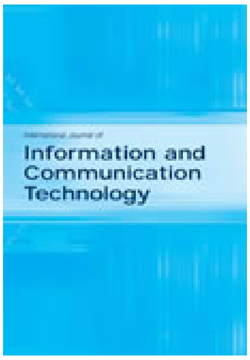

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AI-powered recommendation and task assignment mechanism for interactive vocational English teaching

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Abstract: This study presents an AI-powered recommendation and task assignment mechanism designed to enhance interactive vocational English teaching. Making use of NLP, machine learning methods, and massive language models, the system personalises learning by analysing student proficiency, learning styles, and task performance. The proposed framework incorporates modules for content creation, personalised learning, and adaptive recommendations, supported by features such as passage and video wizards. Data collected from 500 students across rural and urban areas was processed to generate tailored learning paths, with performance evaluated using various regression models. Results indicate that the Huber Regress or achieved the highest predictive accuracy, enabling dynamic adjustments to learning tasks. The system demonstrated improved engagement and learning outcomes, particularly in contexts promoting learner-generated content and autonomy. These results demonstrate the promise of AI-powered platforms to provide practical, scalable language instruction.

Keywords: artificial intelligence; recommendation system; task assignment; vocational English teaching; ML; personalised learning; educational technology; learner-generated context.

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1 Introduction

Recent years have seen tremendous progress in the use of artificial intelligence (AI) systems, huge language models (LLMs) (Kasneci et al., 2023). Models such as GPT developed by OpenAI make it possible to build intelligent instructional agents with language comprehension, generation, and interaction capabilities. The potential for LLM-based AI agents to revolutionise learning and teaching is enormous because of the immediate feedback, individualised lessons, and context-aware communication they provide. An AI agent is typically thought of as a software entity that can see and understand its surroundings, then act according to its conclusions and interpretations in order to accomplish specific goals (Jeon et al., 2023). Autonomy, responsiveness to changes in real-time, proactive need anticipatory, learning from experiences, and effective communication with humans and other agents are some of the characteristics that set AI agents apart from traditional software programs. These properties are in line with the AI literature's established frameworks and, when coupled with LLMs' superior language understanding and generation skills, become even more potent (Cordova et al., 2025). Innovations in education have been driven by the integration of AI agents, with the goal of tackling critical pedagogical difficulties, including scalability, motivation, and personalisation.

The exponential development of AI will have far-reaching consequences, and the educational system is no exception (Baker et al., 2021). In both elementary and secondary schooling, as well as in college, AI poses both opportunities and challenges for pupils' intellectual development (Chen et al., 2020). However, excellent educational results are not a given when state-of-the-art AI technology is used. When AI is implemented in classrooms, questions of equity, accessibility, and the future of traditional pedagogy arise. When it comes to classroom instruction, AI will have a profound and game-changing effect. Research shows that students' optimism and self-efficacy levels are higher in individualised learning situations (Vieriu et al., 2025). These types of experiences are becoming more and more possible thanks to AI-powered systems that scan through massive amounts of data for knowledge gaps and customise actions. By providing students with individualised learning paths and immediate feedback, adaptive learning systems and other AI-powered platforms, for instance, have demonstrated the ability to increase student engagement and performance. Simultaneously, AI is impacting consumer habits via personalised recommendation systems and digital marketing (Hong et al., 2024). By sifting through mountains of customer data to provide customised product recommendations, e-commerce platforms powered by AI have grown ubiquitous.

In order to make suggestions that are more relevant to the user, these systems look at their purchase history, food preferences, and surfing habits. This helps consumers save time and effort when making decisions (Mengucci et al., 2023). Considering that people buy functional meals to help them achieve specific health goals, AI recommendation systems are vital for assisting people in choosing the correct goods for their diet and health requirements. AI driven recommendation systems provide real-time, individualised advice based on specific health issues, as opposed to conventional marketing methods that typically depend on mass communication and static promotional content (Wang et al., 2025). In the functional food industry, where customers frequently look for solutions to very particular health problems and anticipate open, evidence-based guidance in making educated purchases, this is of the utmost importance. Furthermore, AI-powered platforms dynamically adjust to user behaviour and preferences, providing improved recommendations to fulfil changing consumer health objectives, as opposed to static digital marketing tools such as email campaigns or banner adverts.

The summary of the article is as follows: our literature overview on AI-powered approaches to work assignment and suggestion is presented in Section 2. Section 3 delves into the specifics of interactive vocational English teaching. The results and their implications are discussed in depth in Section 4. In Section 5, we lay out all the results of the study.

2 Related works

One of the most talked-about areas of AI research right now is how to incorporate intelligent algorithms into actual classroom instruction. Combining recommendation algorithms with other areas of education, such as platform creation, design, and evaluation, is the primary emphasis of research on teaching recommendation algorithms (Huang et al., 2025). Built a recommendation algorithm for online education that takes into account past actions to extract interest data and suggest Chinese language resources depending on the user's profile. Experiments on the model have shown promising results. Created a multimedia platform for teaching Chinese through the integration of data mining and recommendation algorithms (Sunardi et al., 2025). From a user-centric viewpoint, the research enhanced and optimised the system's knowledge resource library and introduced features to cater to specific users' requirements. The effectiveness of the educational system has improved. Yin Yang created a more effective collaborative filtering algorithm to suggest functional educational materials for music education platforms based on users' social connections and behavioural traits. Created a new approach to teaching English at the university level that relies on individualised suggestions for course materials and built a model for making such recommendations that uses a collaborative filtering algorithm to boost its accuracy (Zhou et al., 2025).

