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RESEARCH ON THE APPLICATION OF MOOCS BASED ON REINFORCEMENT LEARNING IN COLLEGE ENGLISH TEACHING

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Abstract. In the field of teaching college English, this study explores the integration of reinforcement learning concepts with Massive Open Online Courses (MOOCs). "LearnFlex," the suggested framework, is intended to support an environment that is dynamic and flexible for learning. By offering thorough English language courses and utilizing reinforcement learning techniques, LearnFlex leverages the inherent benefits of MOOCs to customize and enhance the learning process for every student. This study's main goal is to assess how well LearnFlex works in the context of teaching college English to improve student performance, engagement, and general satisfaction. Through the integration of educational technology, machine learning, and pedagogical methodologies, LearnFlex aims to offer significant insights that support the ongoing development of efficient and customized online learning. The study contributes to the larger objective of improving teaching strategies by utilizing cutting-edge technologies to build a learning ecosystem that is more adaptable and focused on the needs of students. This study aims to provide insights for future improvements in online education, specifically in the area of language training, by conducting a thorough examination of LearnFlex's effects.

Key words: Reinforcements learning, MOOCs, college English teaching, student engagement, personalized online education

1. Introduction. Massive Open Online Courses (MOOCs) have become a powerful and revolutionary force in the modern educational scene. MOOCs are a paradigm change in education, providing a wide range of worldwide audiences with flexible and easily available learning options [2, 15]. The fundamental quality of MOOCs is their capacity to democratize education by bridging the gap between socioeconomic and geographic constraints that frequently inhibit traditional learning paradigms [15]. MOOCs facilitate self-paced and self-directed learning experiences by giving learners unparalleled access to a plethora of educational content through the use of digital platforms. This method has shown to be very helpful in meeting the different requirements and interests of students, encouraging lifelong learning across a range of subjects. MOOCs have become a powerful and revolutionary force in the modern educational scene [13]. These are a paradigm change in education, providing a wide range of worldwide audiences with flexible and easily available learning options. The fundamental quality of MOOCs is their capacity to democratize education by bridging the gap between socioeconomic and geographic constraints that frequently inhibit traditional learning paradigms. MOOCs facilitate self-paced and self-directed learning experiences by giving learners unparalleled access to a plethora of educational content through the use of digital platforms [6, 16]. This method has shown to be very helpful in meeting the different requirements and interests of students, encouraging lifelong learning across a range of subjects.

The use of MOOCs in college English instruction offers a flexible and dynamic method of teaching the language [19]. MOOCs provide a wide range of benefits for teaching college English that support the advancement of conventional pedagogical approaches [10, 3]. The availability of top-notch English language instruction to a multicultural and international student body is one significant benefit. Students can interact with rich, standardized content regardless of where they are in the world, guaranteeing a thorough and consistent educational experience. Due to MOOCs' inherent flexibility, students can advance at their own speed and according to their own preferences and learning styles [18]. Furthermore, MOOCs' interactive format encourages active engagement and participation through discussion boards, multimedia components, and group projects. These elements not only improve how students engage with the curriculum, but they also help students feel more like a community. MOOCs' flexibility is essential for meeting students' diverse skill levels because they offer

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customized assessments and content to meet each student's needs. Because of their scalability and affordability, MOOCs significantly improve access to high-quality English language instruction while providing a significant response to the drawbacks of conventional teaching techniques [15, 7]. This study investigates how these benefits can be increased by incorporating MOOCs that are enhanced by the principles of reinforcement learning, opening the door to a novel and successful method of teaching college English.

MOOCs have many benefits, but they are not without drawbacks. A noteworthy obstacle pertains to learner engagement and completion rates [23]. MOOCs frequently encounter elevated dropout rates, which can be attributed to various factors, including inadequate personalization, restricted interactivity, and inadequate flexibility to meet individual learning requirements [9, 1]. The integration of reinforcement learning with the machine learning-based C4.5 algorithm is suggested as a solution to these drawbacks. This combined strategy, called "LearnFlex," aims to add personalization and adaptability to MOOCs to increase their efficacy in teaching college English. LearnFlex uses reinforcement learning to dynamically modify learning paths and content according to each student's progress, encouraging long-term engagement [4, 11]. The C4.5 algorithm's integration makes a further contribution by examining learner data to find patterns that allow the system to offer customized interventions and recommendations [5]. Thus, LearnFlex is a creative step toward reducing the drawbacks of traditional MOOCs in the context of teaching college English and fostering a more responsive, flexible, and student-centered MOOC environment.

The burgeoning intersection of educational technology and language training presents a unique opportunity to revolutionize the way college English is taught and learned. This research is motivated by the potential to harness Massive Open Online Courses (MOOCs), enriched with reinforcement learning techniques, to create a more dynamic, personalized, and effective learning environment. "LearnFlex," our proposed framework, stands at the forefront of this educational innovation, aiming to redefine college English teaching through the strategic integration of MOOCs and machine learning principles. The core objective of this study is to meticulously evaluate the efficacy of LearnFlex in enhancing college English education by focusing on three primary outcomes: student performance, engagement, and overall satisfaction. By leveraging the scalability and accessibility of MOOCs, coupled with the adaptive capabilities of reinforcement learning, LearnFlex is designed to offer a tailored educational experience that meets the diverse needs of learners, thereby overcoming the limitations of traditional one-size-fits-all approaches.

