



## RESEARCH ON LEARNING EFFICIENCY IMPROVEMENT STRATEGIES OF PUBLIC ENGLISH PERSPECTIVE BASED ON ANT COLONY ALGORITHM

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**Abstract.** A ground-breaking smartphone app called EngageLearnPro was created to improve learning efficiency improvement strategies in the context of public English education. With the use of cutting-edge technologies like Ant Colony Optimization (ACO) and Long Short-Term Memory (LSTM), this app creates a dynamic and captivating method of language learning. Intelligent sequence modeling is made possible by the combination of LSTM and allows for customized learning paths that adjust based on the progress of each individual user. On the other hand, ACO maximizes the app’s decision-making processes, improving the overall effectiveness of language learning techniques. The decision to use a mobile app environment for this initiative was made in light of the fact that smartphones are widely used and can provide education to a wider range of people. By utilizing the interactive and user-centric qualities of mobile devices, EngageLearnPro makes sure that learning happens naturally in users’ everyday lives. By combining LSTM and ACO technologies, a customized and adaptive learning experience is provided, accommodating a wide range of learning styles. EngageLearnPro offers an inclusive, cutting-edge, and effective platform with the goal of closing the gap in public English education. We hope to transform language learning by combining the best features of LSTM and ACO into a mobile application that is not only efficient but also fun and available to students of all backgrounds and ability levels.

**Key words:** Learning efficiency improvement, public English education, LSTM, ACO, mobile application

**1. Introduction.** Public English instruction stands out as a crucial catalyst for promoting cultural integration and improving language proficiency in diverse communities [1, 8]. In today’s globally interconnected world, where effective communication cuts across linguistic barriers and becomes a basic prerequisite for both personal and professional growth, the importance of English proficiency is highlighted. Because public education systems are made to serve people from a variety of socioeconomic backgrounds, they are essential to democratizing language opportunities by providing equal access to English language instruction [7]. Nevertheless, there are frequently issues with the effectiveness of language education methods in these systems. Problems like outmoded techniques, unequal access to resources, and the requirement for customized methods continue to impede the best possible achievement of language learning objectives [6]. This emphasizes the urgent need for creative fixes and cutting-edge approaches that can handle the particular difficulties in public English education and guarantee a more welcoming, flexible, and productive language learning environment for people from all backgrounds [16, 4].

Machine learning techniques have become powerful tools for improving learning efficiency in the modern era [2]. These approaches, which include deep learning and reinforcement learning, add a new level of customization to individualized learning by utilizing large datasets and complex algorithms [3]. Neural networks in particular, which are deep learning models, show exceptional capacity for pattern recognition, allowing for personalized learning pathways. By offering continuous feedback mechanisms, personalized content recommendations, and real-time adaptability, these techniques improve language learning efficiency [14]. Additionally, learner behavior can be analyzed using machine learning algorithms, which can be used to pinpoint the advantages and disadvantages of educational interventions. In addition to enhancing learning outcomes, the combination of machine learning and language learning technologies advances educational methodologies, resulting in a dynamic environment tailored to each student’s individual needs [4]. As machine learning develops further, it will play a more and more important role in improving learning efficiency by providing creative answers to complex issues in the field of education.

In this proposed study, we introduce a novel mobile application design called “EngageLearnPro”. A strategic choice based on accessibility, engagement, and inclusivity led to promoting learning efficiency improvement

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strategies in the mobile app market within the Public English perspective. Because they are so common and easily incorporated into daily life, mobile apps provide public education systems with a platform to reach a wide range of users. Due to the widespread use of smartphones, these applications offer a portable and practical medium that guarantees users' lives are seamlessly integrated with language learning. Mobile apps' interactive and user-centered design encourages interaction, which makes learning more dynamic and engaging.

The motivation behind the development of EngageLearnPro, a pioneering smartphone application, stems from a commitment to revolutionize public English education through the integration of advanced technologies. In an era where the accessibility and efficiency of educational tools are paramount, EngageLearnPro emerges as a beacon of innovation, designed to bridge the educational divide and foster an inclusive environment for language learners worldwide. At the core of EngageLearnPro's design philosophy is the utilization of Ant Colony Optimization (ACO) and Long Short-Term Memory (LSTM) algorithms. These cutting-edge technologies synergize to create a dynamic, engaging, and personalized language learning experience. LSTM's intelligent sequence modelling capabilities enable the app to offer customized learning paths that evolve in real-time, adapting to the unique pace and progress of each user. This personalization ensures that learners are not just passive recipients of information but active participants in their educational journey.

