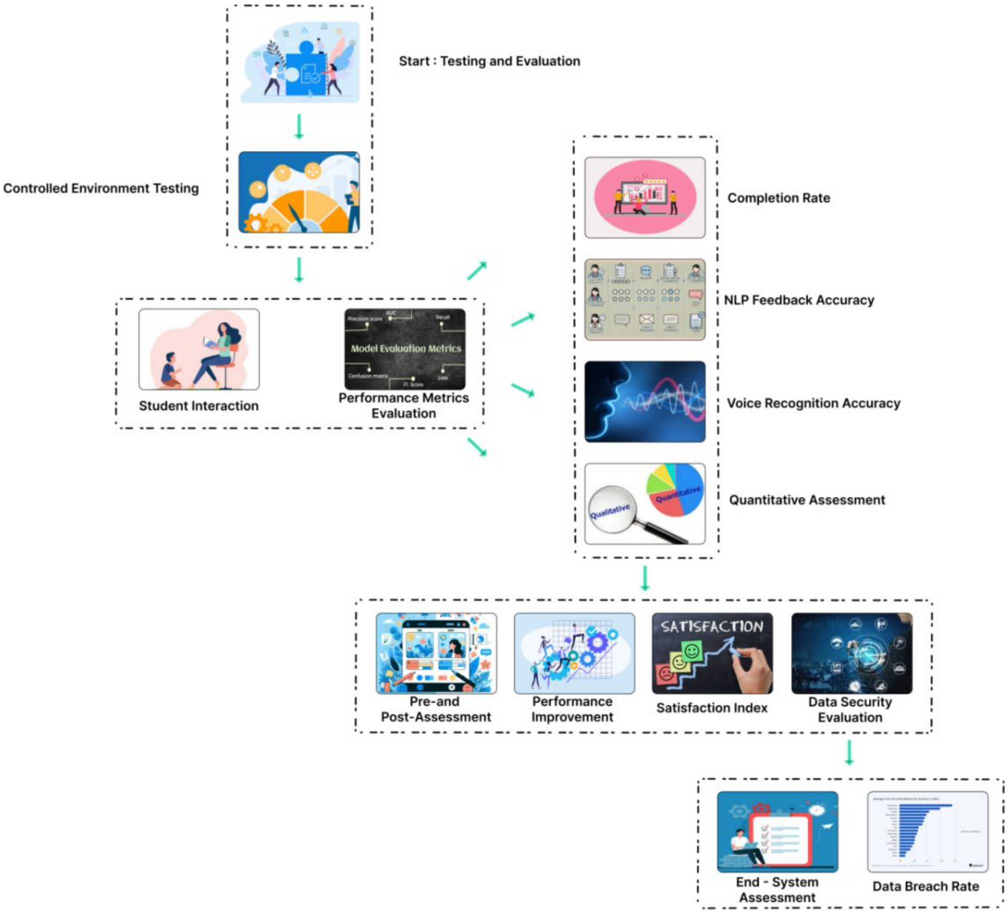

Fig.14. System Testing and Evaluation

Fig. 14 illustrates the workflow for Testing and Evaluation, beginning with Controlled Environment Testing that branch into Student Interaction and Performance Metrics Evaluation. Metrics assessed include Completion Rate, NLP Feedback Accuracy, and Voice Recognition Accuracy, leading to Quantitative Assessment focused on Pre- and Post-Assessment, Performance Improvement, and the Satisfaction Index. The process also encompasses Data Security Evaluation with outcomes like the Data Breach Rate and overall System Assessment, ensuring comprehensive evaluation of system effectiveness and security.