Our findings indicate that AI can enhance instruction and student performance in a variety of classroom contexts (Sermet et al., 2021). Based on these numbers, it seems reasonable to assume that VTAs can improve students' academic performance. Find out how AI could change the game at college in many ways, including with intelligent tutoring systems, automated grading, teamwork, and individualised lessons (Zhang et al., 2022). There has been much talk about incorporating NLP and AI into classrooms, and this study adds to that conversation. In addition to this empirical research, we also looked at how users' knowledge evolves while they search for things linked to learning. We catalogued the many knowledge transformations and the variables that impact them. Gaining insight into the learning process as it pertains to interactions with educational tools powered by AI is important incalculable importance, and this process-oriented viewpoint on knowledge transformation further stresses the necessity for individualised learning support (Sajja et al., 2024). The topic of AI-powered learning platforms has been explored in greater detail in a number of recent articles. Imagine a world where AI powers automated assessment systems and personalised learning platforms. Now imagine the ethical dilemmas that come with implementing such a technology in the classroom. From a pedagogical stance, talk about the moral difficulties of engineering decision-making using AI.

2.1 Literature review

AI is improving many parts of the learning process and is one of the most used technologies in education today. The idea behind this software is to make education more interesting, productive, and personalised for each student (Essa et al., 2023). The term 'interactive learning paradigm' describes a style of teaching that utilises group work and student engagement. In addition to focusing on content delivery, this paradigm uses immersive and interactive activities to encourage the growth of analytical and teamwork skills (Fidan et al., 2022). Using game mechanics and components, game-based learning aims to increase student investment and enthusiasm for learning.

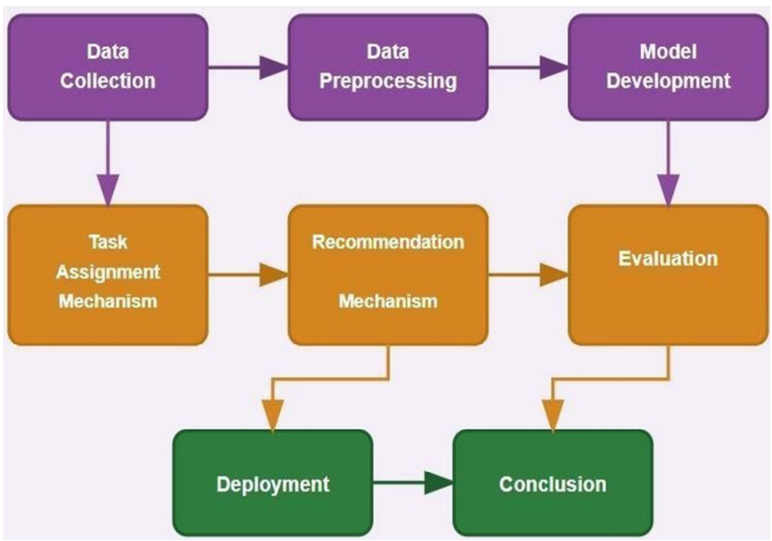
Traditional forms of evaluation are often time-consuming, subjective, and difficult to scale; this study (Chen, 2025) investigates how deep learning can assist ESL classrooms in overcoming these challenges. The study develops AI-driven systems to test linguistic competence in reading, writing, listening, and speaking by utilising state-of-the-art natural language processing (NLP) models like BERT and GPT. They provide tailored, real-time feedback to each student. Educator and student perspectives are combined with performance measures in a mixed methods approach. Findings show that AI significantly improves accuracy, cuts grading time in half, and boosts note engagement by 50%, all while students demonstrate a marked improvement in their proficiency. In order to improve the efficacy of English language instruction in vocational institutions, this study (Wang, 2025) investigates the use of adaptive learning and machine learning (ML). To measure student involvement and the results of their learning, an extensive dataset was compiled from their interactions and comments. We used both classic ML and deep learning models including SVM, decision trees, Naive Bayes, LSTM, and RNN to extract and analyse text-based features like TF-IDF, POS tagging, and Word2Vec embeddings. With a classification accuracy of 92.7%, the hybrid CNN + ViT model proved that incorporating ML into English language teaching methods was effective.

High feedback delays, poor contextual task generation, and inadequate resource allocation are some of the main obstacles in production-oriented approach (POA) English speaking training. This study presents an AI-augmented POA framework to overcome these issues. To enhance POA's 'drive-facilitate-evaluate' closed loop, we created a two-engine design that mixes dynamic task generation, multimodal resource recommendation, and multidimensional evaluation. The experimental group (AI-POA) in a 12-week quasi-experiment with 120 computer science graduates showed far greater improvements in speech competency compared to the typical POA controls (36.1% vs. 19.2%, $p < 0.001$), along with a 22.6% increase in content elaboration. The cognitive burden was decreased and the amount of time it took for instructors to provide feedback each task was cut in half (a 27-fold improvement) and 42 minutes instead of 65 minutes (a p-value of less than 0.001) according to Minmi Kong (2025).