Central to our motivation is the belief that every student's learning journey is unique. Traditional educational models often fail to accommodate individual learning styles, pacing, and preferences, leading to suboptimal outcomes. LearnFlex seeks to address these challenges by employing reinforcement learning algorithms that adapt the learning content and pathways based on real-time feedback from student interactions. This approach ensures that the learning process is continuously optimized for each student, fostering a deeper understanding and mastery of the English language.

The contribution of the paper as follows:

1. The goal of the study is to improve the flexibility and customization of online learning by introducing a novel approach called "LearnFlex".
2. The suggested LearnFlex combines the reinforcement-based DQN technique with the MOOCs-based C4.5 algorithm.
3. Proposed LeanFlex uses reinforcement learning to modify learning paths and content according to each student's progress, introducing dynamic adaptability.
4. The C4.5 algorithm's integration yields analytical insights through learner data analysis, pattern recognition, and customized recommendation generation.
5. The efficacy of the proposed LearnFlex is proved with valid experiments.

1.1. Related work. This study [12] highlights problems with low intelligence and ineffective teaching effects in online college English cross-cultural instruction using MOOCs. Through the use of artificial intelligence and cloud computing, the research presents an enhanced MOOC model and algorithm designed to satisfy the needs of online education. Requirements analysis is used to build functional modules, and control experiments verify the model's functionality and show how effective it is at improving the effectiveness of English language instruction across cultural boundaries in virtual settings. This study [14] investigates how to improve English instruction in China by integrating a Constructive English MOOC system based on the RBF algorithm. The system runs smoothly and efficiently, completing tasks in 3–7 seconds with an astounding 98% efficiency. The platform encourages students to participate actively in their education by developing their capacity for independent research and piqueing their interest in English studies by replacing traditional teaching methods with a technology-enhanced approach. The results of the study demonstrate the benefits of using the RBF algorithm and effective teaching techniques, indicating important new directions in the field and the possibility of revolutionizing English instruction. This study [22] uses artificial intelligence (AI) emotion recognition and neural network algorithms to overcome the shortcomings of conventional cross-cultural English teaching models. The created cross-cultural O2O English teaching system uses background models to track and identify students' emotions along with intelligent recognition and management. Robust performance and efficient online teaching control are demonstrated by the comprehensive O2O teaching model that integrates both online and offline components. The model has been successful in raising student emotional engagement and teaching effectiveness in cross-cultural English instruction, according to the study's statistical tests.

This study [21] improves on traditional teaching quality evaluation by introducing a comprehensive evaluation model for MOOC teaching in accounting using the Rete algorithm. In order to provide a thorough quality assessment, the model evaluates the MOOC teaching mode, compares teaching data with the Rete algorithm, and establishes evaluation standards and weight calculations. The model's usefulness in controlling MOOC accounting teaching quality is demonstrated by its practical application, which also indirectly improves teaching outcomes.

This study [17] focuses on learning objectives and Bloom's taxonomy to address the difficulty of automating the pedagogical classification of MOOCs. The research uses transfer learning through BERT to achieve large-scale and automatic annotation even with a small annotated dataset. The results of the experiments show that the classifier's complexity has little effect on performance; the best results are obtained when dense layers are added to BERT, dropout is included, and ReLU activation functions are used. In the context of MOOCs, the study demonstrates the value of transfer learning for pedagogical annotation, opening the door to better quality control and comprehension of their pedagogical models. The underuse [8] of a wealth of university data is the subject of this study, which focuses on forecasting the chance of withdrawal for incoming students. The application uses the C4.5 algorithm to convert large amounts of data into a decision tree, which allows for the rule-based classification of new students. The tree structure of the system makes it easier to identify possible student withdrawals early on, which helps management make decisions more quickly. The application, which was created using the waterfall model and PHP and MySQL, attempts to improve strategic planning and lower the chance of student attrition by using insights from data.

2. Methodology.

2.1. LearnFlex Overview. In order to create an intelligent and adaptable learning environment for college English teaching, LearnFlex's system architecture integrates DQN and MOOC-based C4.5 techniques was illustrated in Figure **??**. To guarantee a smooth integration of these technologies, this entails identifying system components, data flows, and interactions. Data privacy and ethical considerations are given top priority while a plan is developed to collect learner information, behavioral data, and pertinent contextual information. The next step of the preparation process involves creating a training dataset D that is thorough and includes learner attributes, past interactions, and pertinent features. After that, the MOOC-based C4.5 algorithm is put into practice, beginning with the training dataset's initialization and the feature-representing attributes' definition. To improve the classification process, the C4.5 algorithm is used, which includes creating decision trees, using TG-C4.5 to select the optimal attribute features, parallel processing with Hadoop for scalability, and using MapReduce to calculate the information gain ratio. After that, LearnFlex incorporates the DQN reinforcement learning techniques. This entails putting the DQN training procedure into practice as well as initializing the Q-value function and replay memory rm. C4.5 and DQN work together to enable adaptive decision-making, which improves the system's capacity to adapt to shifting learning dynamics. Various user roles, including instructors, administrators, and students, are taken into account in user-centric design considerations. The design of role-based systems adapted to particular business requirements is informed by an analysis of the behavioral traits and basic information about the user.