With the use of cutting-edge technologies, EngageLearnPro is a novel and creative app that makes learning English more effective and pleasurable. Through Adaptive Learning Paths, the app creates dynamic and personalized learning journeys based on each user's progress. To further increase the effectiveness of language learning, it also makes use of intelligent technologies like Ant Colony Optimization (ACO) for better decision-making and Long Short-Term Memory (LSTM) for intelligent sequence modeling [19, 15, 21]. Real-time feedback mechanisms reinforce language usage, quickly correct errors, and give instant insights into progress [20, 17]. Learning is made interesting and enjoyable by the app's interactive, user-centered design, which includes multimedia and gamification features. Because it makes use of smartphones, EngageLearnPro is widely accessible and aims to make English learning possible for people from a variety of backgrounds. Its inclusive design takes into account different learning styles and skill levels. Through the use of cutting-edge technology, seamless integration into daily life, individualized learning experiences, and a commitment to making learning fun, EngageLearnPro makes learning a language an exciting and positive experience.

The contribution of the paper as follows

1. Proposed the mobile app design of EngageLearnPro, for the promotion of learning efficiency improvement strategies in the mobile app market within the Public English perspective.
2. Novel EngageLearnPro which leverages the techniques of LSTM and ACO, where ACO for better decision-making and LSTM for intelligent sequence modelling.
3. In the context of English learning, a thorough analysis and assessment of the proposed EngageLearnPro are conducted using Chinese colleges.
4. Proposed efficacy was demonstrated with valid experiments

**2. Research Analysis.** [12] The authors of this study discuss the difficulties brought about by the growing size of colleges and universities as well as the growing complexity of teaching duties as a result of an increase in student body and a diversity of course offerings. They suggest a new college scheduling algorithm built on top of an enhanced hybrid optimization strategy based on genetic ant colonies. Improvements like gene infection crossover, fitness-enhanced elimination, and parallel fuzzy adaptive mechanisms are incorporated into the algorithm, which improves convergence, stability, and operating speed. [10] The study investigates the use of an ant colony algorithm-based College English microcurriculum model, utilizing the effectiveness of ant behavior in learning difficult tasks. Teachers have initially resisted using this ant colony algorithm in microcourse design, even though researchers and educators have long used it. This is in spite of the fact that the State supports the use of digital teaching resources. The model's goal is to simplify college students' learning procedures in the context of a foundational course like College English by taking inspiration from the cooperative and algorithmic behavior of ants. [13] Through the use of a bipartite graph model derived from graph theory and clustering analysis on student performance data, this study presents a comprehensive approach to teaching quality evaluation in performing arts courses. The evaluation process is made more robust by applying an ant colony algorithm that takes memory capacity and prior knowledge mastery into account. The results provide theoretical and practical insights for the development of performing arts courses, highlighting the need for