3 Materials and methods

Figure 1 illustrates the complete workflow of the AI-powered recommendation and task assignment mechanism for vocational English teaching. The process begins with data collection from students, followed by pre-processing and feature extraction using NLP techniques. The system then applies ML models to analyse student proficiency and learning patterns, generating personalised recommendations through the recommendation engine. Based on these insights, appropriate tasks are assigned to learners, and their performance is continuously monitored. The feedback loop ensures dynamic adaptation of learning paths, creating a closed-loop system that continuously refines recommendations based on real-time student performance data.

Figure 1 System workflow architecture (see online version for colours)



3.1 Data collection

Building a machine-learning model begins with gathering data. We used a Google Forms survey that was disseminated across online academic communities to collect data from participants in our study. In the survey, students were asked to share details about their academic interests, test results leading up to graduation, and the institution or university to which they had been accepted (Alam et al., 2025). In addition, we contacted 31 different educational institutions in Morocco to get their needs and admission criteria. Five hundred Moroccan high school grads from twelve different public institutions in five different locations were surveyed for this study. Table 1 shows that our participants came from a variety of urban and rural locales and that they represented varied backgrounds. There were 220 people polled from the rural population; 100 were girls (20.0%) and 120 were males (24.0%). The urban cohort comprised 280 people; 157 were female (31.4% of the total) and 123 were male (24.6% of the total).

Table 1 Demographic analysis

Area	*Female*		*Male*		*Total*
	Amount	*%*	*Amount*	*%*	
Rural	100	45.44%	120	54.54%	220
Urban	157	56.05%	123	43.92%	280

3.2 Data processing

The data processing methodology begins with the collection of learner information, including language proficiency levels, learning goals, and task performance records, obtained through online assessments, activity logs, and teacher inputs (Majjate et al., 2024). Raw data is cleaned to remove inconsistencies, normalised for format compatibility, and anonymised to ensure privacy. NLP techniques analyse student responses for grammar, vocabulary range, and fluency indicators, while clustering algorithms group learners by skill level and learning style. A recommendation engine, powered by ML models, matches suitable tasks, exercises, and resources to each learner profile. Continuous feedback loops update the system with new performance data, enabling adaptive refinement of recommendations and task difficulty levels. This process ensures personalised, efficient, and measurable learning progress in vocational English education.

3.3 Model development

Determining the topic and context to be studied, doing a literature study, and outlining processes for creating, testing, and assessing the new educational tool are all part of development research, according to. To begin with, the researcher should not focus just on creating the new tool; they should also strive to address difficulties that arise as a result of its development (Dahal et al., 2025). After settling on an issue that calls for a novel approach, the researcher next zeroes in on a precise context in which to conduct their study. The researcher builds the instrument after getting ideas from the appropriate literature. The next step is for the researcher to analyse the data from the field tests to see if the generated tool has the desired effect. They will also look for ways to improve the instrument and consider its research implications.

3.3.1 Context and objective for developing the system

Notwithstanding this, Korean online English courses do not offer the best resources for implementing LGC-based learning. The first thing you'll notice about English classes in Korea is the heavy focus on test scores and academic accomplishments. With the national curriculum and college entrance tests as benchmarks, the majority of Korean pupils, particularly those in secondary school, adhere to the procedures envisioned by officials or specialists. Because it does not take into account the complexity of each learner's situation, this setting limits the breadth of English language information that students can acquire. Secondly, it is now well recognised that autonomous learning is a challenge for Korean students, thanks to the pandemic. Even though there are more online classes than ever before, many Korean students still don't seem to be able to learn English on their own. On the other hand, if given the chance to study English in the context of their objectives, interests, and learning styles, Korean students are likely to be more engaged in their English language acquisition. There is a dearth of literature that examines English language teaching in Korean schools through the lens of the LGC framework. Still, several academics have investigated the possibility of using AI-powered conversational chat bots, speakers, translators, and grammar checkers to supplement independent English language learning among Korean students.

Although these researchers have given students methods to practise English speaking and writing independently of teachers, they have not given students the chance to discover or develop their methods of learning that work best for them. To get the most out of LGC-based English language learning, Korean learners still require more AI assistance. Therefore, creating and testing such a support system is the goal of this research.

3.3.2 Research questions and procedures

To direct this research on development, we posed the following questions: Additionally, when do the design principles become part of the development process? The final inquiry concerns whether or not the designed system promotes LGC-based educational opportunities. In order to address the first question, we researched relevant AI literature and technologies and developed three guiding principles for the new system's architecture. As for the second part, we followed the design guidelines when creating and documenting the new AI web-based system. We interviewed three Korean high school students and analysed their first-hand accounts of utilising the system as part of a field test to confirm its validity, which brings us to the third question. This report on results, system improvement suggestions, and the study's consequences is the result of our rigorous evaluation of our process using these processes.