Next, the system is deployed in the College English Teaching environment after being initialized and incorporating both DQN and C4.5 techniques based on MOOCs. A loop for continuous improvement is created to

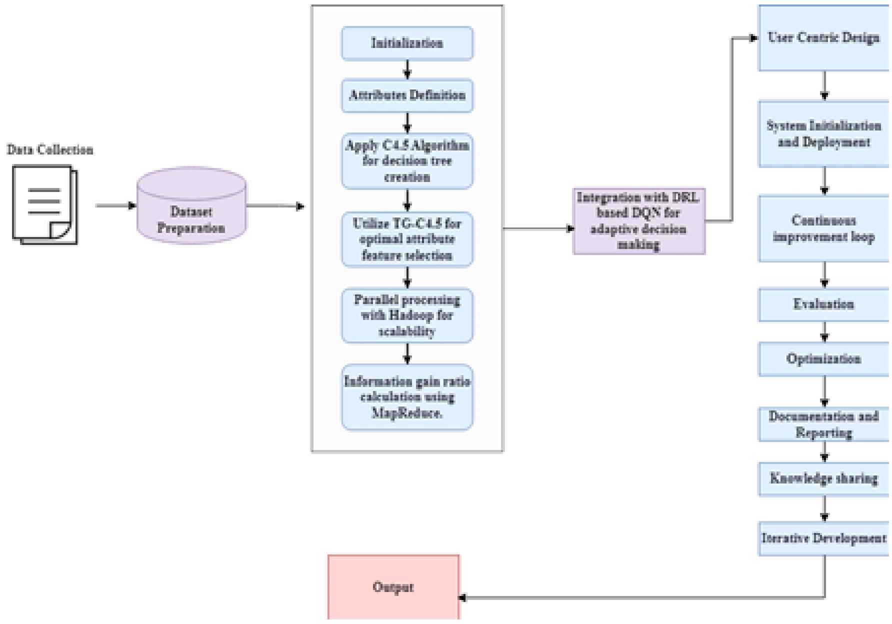

Fig. 2.1: Proposed LearnFlex Design

track system performance, collecting user input by watching and iteratively improving the LearnFlex algorithm in response to input. During the evaluation phase, the LearnFlex system's efficacy is evaluated with respect to user satisfaction, learning outcomes, and adaptability to changing educational needs. After that, optimization enables parameter and algorithm improvements based on the evaluation's findings. The process relies heavily on reporting and documentation, with the methodology, algorithms, and system components all having extensive documentation. The LearnFlex system generates thorough reports that include recommendations and results. In order to spread discoveries and insights, academic publications, conferences, and knowledge-sharing platforms place a strong emphasis on knowledge sharing. The LearnFlex system is continuously evolving and being improved with the iterative development approach. Finally this allows the provision of a customized and successful learning environment.

2.2. Proposed LearnFlex Approach.

2.2.1. MOOCs based C4.5 algorithm. This section discusses the C4.5 concept, which is based on MOOCs and was taken from the study [4]. The MOOCs-based C4.5 diagrammatic flow is depicted in Figures 2.1 & 3.1 and 3.2 of the study. We now carry out the simple algorithmic steps as follows.

The MOOCs-based C4.5 algorithm takes into account various learning styles, behaviors, and course content in order to manage the complex data from online courses. This tool performs a few crucial tasks. In order to help the system determine what might be most effective for each individual, it first arranges and makes sense of the data about each student. It's similar to customizing the educational process to meet each student's needs. Based on the C4.5 algorithm, this tool is also highly effective in generating decision trees, which aid in the system's intelligent decision-making regarding how to teach, what content to deliver, and even suggesting customized learning plans. Furthermore, it excels at managing multiple types of data simultaneously, which helps it overcome the difficulties of online learning. It increases the precision of identifying students' areas of strength and weakness, which is critical in the teaching of English. It also becomes even more potent when combined with Hadoop, a big data platform, allowing it to handle massive volumes of data effectively. All things considered, LearnFlex is made smarter by this tool the MOOCs-based C4.5 algorithm which aids in the efficient use of data to produce a customized and successful learning environment for college students studying English.

The system employs advanced load balancing techniques to distribute traffic evenly across servers, preventing any single server from becoming a bottleneck. This not only enhances performance but also ensures a smooth and responsive experience for all users. LearnFlex leverages CDNs to cache and deliver content from servers closest to the user's location. This significantly reduces bandwidth usage and lowers the server load, enabling faster content delivery even in high-demand scenarios.