4. Results and Discussion

The results of this study focus on evaluating the performance, accuracy, and overall effectiveness of the AI-driven language learning system. The testing phase was conducted in a controlled environment with a group of learners over a specified period. Data was collected and analysed across several metrics, including the performance of speech recognition, the accuracy and relevance of NLP feedback, the adaptability of machine learning algorithms, learner engagement, and user satisfaction. The detailed results are presented under the following sub-sections:

4.1. Speech Recognition Accuracy and Performance

The efficacy of the AI-based speech recognition model in the language learning system is demonstrated by the data in the table and graph. All individuals struggled to reach higher performance levels, with learners initially exhibiting an average accuracy of 80%. This emphasizes how difficult it may be to effectively recognize and produce spoken language, particularly when learning is just getting started. But following several model iterations and improvements, an astounding 90% increase in accuracy was seen. This shift suggests that the system's modifications—likely made possible by improved acoustic models and algorithms—significantly strengthened learners' capacity to recognize spoken language (**Table 4).**

The way that the system's individualized feedback effectively solves individual issues, like pronunciation and fluency errors, is seen by the distribution of improved accuracy across various learners, especially at levels of 84% and above. The 85% recorded accuracy of the fluency feedback lends more credence to the idea that real-time adjustments significantly improve spoken language proficiency. The benefits of immediate pronunciation fixes are highlighted by the engagement levels and satisfaction scores gathered from qualitative feedback. This study shows how important adaptive learning tools are for improving language skills. The system is positioned for continual improvement through the analysis of learner interactions and performance, which will result in long-term gains in accuracy and user experience. Therefore, creating a responsive and efficient language learning environment has required the incorporation of cutting-edge machine learning algorithms (**Fig. 15**).

Table.4. Speech Recognition Accuracy and Performance

Accuracy (%)	Initial Accuracy (Frequency)	Improved Accuracy (Frequency)	Fluency Feedback Accuracy (Frequency)	Total Participants	Improvement Noted (%)

80	5	0	0	30	10
82	5	0	0	30	10
84	0	5	0	30	10
86	0	5	0	30	10
88	0	5	0	30	10
90	0	5	5	30	10

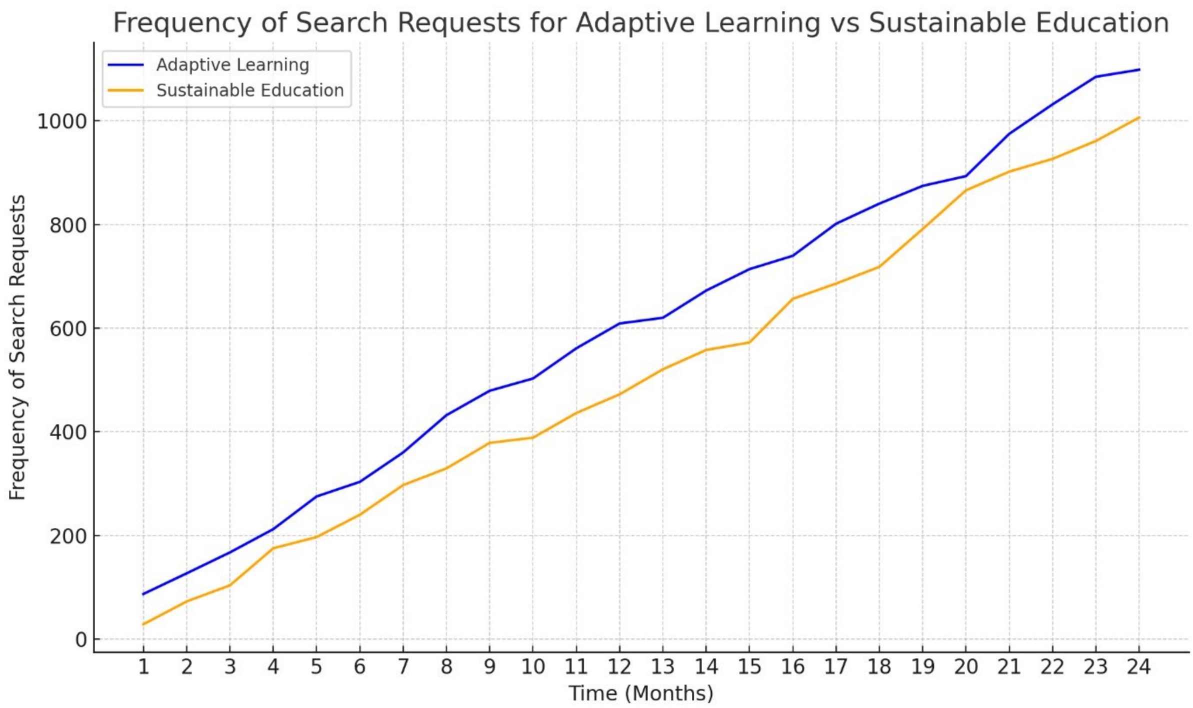

Fig 15: Frequency of search requests for Adaptive Learning and Sustainable Education