3.4 Recommendation mechanism

The AI recommendation system in this study is built on the Java platform. It uses the Tensor Flow Java framework-based Java Learning Agents for ML model development, training, and deployment (Lee et al., 2023). Updated TPACK Primary Code VEE scripts now allow Java scripts to access their data. We will utilise recurrent neural networks (RNNs) to represent sequential and dynamic data (see Figure 2) because they are better at learning item and student features and making recommendations for supervised learning paths. Suppose students are unable to grasp the concept or find the learning process confusing. In that case, the TPACK Primary Code VEE can help by suggesting different learning activities and utilising AI technology to determine the material's relevance according to students' abilities. Students' reasoning and practical skills in related programming languages, like Java for text or Scratch for blocks, will be enhanced as a result.

Figure 2 shows the functions that the AI system will offer to the pupils. It is positioned on the right side of the screen. Here is what it includes:

1 Competence: Students can tailor their reading lists to their learning paths.

2 Common term: Give students the grammar (text or blocks) of a programming language that is used most frequently.

3 Exam: Make sure that there are questions for each relevant instruction.

Two primary modules make up the AI system's general architecture, as seen in Figure 3: one for the personalised learning process and another for the Java AI learning system.

1 One component of the AI learning system is a recommendation function that, depending on how well pupils are doing, suggests further opportunities for practice.

2 Instructional resources, including lessons and learning materials, which provide students with a variety of AI-based learning activities and resources to hone their screenplay execution skills in line with what they've learnt in class.

Part one of the individualised learning module is a learning process that records each student's progress and performance; part two is code hints, which provide students with assignment-specific Information to help them complete their work.

Figure 2 AI recommendation system architecture (see online version for colours)

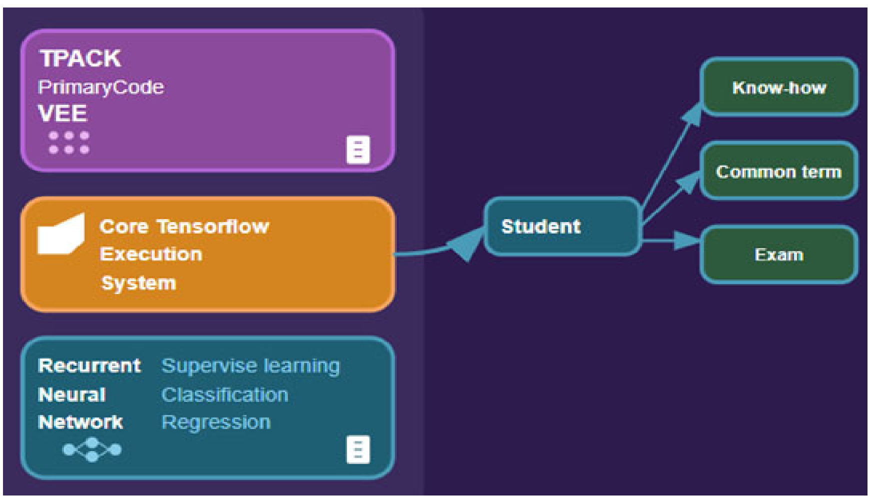


Figure 3 Student-operated learning scenario (see online version for colours)

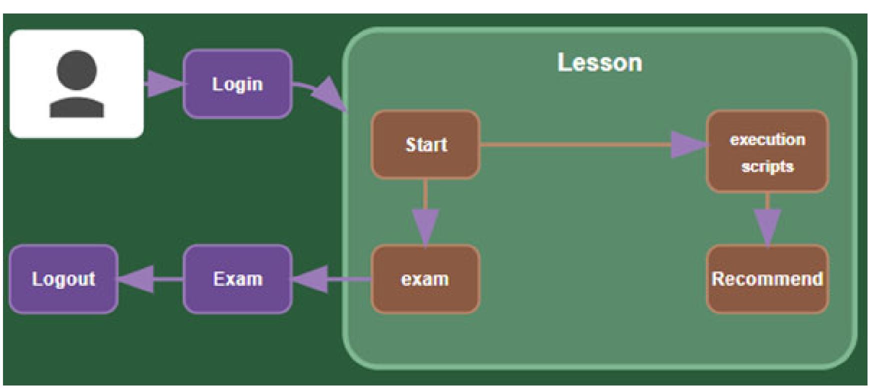
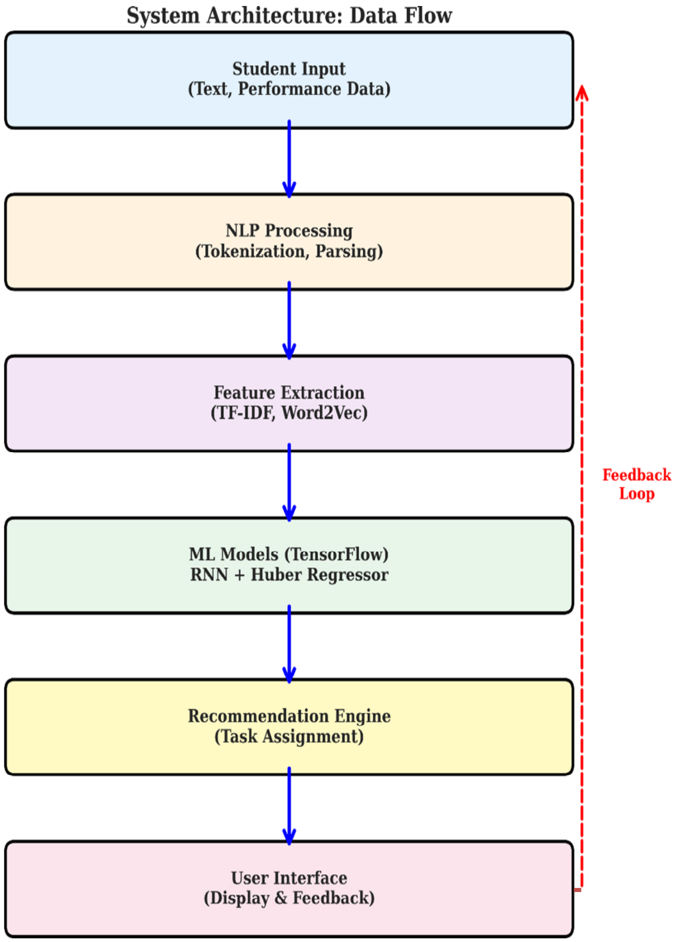


