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# Reinforcement Learning–Based Adaptive AI for Progressive Language Development in Immersive Virtual Reality

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*Abstract*—**The development of adaptive English skills in virtual reality (VR) is within the scope of effective personalization of learning paths. Current approaches tend to have limited real-time flexibility and fail to combine semantic comprehension and information about learner engagement, therefore being rather inefficient. The proposed solution is to use Deep Q-Network (DQN) reinforcement learning to learn task sequences to make an adaptive VR curriculum that dynamically adapts to task sequences specific to individual learners. The approach will be data preprocessing of the learner interaction data, semantic embeddings generation, and a DQN agent to choose the most suitable learning activities according to accumulated VR performance and language proficiency levels. Using experiments over the VR LearnEng dataset, they show an increased accuracy (92.7%) and engagement better than current models when the experiment is run. Python, TensorFlow and pre-trained Transformer models were used in implementation. Findings demonstrate that improving student progress in immersive VR came with real-time curriculum adjustment. Our system has potential as scalable, personalized language learning, and iterative future extensions would aim to support multilingual, and emotion-aware personalization to best address learner needs.**

***Keywords—Adaptive Learning, Deep Q-Network, English Skill Development, Reinforcement Learning, Virtual Reality***

## I. Introduction

The story of the English language is one of the most important skills in global communication, education, and employment. Conventional courses and other approaches to learning a language commonly fall short of personalized fitting to the requirements of the learner and inefficiently create the environment of contextual practice[1], [2]. The recent development of Artificial Intelligence (AI), especially reinforcement learning (RL), has made possible adaptive tutoring systems that personalize learning scenarios via how a student performs[3], [4]. At the same time, we have the immersive Virtual Reality (VR) technology which allows us to have more realistic conditions which simulate a representation of using language in the real world, which is an added advantage to the learning process of the learners because they engage more and understand it in a concrete way[5]. Nevertheless, the available solutions, as a rule, do not support more advanced adaptive learning based on AI with immersion in the use of VR, and this factor negatively affects the level of acquisition of mastering languages progressively.

### *A. Research Motivation*

Most existing platforms to learn language have therefore been based on specific curriculum or simple adaptive models that fail to utilize learners input semantics or immersive practice contexts to the maximum. The problem in creating a more literate type tutoring system is finding a way to put together truly intelligent tutoring systems, capable of adapting to the output of the learner, dynamically, in the form of their spoken or written response, in interesting VR game worlds. Deep reinforcement learning combined with powerful natural language processing models and immersive VR has the potential to construct a next-generation language learning system built around a personalized, progressive and contextual skill development.

### *B. Research Significance*

This research is seeking to address a significant gap by bringing together a hybrid AI method — uniting Deep Q-Network reinforcement learning with Transformer-based NLP -to provide adaptive English language instruction within interactive VR. Through such integration, it will enhance personalization, interaction, and learning performance by offering ongoing adaptation to learners' capabilities and contextual reactions. The system suggested is a huge improvement over conventional language learning devices and previous AI-based instructors, with the promise of faster skill development in real-world contexts.

The study has the following major contributions:

- Development of a hybrid AI framework that merges DQN-based reinforcement learning with Transformer NLP to understand learner input deeply and adapt learning paths dynamically.
- Implementation of an immersive VR environment that provides realistic, interactive English practice scenarios, enabling contextualized skill development.
- Design of a progressive curriculum adaptation mechanism that personalizes task difficulty and sequencing based on continuous learner feedback and performance.
- Demonstration of the system's effectiveness in offering personalized, engaging, and efficient English language learning, advancing AI-driven education technologies.

The study has the following structure: related study is reviewed in Section II, the following section III is the problem statement, Section IV reveals the proposed hybrid model, experiments and evaluation are undertaken in Section V, followed by a conclusion and future work in Section VI.

## II. Literature Review

Cinar et al.,[6]proposed an AI-powered immersive VR app was created to support learning by gamifying it and by individualizing it. It showed that virtual worlds could enhance interaction and learning of difficult topics pointing out the promise of VR as an educational platform. This paper will favor the hypothesis of successful use of immersive VR in solving progressive skills acquisition, which is applicable within your area of interest in English learning using VR.