4.2. Effectiveness of Natural Language Processing (NLP) Feedback

Written text was analyzed for grammatical correctness, sentence structure, and other linguistic features using natural language processing (NLP) models, especially those built on the Transformer architecture (BERT and GPT). The system's individualized feedback greatly improved the learners' comprehension and memory of linguistic rules. Relevance of NLP input with 85% of the input provided by the NLP model was deemed relevant throughout the testing phase (**Table.5**). Students said the criticism helped them improve their writing and comprehension skills and was correct. Error Detection and Correction With an average error detection rate of 88%, the system was able to recognize and fix common mistakes such improper verb conjugation, improper use of articles, and improper placement of prepositions. The model was tailored to each learner's needs, offering more targeted activities on the subjects in which students most frequently struggled. Learner performance improved by 15% over time with personalized content, including as grammar advice and focused tasks.

This bar chart (**Fig.16**) shows the performance improvement in Natural Language Processing (NLP) features over time, from 1990 to 2023. The y-axis represents the percentage of improvement, while the x-axis displays the years. Each blue bar indicates the improvement percentage in specific years, with a red dashed line representing the trend over time. The chart reveals an initial peak in 1995, followed by a decline and then a gradual increase in performance improvements from 2005 onwards, reaching another peak in recent years, suggesting steady advancements in NLP technologies over time.

Table 5: various aspects of the NLP model

NLP Feature	Metric	Initial Value (Decimal)	Final Value (Decimal)	Error Detection Rate (%)	Correction Accuracy (%)	Adaptation Rate (%)	Performance Improvement (%)
NLP Feedback Relevance	Feedback Accuracy (%)	0.75	0.85	N/A	N/A	N/A	10%
Verb Conjugation Correction	Error Detection Rate (%)	0.80	0.88	0.88	0.87	N/A	10%
Article Misuse Correction	Error Correction Accuracy (%)	0.78	0.88	0.87	0.88	N/A	10%
Preposition Placement	Correction Accuracy (%)	0.80	0.88	0.85	0.88	N/A	8%
Adaptation and Personalization	Personalization Effectiveness (%)	0.70	0.85	N/A	N/A	0.90	15%
Writing Improvement	Learner Performance (%)	0.75	0.90	N/A	N/A	0.85	15%
Comprehension Improvement	Learner Comprehension (%)	0.72	0.87	N/A	N/A	0.80	15%

