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# Adaptive Learning Optimization for English Proficiency Using PSO

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Abstract. *This study explores the effectiveness of a Particle Swarm Optimization-based (PSSO) approach for optimizing study time allocation across the four essential English skills: listening, speaking, reading, and writing. Conducted over a six-month period from July to December 2023, the study compared a PSSO-optimized group, whose study times were adjusted based on skill proficiency assessments after each cycle, with a control group that adhered to an even, static distribution of time. The findings indicate a clear advantage for the PSSO group, whose improvement rates across the cycles averaged 5.2%, 9.9%, and 15.8%, showing progressive increases after each adjustment, in contrast to the control group's more modest gains of 2.8%, 5.2%, and 7.8% over the same intervals. This experiment highlights that a dynamic, proficiency-responsive allocation of study time can yield substantial enhancements in overall language proficiency compared to static methods, supporting the adoption of adaptive learning models to optimize student outcomes.*
**Keywords:** Adaptive learning; English proficiency; Skill optimization; Particle Swarm Optimization; Study time allocation

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1. **Introduction.** The effective acquisition of English language skills remains a priority for educators and institutions globally, particularly as English maintains its role as a dominant international language. However, conventional approaches to teaching English often overlook the varied learning needs and progress rates of students. These methods generally allocate equal study time to listening, speaking, reading, and writing skills, which may not yield optimal language proficiency for every learner. This issue has led to

the exploration of adaptive learning strategies that tailor study schedules to the individual learner's profile[1, 2].

Recently, optimization algorithms have become valuable tools in educational technology. Among them, Particle Swarm Optimization (PSO) has gained attention for its simplicity, efficiency, and ability to address complex optimization problems. Inspired by natural behaviors such as bird flocking, PSO models a group of particles exploring a solution space. Each particle updates its position based on its own experience and that of neighboring particles, allowing the group to move toward an optimal solution [3, 4]. PSO has been applied across various domains, including robotics and healthcare, and more recently in education to optimize learning paths and resource distribution [5].

In language learning, PSO provides a novel approach to optimizing study time allocation across different skills. Research shows that the rate of improvement in listening, speaking, reading, and writing differs due to factors like cognitive load, prior knowledge, and learning strategies [6]. By integrating PSO with learning models, study time can be adjusted dynamically to maximize overall proficiency.

The Learning Curve model, widely used in skill acquisition, serves as the foundation for predicting future performance based on past learning outcomes. Studies indicate that language skill progression often follows a non-linear trajectory, with rapid initial gains followed by slower improvements as proficiency increases [7, 8]. Incorporating this model into an optimization framework enables more accurate predictions of the benefits learners receive from additional practice in each skill. For instance, listening and reading generally show quicker early improvements, while speaking and writing require extended practice [9]. Thus, an adaptive approach that adjusts time allocation based on these patterns is crucial for maximizing overall language competence.

This paper introduces an innovative model for English teaching, combining PSO with adaptive learning principles. The primary contribution of this research is the use of PSO to generate personalized study plans that account for variations in learning rates across the four skills. This approach aims to optimize study time distribution to achieve the best overall performance. The research builds on prior educational optimization work [10, 11], focusing specifically on second language acquisition (SLA) and incorporating insights into the learning dynamics of specific skills

## 2. **Literature Review.**

### 2.1. **Learning Curve in Language Acquisition.**

The Learning Curve has been widely applied to model skill acquisition across various domains, including second language learning. This model is used to describe how learners improve their performance over time through repeated practice. In second language acquisition (SLA), the Learning Curve illustrates the non-linear progression of learners, where early stages show rapid improvements that gradually taper off as proficiency increases. This phenomenon is linked to the cognitive load required to master new linguistic structures and vocabulary, as well as the diminishing returns in performance as learners approach their potential limit in language competence [12,13]. Studies in SLA have confirmed that learning curves are not uniform across the four core language skills—listening, speaking, reading, and writing. For example, receptive skills such as listening and reading tend to exhibit faster initial improvements due to the passive nature of these skills, which rely more on comprehension than active production [14]. In contrast, productive skills like speaking and writing often show slower progress, as they require greater cognitive effort for learners to actively produce language [15,16].

Research has also demonstrated that the Learning Curve model is applicable not only to individual learners but also to groups, with similar learning patterns observed across diverse language learners. This supports the idea that language acquisition follows predictable stages, though the rate of learning can vary depending on factors such as exposure, motivation, and learning strategies [17]. Additionally, variations in the steepness of the learning curve are often attributed to external influences like instructional quality and feedback frequency, which significantly impact how quickly learners progress [18]. In second language research, the Learning Curve is frequently used to predict learners' future performance based on their past progress, aiding educators in tailoring instruction to better meet individual learning needs. As such, it provides a critical tool in designing more efficient language programs that adjust teaching methods and resources according to the learner's current stage of acquisition.

2.2. **Optimization in Education.** Optimization algorithms have been extensively applied in educational contexts to enhance learning efficiency, allocate resources, and improve instructional strategies. Among these, Particle Swarm Optimization (PSO) has shown particular promise for optimizing various aspects of education due to its simplicity and adaptability. PSO, a population-based algorithm, works by iteratively improving candidate solutions based on individual and collective experience, making it well-suited to solving complex educational problems such as curriculum design and personalized learning [4].

One of the key areas where PSO has been utilized is in optimizing learning paths for individual students. By analyzing the student's performance and progress, PSO can adjust study schedules and resource allocation dynamically. This enables students to focus on areas where they need improvement, leading to more efficient learning outcomes [5]. PSO has also been successfully implemented in curriculum optimization, where it ensures that the sequence and structure of topics are aligned with student learning patterns, minimizing redundancy and cognitive overload.

In e-learning systems, PSO has been employed to manage the allocation of digital resources and optimize learning activities. These systems utilize PSO to adapt the content and difficulty level in real-time, ensuring that students remain engaged and challenged according to their current abilities. Furthermore, PSO has been applied to optimize course scheduling and resource allocation, ensuring that institutional resources such as classrooms and instructors are efficiently used to meet the needs of both students and educators [19].