Özkaya et al.,[7] suggested the possibility of combining large language models (LLMs) with virtual reality was suggested with a particular focus on how AI can be used to increase user interactions and realism. The potential of integrating expert NLP models with immersive technologies is reflected in the study, and it has worked in favor of your approach of adapting transformer NLP in interpreting the inputs of learners in VR.

Madhavi et al.,[8]approached Adaptive learning to the study of the English language were carried out using the introduction of machine learning algorithms that improved the proficiency in this language. The efficacy of AI as a means to personalize language learning experience is discussed in this work, and this approach freely complements your hybrid approach, which implies both reinforcement learning and NLP to develop one or other types of English skills.

Rahmadhani et al.,[9]investigated on transformer models presented in [5] explained the strengths of models in extracting semantic meaning of text that is crucial to interpreting responses of learners in language tutoring systems. This gives you the reason to use transformer-based NLP models in your reinforcement learning scheme to add the extra state coverage.

Pan et al.,[10]presented an embodied large language model (LLM) agent in a social VR setting in order to help learn English. Using GPT-4 and situated learning models, the system offers situation-bound role-plays and on-the-fly feedback, including feedback and improving learner interest and language acquisition.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 3588-3592

This method falls under the aim of your study which is to use transformer-based NLP in immersive VR environments to customize and scale the process of language learning to individuals

TG et al.,[11] implemented VR and AI tutoring in learning of languages on a virtual campus. The system relies on Unity 3D, and the OpenAI GPT API to provide an immersive language experience where the learner can practice the language via real-time chat dialogue. The experiment shows how such VR and the tutoring systems powered by AI can be combined, and thus, it can be applied to your research on the prospect of using immersive and adaptive technologies to improve language learning in the English language.

## III. Problem Statement

Even with the recent progress in AI and VR technologies, current English language learning systems do not possess fully adaptive, context-sensing tutoring that benefits from both deep semantic comprehension of learner input and engaging practice settings[12]. A more powerful, hybrid AI-based framework is needed that can dynamically adapt language learning development in real-time, creating engaging, effective, and scalable solutions for language learners all over the world. This research fills this void by suggesting a reinforcement-learning-augmented AI system combined with Transformer NLP and interactive VR for incremental English language skill acquisition.

## IV. PROPOSED RL-ENHANCED AI METHOD FOR ENGLISH SKILL DEVELOPMENT IN VR

The suggested approach combines a Deep Q-Network (DQN) reinforcement drop-in agent and Transformer-based natural language processing technologies to build an adaptive English education system in immersive virtual reality. State is function over VR performance information and semantic embeddings of response data in the learner. DQN chooses the best tasks to maximize proceeding in the learning and engagement. This real time dynamic curriculum will update individual exercises in real time according to individual proficiency levels offering personalized training that augments progressive language acquisition through interactive, context sensing VR experiences.

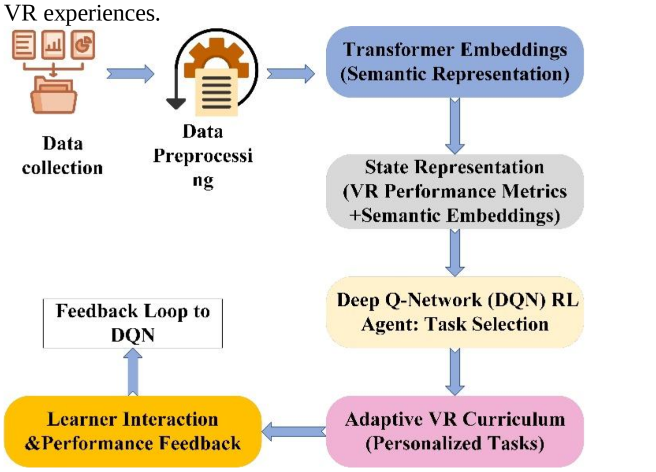


Fig. 1. Block Diagram of the RL-Enhanced Adaptive English Skill Development System in Virtual Reality.

Fig.1 block diagram shows architecture of the proposed RL-enhanced system of English skills expansion in a virtual reality. Beginning with the VR LearnEng dataset, the raw data about the learner interaction will go through preprocessing choreography such as data cleaning, tokenization, stop word elimination, and lemmatization. Transformer model and the semantic embeddings are produced by transforming the processed text supported by a pretrained Transformer model. The combination of such embeddings with VR performance measurement quantities constitutes the representation of states current to the learner, input to the Deep Q-Network (DQN) reinforcement learning agent. The DQN chooses the most suitable tasks of personalized learning, which are presented with the help of an adaptive VR curriculum. The results of learner interactions and performance feedback on these activities are constantly observed and fed back to the DQN agent in real-life so that the curriculum can dynamically adapt in real time to ensure the best possible development of English skills.