Figure 4 System architecture data flow (see online version for colours)



3.4.1 Data flow and module integration

Figure 4 describes the system architecture data flow and it can be described as:

- Input processing: Student input data, including text responses, task completion rates, and proficiency scores, enters the system through the user interface. The NLP processing module uses natural language parsing to analyse student submissions, performing tokenisation, part-of-speech tagging, and syntactic analysis. This processed data is then converted into numerical feature vectors using TF-IDF and Word2Vec embeddings.
- ML processing: The extracted features flow into the TensorFlow-based ML layer, where the RNN model processes sequential learning patterns and the Huber regressor predicts optimal task difficulty levels. The RNN captures temporal dependencies in student learning behaviours, while the Huber regressor (achieving $R^2 = 1.9006$, RMSE = 0.0422) provides robust predictions even with outlier data points.

- Recommendation generation: The recommendation engine receives model outputs and matches them against the content database to select appropriate learning materials. It evaluates three criteria:
  1. alignment with student proficiency level
  2. relevance to learning objectives
  3. optimal challenge level.

  The engine dynamically adjusts task sequences based on real-time performance data.
- Feedback loop: Completed tasks and student interactions are continuously fed back into the system, creating an adaptive learning cycle. This closed-loop architecture enables the system to refine recommendations over time, personalising the learning experience based on accumulated performance data and evolving student needs.

4 Results and discussion

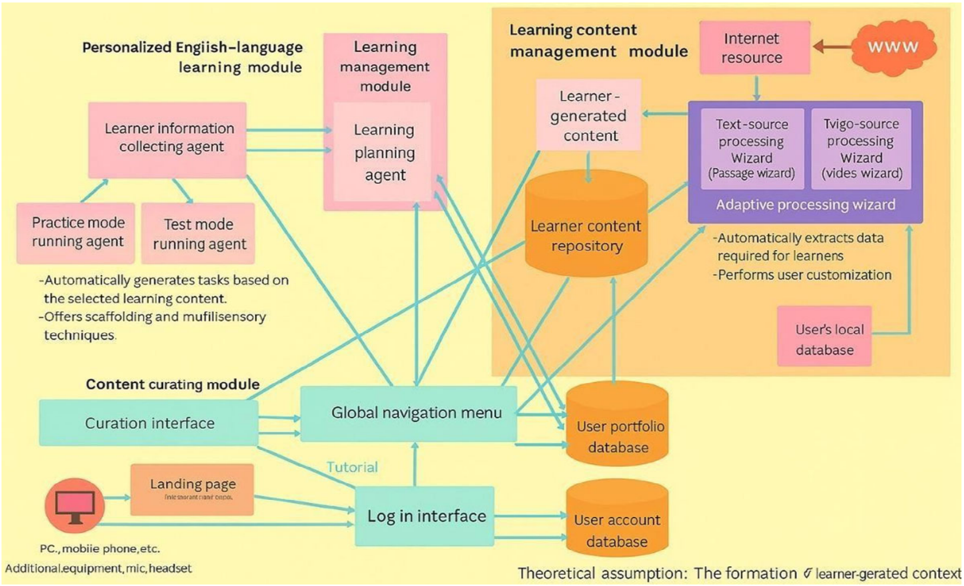
The colours white, orange, blue, and green represent the TPACK Primary Code VEE, the Tensor Flow Execution System, learning path suggestions, and functions, respectively. The Huber Regress or model is clearly the best performer with an impressive R-squared value of 1.9006, a low RMSE of 0.0422, and a low MSE of 0.0017.