Recently, new optimization algorithms and enhancements have emerged, demonstrating strong capabilities in solving complex problems. Wu et al. [20] proposed a spectral convolutional neural network model based on adaptive Fick's Law for hyperspectral image classification, showcasing how adaptive mechanisms can enhance classification accuracy in high-dimensional spaces. Additionally, researchers have explored chaotic-based optimization strategies to improve algorithmic convergence and robustness. For example, the Chaotic-Based Tumbleweed Optimization Algorithm (CTOA) has been shown to improve performance in complex search spaces [21]. Similarly, the CPPE algorithm integrates chaotic maps to refine phasmatodea population evolution, enhancing global optimization capabilities [22]. These advancements highlight the ongoing evolution of optimization techniques, underscoring the potential of hybrid and adaptive approaches such as the PSSO framework in educational applications.

These applications demonstrate the potential of optimization algorithms like PSO to transform educational processes by personalizing learning, improving resource management, and enhancing the overall efficiency of educational systems.

2.3. **Relevant Studies in Language Acquisition.** Numerous studies have examined the relationship between study time allocation and skill development in language acquisition. Research consistently highlights that an effective distribution of study time across different language skills—listening, speaking, reading, and writing—can significantly influence a learner's overall proficiency. However, the optimal allocation of time often depends on individual learner characteristics, skill difficulty, and external factors such as instructional methods.

One of the foundational studies by Lightbown and Spada emphasizes that learners who spend more time on structured practice in receptive skills (listening and reading) tend to show faster initial improvement compared to those who allocate equal time to productive skills (speaking and writing) [2]. This pattern aligns with the cognitive load theory, which posits that receptive tasks place a lower cognitive burden on learners, allowing for quicker gains in comprehension.

Recent studies have adopted a more granular approach, investigating how adaptive learning systems can optimize time allocation based on a learner's real-time performance. In this context, dynamic study time allocation has proven effective in maximizing gains in complex skills like writing and speaking. For example, Derwing and Munro's research on pronunciation instruction found that learners who concentrated more time on productive skills, particularly speaking, showed measurable improvements in accent reduction and fluency over time [7]. Similarly, studies using adaptive learning technologies have demonstrated the importance of adjusting study time dynamically, ensuring that learners are not over-investing in areas they have already mastered [19].

Furthermore, PSO and other optimization algorithms have been applied to find the optimal time distribution for language learners. These studies utilize data-driven approaches to tailor study schedules to individual learners, maximizing their overall proficiency across all four skills. Research conducted by Shirvan et al. showed that learners who used adaptive systems driven by PSO outperformed those who followed static study schedules, particularly in developing speaking and writing proficiency [18].

Studies also highlight that the order and intensity of practice matter. A longitudinal study by Li et al. suggested that learners benefit more from intensive bursts of practice in productive skills, interspersed with consistent but lower-intensity practice in receptive skills [16]. This approach helps maintain engagement and reduces cognitive overload, which can occur if too much time is spent on any single skill at once.

While previous research has explored adaptive learning and optimization-based approaches in educational settings, significant gaps remain. Existing studies primarily focus on static or semi-dynamic learning path optimizations, where adjustments to study schedules are either predetermined or updated at fixed intervals, rather than continuously adapting in response to real-time learning progress. Additionally, many approaches distribute study time based on general heuristics rather than individualized performance tracking, which can limit the effectiveness of personalized learning.

Another key limitation is that prior research often emphasizes skill development in isolation rather than optimizing time allocation across multiple interdependent language skills. Listening, speaking, reading, and writing progress at different rates, and a rigid time allocation strategy does not account for these variations. Furthermore, while prior studies have examined adaptive learning techniques, they typically lack real-time optimization mechanisms that dynamically adjust study time based on ongoing proficiency assessments. Without such adjustments, learners may spend excessive time on skills they have already mastered while neglecting weaker areas.

This study aims to bridge these gaps by introducing a PSSO framework that continuously optimizes study time allocation in response to individual learning trajectories.

Unlike traditional methods, this approach allows for real-time adjustments, ensuring that learners receive targeted time investments based on their evolving proficiency in each language skill. By integrating PSSO with the Learning Curve model, this research contributes to the development of a fully adaptive and efficiency-driven framework for second language acquisition.

## 3. Methodology.

3.1. **System Design.** The system design focuses on optimizing study time allocation across language skills by leveraging the Learning Curve Model and Particle Swarm Optimization (PSO), as depicted in Figure 1. The initial phase involves gathering and analyzing data about learners, including baseline performance in key language skills such as listening, speaking, reading, and writing. This data collection is fundamental for establishing the starting point for each learner, which later informs how the model will be configured. Through comprehensive analysis, learners' unique profiles are developed, helping to accurately predict their learning trajectories.

Once the initial data is analyzed, the next step is estimating key parameters in the Learning Curve Model. This model helps capture the non-linear progression typically seen in language acquisition, where learners show rapid initial improvements followed by a gradual slowdown. By estimating these parameters, the model can provide individualized predictions of future proficiency, helping to create a more accurate foundation for time optimization. The Learning Curve plays a crucial role in guiding the optimization process by ensuring time allocations reflect each learner's potential improvement across the four skills.

Following the parameter estimation, the Learning Curve Model is integrated into the PSO framework. PSO acts as the core optimization algorithm, iterating over various time allocation strategies and adjusting these allocations based on feedback from the learning process. Each particle in the PSO represents a potential time distribution for the four language skills, and its effectiveness is assessed through the Learning Curve predictions. As the particles evolve, the system refines these allocations, ultimately arriving at a configuration that maximizes the learner's overall proficiency.