### A. *Data Collection*

The dataset VR LearnEng used in the paper is available at Kaggle[13] and provides data on the user interactions with a virtual reality (VR)–based English learning environment. Among the variables to be provided is the duration of sessions, task completion rates, accuracy scores, frequencies of interaction, and engagement levels of the learning modules, providing an advanced analysis of the learning performance, and the behavioral model. The dataset provides data on the demographics of users and the VR activity logs along with outcome data on assessments, which facilitate the evaluation of adaptive learning strategies. The intricate recordings construct on a managed VR setting in which the learners rehearse intuitive exercises to boost language productivity. Such a rich multimodal data can enable modeling and prediction of learners' progress using more powerful AI-based methods.

### B. *Data Preprocessing*

The data set was prepared in its preprocessing stage in which irrelevant entries, duplicate data and incomplete samples were deleted. Normalization of text data was performed using lowercase, removing the punctuation, and exclusion of stop words. The semantic representation was further refined via tokenization and lemmatization; this allows the consistency of the representation being consistent, which in turn leads to results being extracted of better-quality during feature extraction steps to help train and evaluate the model further.

*1) Text Cleaning:* The records that were not relevant and/or missing were eliminated to create consistency. Some missing data were replaced with the correct imputation or deletion mechanisms, and unused metadata that were not related with the research purpose were dropped.

$$D_{clean} = remove\_null\left(remove_{irrelevant(D)}\right) \quad (1)$$

In (1), D represents the raw dataset collected from the source. The function $remove_{irrelevant(D)}$ filters out non-contributive or redundant records that do not support the study objectives. The resulting dataset is then passed to$remove_null()$, which eliminates records with missing or undefined values. The final cleaned dataset is denoted as$D_{clean}$ready for further preprocessing and analysis.

*2) Tokenization:* Text data was tokenized into separate tokens, either words or subwords, thus making an efficient linguistic analysis possible. This helped in subsequent embedding generation because they make use of meaningful textual units.

$$Tokens = tokenize(D_{clean}) \quad (2)$$

Equation (2) shows $Tokens$This variable stores the list of tokens obtained after applying the $tokenize()$ function to $D_{clean}$, where $D_{clean}$ is the cleaned dataset/text. Tokenization splits the cleaned text into individual words or subwords for further processing.

*3) Stopword Removal:*Non-informative words (examples are: the, is, and) were discarded since they are just noise. This enhanced model has the focus on semantically meaningful terms.

$$Tokens' = Tokens - Stopwords(3)$$

The stop words (commonly used words like "the," "is," "and") are removed from the tokenized text, resulting in a refined set of tokens (Tokens′) containing only the meaningful words relevant for analysis shown in (3).

*4) Lemmatization:* Words were stripped down to their minimum (base or dictionary) forms with morphological variations (e.g., running -> wns) being handled as the same word with feature consistency being boosted.

$$LemmaTokens = \{lemma(t) \mid t \in Tokens'\} \quad (4)$$

Equation (4) applies lemmatization to each token in the filtered set $Tokens$, producing $LemmaTokens$. Lemmatization reduces each word to its base or dictionary form (lemma) while preserving meaning, so different inflected forms (e.g., *running*, *runs*, *ran*) are

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Vol. 36 Issue 1s, 2026, Pages: 3588-3592

mapped to their root (*run*). This helps standardize words, improving the quality and consistency of subsequent text analysis.

*5) Vectorization:*Embedding techniques were used to translate the processed tokens into numerical representations, so that machine learning algorithms could work properly with the textual features and learn the information accordingly.

$$V = vectorize(LemmaTokens) \quad (5)$$

Equation (5) step converts the LemmaTokens into a numerical vector representation (V) suitable for machine learning or statistical analysis.