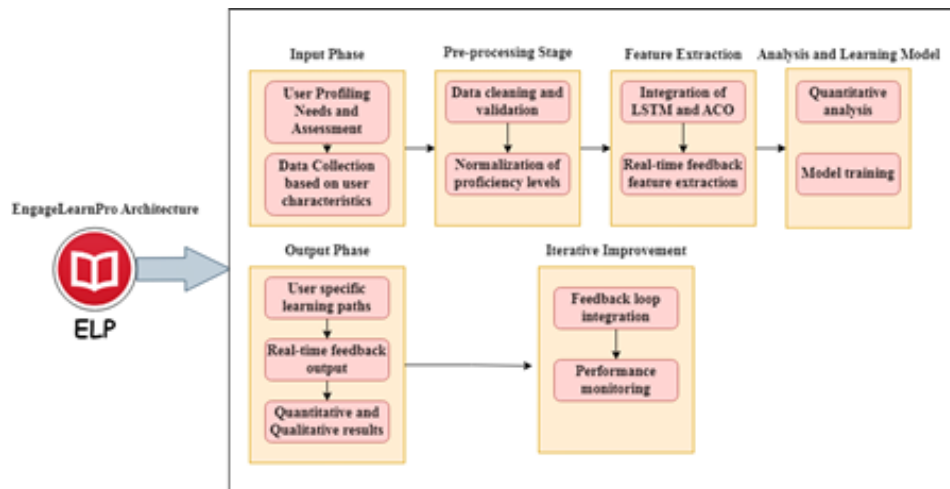


Fig. 3.1: Proposed EngageLearnPro App Design

specialized courses in art performance majors and suggesting targeted training for unqualified teachers based on the PDCA principle. [18] The study offers a multimedia comprehensive framework that integrates big data technology and multimedia teaching modes to address the problem of diverse materials in college English translation. An ant colony optimization algorithm serves as the foundation for the recursive neural network algorithm, which is tested and shown to significantly increase accuracy and retention rate. The suggested method offers a promising way to improve college English translation teaching models by skillfully integrating big data and multimedia into the English teaching process.

**3. Proposed design of EngageLearnPro.** EngageLearnPro's methodology is divided into discrete stages to guarantee a thorough and data-driven approach to individualized language learning. To understand the diverse needs of English language learners, a comprehensive needs assessment and user profiling are carried out during the input phase. This entails gathering necessary input data, such as user demographics, skill levels, and preferred methods of learning. Concurrently, information is acquired regarding language ability, past educational experiences, and personal preferences in order to further customize learning pathways. Pre-processing involves standardizing proficiency level scales to create a uniform scale for consistent analysis, as well as cleaning and verifying the gathered data to assure accuracy. Advanced algorithms for sequence modeling and effective learning strategies, such as LSTM and ACO, are integrated during the feature extraction phase. Features are taken out for real-time feedback systems and adaptive learning pathways, giving useful information about user progress, mistakes, and proper language usage. Quantitative analysis is used to assess EngageLearnPro's efficacy as we move on to the analysis and learning model phase. This entails analyzing the overall impact on language learning and using pre- and post-assessment scores for proficiency level analysis. Then, using the features that were extracted, machine learning models are trained to find patterns in user behavior and results, which helps to improve the learning model. Personalized learning paths with adaptive features based on the unique characteristics and progress of each user are generated as outputs during the output phase. Users receive real-time feedback that emphasizes areas for development and reinforces the proper use of language. To gauge EngageLearnPro's overall impact, both quantitative and qualitative results such as user feedback and proficiency level improvements are provided. The iterative improvement phase, which brings the methodology to a close, establishes a continuous feedback loop to incorporate user feedback into the learning model. By using this data, features are improved iteratively, learning paths are adjusted, and the user experience is enhanced overall. EngageLearnPro is continuously improved to meet changing user needs through data-driven enhancements through ongoing performance monitoring that makes use of usage analytics and user feedback.

**3.1. Proposed EngageLearnPro feature Extraction.** Recent research of [9, 7, 11, 5] examines the state-of-the-art mobile app technology utilized to increase the effectiveness of English language learning. Under the studies, there are lucid discussions. Based on the discussions, we are now going to carry out the suggested EngageLearnPro feature extraction procedure.

EngageLearnPro utilizes cross-platform development frameworks to ensure consistent functionality and user experience across iOS and Android devices. This approach allows the app to maintain high performance and adapt to the specific hardware and software configurations of each platform. The app features an adaptive design that adjusts to different screen sizes and resolutions, ensuring that the learning experience is seamless on a wide range of devices, from high-end smartphones to more basic models with limited processing power. EngageLearnPro incorporates performance optimization techniques such as efficient memory management, data compression, and lazy loading of resources to minimize the app's footprint and ensure smooth operation even on devices with lower hardware capabilities.

**3.1.1. LSTM for intelligent sequence modeling.** Long Short-Term Memory (LSTM) is essential for developing a dynamic and adaptable learning environment when using EngageLearnPro to improve English learning efficiency. Neural network architectures known as long short-term memory (LSTMs) are excellent at understanding and simulating sequential patterns, which makes them especially useful for language learning tasks. By using LSTMs to intelligently model sequences, EngageLearnPro is able to gradually understand and retain the subtleties of English language learning. This implies that the system can make dynamic adjustments to its learning approach based on a user's progress data, guaranteeing an effective and personalized learning trajectory. To maximize each learner's experience, LSTMs, for instance, can dynamically adjust the course material based on an analysis of how the learner interacts with the content and identify difficult areas.