In the next step, the optimized time allocation derived from the PSO is applied to the learners' study schedules. This process is not static; the allocations are continuously updated based on the learners' ongoing performance. This real-time adjustment ensures that learners focus on the areas where they need the most improvement while maintaining balance across all skills. Data is collected once again after the optimized schedules are applied, and the learners' progress is evaluated against the baseline measurements. This step involves both quantitative assessments, such as post-test scores, and qualitative feedback from learners about their experience. By comparing these results, the system can determine the impact of the PSO-optimized time allocations. Finally, the results are consolidated, and conclusions are drawn regarding the overall effectiveness of the system. This final stage involves reporting on the success of the optimization and providing insights into potential refinements for future iterations.

3.2. **Learning Curves.** Learning Curves are graphical representations that depict the relationship between learning effort, such as time or practice, and performance improvement. In the context of language acquisition, Learning Curves demonstrate how learners initially make rapid progress, which slows as they approach mastery.This phenomenon of diminishing returns is critical for understanding how learning progresses over time. In educational settings, Learning Curves help educators adjust teaching strategies to optimize study time and maximize student progress. They are particularly valuable in language

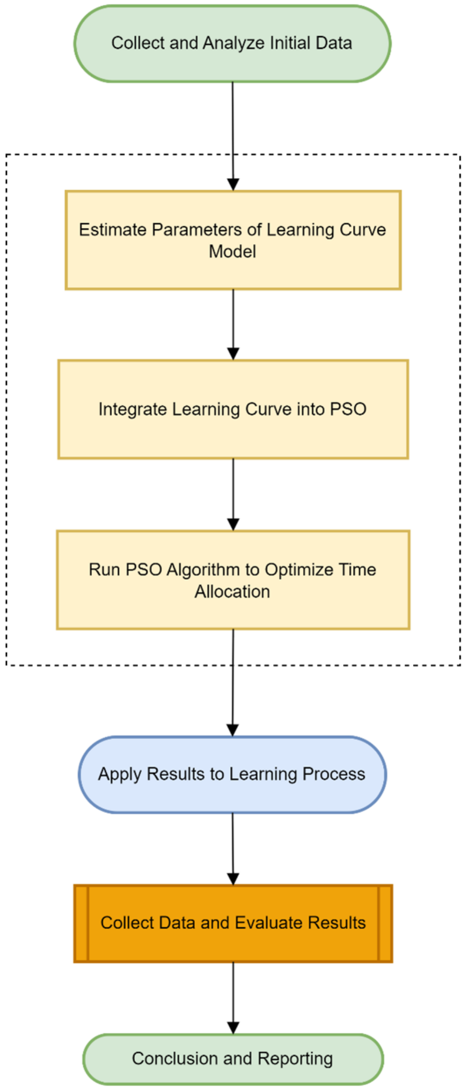



FIGURE 1. Workflow in systems

learning, where different skills like listening, speaking, reading, and writing may have varying rates of improvement. Incorporating Learning Curves in research allows for the modeling of individual learning behaviors and aids in personalizing time allocation for learners, ensuring more efficient learning processes.

In this research, the exponential model has been selected as the most appropriate for representing the Learning Curves due to its ability to capture diminishing returns. The formula used in this model expresses performance as a function of both time and learning rate, reflecting how performance improves quickly at first and then plateaus. The mathematical formulation is given by:

$$P_i(t_i) = P_0(1 - e^{-\alpha_i t_i}) \tag{1}$$

where $P_i(t_i)$ represents the performance in skill $i$ at time $t_i$, $P_0$ is the maximum potential performance, $\alpha_i$ is the learning rate, and $t_i$ is the time allocated to skill $i$. As demonstrated in Figure 2, different values of $\alpha_i$ reflect varying rates of improvement. A higher learning rate leads to quicker mastery, while a lower rate indicates slower progress. The figure shows that learners with a higher $\alpha_i$ achieve faster performance gains compared to those with lower values, highlighting how the learning rate influences overall skill development.

This model is essential for accurately predicting student progress and optimizing time allocation to maximize learning outcomes.

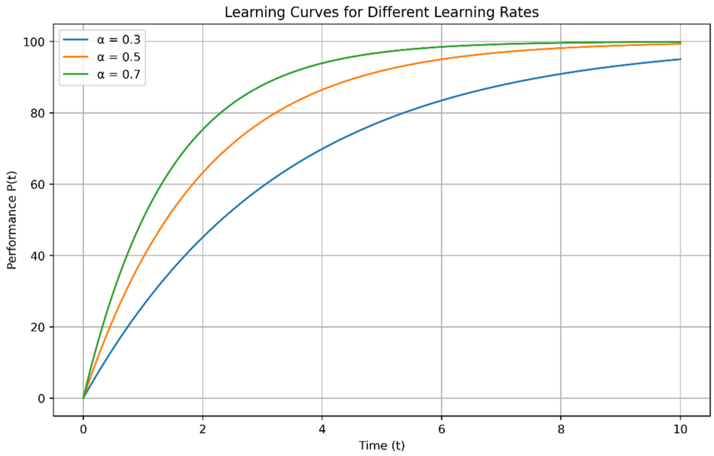



FIGURE 2. Learning Curves

3.3. **PSSO Framework for Time Allocation Optimization in Language Learning.**

PSO is an algorithm inspired by the natural movement of birds in a flock. Each individual, or "particle," moves within a search space, adjusting its position based on its own experience and the best solutions found by others. Through repeated iterations, the group collectively finds an optimal solution. Unlike rule-based learning systems, which rely on fixed study schedules, PSO continuously adapts study time allocation based on real-time performance, ensuring that learners focus on the areas where they need the most improvement.