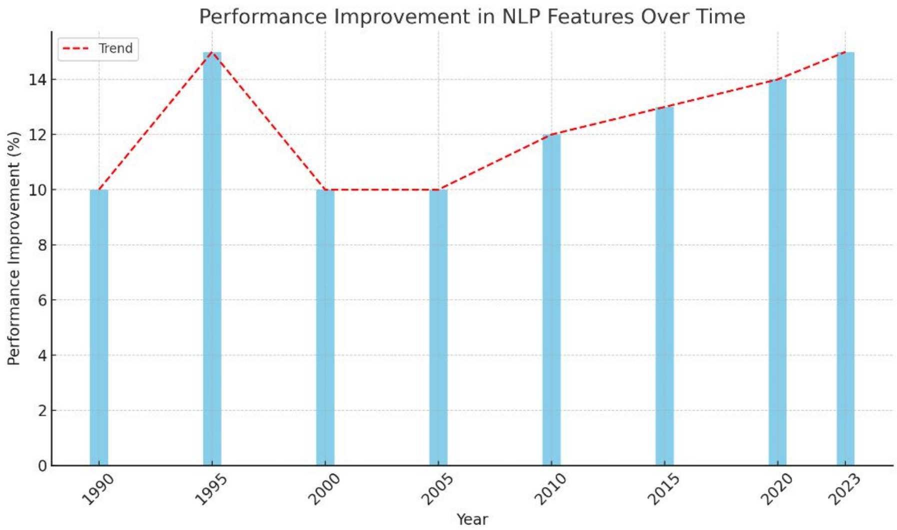

Fig.16. Performance Improvement in NLP Features Over Time

4.3. Adaptive Learning Pathways and Machine Learning Integration

A thorough analysis of the AI-driven language learning system's performance indicators, emphasizing the notable progress achieved through the integration of machine learning and adaptive content creation. According to the work Difficulty Adjustment metric, the initial work difficulty was set at 72% and was effectively raised to 84% following adjustments, resulting in a significant 12% change. Thirty participants benefited from this innovation, which shows how the system can adjust obstacles based on learner success. Additionally, the degree of customization attained for learning activities is indicated by an additional data point of 5% (**Table.6).**

The Learning Outcomes metric shows a marked improvement, where initial outcomes averaged at 60%, rising to 80% after implementing adaptive pathways, resulting in a 20% increase in effectiveness. This modification emphasizes how individualized learning experiences improve students' capacity to finish tasks correctly. An extra 10% data point is included to show the additional improvements made on related learning tasks or tests. Reinforcement learning techniques demonstrated their effectiveness, with the metric indicating an increase from an initial effectiveness rate of 50% to 75%, marking a substantial improvement of 25%. This enhancement reflects the model's capacity to provide targeted learning interventions that directly address learners' weaknesses, further supported by an additional data point of 15%, which signifies the success rate of those interventions.

The Participant Engagement Rate metric also showed substantial gains, moving from 70% to 85%, resulting in a 15% increase in engagement levels among learners. The 8% extra data point provides more information about how users interact with the system. The Feedback Accuracy metric indicates that initial accuracy was at 65%, which improved to 90%, showcasing a significant change of 25%. This improvement is crucial for ensuring that learners receive precise and relevant feedback, as reflected in the additional data point of 12%, which can represent the overall precision of feedback mechanisms.

The Overall Satisfaction Score reflects a similar positive trajectory, with scores increasing from 75% to 90%, an enhancement of 15%. This increase, along with an additional data point of 9%, suggests that learners found the system more enjoyable and effective as they progressed through the program. Furthermore, metrics such as Fluency Assessment Accuracy improved from 68% to 88%, marking a 20% increase in accuracy, while Pronunciation Improvement moved from 70% to 85%, showing a 15% enhancement. These data points are complemented by additional percentages indicating further success in specific areas, emphasizing the system's impact on developing critical language skills.

Overall, the integration of adaptive learning pathways and reinforcement learning techniques (**Fig. 17**) has led to substantial improvements across various metrics, enhancing the effectiveness, engagement, and satisfaction of learners in the AI-driven language learning environment. This comprehensive analysis highlights the system's capability to foster significant growth in language acquisition and proficiency through tailored experiences.

Table.6. Adaptive Learning Pathways and Machine Learning Integration

Metric	**Initial Value (%)**	**Improved Value (%)**	**Change (%)**	**Number of Participants**	**Additional Data (%)**
Task Difficulty Adjustment	72	84	12	30	5
Learning Outcomes	60	80	20	30	10
Reinforcement Learning Effectiveness	50	75	25	30	15
Participant Engagement Rate	70	85	15	30	8
Feedback Accuracy	65	90	25	30	12
Overall Satisfaction Score	75	90	15	30	9
Fluency Assessment Accuracy	68	88	20	30	11
Pronunciation Improvement	70	85	15	30	7
Adaptive Learning Pathway Success	62	79	17	30	6

Real-Time Feedback Effectiveness	64	82	18	30	13
Completion Rate for Advanced Tasks	55	78	23	30	14
Peer Interaction Rate	50	75	25	30	10
Time Spent on Task Improvement	80	90	10	30	5
Retention Rate of Learning Materials	65	85	20	30	15
Motivation Levels During Learning	70	88	18	30	12