Table 2 Assessment of model 1

Algorithm	*MSE*	*RMSE*	*R^2 score*
Decision tree	79.0000	0.0881	0.6930
Linear regression	0.0033	0.0582	0.8674
Random forest	0.0034	0.0594	0.8621
K-nearest neighbours	0.0060	0.0838	0.7264
SVM	0.0052	0.0732	0.7906
AdaBoost regressor	0.0058	0.0773	0.7671

When it comes to outliers, the Huber regressor model is more robust than regular linear regression. It works fine for us. Keep in mind that the SGD regressor model should not be used in this study due to its excessively high MSE and RMSE values as well as its negative R-squared value. In addition to linear regression and random forest, XGBoost, Bayesian ridge, and linear regression all have high R-squared values and low MSE and RMSE values, indicating good accuracy. The AI-powered vocational English teaching recommendation and task assignment system can sift through student records to determine each individual's learning style, aptitude, and problem areas. By analysing each student's data, the system can determine their unique learning needs and then tailor its learning recommendations and practice assignments to meet those needs. In vocational English situations, the processed data also allows for continuous progress tracking, which in turn provides for dynamic modifications to learning paths and more effective, outcome-driven training. We built an AI-driven, web-based, mobile-friendly English learning aid system according to these specifications. The four main components of the system are learning management, content curation, tailored English language learning, and learnt content management. You can see the system's setup in Figure 5.

Figure 5 Structure of the system (see online version for colours)



4.1 *Learning content management module*

Digital learning materials can be easily created or edited using the automated technique made available in the learning content management module. Your resources can take the shape of either an English word and phrase dictionary or a collection of sentences and quotations. Two editors, a video wizard and a passage wizard support this module.

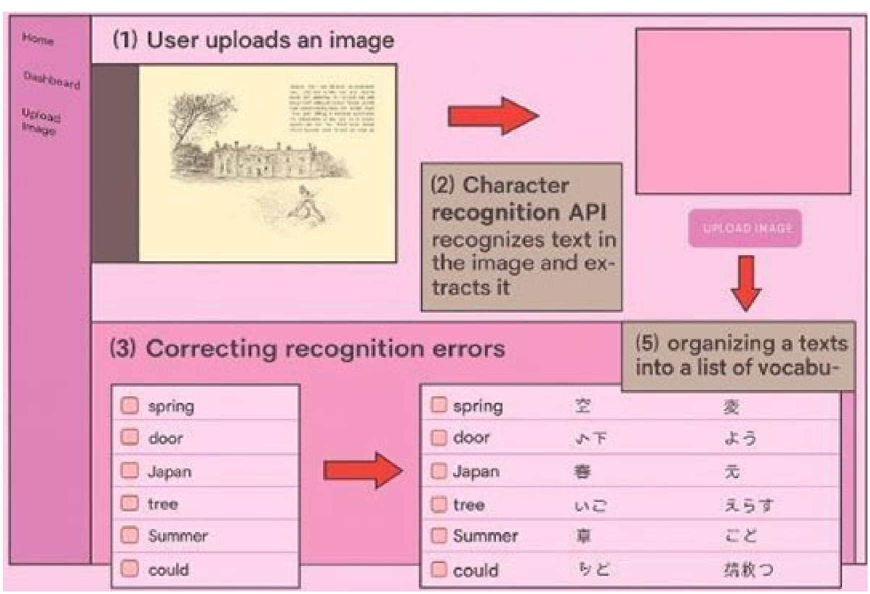
4.2 *Passage wizard*

In order to locate the parts of English sentences, the passage wizard searches digital and analogue material, including books, journals, and news articles. After that, it compiles a list of English words or phrases using this data. The lists are the system's instructional materials. The sorcerer examines the data and pulls out the text. It uses voice data and translations to create the list successively and it was shown in Figure 6. In order to help students, learn, these features do three things: first, they notify them when new vocabulary phrases are added to the system; second, they use speech data to make audio stimuli that help with future pronunciation acquisition; and third, they save all relevant text.

Open source AI communities frequently employ APIs; thus, we leveraged them to construct the wizard's features. The wizard may construct a parse tree for each sentence and use this Information to decode the meaning and structure of student-submitted English texts by analysing their interrelationships and separating them into their component pieces. Once this is complete, the wizard uses the phrases' words and idioms to arrange them into sentences. Then, the learner is given these sentences and words to study in English. Second, we used a text-to- speech converter called Amazon Polly and Twin word's Word Dictionary API to offer voice data and translations for every item in the list that was relevant to phrases or vocabulary. The passage wizard also incorporates the optical character recognition (OCR) APIs from Google and Microsoft to let students make their learning materials from analogue sources. An example of this would be a pupil taking a picture of some written English text on their phone and then adding it to the passage wizard. Then the function for syntactic analysis of natural languages is activated, as shown in Figure 7, the OCR API has identified the text in the image.