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**Algorithm 1** Intelligence sequence modeling

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- 1: **Input:**  $E$ : Sequence of input, where  $E = \{E_1, E_2, \dots, E_t\}$ ,  $H_{t-1}$ -previous hidden state,  $C_{t-1}$ -Previous Cell state, Weight matrices  $w_{Fo}, w_{In}, w_{Ou}, w_c$ ; Bias Terms  $b_{Fo}, b_{In}, b_{Ou}, b_c$ .
  - 2: **Output:**  $h_t$ -current hidden state,  $c_t$ - current cell state
- Initialization**
- 3: Initialize  $h_o, c_o$  as the initial hidden and cell states.
  - 4: Define weight matrices  $w_{Fo}, w_{In}, w_{Ou}, w_c$
  - 5: Define Bias term  $b_{Fo}, b_{In}, b_{Ou}, b_c$ .
  - 6: for each time step  $t$
  - 7: calculate forget gate  $Fo_t = \sigma(w_{Fo} \cdot [h_{t-1}, E_t] + b_{Fo})$
  - 8: Calculate the input gate  $In_t = \sigma(w_{In} \cdot [h_{t-1}, E_t] + b_{In})$
  - 9: Calculate Candidate cell state  $\bar{c}_t = \tanh(w_c \cdot [h_{t-1}, E_t] + b_c)$
  - 10: Update cell state  $c_t = Fo_t * c_{t-1} + In_t * \bar{c}_t$
  - 11: Calculate output gate  $Ou_t = \sigma(w_{Ou} \cdot [h_{t-1}, E_t] + b_{Ou})$
  - 12: Calculate hidden state  $h_t = Ou_t * \tanh(c_t)$
  - 13: Output the current hidden state  $h_t$  and cell state  $c_t$  at each time step  $t$
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Intelligent sequence modeling is achieved through the use of the (LSTM) process within the algorithmic structure of EngageLearnPro. The algorithm reflects the essential steps in LSTM computation and is expressed as a set of equations. Establishing the initial hidden state  $H_o$  and cell state  $C_o$  as well as defining weight matrices  $w_{Fo}, w_{In}, w_{Ou}, w_c$  and bias terms  $b_{Fo}, b_{In}, b_{Ou}, b_c$  are all part of initialization. The algorithm determines the forget gate  $Fo_t$ , input gate  $In_t$ , and candidate cell state  $\bar{c}_t$  for each time step ( $t$ ). The sigmoid ( $\sigma$ ) and hyperbolic tangent  $\tanh$  functions are used in these calculations. Based on the input and forget gates, the cell state is updated. After determining the output gate  $Ou_t$ , the hidden state's current value  $h_t$  is calculated by multiplying the product of the output gate and the hyperbolic tangent of the updated cell state. The current hidden state  $h_t$  and cell state  $c_t$  are produced as the result of repeating this process at each time step. EngageLearnPro's LSTM algorithm allows it to dynamically modify its learning approach, capturing and remembering crucial data for efficient English learning.

**3.1.2. ACO based Decision Making.** ACO is a useful algorithmic tool to improve learning efficiency in the context of EngageLearnPro. The application of ACO, which is used to optimize decision-making processes

within the platform, is inspired by the foraging behavior of ants. The ACO in EngageLearnPro assists in identifying the most efficient learning strategies, much like ants leave pheromone trails to communicate and direct others toward the best paths. It functions by modeling the cooperative investigation of multiple learning trajectories, where each trajectory stands for a possible learning decision. Based on user interactions, the algorithm assesses the effectiveness of various paths and gradually improves them to accommodate unique learning styles. EngageLearnPro's ability to integrate ACO allows it to dynamically modify its approach, guaranteeing that the learning environment is efficient, adaptable, and customized to users' changing needs and preferences. The ACO algorithm is adapted from the study [19].

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**Algorithm 2** ACO based Decision Making
 