The MOOCs-based C4.5 algorithm in LearnFlex starts with initializing the training dataset D and defining attributes A. Attribute selection is performed using the TG-C4.5 algorithm, denoted as $TG - C4.5 = taylorseries(C4.5,\ GINIIndex)$ here $GINIIndex$ is introduced to enhance classification performance. The $GINI\ index$ (Gini) is defined as

$$Gini = 1 - \sum_{i=1}^{n} \left(\frac{|DC_I|}{|D|} \right)^2$$

capturing the impurity of a dataset. For a specific attribute A, $GiniSplitA(D)$ is computed as $GiniSplitA\left(D\right) = \sum_{j=1}^{m} \left(\frac{|D_j|}{D} Gini(D_j) \right)$. The mean sum of GINI indices $(Sum - GiniAF(D))$ is then calculated as

$$\frac{1}{s} \sum_{i=1}^{s} \sum_{j=1}^{x} \left(\frac{|D_{ij}|}{|D|} Gini(D_{ij}) \right)$$

To improve $GainRatio$ (A) calculation, the algorithm considers this mean sum:

$$GainRatio\left(A\right) = \frac{Gain(A)}{SplitInfoA\left(T\right) - \alpha.Sum - GainSplitAF(D)}$$

Here, α is a tuning parameter. Decision trees are designed in the root node using $C4.5\ (D,\ A)$, and $TG - C4.5$ is applied for optimal attribute feature selection. The algorithm integrates parallel processing with Hadoop, employing $HD - TG - C4.5$ for large-scale data processing. The Gain Ratio Calculation with MapReduce in the proposed MOOCs-based C4.5 algorithm involves a series of steps aimed at optimizing the decision tree structure and enhancing the algorithm's effectiveness. In next step parallel statistics are employed to calculate the information gain ratio for a specific attribute feature A using the MapReduce paradigm. The *Gain Ratio* ($GainRatio(A)$) is determined as the ratio of the Gain for attribute A to the Split Information for A subtracted by a weighted sum. Moving to Step 16, the algorithm adjusts or replaces misclassification results in the training set with probability errors, refining the classification accuracy by considering the likelihood of errors. Next, it introduces the calculation of the probability $P_{wj} \in \left[\frac{nwj}{V+s}, \frac{nwj+s}{V+s} \right]$ for each node using the Integrated Error Probability (IEP) model, contributing to a probabilistic approach to pruning.It focuses on estimating values for the number of nodes and subsets $n\left(t\right)$ a crucial step in determining the structure of the decision tree. Pruning decisions are made in the next step based on a condition related to the number of nodes $n\left(t\right) \leq n\left(T_i\right) + SE\left[n(T_i)\right]$ leading to the removal of specific branches and optimizing the decision tree structure. The algorithm analyzes user basic information and behavioural characteristics, highlighting the importance of understanding individual learner attributes for personalized learning experiences. Next, it integrates the algorithm into the design of an education system for predicting performance, emphasizing practical applications in the educational environment. Consideration of different user roles and their corresponding business requirements is addressed, ensuring a tailored approach to diverse stakeholders. The final step, involves continuous monitoring of system performance and gathering feedback, facilitating an iterative process for enhancements and refinements based on real-world outcomes and user experiences.

Algorithm 1 focuses on estimating values for the number of nodes and subsets $n(t)$ a crucial step in determining the structure of the decision tree. Pruning decisions are made in the next step based on a condition related to the number of nodes n leading to the removal of specific branches and optimizing the decision tree structure. The algorithm analyzes user basic information and behavioural characteristics, highlighting the importance of understanding individual learner attributes for personalized learning experiences. Next, it integrates the algorithm into the design of an education system for predicting performance, emphasizing practical applications

Algorithm 1 MOOCs based C4.5 algorithm

1: Initialize the training dataset D with learner information and behavioral characteristics.
2: Define attributes A representing features in the dataset.

Attribute selection using TG-C4.5 algorithm

3: Apply Taylor series based C4.5 Algorithm to calculate information gain rate.
4: Utilize TG-C4.5 algorithm for optimal attribute feature selection.

$$TG - C4.5 = taylorseries(C4.5,\ GINIIndex)$$

GINI Index and splitting information

5: Introduce GINI index to improve classification performance
6: Define the GINI index as $Gini = 1 - \sum_{i=1}^{n} \left(\frac{|DC_I|}{|D|}\right)^2$
7: For attribute A, compute $GiniSplitA\,(D) = \sum_{j=1}^{m} \left(\frac{|D_j|}{D} Gini(D_j)\right)$
8: Calculate the mean sum of GINI indices using $Sum - GiniAF\,(D) = \frac{1}{s}\sum_{i=1}^{s}\sum_{j=1}^{x}\left(\frac{|D_{ij}|}{|D|}Gini(D_{ij})\right)$
9: Improve the GainRatio calculation by considering the mean sum of GINI indices
Compute $GainRatio\,(A) = \frac{Gain(A)}{SplitInfoA(T) - \alpha.Sum - GainSplitAF(D)}$

MOOC teaching system integration

10: Design decision trees in the root node to select and train optimal attribute features by utilizing $DecisionTree = C4.5(D, A)$
11: Apply the TG-C4.5 algorithm for optimal attribute feature selection.