The choice of PSO for this study is motivated by its ability to efficiently handle multi-dimensional optimization problems with dynamic variables. Traditional optimization methods, such as genetic algorithms or reinforcement learning, often require extensive computational resources and complex parameter tuning. PSO, in contrast, provides a balance between simplicity and efficiency, making it particularly well-suited for applications where adaptive decision-making is required in real time. Additionally, prior research has demonstrated PSO's effectiveness in education-related optimization tasks, including curriculum scheduling and learning path personalization, further supporting its suitability for study time allocation. Building upon these advantages, we integrate PSO into a self-adaptive framework to further enhance its optimization capabilities in educational applications. By incorporating real-time adjustments based on student performance, this approach ensures that study time is allocated dynamically to maximize proficiency gains. This leads to the development of the *Particle Swarm Optimization combined with Self-adaptive Swarm Optimization (PSSO)* framework, specifically designed to optimize study time distribution across the four key language skills—listening, speaking, reading, and writing.

Particle Swarm Optimization combined with Self-adaptive Swarm Optimization (PSSO) framework is utilized to optimize the allocation of study time across the four key language skills—listening, speaking, reading, and writing. Each particle in the swarm represents a potential solution for time allocation. Let $n_{nn}$ denote the total number of particles in the swarm, where each particle $x_i = [t_{i,1}, t_{i,2}, t_{i,3}, t_{i,4}]$ represents the time allocated to the four language skills. The total time allocated for each particle is constrained by

$$\sum_{j=1}^{4} t_{i,j} = T_{\text{total}} \tag{2}$$

where $T_{\text{total}}$ represents the total available study time, such as 10 hours per week. Particles are initialized randomly within the solution space while ensuring that the total time constraint is met. The fitness of each particle is evaluated using the *Learning Curve Model*, which predicts the learner's performance over time in each skill. For each skill $j$, the performance is modeled as:

$$P_j(t_j) = P_{0j}(1 - e^{-\alpha_j t_j}) \tag{3}$$

where $P_j(t_j)$ is the predicted performance in skill $j$ after $t_j$ hours of practice, $P_{0j}$ represents the maximum possible performance in skill $j$, and $\alpha_j$ is the learning rate, indicating the speed at which the learner improves in skill $j$. The total fitness $F_i$ of each particle is calculated by summing the predicted performances across all skills:

$$F_i = \sum_{j=1}^{4} P_j(t_{i,j}) \tag{4}$$

with the goal of maximizing $F_i$, thus finding the optimal allocation of time across the four skills.

The system's effectiveness lies in its iterative refinement of study time allocation based on real-time proficiency tracking. Initially, students' baseline proficiency is assessed, and time is distributed according to the Learning Curve model. After each learning cycle, the system evaluates individual progress and dynamically reallocates time to focus on weaker skills. For instance, if a student demonstrates rapid improvement in reading but slower progress in speaking, the system shifts additional time to speaking in the next cycle. Over successive cycles, this targeted allocation ensures that learning efforts are directed where they are most needed, leading to more efficient skill development.

For example, suppose a student begins with proficiency scores of 75 in listening, 65 in reading, 50 in speaking, and 40 in writing. In the first cycle, the PSSO framework allocates more study time to speaking and writing, recognizing them as the weaker skills. After one cycle, the student's writing improves significantly, while speaking remains a challenge. The system then reallocates additional time to speaking in the next cycle, ensuring that the student receives targeted support where it is most needed. This process continues iteratively, leading to balanced proficiency improvements over time.

The velocity update of each particle is based on both its personal best position $P_i^{best}$ and the global best position $g_j^{best}$ found by the swarm. The velocity for each skill $j$ is updated using the formula:

$$v_{i,j}(t+1) = \omega v_{i,j}(t) + c_1 r_1 (P_{i,j}^{best} - x_{i,j}(t)) + c_2 r_2 (g_j^{best} - x_{i,j}(t)) \tag{5}$$

where $v_{i,j}(t)$ represents the velocity of particle $i$ at time $t$ for skill $j$, $\omega$ is the inertia weight that controls the influence of the previous velocity, $c_1$ and $c_2$ are cognitive and social acceleration coefficients, and $r_1, r_2$ are random values uniformly distributed between [0,1].

The position of each particle is updated as:

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \tag{6}$$

while ensuring that the total time allocation remains constrained by: $\sum_{j=1}^{4} x_{i,j}(t+1) = T_{total}$. To enhance the model's adaptability, a *self-adaptive mechanism* is employed to adjust the learning rate $\alpha_j$ for each skill based on the learner's actual progress. If the actual performance $P_j^{actual}(t_j)$ exceeds the predicted performance $P_j^{predicted}(t_j)$, the learning rate $\alpha_j$ is decreased to reflect faster-than-expected progress. Conversely, if actual performance lags behind predictions, the learning rate is increased to allocate more time to that skill. This update is governed by the formula:

$$\alpha_j^{new} = \alpha_j \cdot \left(1 + \frac{P_j^{actual}(t_j) - P_j^{predicted}(t_j)}{P_j^{predicted}(t_j)}\right) \tag{7}$$

This mechanism allows the model to dynamically reallocate time based on real-time feedback, ensuring that the learner focuses on the skills requiring the most improvement. The algorithm continues iterating until convergence is reached, when the global best fitness $g_j^{best}$ stabilizes, indicating that the optimal time allocation has been found. The final solution $x^* = [t_1^*, t_2^*, t_3^*, t_4^*]$ represents the optimal distribution of study time across the four language skills.

To further analyze the efficiency of the allocation, the *learning efficiency* $E_j$ for each skill is defined as:

$$E_j = \frac{P_j(t_j) - P_j(0)}{t_j} \tag{8}$$

which measures how effectively time is being used to improve performance in skill $j$. The overall learning efficiency is calculated as:

$$E_{total} = \frac{\sum_{j=1}^{4} P_j(t_j) - \sum_{j=1}^{4} P_j(0)}{T_{total}} \tag{9}$$

providing a holistic view of how well the allocated time is used to improve overall language proficiency. This efficiency metric, combined with the adaptive time allocation mechanism, ensures that the PSSO framework maximizes both learning outcomes and time utilization across all skills. The dynamics of the PSSO framework for optimizing study time allocation across language skills are demonstrated visually in Figure 3.