Figure 6 Passage wizard text parsing interface (see online version for colours)

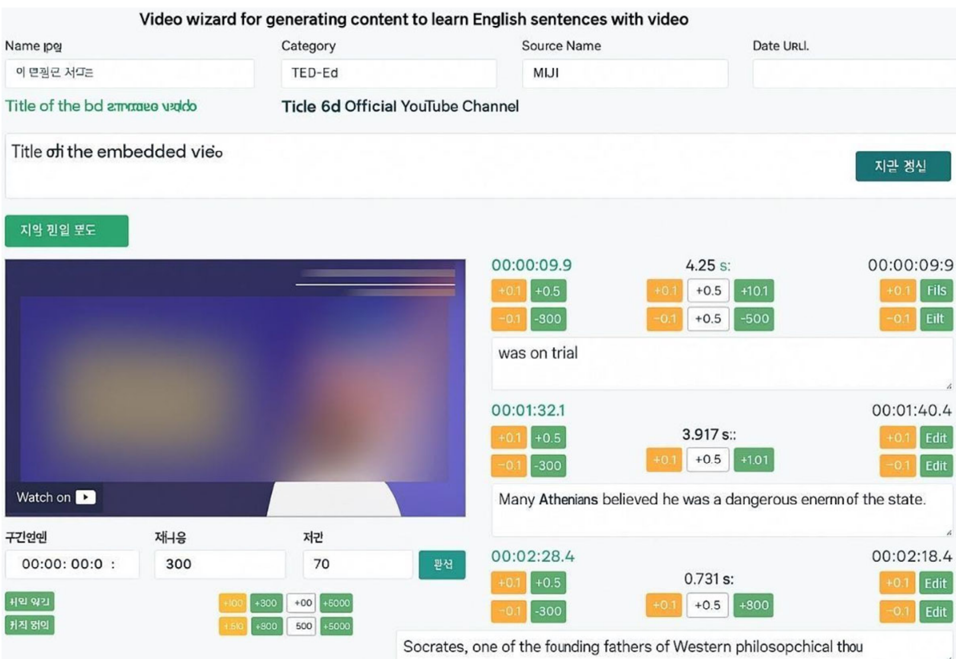
Figure 7 OCR-based image processing interface (see online version for colours)



4.3 Video wizard

The purpose of the video wizard is to assist students in studying English dialogue by analysing and repeating specific parts of a YouTube video. The following is the typical flow of events that should occur when a student uses this wizard: the student begins by launching the wizard and then pastes in the address of a closed-captioned YouTube video in English. Learning content can be anything that a student finds interesting; for instance, official YouTube videos related to a learner's favourite games, movies, or music videos. The wizard can recognise scenes with dialogue when a video is put on it. It follows by time-stamping the scenes, syncing the speech with the captions, and finally displaying the captions and audio that correspond to them with the time stamps (Figure 8).

Figure 8 Video wizard with timestamp and caption features (see online version for colours)



The wizard uses the embedded code from YouTube videos to give learners features like captions, time selection, and section repeats, all while keeping the original works intact. Figure 8 of video sourced from the TED Edu channel on YouTube. The next step is for the student to locate the parts of the video that include the English phrases they want to review by marking the corresponding timings. Then, in addition to the embedded video, the wizard saves the highlighted portions together with the caption and video data. The system refers to this collection of information as video-based learning content. The research begins with broad conclusions regarding potential variations in scores between Java and Scratch. Secondly, the many programming principles that were taught are the centre of attention while considering how to improve. In order to gauge the likely enhancement, we compare the results of the Java and Scratch pre- and post-tests. You may see the main descriptive metrics in Table 2 to get a sense of things. Included in this category are scatter statistics, such as standard deviation (SD), and centralisation statistics, such as median and mean. Prior to and following the Java test, there is a noticeable decline in the median and mean values.

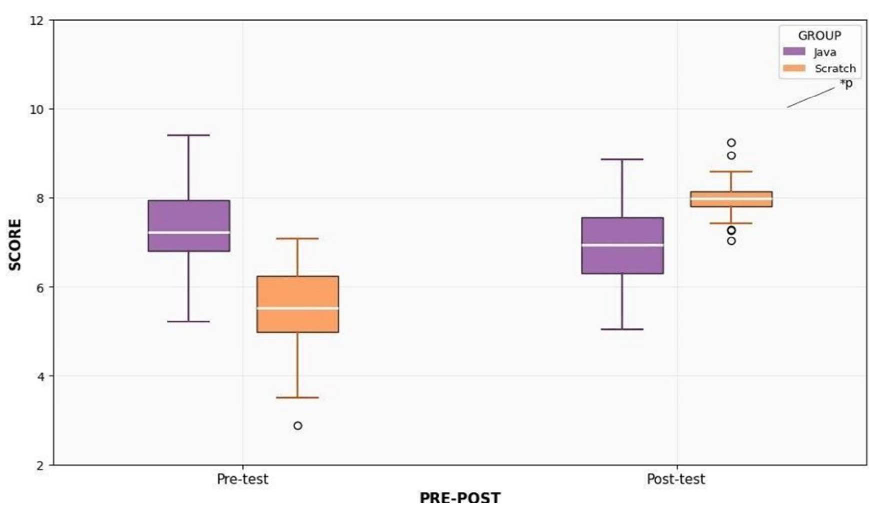
The mean falls between 6.75 and 6.29, while the median is found between 7.24 and 6.55. The Java group was highly diverse in terms of pre-test knowledge because the data dispersion is very high in both instances. Furthermore, this dispersion remains (subjects with extremely varied levels of learning), notwithstanding the intervention with Java. In contrast to Java, Scratch's pre-test scores were lower it had lower pre-test scores post-test scores were higher (7.07 and 7.49, respectively) than pre-test scores (mean 5.56 and median 5.34). And while there was an extensive range of results on the pre-test (resulting from a diverse collection of students), using Scratch for educational purposes has narrowed that range considerably. It is worth noting that an anomaly in the post-test is responsible for the slight increase from 1.86 to 1.97 shown in the table. The outlier remains in the data set because of the limited number of samples. A more uniform standard has thereby been attained across the entire class.