Parallel Processing with Hadoop

12: Implement parallel decision algorithms using the Hadoop platform framework.
13: Design HD-TG-C4.5 for processing large scale data

$$HD - TG - C4.5 = ParallelProcessing(D, Hadoop)$$

14: Utilize Hadoop Distributed File System (HDFS) and Hadoop MapReduce for efficient data processing.
Gain Ratio Calculation with MapReduce
15: Perform Parallel statistics on the information gain ratio of attribute feature

$$GainRatio\,(A) = MapReduce(InformationGainRatio)$$

$$GainRatio\,(A) = \frac{Gain(A)}{SplitInfoA\,(T) - \alpha.Sum - GainSplitAF(D)}$$

$$Sum - GiniAF\,(D) = \frac{1}{s}\sum_{i=1}^{s}\sum_{j=1}^{x}\left(\frac{|D_{ij}|}{|D|}Gini(D_{ij})\right)$$

16: Replace the misclassification result of the training set with probability error.
17: Calculate the probability of each node using the IEP model

$$P_{wj} \in \left[\frac{nwj}{V+s}, \frac{nwj+s}{V+s}\right]$$

Probability based Pruning

18: Estimate the values for the number of nodes and subsets

$$n\,(t) = \max\{e\,(pt) + 0.5 | pt \in kt\,(w)\}$$

MOOCs based algorithm output

19: Prune when the condition is satisfied

$$n\,(t) \le n\,(T_i) + SE\,[n(T_i)]$$

20: Analyse the user basic information and behavioural characteristics.
21: Design as education system for performance prediction.
22: Consider different user roles and their corresponding business requirements.
23: Monitor system performance and gather feedback.

in the educational environment. Consideration of different user roles and their corresponding business requirements is addressed, ensuring a tailored approach to diverse stakeholders. The final step, involves continuous monitoring of system performance and gathering feedback, facilitating an iterative process for enhancements and refinements based on real-world outcomes and user experiences.

2.2.2. Integrating DQN for adaptive decision making. One of the main functions of the Deep Q-Network (DQN) integration in the LearnFlex system is to improve adaptive decision-making. Using techniques from reinforcement learning, DQN is used to optimize workload scheduling decisions. The main goal is to develop a dynamic and intelligent system that can adjust on its own to changing circumstances in the context of teaching college English. With the help of DQN, LearnFlex is able to maximize expected rewards when making decisions by drawing on past experiences that are stored in a replay memory. LearnFlex can now customize its recommendations and responses thanks to this integration, giving students a more successful and individualized learning experience. LearnFlex aspires to provide an adaptive, intelligent, and data-driven educational platform that meets the specific needs of each individual learner by fusing MOOC-based C4.5 algorithms with DQN.

Input: $n_{min}, n_{max}, \Delta, \alpha, \gamma, \delta$
Output: Workload Scheduling Decision
Initialize replay memory rm to capacity n
Initialize action value function Q with random weights θ
Initialize target action value function $\widehat{Q}$ with weights $\theta = \theta^-$
for e **do**pisode $= 1, m$ do
    Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\sigma_1 = \sigma_1(s_1)$
    for do$t = 1, T$ do
        with probability δ select a random action a_t
        otherwise select $a_t = \max_a Q(s_t, a, \theta)$
        Execute action s_t and observer reward r_t and next state x_{t+1}
        Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\sigma_{t+1} = \sigma(s_{t+1})$
        Store transition $(\sigma_t, a_t, r_t, \sigma_{t+1})$ in replay memory rm
        Sample random minibatch of transitions $(\sigma_J, a_J, r_J, \sigma_{J+1})$ from replay memory rm
        Set $y_j = \begin{cases} r_J \\ r_{J+\gamma} \max_a \hat{Q}(s_{J+1}, a', \theta^-) \end{cases}$
        Perform gradient descent step on $(Y_J - Q(s_J, a_J, \theta))^2$ with respect to the network
    Parameters ϑ
        Every C steps reset $\hat{Q} = Q$
    end for
end for
    Online making workload scheduling decision
Load the parameters ϑ;
Calculate action-value $Q(s_t, a; \theta)$
Output $a_t = argmaxQ(s_t, a; \theta)$

In the LearnFlex system, the algorithm entails training a DQN for adaptive workload scheduling decisions. First, two action-value functions, Q and $\hat{Q}$, are initialized with random weights in a replay memory rm. Episodes are used in the training process to select states and actions at random or in an attempt to maximize the Q-value. Transitions are recorded in the replay memory, and rewards are tracked. The Q-network parameters are updated using a gradient descent step to minimize the temporal difference between the target and predicted Q-values after a random minibatch of transitions is sampled on a regular basis. Periodically, the target network is reset. The algorithm moves into the online decision-making stage after training. The trained parameters are loaded, and action values for the possible actions and the current state are computed. The action with the highest computed Q-value is chosen to make the decision. During online execution, this procedure is repeated, giving the LearnFlex system the ability to schedule workload adaptively using the learned Q-values.