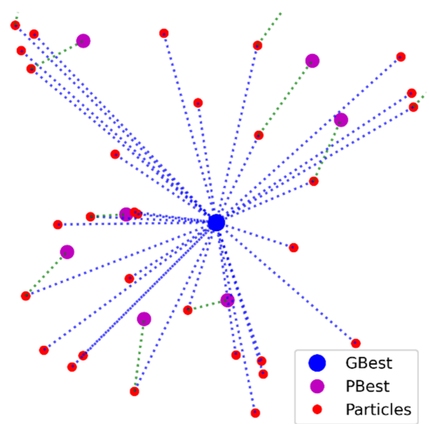



FIGURE 3. Illustration of the PSSO

## 4. **Experiment Design.**

### 4.1. **Experiment Setup.**
The experiment was conducted on a high-performance system equipped with an Intel Xeon 32-core processor, 64GB RAM, and NVIDIA GeForce RTX 3090 GPU to leverage parallel processing. The setup used Python 3.9.7, along with NumPy 1.21.2 for efficient numerical computations and Matplotlib 3.4.3 for visualization.

The study involved 102 undergraduate students enrolled in an English language proficiency course at a university. Participants had diverse linguistic backgrounds, with varying levels of prior English exposure. To ensure homogeneity in initial proficiency, students were required to complete a standardized placement test covering listening, speaking, reading, and writing skills. Based on their scores, participants were categorized into three proficiency levels: beginner, intermediate, and advanced. For group selection, students were randomly assigned to either the control group (fixed time allocation) or the experimental group (adaptive PSSO-based allocation) while maintaining an equal distribution of proficiency levels across both groups. This randomization ensured that differences in initial skill levels did not bias the effectiveness of the adaptive learning model. Furthermore, demographic factors such as age and prior English learning experience were analyzed to confirm that both groups were comparable in background characteristics.

The core objective of this experiment was to personalize the study plans by integrating student preferences into the optimization process. Student aspirations and motivations were collected through a survey designed to assess:

- Skills the students want to improve the most.
- Skills the students feel most confident in.
- Motivation and interest levels for each skill, rated on a scale from 1 to 5.

The survey data was then transformed into two key parameters for the PSSO model:

Priority Weights ($W_i$): These weights were assigned to each skill based on the student's preference to improve or not improve that skill. If a student indicated a strong desire to improve a particular skill, that skill was given a higher weight, reflecting its importance. The formula for calculating the priority weight for each skill is:

$$W_i = 1 + k \times p_i \tag{10}$$

where $p_i$ represents the student's preference for improving skill $i$ ($p_i = 1$ if the student wants to improve the skill, and $p_i = 0$ otherwise), and $k$ is a constant. For example, if a student prioritizes improving *Speaking*, the weight for *Speaking* is calculated as: $W_{\text{Speaking}} = 1 + 0.5 \times 1 = 1.5$. Skills that were not prioritized by the student received the default weight: $W_i = 1 + 0.5 \times 0 = 1$. The learning rate for each skill was adapted based on the student's motivation, denoted by $m_i$, which was normalized to fall within the range $[-0.5, 0.5]$. The adjusted learning rate for skill $i$ is calculated as follows:

$$\alpha'_i = \alpha_i \times (1 + m_i) \tag{11}$$

where $m_i$ is the normalized motivation score. For instance, if a student rated their motivation for improving *Speaking* as 5 (on a scale of 1 to 5), the normalized value $m_{\text{Speaking}}$ is: $m_{\text{Speaking}} = \frac{5-3}{6} = 0.333$. If the initial learning rate for *Speaking* was $\alpha_{\text{Speaking}} = 0.2$, the adjusted learning rate becomes: $\alpha'_{\text{Speaking}} = 0.2 \times (1 + 0.333) = 0.266$. Skills with lower motivation ratings would have correspondingly lower learning rates.

The predicted performance in each skill was modeled using an exponential learning curve, adjusted for each student's personalized learning rate ($\alpha'_i$). The performance in skill $i$ after time $t_i$ is modeled as:

$$P_i(t_i, \alpha'_i) = P_{0i}(1 - e^{-\alpha'_i t_i}) \tag{12}$$

where $P_i(t_i, \alpha'_i)$ is the predicted performance for skill $i$ after $t_i$ hours of study, $P_{0i}$ is the maximum achievable performance, and $\alpha'_i$ is the adjusted learning rate.

The fitness of each particle was evaluated based on the priority weights and predicted performance in each skill. The objective function used to assess the fitness of a particle was:

$$F = \sum_{i=1}^{4} W_i \cdot (P_{\text{target},i} - P_i(t_i, \alpha'_i))^2 \tag{13}$$

where $W_i$ is the priority weight for skill $i$, $P_{\text{target},i}$ is the target or desired performance for skill $i$, and $P_i(t_i, \alpha'_i)$ is the predicted performance based on the adjusted learning rate and allocated time. The goal of the algorithm was to maximize the total fitness score $F$, thereby optimizing the distribution of study time to enhance the performance of the skills most important to the student.

We selected a swarm size of 30 particles, each representing a candidate solution for study time allocation. The PSSO algorithm ran for 100 iterations to ensure convergence toward an optimal solution. Parameters were balanced between exploration and exploitation. The inertia weight $w = 0.5$ moderated the influence of previous velocities, while the cognitive coefficient $c_1 = 1.5$ and social coefficient $c_2 = 1.5$ balanced individual learning and global influence.

The Table 1 below summarizes the key parameters used for the PSSO algorithm:

Table 1. Parameters setup

| **Parameters** | **Value** |
|---|---|
| Swarm size | 30 |
| Number of iterations | 100 |
| $w$ | 0.5 |
| $c_1$ | 1.5 |
| $c_2$ | 1.5 |
| $\alpha_j$ | adaptive |

4.2. **Data Collection.** The data for this study was collected from 102 students to personalize their learning plans and optimize the study time allocation across four core language skills: listening, speaking, reading, and writing. The process began with an initial survey, where students indicated the skills they most wanted to improve, their confidence levels in each skill, and rated their motivation and interest on a scale from 1 to 5. This survey data was used to calculate priority weights $W_i$ for each skill, and to adjust the initial learning rates $\alpha_i$ to reflect student preferences and motivations.