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1:  $global\_best \leftarrow$  Build initial solution
2: Calculate pheromone trails limits:  $\tau_{min}$  and  $\tau_{max}$ 
3: Set pheromone trails values to  $\tau_{max}$ 
4:  $source\_solution \leftarrow global\_best$ 
5: for  $i \leftarrow 1$  to  $\#iterations$  do
6: for  $j \leftarrow 0$  to  $\#ants - 1$  do
7:  $route_{ant(j)}[0] \leftarrow u\{0, n - 1\}$  // Select first node randomly
8:  $min\_new\_edges \leftarrow calc\_num\_new\_edges()$ 
9:  $new\_edges \leftarrow 0$ 
10:  $K \leftarrow 1$ 
11: while  $K < n$  do
12:  $u \leftarrow route_{ant(j)}[K - 1]$ 
13:  $v \leftarrow select\_next\_node\ u \leftarrow route_{ant(j)}$ 
14:  $route_{ant(j)}[K] \leftarrow v$ 
15:  $K \leftarrow K + 1$ 
16: if  $(u, v) \notin source\_solution$  then
17:  $new\_edges \leftarrow new\_edges + 1$ 
18: Add  $v$  to  $LS\_checklist$ 
19: if  $new\_edges \geq min\_new\_edges$  then
20:  $u \leftarrow succ(source\_solution, v)$  // ...forward
21: while  $u \notin route_{ant(j)}$  do
22:  $route_{ant(j)}[K] \leftarrow u$ 
23:  $u \leftarrow succ(source\_solution, u)$ 
24:  $K \leftarrow K + 1$ 
25:  $u \leftarrow pred(source\_solution, u)$  // ...or backward
26: while  $u \notin route_{ant(j)}$  do
27:  $route_{ant(j)}[k] \leftarrow u$ 
28:  $u \leftarrow pred(source\_solution, u)$ 
29:  $k \leftarrow k + 1$ 
30:  $local\_search(route_{ant(j)}, LS\_checklist)$ 
31:  $iter\_best \leftarrow select\ shortest\ route_{ant(0)} \dots, route_{ant(\#ants-1)}$ 
32: if  $global\_best = \emptyset$  or  $iter\_best$  is shorter than  $global\_best$  then
33:  $global\_best \leftarrow iter\_best$ 
34: Update pheromone trails limits  $\tau_{min}$  and  $\tau_{max}$  using  $global\_best$ 
35: Evaporate pheromone according to  $\rho$  parameter
36:  $source\_solution \leftarrow Choose\ between\ global\_best\ and\ iter\_best$ 
37: Deposit pheromon

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▷ Complete  $route_{ant(j)}$  following source solution

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With its foundation in ACO, the EngageLearnPro decision-making algorithm prioritizes improving the learning paths available on the platform. The first step in the process is to initialize a global best solution, which serves as the foundation for the lessons that follow. Pheromone trails are created with predetermined boundaries that are initially set at maximum values, reflecting the allure of different learning paths. Counting the number of new edges in the learning route, individual ants representing different learning paths navigate

randomly chosen nodes over the course of iterations. The algorithm improves the flexibility and variety of learning paths by updating the route by taking into account nodes that are not present in the source solution. Interestingly, the algorithm uses local search to improve the efficiency of learning routes. This leads to a global update where the global best solution is adjusted based on its emptiness or the superiority of the iteration's best route. The iteration's best route, representing the shortest path among the ant population, is identified. Then, based on this global best solution, pheromone trail limits are updated, impacting the appeal of particular routes. Pheromone deposition and evaporation are steps that follow. Pheromone deposition is influenced by the decision to select between the global best and the iteration's best solution, which shapes the learning paths. The goal of this iterative and adaptive process is to continuously improve the learning paths in EngageLearnPro by dynamically adapting to changing user preferences and needs. In the end, the algorithm aims to maximize the educational process by creating more efficient and interesting avenues for language learning.

Providing in-app surveys, direct feedback forms, social media interactions, and email communications. This variety ensures a broad spectrum of insights, from usability issues to suggestions for new features. Collected feedback is categorized into various segments such as app performance, user interface (UI) design, learning content quality, and algorithmic suggestions. Advanced data analysis techniques, including natural language processing (NLP), are employed to sift through the feedback, identifying common themes, user needs, and potential areas for enhancement.

#### 4. Tests and Validation.

**4.1. Simulation Plan.** This section examines the effectiveness of EngageLearnPro using a simulation of English classroom instruction; the dataset's original source is taken from the study [22].