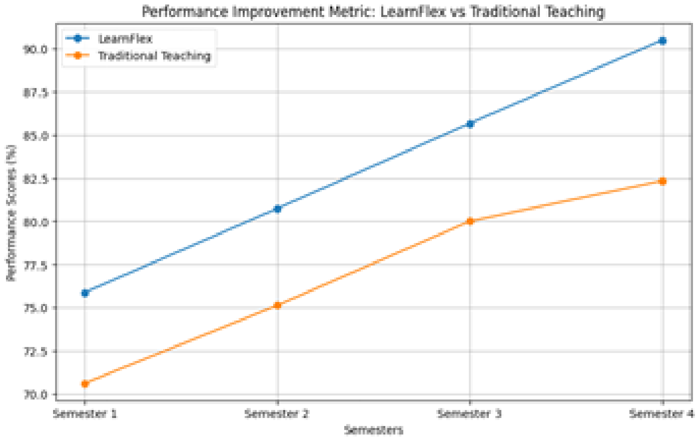

Fig. 3.1: Performance Comparison

3. Results and Experiments.

3.1. Simulation Setup. We move forward with the evaluation of the suggested LearnFlex based on the study [20]. Based on the dataset that comprises universities, colleges, and schools. Here, we evaluate the proposed LearnFlex using data from colleges.

3.2. Evaluation Criteria. The Figure 3.1 shows that the LearnFlex framework is significantly more effective than traditional teaching methods in improving student performance. LearnFlex continuously outperformed conventional methods in terms of academic achievement during the observed periods. The LearnFlex scores show a consistent upward trend, ranging from 75.89 to 90.47. The scores for the traditional teaching approach, on the other hand, range from 70.64 to 82.34, indicating a somewhat slower and less noticeable improvement trajectory. The significant improvement in performance highlights LearnFlex's beneficial effects on college English learning outcomes for students. The upward trend in LearnFlex scores indicates the platform's efficacy and adaptability in meeting the varied needs of students, which in turn creates an environment that promotes better learning outcomes and more fulfilling educational experiences in general.

The efficacy of LearnFlex in improving student engagement is demonstrated by multiple metrics, indicating noteworthy improvements over conventional teaching approaches were present in Figure 3.2. First off, LearnFlex outperforms the conventional approach with an astounding participation rate of 85.77% compared to 70.27% for the former. This notable rise suggests that LearnFlex successfully promotes a greater degree of student participation in learning activities. When it comes to the interaction of materials, LearnFlex performs exceptionally well, scoring 90.22%, while traditional approaches fall short at 75.89%. This disparity indicates a more in-depth examination of learning resources as LearnFlex users interact with course materials in a more comprehensive manner. When it comes to learning activities, LearnFlex is still ahead of the competition, with an 80.34% score as opposed to 79.42% for the traditional method. While both strategies demonstrate respectable levels of student involvement, LearnFlex guarantees that students stay actively engaged throughout a variety of educational tasks, making for a more dynamic learning environment. Another area where LearnFlex excels is communication, where it achieves an amazing 95.06%, compared to 80.44% for traditional methods. LearnFlex's capacity to establish an engaging and cooperative learning environment is demonstrated by its exceptional communication-fostering capabilities. Traditional approaches, on the other hand, show a clear weakness in this area. With an overall engagement metric of 80.12% as opposed to the traditional method's 60.75%, LearnFlex is clearly a comprehensive solution. This notable difference suggests that LearnFlex's dynamic and adaptable features greatly enhance students' overall engagement in a comprehensive way. Taken as a whole, the metrics show that LearnFlex improves engagement in a number of ways, which makes it a more impactful and promising approach than more conventional teaching techniques.