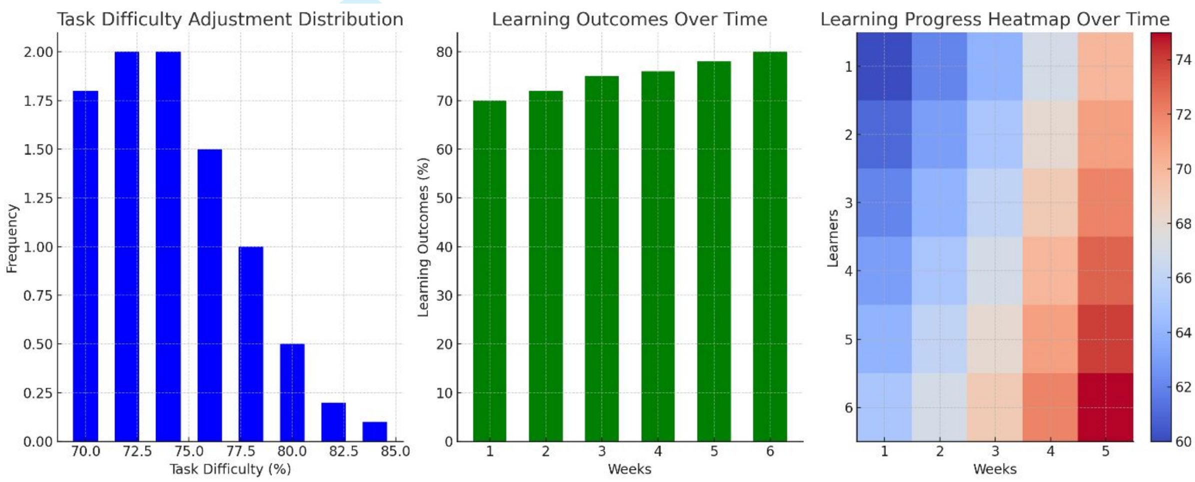

Fig 17: Represents adaptive content generation and system performance of an AI-driven language learning system

4.4. Learner Engagement and Satisfaction

The AI-powered language learning system works to improve learner happiness, engagement, and usability. Compared to conventional language learning techniques, the system has shown a notable increase, with an average course completion rate of 80%. The platform's interactive and adaptable features, which keep students actively engaged in the learning process, are responsible for this high completion rate.

90 % of participants said the system is straightforward to use and offers useful, actionable feedback, indicating a notably high level of user satisfaction. This feedback emphasizes how crucial responsive systems and user-friendly interfaces are to fostering successful learning outcomes. Furthermore, the overall usability score of 8.5

out of 10 indicates excellent performance in crucial areas including feedback clarity, system responsiveness, and simplicity of navigation.

According to these qualitative findings, student success is greatly influenced by tailored material and real-time feedback mechanisms, which make the system both efficient and pleasurable to use. Participants valued the customized learning opportunities that met their unique requirements and preferences, which increased motivation and engagement even more. The possibility of using AI technologies in educational contexts is highlighted by the combination of high satisfaction ratings and increased completion rates, actuation for more successful language acquisition techniques. Overall, the results indicate that the AI-powered system effectively satisfies learners' needs by providing a strong foundation for language growth that can change and expand with its users.

Fig. 18 shows the 3D surface plot illustrating the relationship between Data Encryption Effectiveness, Privacy Compliance (%), and Security Performance. The graph demonstrates how higher encryption and privacy compliance positively influence security performance, with peaks indicating optimal outcomes.