This simulation plan's goal is to thoroughly assess how the EngageLearnPro Mobile App affects students' learning outcomes and levels of interest in the context of teaching English in a classroom. There are two classes of 61 business English students participating in the experimental design. While the Control Class uses conventional teaching techniques, the Experimental Class makes use of the EngageLearnPro mobile app. In order to determine the starting proficiency level of students in both classes, pre-experiment tests are administered, and information on smartphone ownership and mobile network status is gathered. During the implementation stage, instructors in the Experimental Class use the EngageLearnPro Mobile App in their English lessons, while the Control Class follows traditional teaching strategies that place limitations on the use of mobile devices. The main goals of observation techniques are to evaluate student participation, classroom performance, and EngageLearnPro's real-time interactivity. Learning outcomes are measured using post-experiment tests administered at the end of a semester. Improvement is assessed by comparing the test results with pre-experiment data. Evaluation metrics encompass comparing test results from before and after the experiment, gauging student involvement and interaction, and analyzing the general dynamics and efficacy of the classroom. Improved learning outcomes in the Experimental Class, higher interest and participation attributable to EngageLearnPro's interactive features, and observational data offering insights into the effect on real-time interactivity are among the anticipated results.

#### 4.2. Evaluation Criteria.

**4.2.1. Comparison before testing.** Figure 4.1 presented performance metrics for two different classes: the Experimental class and the Control class that cover a range of performance categories. These categories include the number of students who scored below 60, the number of students who scored between 60 and 80, the number of students who scored between 80 and 100, and the average score attained. Each metric provides information on the performance of the classes as well as the distribution of proficiency, engagement levels, and overall academic achievement of the students. This extensive dataset makes it possible to assess the educational dynamics of the classes in a more nuanced way, offering insights into things like academic proficiency, student motivation, and the distribution of scores across various performance thresholds. The scores are collected before testing the proposed app of EngageLearnPro.

#### 4.3. Post Testing Results.

**4.3.1. Experimental class test results using EngageLearnPro App.** The EngageLearnPro app's performance for the Experimental class are shown in Figure 4.2 across various performance categories. Of the

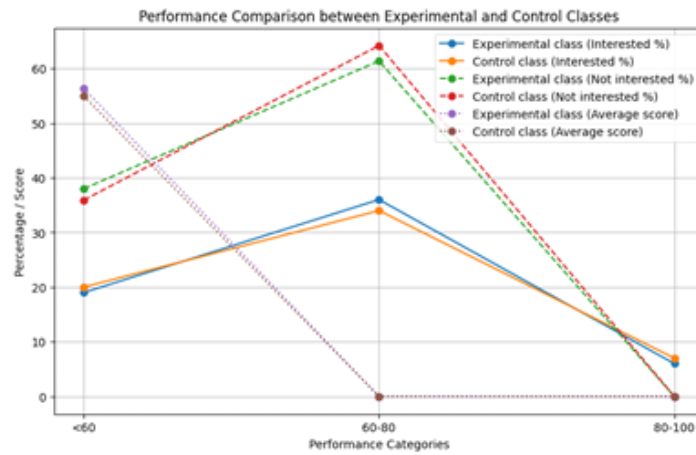


Fig. 4.1: Comparison results before testing

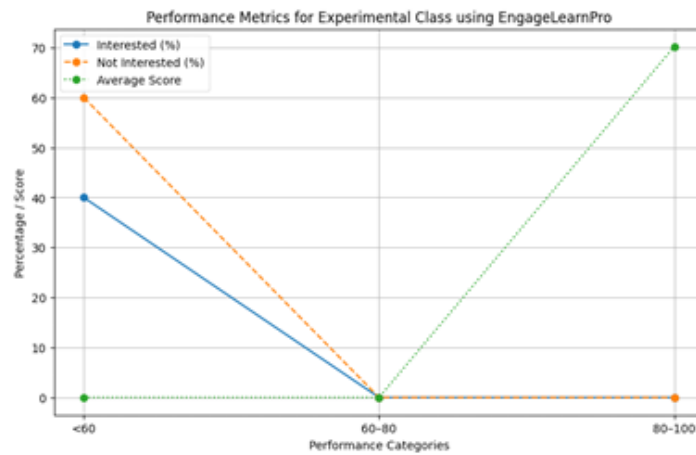


Fig. 4.2: Experimental using EngageLearnPro App

students in the Experimental class, 40% show an interest in learning, according to the 'Interested Percentage' line; the remaining 60% do not show any interest. The 'Average Score' line indicates a high average score of 70.2%, indicating a positive correlation between academic performance and the EngageLearnPro app. This pattern shows that students are distributed evenly across proficiency levels, demonstrating the effectiveness of the app in capturing users' attention and creating a positive learning environment.