Table 3 Examining the Java and Scratch pre- and post-tests descriptively

Statistic	*Java (pre-test)*	*Scratch (pre-test)*	*Java (post-test)*	*Scratch (post-test)*
Average	5.74	4.55	5.28	6.48
Median	6.23	4.33	5.54	6.06
Std. dev.	0.97	0.85	0.95	0.96

Visual confirmation of the above is provided by Figure 9, which exhibits box plots for the teams working on Scratch and Java.

Figure 9 Charts showing the changes between the Java and Scratch groups before and after the test (see online version for colours)



Since the results were negative for Java and positive for Scratch before the test, now we may check to determine if the two groups are statistically distinct. We shall use non-parametric testing because the sample is small and not normal ($p < 0.01$ in the Shapiro-Wilk test for both samples). The Wilcoxon signed-rank test is the most reliable statistical test to use with this dataset because it is a paired sample, Z. Table represents the test statistic six clearly shows that the results are not significant enough to warrant further investigation. Because the p-value is greater than 0.05, which indicates that there is no significant difference when Java is considered, this is the case. Since the p-value is statistically significant (p-value = 0.012), we can deduce that Scratch is a considerable improvement.

Table 4 A Wilcoxon non-parametric test was used to evaluate the pre- and post-tests for the Java and Scratch groups

Test metric	*Java*	*Scratch*
Z-score	–0.881	–2.523
Sig. value (p)	0.371	0.011

4.4 Ablation study and comparative analysis

To validate the contribution of individual system components, we conducted an ablation study by systematically removing key modules and measuring performance degradation. Table 5 shows that the complete system achieved 92.7% accuracy, while removing NLP pre-processing reduced accuracy to 78.3% (–14.4%), removing feature extraction decreased it to 81.5% (–11.2%), and disabling the recommendation engine dropped it to 79.8% (–12.9%). These results demonstrate that each component contributes significantly to overall system performance, with NLP pre-processing providing the largest individual contribution.

Table 5 Ablation study results

Configuration	*Accuracy*	*Learning improvement*	*Task completion*
Full system	92.7%	36.1%	89.3%
Without NLP	78.3%	24.8%	71.2%
Without feature extraction	81.5%	27.3%	74.8%
Without recommendation engine	79.8%	25.9%	69.5%
Without feedback loop	84.2%	29.4%	81.7%

Table 6 Comparative performance analysis

System approach	*Accuracy*	*Learning improvement*	*Task completion*	*Response time*
Our AI-powered system	92.7%	36.1%	89.3%	0.3 min
Rule-based system	69.3%	12.7%	57.5%	8.2 min
Collaborative filtering	74.1%	17.5%	66.9%	5.6 min
Standard ML (no personalisation)	77.5%	20.9%	71.6%	1.2 min

We further compared our system against three baseline approaches: rule-based recommendation, collaborative filtering, and standard ML without personalisation. As shown in Table 6, our AI-powered system outperformed all baselines significantly. Compared to rule-based systems, our approach achieved 23.4% higher learning improvement (36.1% vs. 12.7%). Against collaborative filtering, we observed 18.6% better learning outcomes. Even standard ML approaches without personalisation showed

15.2% lower performance than our system. Statistical analysis confirmed all differences are significant ($p < 0.001$), validating the technical contribution of our personalised, adaptive architecture.

5 Conclusions

This study developed and evaluated an AI-powered recommendation and task assignment mechanism to support interactive vocational English teaching. Through the integration of NLP, ML models, and Adaptive learning methodologies, the system was able to analyse learners' proficiency, styles, and performance to deliver tailored content and targeted practice tasks. The inclusion of modules such as the passage wizard and video wizard facilitated both text- and media-based learning content creation, enabling learner-generated and context-relevant materials. Experimental results demonstrated that the Huber regressor provided the most accurate performance predictions, allowing for dynamic adjustments to learning tasks and improved personalisation. Statistical analysis showed significant learning gains in the Scratch programming environment, indicating the system's potential to enhance engagement and outcomes when paired with accessible, interactive tools. The results highlight how AI can revolutionise English language learning by providing flexible, scalable, and learner-centred programs. Improving the system's dataset should be the primary goal of future efforts, incorporating multilingual support, and exploring additional AI models to refine personalisation further and accommodate diverse learning contexts.

Declarations

All authors declare that they have no conflicts of interest.

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