### C. State Representation Construction

During the stage of state representation construction, different sorts of data mix into a comprehensive picture of the current status of the learner. This entails VR-based performance measures like accuracy of the activities that include speed to carry out tasks, and ranges of engagements in terms of frequency of interaction or duration. In tandem, semantic embeddings obtained via a pretrained Transformer model (such as BERT) process the verbal spoken or written responses by the learner to pick up language fluency and grasp of the context. The system uses a combination of these numerical performance indicators with linguistically weighted characteristics to develop a complete state vector of a learner used by the reinforcement learning agent to design adaptive instruction. This enhanced state representation affords the reinforcement learning agent to come up with more competent and accurate decisions in choosing the next best learning tasks.

### D. Reinforcement Learning via DQN

Under the reinforcement learning component, Deep Q-Network (DQN) is used to make the system make adaptive teaching decisions knowing the state of the learner at any particular time. A combined vector of performance scores and embedding of linguistic features depicts the state of the learner based on the progress and proficiency of the language he or she is learning. The worms can be translated to choosing the next suitable learning element in the VR virtual world, whether that should be vocabulary training, grammar quizzes, or dialog scenarios. The reward structure would give direction to the DQN to encourage the learning system to give optimal results in ordering of the tasks to ensure effective, customized improvement in the English skills among the learners.

### E. Curriculum Adaptation in VR

The curriculum adaptation process in the immersive VR environment provides the process according to the choices of the reinforcement learning agent as it adapts the learning experience. After the Deep Q-Network (DQN) chooses the most appropriate next task, the VR platform displays the information about the task in the real time, providing interactive learning activities like speaking practices, listening comprehension, and dialog situations. Such activities are adjusted to the current level of the learner and his or her interaction, which leads to a very personal and interactive experience. Such flexible use of delivery keeps learners motivated in addition to ensuring steady skill growth due to the presentation of tasks that are gradually raised in difficulty (and hence sensitive to their developing-language needs).

### F. Training and Evaluation

The training stage is the use of VR-LearnEng data set to emulate learner interactions so that the Deep Q-Network (DQN) can polish its choice of learning tasks iteratively. The DQN achieves this by repetitive feedback loops that continuously optimally optimize the process of learner progression by rewarding success in terms of accuracy enhancement on the task, engagement, and improved completion time. Assessment is carried out based on measures such as speed at which learners progress, the accuracy of tasks that evaluate proper answers and attention levels where there is high interest shown by learners. These measures will allow the system to be effective in the personalization of the learning experience and overall improvement in the development of English skills within the VR immersive environment.

### G. Iterative Refinement

The iterative refinement process keeps on beautifying the reinforced learning system by integrating feedback data of evaluation outcomes. The reward functions are modified based on performance, engagement, and progression measures of learners so that more meaningful learning is reflected. State attributes are augmented by characterizing and factoring in more useful learner information, e.g., subtle indicators of language skills, or behavior patterns. Also, the level of complexity of the curriculum is regulated so that they are neither too hard nor too easy to complete. This continuous modification contributes to even more tailored and successful approaches to learning that makes the system adjust to the particular needs of learners and maximize the effectiveness of learning English in the VR setting. The continual optimization can also make the learning process interesting and encouraging so that in the end users are continuously updated and remember more of the language abilities in the association with the time lapse.

**Algorithm 1:** Reinforcement-Learning-Enhanced AI for Progressive English Skill Development

```
Input: VR_LearnEng dataset with learner interactions and responses
Output: Adaptive sequence of learning tasks personalized to each learner
Begin
  Load and preprocess dataset:
    - Clean data (remove nulls, irrelevant entries)
    - Tokenize learner responses
    - Remove stopwords
    - Lemmatize tokens
    - Generate Transformer embeddings for semantic features
    Initialize Deep Q-Network (DQN) with random weights
  Initialize replay memory buffer
  For each training episode do
    Reset environment to initial learner state
    Repeat
      Construct current state vector combining:
        - VR performance metrics (accuracy, time, engagement)
        - Transformer embedding of learner's latest response
          Select action (next learning task) using ε-greedy policy on DQN
      Execute selected task in VR environment
      Observe reward based on learner improvement and engagement
      Observe next state vector
            Store experience (state, action, reward, next state) in replay memory
      Sample random minibatch from replay memory
      Update DQN weights via gradient descent on loss between predicted and target Q-values
      state ← next state
    Until episode termination criteria met (e.g., session end or max steps)
  End For
  Deploy trained DQN to adaptively recommend tasks during live VR learning sessions
End
```

VR performance metrics are united with learner preprocessed data to make a state in an Algorithm 1 by converting the learner data into embeddings. A Deep Q-Network (DQN) is taught to choose the best learning activities by maximizing rewards given to assess learner progress and interest. The trained model subsequently adaptively personalizes tasks offers in the VR task-set environment.