Following the survey, students took a baseline assessment test to determine their starting proficiency in the four skills. This test helped establish the initial learning rates for each skill, providing a foundation for the PSSO model to optimize their study plans. The students were divided into two groups: one group followed a study schedule where the time was evenly distributed across the four skills, while the second group had their study time optimized using the PSSO model based on their individual learning preferences and performance.

Over the course of the six-month study, students participated in assessments every two months to track their progress. These evaluations allowed the learning rates to be adjusted dynamically based on their actual performance. For the PSSO group, study time was adjusted in an adaptive manner based on individual student progress, allowing more focus on areas where improvement was slower and less time on skills where progress was faster. The control group, on the other hand, followed a fixed schedule with an equal distribution of time across all four skills. The comparison between these two groups provided insights into the effectiveness of adaptive time allocation versus a uniform, evenly distributed study schedule.

4.3. **Evaluation Metrics.** The effectiveness of the two study time allocation strategies PSSO was assessed using two key metrics: *overall proficiency score* and *improvement rate*. The *overall proficiency score* was calculated by summing the individual proficiency scores across the four core language skills: listening, speaking, reading, and writing. This metric provides a comprehensive measure of a student's language abilities after the study. The formula for the overall proficiency score $S_{P4}$ (Skill Proficiency Aggregate) is:

$$S_{P4} = \frac{1}{4}(S_{\text{listening}} + S_{\text{speaking}} + S_{\text{reading}} + S_{\text{writing}}) \tag{14}$$

where $S_{\text{listening}}$, $S_{\text{speaking}}$, $S_{\text{reading}}$, and $S_{\text{writing}}$ represent the proficiency scores in each skill.

The *improvement rate* measures the percentage increase in a student's proficiency from the baseline test to the final test. It is calculated for each skill and averaged across the four skills to give an overall improvement rate. The formula for the improvement rate ($I_i$) in skill $i$ is:

$$I_i = \frac{S_{\text{final},i} - S_{\text{baseline},i}}{S_{\text{baseline},i}} \times 100 \tag{15}$$

where $S_{\text{final},i}$ is the final proficiency score in skill $i$, and $S_{\text{baseline},i}$ is the baseline score in the same skill. The overall improvement rate is the average of the improvement rates across all four skills.

## 5. **Experiment Results.**

5.1. **Baseline Data and Group Formation.** The experimental study spanned over a total of eight months, starting from June 2023 and concluding in January 2024. The timeline was carefully structured to allow for periodic evaluations and adjustments, ensuring thorough data collection and effective monitoring of student progress over time.

In the initial phase of the experiment, data collection was a key focus. We surveyed 102 students, each of whom was administered a baseline assessment. This assessment covered all four language skills: Listening, Speaking, Reading, and Writing. The assessment aimed to evaluate each student's starting proficiency in these skills, giving us a comprehensive understanding of their abilities before the experiment began. The results of this assessment were then recorded as initial proficiency scores. The baseline assessment results were depicted in the following figures: Figure 4 shows the score distribution for all four language skills, while Figure 5 highlights the overall proficiency of students before group division.

Based on these initial scores, the students were randomly divided into two groups: one group that would follow a Proficiency-Score Sensitive Optimization (PSSO) strategy, and another group that would follow an even time distribution strategy across the four skills. This random division ensured an unbiased start for both groups, and careful attention was given to balancing the proficiency levels between the two groups to avoid skewing results.