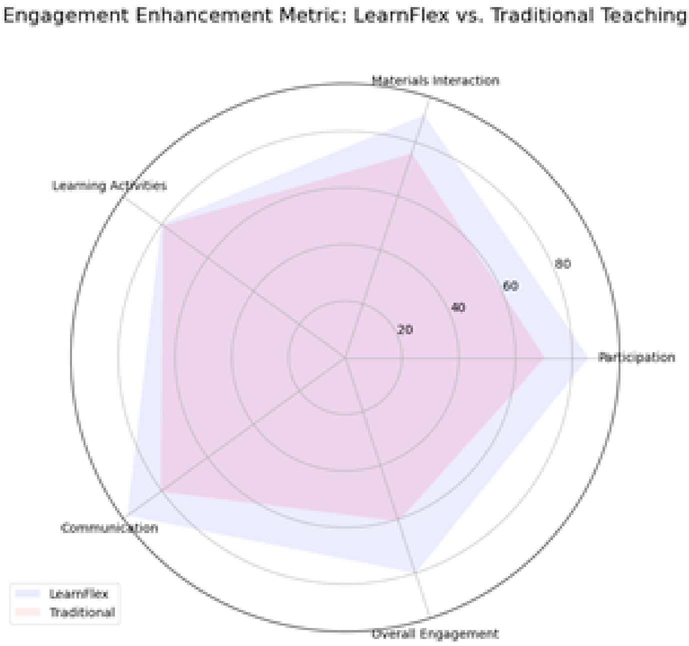

Fig. 3.2: Student Engagement Comparison

An extensive examination of user satisfaction ratings shows that the suggested LearnFlex is demonstrably effective when compared to traditional teaching methods, illustrated Figure 3.3. These scores, which range from 1 to 5, represent how satisfied students are overall with different aspects of their educational experience. LearnFlex has a usability score of 4.2, which is higher than traditional methods' score of 3.8. This discrepancy highlights the LearnFlex platform's greater usability by showing that students believe it to be more approachable and user-friendly. In terms of content relevance, LearnFlex performs better than traditional methods, scoring 4.5 out of 4.0. This discrepancy suggests that learners view the information in LearnFlex as more individualized and relevant to their particular learning requirements, which raises the overall significance of the course content. LearnFlex's learning process receives an astounding 4.8, vastly surpassing the 4.1 score assigned to conventional methods. This significant difference emphasizes that LearnFlex environments provide students with a more engaging and enriching educational experience than traditional classroom settings. Regarding assistance, LearnFlex receives a satisfaction rating of 4.3, which is higher than the 3.9 that traditional approaches receive. This indicates that LearnFlex does a great job of offering the required frameworks for support, creating an atmosphere in which students feel sufficiently assisted throughout their educational journey. LearnFlex is clearly superior, as evidenced by the overall satisfaction metric 4.6, which averages scores from a variety of categories. Traditional methods score 4.2. This conclusion demonstrates that LearnFlex provides students with a thorough and satisfying learning experience, not only meeting but exceeding their expectations. In essence, LearnFlex is an excellent pedagogical framework that is responsive to the changing needs of students and goes above and beyond conventional approaches to create a positive and productive learning environment.

4. Conclusion. In conclusion, the LearnFlex framework that has been suggested, which combines DRL-based DQN methods with MOOCs-based C4.5 algorithms, is a revolutionary development in the field of teaching college English. The well-thought-out system architecture uses C4.5 to make efficient decisions based on learner characteristics and integrates MOOCs to improve adaptability. This procedure is further improved by the TG-C4.5 algorithm, which takes into account the peculiarities of online learning environments. Simultaneously, the incorporation of DQN methodologies incorporates reinforcement learning, guaranteeing flexible decision-making and customized experiences. The user-centric design, which accommodates the various roles of teachers, admin-

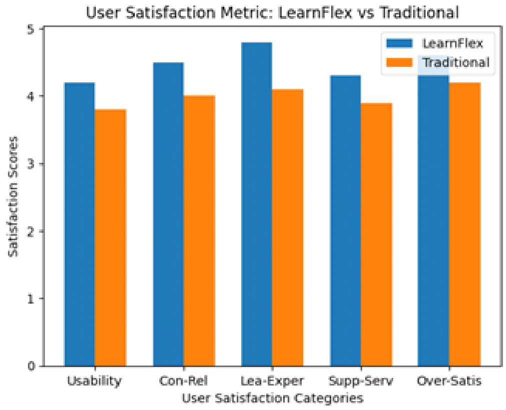

Fig. 3.3: User Satisfaction

istrators, and students, complements the algorithmic prowess. LearnFlex shows efficacy in enhancing learning outcomes, user satisfaction, and adaptability to changing educational needs through methodical initialization, continuous improvement loops, and a strong evaluation framework. The C4.5 algorithm, which is based on MOOCs, greatly enhances personalized learning by being highly scalable and adept at creating decision trees. Massive datasets in MOOCs present challenges for scalability, but Hadoop's parallel processing capabilities further improve it. All things considered, LearnFlex shows itself to be an intelligent, scalable, adaptive system that is ready to transform the way college English is taught by fusing state-of-the-art algorithms and technologies into a framework that is performance-driven and centered on the needs of the user.

5. Limitations and Discussions. LearnFlex is a promising framework for bettering college English instruction, but it has a number of issues that need to be acknowledged and discussed carefully in order to be improved. The significant reliance on learner data raises privacy concerns, necessitating a careful balancing act between personalization and privacy. Algorithmic complexity is introduced by the combination of DRL-based DQN and MOOCs-based C4.5, which presents difficulties for system upkeep and user-friendliness. Further research is necessary to generalize LearnFlex's success outside of the English classroom, taking into account the various ways that students learn different subjects. In areas with inadequate infrastructure, accessibility issues, such as technology requirements, may limit its effectiveness. Further investments in professional development are warranted because teacher training is essential for effective deployment. Important topics for discussion include striking a balance between standardized quality and personalization, creating feedback loops, addressing cost-effectiveness and scalability, and taking social and cultural nuances into account. Participating in these conversations will help to improve LearnFlex and create a dynamic, flexible learning environment for college English instructors. Future online learning platforms will likely incorporate more sophisticated tools for collaboration and community building, mimicking the social learning environments of traditional classrooms. These tools will support real-time collaboration on projects, peer-to-peer learning, and mentorship opportunities, breaking down the barriers of isolation often associated with online education.