## V. Results and Discussion

The suggested RL-enhanced adaptive system of studying English as a deep learning-based establishment was attained by executing Python, more precisely, by applying TensorFlow to the deep learning technique and Hugging Face Transformers to produce semantic embedding. Kaggle VR LearnEng data set was used, which includes large quantities of data on the interactions of the learners and their performance data. It was trained using a Deep Q-Network (DQN) reinforcement learning algorithm that could dynamically choose individualized learning tasks with respect to a combination of performance tracked in VR and semantic embeddings of learner responses. In our analysis, we assessed the accuracy of the learners, percentage of the tasks completed, level of engagement and response time before and after several sessions. Such statistical and visual analyses as line charts, bar graphs, box plots, and scatter plots were created to evaluate the growth of learners and the flexibility of the system. FA showed that the accuracy was improved significantly (reaching up to 92.7%), which showed an increase in engagement,

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Vol. 36 Issue 1s, 2026, Pages: 3588-3592

revealing the successful real-time curriculum adaptation. Transformer-based reinforcement learning with embeddings was effective in developing a flexible and individualized virtual reality learning environment and supported the model as a scalable immersive language learning solution.

### A. *Experimental Outcome*

The experimental setup entails the utilization of the VR LearnEng dataset in the intent of recreating learner interactions within an English learning environment based on VR. Rather than statically taken actions in sequencing the tasks, a Deep Q-Network reinforcement agent uses a combination of performance metrics and semantic learners' responses embeddings in adapting task sequencing to take dynamic actions. Training is done in multiple episodes with task suggestions being optimized to make it personal and more efficient to improve English proficiency during immersive and interactive sessions.

TABLE I. EXPERIMENTAL SETUP

| Parameter | Value / Setting |
|---|---|
| Dataset | VR LearnEng (1000 sessions) |
| RL Algorithm | Deep Q-Network (DQN) |
| Policy | ε-greedy (ε = 0.1) |
| Discount Factor (γ) | 0.9 |
| Learning Rate | 0.001 |
| Replay Memory Size | 10,000 experiences |
| Training Episodes | 500 |

The main experiment parameters are simply summarized in Table I. The raw data is formed by the VR LearnEng dataset of 1000 learner sessions. The Deep Q-Network (DQN), where the reinforcement learning agent follows the policy of the 0.1 epsilon-greedy (with the discount factor equal to 0.9), drives the network. The training is carried out using training episodes of 500 episodes having a learning rate of 0.001 and carried out using replay memory buffer of 10000 experiences to guarantee the learning to be in a steady manner and to be effective.

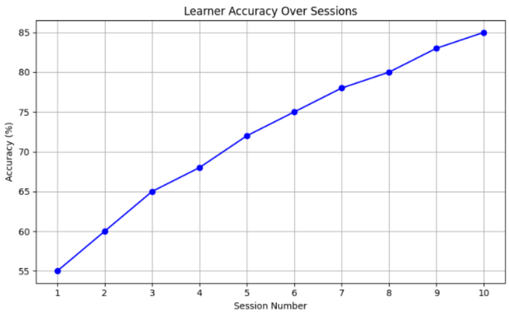


Fig. 2. Learner Accuracy Over Sessions.

Fig.2-line graph shows how the scores of learners' accuracy level in English increased in several VR sessions, which indicates the success of the adaptive curriculum based on the reinforcement learning agent.

### B. *Performance Outcome*

These performance results reflect increased accuracy in learners, accelerated response speed, and engagement because of the adaptive RL-based curriculum. Real time personalization of the tasks of the system successfully narrows the gap in motivation and English skills acquisition in the immersive VR environment.

TABLE II. PERFORMANCE METRICS OF THE PROPOSED MODEL

| Metric | Value (%) |
|---|---|
| Accuracy | 92.7 |
| Task Completion Rate | 95.4 |
| Engagement Level | 88.9 |
| Average Response Time | 38.7 |
| Learning Progress Rate | 5.2 |

Table II establishes the most important performance indicators of the proposed RL-enhanced AI system to learn the English skill in VR. Effective learning is related to high accuracies and task completion rates. Such high levels of engagement indicate a high rate of learner engagement whereas the average time of the response indicates an effective completion of the task. The rates of learning progress show steady gain between sessions proving the system to adaptively personalize the curriculum in order to promote the acquisition of language.