**4.3.2. Control Class test results (Without EngageLearnPro App).** The results of the Control Class show that it can be difficult to engage a sizable portion of students when employing traditional teaching methods, with 33.50% of students expressing interest and 65.50% not interested was shown in Figure 4.3. The marginally lower percentage of interested students than in the Experimental Class may point to the inadequacies in traditional teaching strategies for maintaining high interest. The Experimental Class's average score of 55.8 indicates that the Control Class attains similar academic results. The aforementioned data underscores the constraints of conventional pedagogical approaches in sustaining widespread student interest and involvement. The outcomes of the Control Class highlight the potential of the EngageLearnPro app, which can address issues with traditional teaching methods while producing similar academic results thanks to its interactive

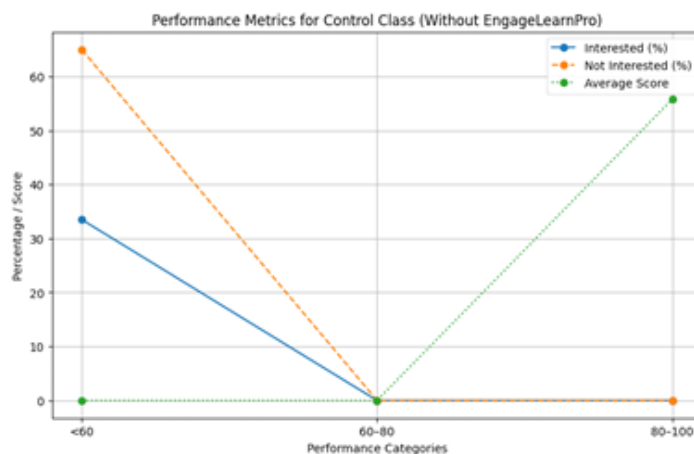


Fig. 4.3: Control Class results without using EngageLearnPro App

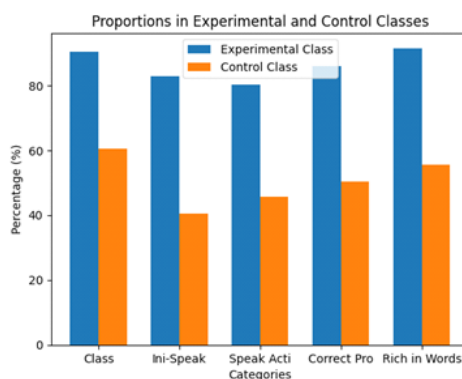


Fig. 4.4: Overall Performance indications based on Experimental and Control Class of EngageLearnPro

and adaptive features. This demonstrates how effective EngageLearnPro is at fostering a more dynamic and captivating learning environment in the context of teaching English to the general public.

**4.3.3. Performance Analysis.** The effectiveness of the EngageLearnPro app is demonstrated by the Figure 4.4, which compares and contrasts important language learning categories between the Experimental and Control classes. The Experimental class shows a significantly higher percentage (82.74%) in the "Initiative to Speak" category than the Control class (40.34%), suggesting that the app encourages students to be proactive in their verbal communication. In similar fashion, the Experimental class does better than the Control class in areas like "Rich in Words" (91.46% vs. 55.47%), "Speak Actively" (80.25% vs. 45.77%), and "Correct Pronunciation" (85.89% vs. 50.22%). These differences highlight how the app promotes active engagement, improves pronunciation, and enhances vocabulary acquisition. The increasing percentages in these language proficiency categories show that EngageLearnPro is more effective than traditional teaching methods at creating a dynamic and engaging learning environment. The app's beneficial effects on various facets of language learning in the Experimental class are clearly depicted in Figure 4.4, which supports the idea that it can improve language learning outcomes in general.

**5. Conclusion.** In conclusion, the research on the effectiveness of the EngageLearnPro app for language learning provides strong proof of its beneficial effects on student proficiency and engagement when compared



to conventional teaching techniques. The app's success in fostering a lively and engaging learning environment was demonstrated by the Experimental class's consistent displays of increased interest, active participation, and improved language skills. To guarantee generalizability, a larger dataset and a variety of learner groups are nevertheless required. Furthermore, the study concentrated on immediate results; a longitudinal approach would reveal information about the app's long-term effects. Subsequent investigations may examine the incorporation of increasingly sophisticated technologies, evaluate the app's flexibility in various educational settings, and examine particular aspects that enhance its effectiveness. Notwithstanding these drawbacks, the study's encouraging results imply that EngageLearnPro has potential as a cutting-edge tool for improving language learning encounters, opening the door for more developments in technology-driven education.

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