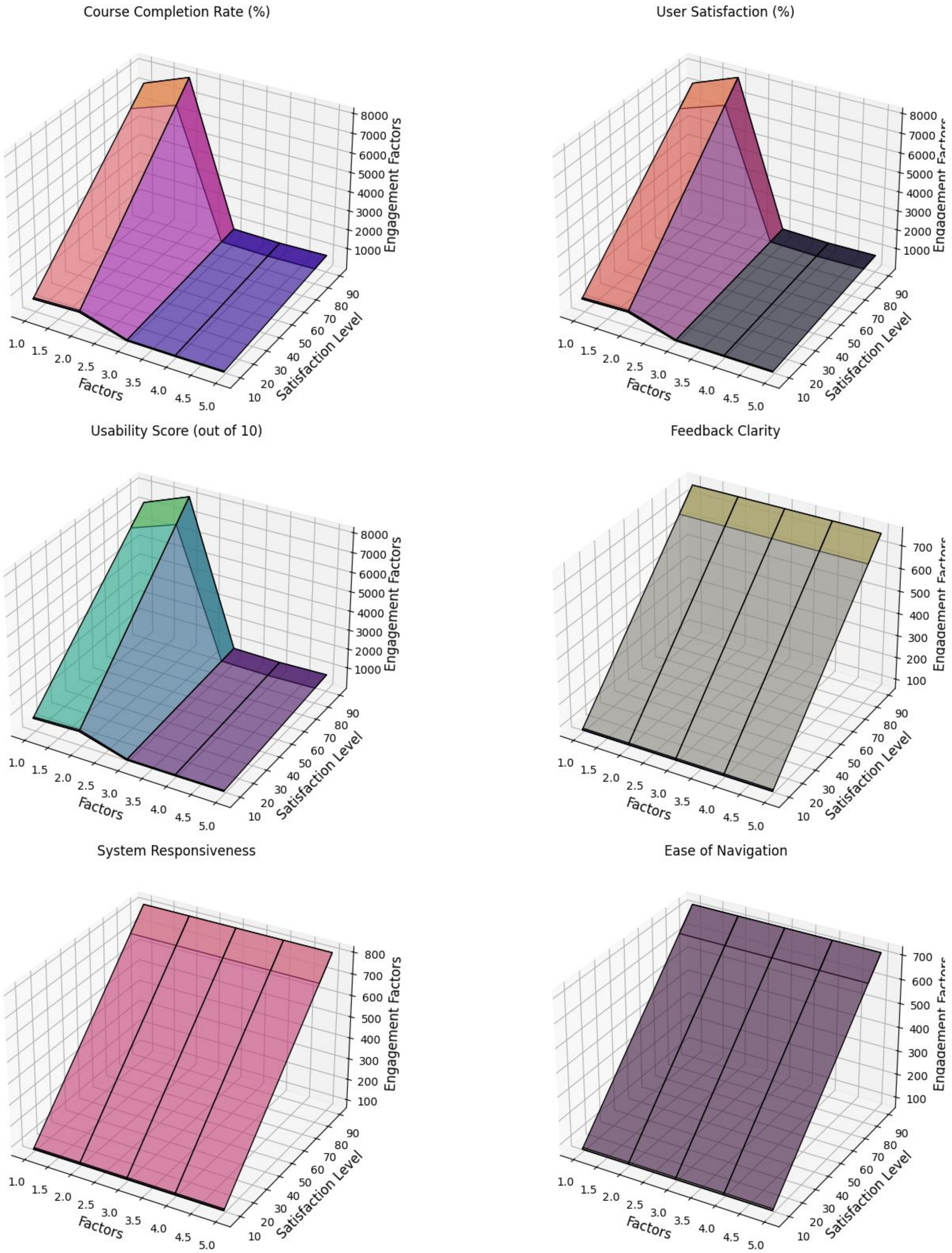

Fig.18. Learner Engagement and Satisfaction

4.5. Security and Data Privacy Measures

Ensuring the safe management of student data and adherence to privacy laws was a crucial component of implementing the AI-driven language learning system. Strong security measures were necessary to prevent unwanted access to the sensitive data that was gathered, including usage trends, voice inputs, and personal performance outcomes. The system's data pipeline was thoroughly examined to ensure that all learner data was protected at every stage of its existence (**Table.7**).