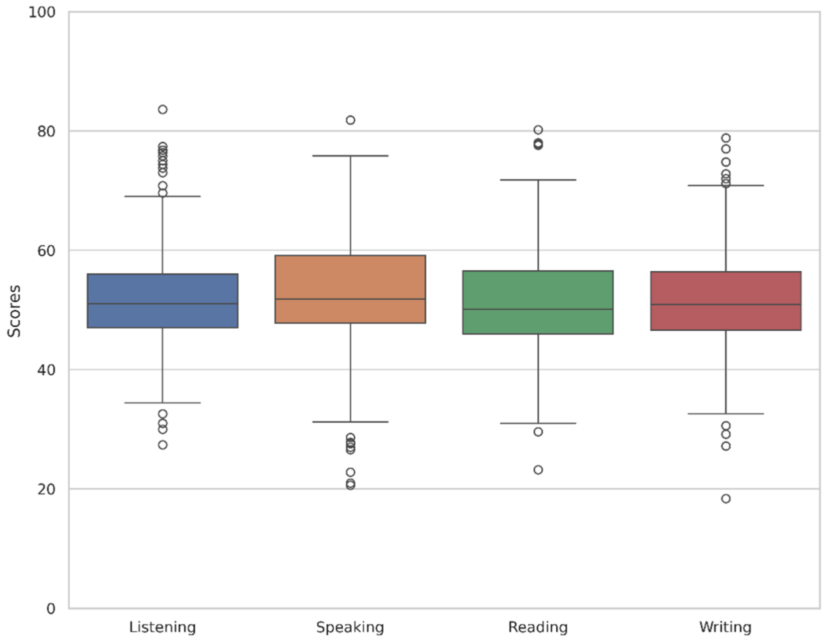



FIGURE 4. Initial score distribution across four skills

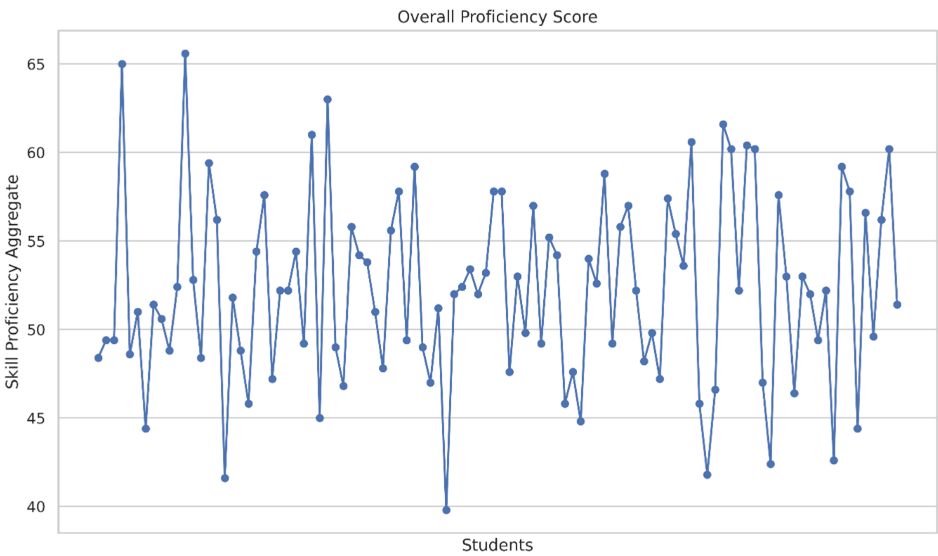



FIGURE 5. Overall Proficiency Scores distribution among students

Once the groups were formed, regular assessments were scheduled to track the progress of each student. Every two months, both groups participated in skill evaluations to gauge improvement in each language skill. These evaluations were essential for adjusting the learning times in the PSSO group, which received an adaptive learning approach, while the control group maintained equal time allocations for each skill.

Figure 6 displays a comparison between the PSSO and Even Distribution groups after the initial phase, highlighting their overall proficiency across the skills.

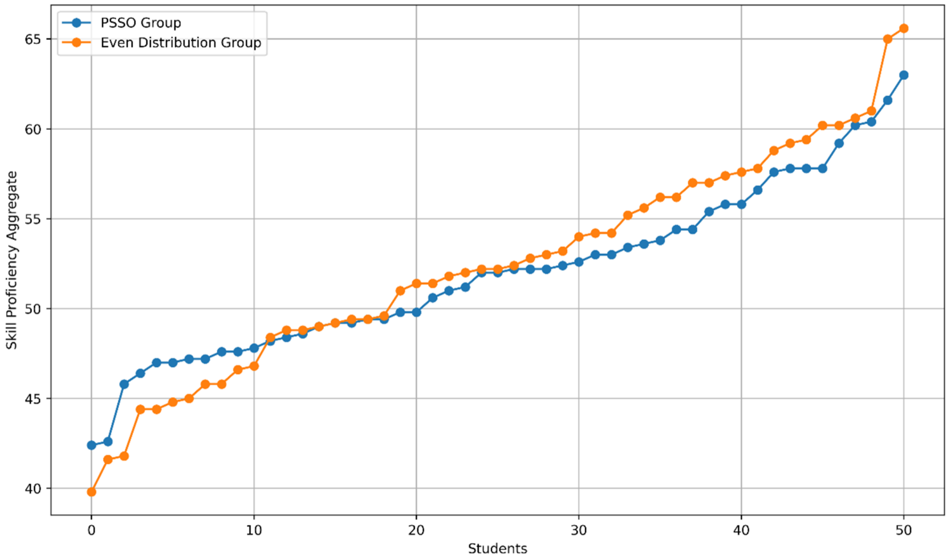



FIGURE 6. Overall Proficiency Scores distribution among two group students

5.2. **Time Allocation Optimized.** The PSSO algorithm effectively optimized the study time allocation for each student across three distinct cycles: Cycle 1 (07/2023 - 08/2023), Cycle 2 (09/2023 - 10/2023), and Cycle 3 (11/2023 - 12/2023). Each cycle represents a two-month period during which the distribution of study time was adjusted based on the students' test results. This approach ensured that the time devoted to each skill (Listening, Speaking, Reading, and Writing) was tailored to support areas of improvement while maintaining overall balance.

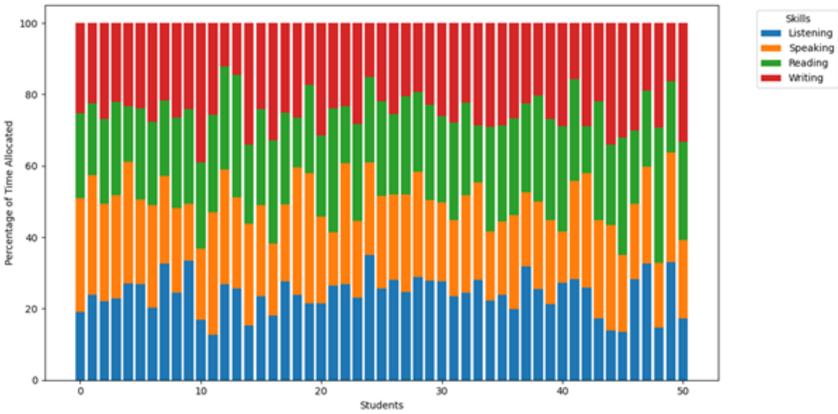
Figures 7a, 7b, and 7c illustrate the percentage of time allocated to each skill per cycle. These figures show the evolution of time distribution among skills, reflecting the adjustments made after each assessment cycle.

In Figure 7a (Cycle 1), initial time allocation is seen, with a broader distribution across the skills based on students' preliminary proficiency levels. By Cycle 2 (Figure 7b), adjustments are visible as the algorithm reallocates time based on the mid-term assessment results, focusing more on underperforming areas for each student. Finally, in Figure 7c (Cycle 3), further fine-tuning of study time is apparent, displaying a personalized distribution that aligns closely with each student's learning progress and goals. These adjustments highlight the PSSO's adaptive capability in optimizing study time allocation across skills in a dynamic learning environment.