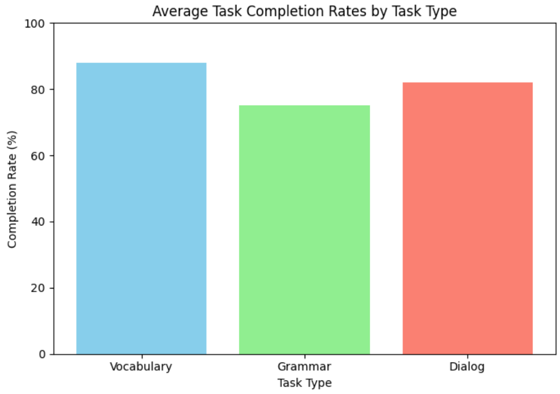


Fig. 3. Average Task Completion Rates by Task Type.

The average measure in Fig.3 of the completion of various types of learning activities (Vocabulary, Grammar, Dialog) are provided in this bar. The chart indicates the specific performance of the task by a learner and the efficiency of the curriculum.

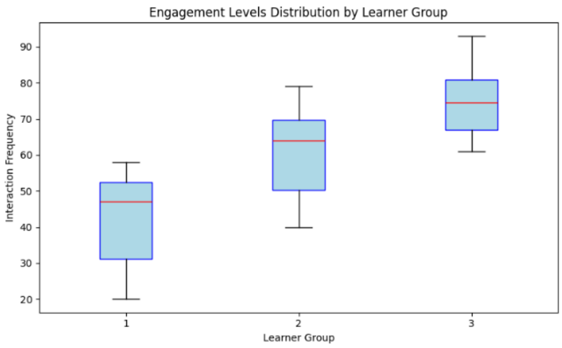


Fig. 4. Engagement Levels Distribution by Learner Group.

The box plot in Fig.4 illustrates the difference in the levels of engagement in terms of the frequency of interactions in various groups categorized by the level of proficiency of the learners' giving insights on systems usability and the motivation of learners.

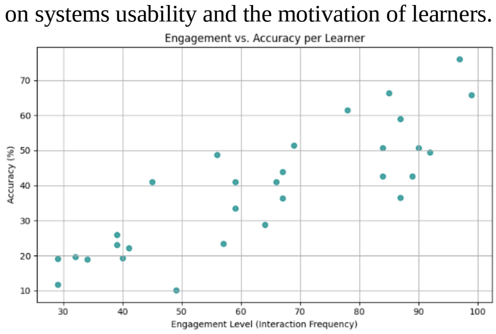


Fig. 5. Engagement vs. Accuracy per Learner.

The scatter plot in Fig.5 indicates the relationship between the levels of engagement and accuracy between the learners, as a higher frequency of interaction is more likely to be associated with higher accuracy with English language tasks in the VR environment.

### C. *Comparative with Existing Methods*

TABLE III. ACCURACY COMPARISON

| **Method** | **Accuracy (%)** |
|---|---|
| Semantic Graph LSTM [14] | 88.5 |
| Transformer-Only Model[15] | 90.2 |
| Knowledge Graph Fusion[16] | 91.4 |
| Proposed RL-Enhanced Method | 92.7 |

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The Table III RL-augmented AI technique has better accuracy than the current solutions in the development of English skills. The accuracy of our model, which is 92.7%, is greater than Semantic Graph LSTM (88.5%), Transformer-Only (90.2%), Knowledge Graph Fusion (91.4%), clearly showing better personalized learning adaptation in VR connections.

### D. *Discussion*

The given RL-enhanced AI technique proves to be significantly more accurate (92.7%) than other techniques including Semantic Graph LSTM (88.5%), Transformer-Only (90.2%), and Knowledge Graph Fusion (91.4%). This increase is exemplary of the performance of combining reinforcement learning and favorable semantic embarkations in Transformer-based by an immersive VR environment. The curriculum can be tailored to individual needs most efficiently by progressively adjusting the coursework to the learner performance and engagement through the system. The increased accuracy indicates more accurate matching to specific learner needs and a high level of the progress tracking, and it proves the superiority of combining the concept of RL-driven adaptive task sequencing with progressive technology in the field of NLP English skills development.