REFERENCES

[1] S. S. Ahmed, E. Khan, M. Faisal, and S. Khan, *The potential and challenges of moocs in pakistan: a perspective of students and faculty*, Asian Association of Open Universities Journal, 12 (2017), pp. 94–105.
[2] M. H. Baturay, *An overview of the world of moocs*, Procedia-Social and Behavioral Sciences, 174 (2015), pp. 427–433.
[3] J. Chen, *An e-portfolio-based model for the application and sharing of college english esp moocs.*, Higher Education Studies, 7 (2017), pp. 35–42.
[4] X. Chen, *Design and research of mooc teaching system based on tg-c4. 5 algorithm*, Systems and Soft Computing, 5 (2023), p. 200064.

[5] J. Dai, *Selective forwarding unit placement in edge computing based on dqn for real-time communications*, in GLOBECOM 2022-2022 IEEE Global Communications Conference, IEEE, 2022, pp. 4510–4516.
[6] R. Deng, P. Benckendorff, and D. Gannaway, *Progress and new directions for teaching and learning in moocs*, Computers & Education, 129 (2019), pp. 48–60.
[7] Y. Ding and H.-z. Shen, *English language moocs in china: Learners' perspective.*, The EuroCALL Review, 28 (2020), pp. 13–22.
[8] D. Erlan, *C4. 5 algorithm application for prediction of self candidate new students in higher education*, JOIN (Jurnal Online Informatika), 3 (2018), pp. 22–28.
[9] H. Fournier, R. Kop, and G. Durand, *Challenges to research in moocs*, MERLOT Journal of Online Learning and Teaching, 10 (2014).
[10] B. Gao, *Highly efficient english mooc teaching model based on frontline education analysis*, International Journal of Emerging Technologies in Learning (Online), 14 (2019), p. 138.
[11] Z. Huang, Q. Liu, C. Zhai, Y. Yin, E. Chen, W. Gao, and G. Hu, *Exploring multi-objective exercise recommendations in online education systems*, in Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 2019, pp. 1261–1270.
[12] X. Huiying and M. Qiang, *College english cross-cultural teaching based on cloud computing mooc platform and artificial intelligence*, Journal of Intelligent & Fuzzy Systems, 40 (2021), pp. 7335–7345.
[13] S.-W. Kim, *Moocs in higher education*, Virtual learning, 1 (2016), pp. 1–17.
[14] D. Liu, *Development and application of constructive english mooc system based on rbf algorithm*, in 2023 International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), IEEE, 2023, pp. 1–6.
[15] M. Mellati and M. Khademi, *Mooc-based educational program and interaction in distance education: Long life mode of teaching*, Interactive Learning Environments, 28 (2020), pp. 1022–1035.
[16] M. Pérez-Sanagustín, I. Hilliger, C. Alario-Hoyos, C. D. Kloos, and S. Rayyan, *H-mooc framework: reusing moocs for hybrid education*, Journal of Computing in Higher Education, 29 (2017), pp. 47–64.
[17] H. Sebbaq and N.-e. El Faddouli, *Fine-tuned bert model for large scale and cognitive classification of moocs*, International Review of Research in Open and Distributed Learning, 23 (2022), pp. 170–190.
[18] H. M. Shalatska, *The efficiency of moocs implementation in teaching english for professional purposes*, Information technologies and teaching aids, 66 (2018), pp. 186–196.
[19] K. Wang and C. Zhu, *Mooc-based flipped learning in higher education: students' participation, experience and learning performance*, International Journal of Educational Technology in Higher Education, 16 (2019), pp. 1–18.
[20] R. Zang and L. Wang, *Personalized teaching model of college english based on big data*, in Journal of Physics: Conference Series, vol. 1852, IOP Publishing, 2021, p. 022013.
[21] L.-m. Zhang, *Comprehensive evaluation model of mooc teaching quality of accounting major based on rete algorithm*, in e-Learning, e-Education, and Online Training: 7th EAI International Conference, eLEOT 2021, Xinxiang, China, June 20-21, 2021, Proceedings Part II 7, Springer, 2021, pp. 379–391.
[22] M. Zhang and L. Zhang, *Cross-cultural o2o english teaching based on ai emotion recognition and neural network algorithm*, Journal of Intelligent & Fuzzy Systems, 40 (2021), pp. 7183–7194.
[23] S.-H. Zhong, Q.-B. Zhang, Z.-P. Li, and Y. Liu, *Motivations and challenges in moocs with eastern insights*, International Journal of Information and Education Technology, 6 (2016), p. 954.

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