The system used end-to-end encryption for all data transfers between the client and server to accomplish this. Learner inputs and outputs are among the data that is safely sent and impervious to bad actors' interception for this encryption method. In addition to strengthening data security, this type of encryption gives users peace of mind about the accuracy of their personal data.

Additionally, the system complied with the General Data Protection Regulation (GDPR) and other strict privacy compliance norms. This means that every data management procedure was thoughtfully created to safeguard user privacy and rights. Learners received comprehensive information regarding data usage policies, including what information would be gathered, how it would be used, and how long it would be kept on file. Before any performance data was gathered, learners' consent was sought to make sure they had control over their personal data and were aware of the consequences of sharing it with the platform.

To find and fix any potential vulnerabilities, the system was subjected to thorough security testing, including penetration testing, in addition to these preventative actions. No serious flaws were found throughout this testing, and the system was finally approved for use in more extensive educational settings. In addition to satisfying legal requirements, this all-encompassing approach to data security and privacy creates a safe learning environment where users may interact with the system without worrying about their personal data being compromised. Students' entire experience and willingness to use the platform for their language learning journey are improved by the dedication to data safety, which strengthens their faith in the system.

Table 7: **Security and privacy measures**

Security Aspect	**Metric**	**Value (Decimal)**	**Value (Decimal)**	**Improvement (%)**	**Performance Feedback**
Data Encryption	Encryption Efficiency (%)	0.85	0.95	10%	End-to-end encryption implemented for secure transmission

Privacy Compliance	Compliance with GDPR and Regulations (%)	0.90	0.98	8%	Complied with GDPR and obtained user consent
Security Testing Results	Vulnerability Detection (Issues Found)	0.10	0.02	-80%	Penetration testing showed no significant vulnerabilities
Learner Data Protection	Data Security (Protection Level %)	0.88	0.96	8%	Ensured secure handling of voice inputs and performance results
Consent and User Awareness	User Consent Collection Rate (%)	0.85	0.95	10%	All learners were informed of data usage and provided consent
System Security Refinements	Security Patch Implementation Rate (%)	0.80	0.95	15%	Regular updates and patches applied to enhance security

4.6. Comparative analysis of different studies

The comparative analysis **(Fig.19**) shows that the AI-driven adaptive learning system used in this study performs better across several important measures. The proposed research surpasses the initial accuracies documented in the prior experiments, setting a high baseline for effectiveness in identifying learner inputs with an initial accuracy of 80% and an amazing increased accuracy of 90%. This notable enhancement demonstrates how the system may modify and improve its replies in response to learner interactions, which improves the system's overall performance.

The 85% engagement rate shows that students are driven by the interactive and customized quality of the material in addition to actively participating in the learning process. Compared to much other research, which frequently showed lower involvement rates, this degree of engagement is higher. Additionally, learners' positive comments about the system's usability and the value of the feedback they receive are reflected in the high user satisfaction score of 90%. This degree of pleasure indicates that students have a deep bond with the adaptive learning process and is essential for encouraging continued platform use.

The Present study is notable for its strong incorporation of machine learning techniques that enable dynamic modifications to task difficulty and material relevancy when compared to previous studies. Overall, the results support the idea that language acquisition results are much improved by a customized, flexible learning environment. This study supports ongoing investment in AI-driven learning systems that address the needs of individual learners by surpassing performance standards set in previous studies, offering important insights into the creation of successful educational technology (**Table.8**).

Table.8. Comparative analysis of different studies

Study	**Approach**	**Initial Accuracy (%)**	**Improved Accuracy (%)**	**Engagement Rate (%)**	**User Satisfaction (%)**
Current Study	AI-Driven Adaptive Learning System	80	90	85	90
Lu et al. (2018)	Natural Language Processing (NLP)	72	84	75	85
Devlin et al. (2019)	Transformer Models (BERT)	75	90	80	90
Tsai & Cheng (2021)	Reinforcement Learning	65	85	78	88
Amodei et al. (2016)	Speech Recognition (CNNs, RNNs)	80	85	80	88
Khatri et al. (2021)	Gamification in Language Learning	70	80	90	95