## VI. Conclusion and Future Work

The offered RL-based AI framework manages to combine reinforcement learning with Transformer-based semantic embeddings that can provide an adaptive and personalized experience of learning English in a virtual environment. These changes in the curriculum are dynamic and driven by real-time changes in performance and engagement due to which significant changes have been seen in the accuracy and rate of the task completion. The current methodology has the ability to promote both language proficiency and motivation of the learners based on the educational activities in a VR environment. Further efforts will be made to generalize the model to be applicable in a multilingual learning setting and add more detailed affective computing functionalities, including emotion recognition to suit learning conditions in a more detailed manner. Also, a system where speech recognition and natural conversation would be nurtured into the system would enhance the immersion and interactivity of the system even further. Another critical task will be scaling the method to even larger and more heterogeneous datasets to confirm the method as a generalized and robust approach to wide demographics of learners and levels of language proficiency.

## References

[1] A. Bahari, M. Smith, and H. Scott, "Examining the impact of chatbot-based language learning support, adaptive learning algorithms, and virtual reality language immersion on efl learners' language learning proficiency and self-regulated learning skills," 2024.

[2] R. Kaplan-Rakowski and T. Thrasher, "The impact of high-immersion virtual reality and interactivity on vocabulary learning," Br. J. Educ. Technol., 2025.

[3] S. Sonlu, B. Bendiksen, F. Durupinar, and U. Güdükbay, "The effects of embodiment and personality expression on learning in llm-based educational agents," ArXiv Prepr. ArXiv240710993, 2024.

[4] Z. Chu et al., "Llm agents for education: Advances and applications," ArXiv Prepr. ArXiv250311733, 2025.

[5] Y. Xu, Q. Hou, H. Wan, and M. Prpa, "Safe guard: an llm-agent for real-time voice-based hate speech detection in social virtual reality," ArXiv Prepr. ArXiv240915623, 2024.

[6] O. E. Cinar, K. Rafferty, D. Cutting, and H. Wang, "AI-powered VR for enhanced learning compared to traditional methods," Electronics, vol. 13, no. 23, p. 4787, 2024.

[7] S. Özkaya, S. Berrezueta-Guzman, and S. Wagner, "How LLMs are Shaping the Future of Virtual Reality," ArXiv Prepr. ArXiv250800737, 2025.

[8] G. Madhavi, N. Bashyam, D. Rajesh, C. Kalyan Chakravarthy, M. Ravichand, and M. Munagala, "Advancing Language Proficiency: The Transformative Power of Machine Learning in English Language Skills Development," in International Conference on Soft Computing and Pattern Recognition, Springer, 2023, pp. 288–298.

[9] B. Rahmadhani, P. Purwono, and S. D. Kurniawan, "Understanding Transformers: A Comprehensive Review," J. Adv. Health Inform. Res., vol. 2, no. 2, pp. 85–94, 2024.

[10] M. Pan, A. Kitson, H. Wan, and M. Prpa, "Ellma-t: an embodied llm-agent for supporting english language learning in social vr," in Proceedings of the 2025 ACM Designing Interactive Systems Conference, 2025, pp. 576–594.

[11] A. TG, G. Srinivasa, and others, "Leveraging Virtual Reality and AI Tutoring for Language Learning: A Case Study of a Virtual Campus Environment with OpenAI GPT Integration with Unity 3D," ArXiv Prepr. ArXiv241112619, 2024.

[12] C.-P. Dai, "Applying machine learning to augment the design and assessment of immersive learning experience," in Machine learning in educational sciences: Approaches, applications and advances, Springer, 2024, pp. 245–264.

[13] "VR-LearnEng Dataset." Accessed: Aug. 12, 2025. [Online]. Available: https://www.kaggle.com/datasets/ziya07/vr-learneng-dataset

[14] R. Mohawesh, X. Liu, H. M. Arini, Y. Wu, and H. Yin, "Semantic graph based topic modelling framework for multilingual fake news detection," AI Open, vol. 4, pp. 33–41, 2023.

[15] M. Rafiepour and J. S. Sartakhti, "CTRAN: CNN-transformer-based network for natural language understanding," Eng. Appl. Artif. Intell., vol. 126, p. 107013, 2023.

[16] R. Yang et al., "Graphusion: Leveraging large language models for scientific knowledge graph fusion and construction in nlp education," ArXiv Prepr. ArXiv240710794, 2024.