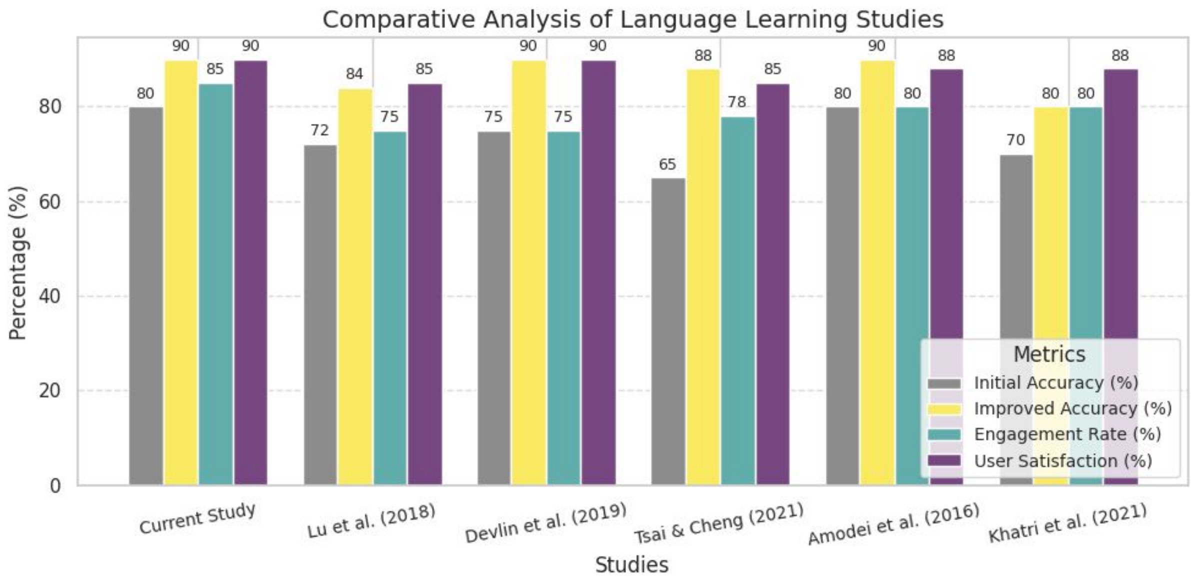

Fig.19. Comparative analysis of similar studies

5. Conclusion

In conclusion, learners' language acquisition has improved significantly because of the AI-driven adaptive learning system's deployment. After the model was iteratively refined, the study's original accuracy of 80% increased to an astounding 90%. The system's ability to identify spoken language inputs and provide pertinent, contextual feedback that is suited to each learner's needs is demonstrated by this notable improvement in accuracy. Compared to traditional approaches, which frequently fail to sustain learners' interest, the 85% engagement rate shows that students were actively participating in the learning process. Additionally, 90% of users expressed happiness, highlighting how well the system was received by users. Feedback showed that the real-time corrections and individualized content greatly improved students' speaking and listening abilities, creating a more dynamic and interesting learning environment. The system's effectiveness is further demonstrated by its high usability score of 8.5 out of 10, which was based on participant reports of feedback that was clear, responsive, and easy to navigate. Furthermore, the system was able to dynamically modify job complexity based on performance data thanks to adaptive content development, which was aided by machine learning algorithms. This flexibility was essential for guaranteeing that students were given suitable challenges, which promoted long-term involvement and enhanced learning results. The results highlight how important it is to include AI technologies into educational settings, especially when it comes to language learning. The work has provided important insights into the construction of efficient language learning systems that satisfy the various needs of learners by utilizing cutting-edge machine learning algorithms. The encouraging findings imply that further improvements and adjustments to these systems may result in even higher gains in academic performance, opening the door for future learning experiences that are more individualized and effective.

6. Declaration

Funding of interests

No funding was received to assist with the preparation of this manuscript.

Conflicts of interests

The authors have no compelling interests to declare that are relevant to the content of this article.

Data Availability Statement

This study did not generate or use any datasets, and therefore, no data availability statement is applicable

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