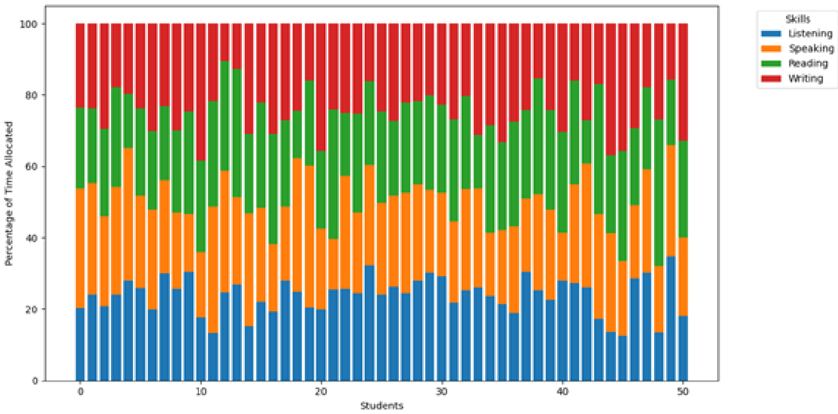
5.3. **Performance Improvement.** This section presents a comprehensive analysis of the overall proficiency score $S_{P4}$ and the improvement rates achieved by students over three study cycles. The evaluation focuses on comparing the effectiveness of the PSSO method, which allocates study time dynamically based on individual proficiency, against a traditional even distribution approach that maintains a fixed allocation across all skills. The goal is to assess how these two methods impact student progress over time, specifically across three cycles: Cycle 1 (July - August 2023), Cycle 2 (September - October 2023), and Cycle 3 (November - December 2023).

As displayed in Figures 8, the trends in $S_{P4}$ scores illustrate notable distinctions between the two groups.

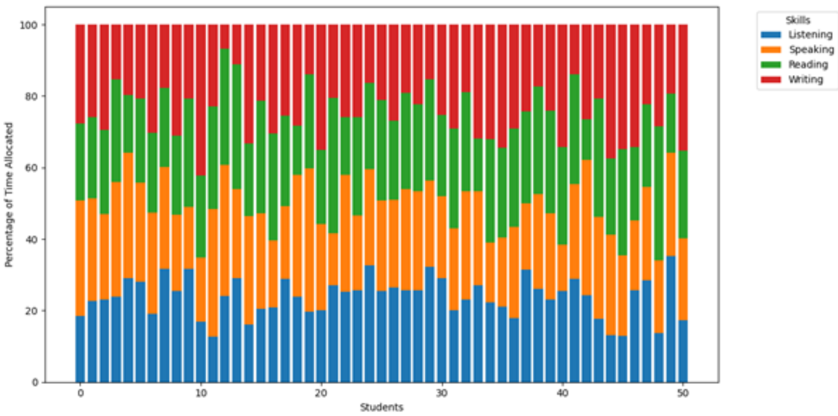
The PSSO group demonstrates a consistent upward trajectory in skill proficiency, underscoring the algorithm's adaptability and capacity to effectively adjust study time in




(A)



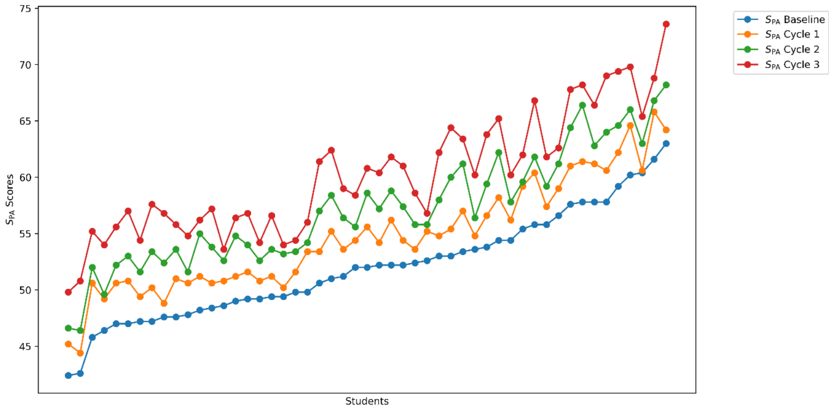

(B)



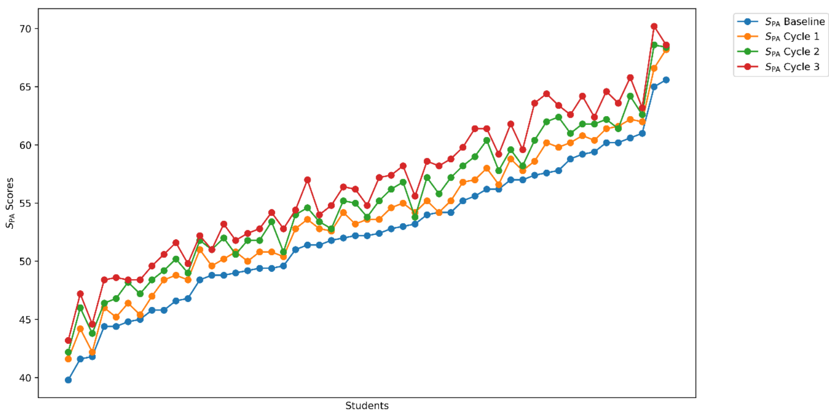

(C)

FIGURE 7. Study time allocation per skill for each student: (a) Cycle 1 (07/2023 - 08/2023); (b) Cycle 2 (09/2023 - 10/2023); (c) Cycle 3 (11/2023 - 12/2023).

response to individual learning needs. This improvement suggests that PSSO's dynamic allocation, which adapts to proficiency scores after each test cycle, enables students to maximize their potential more efficiently. By contrast, the even distribution group, where study time was equally divided across skills without adaptive adjustments, shows only a gradual increase in $S_{P4}$ scores. This steady but modest growth indicates limited flexibility in responding to skill-specific proficiency shifts, underscoring the importance of a tailored study allocation.




(A)




(B)

FIGURE 8. Overall proficiency score progression for each student under different methods: (a) PSSO method; (b) Even distribution method.

Table 2 provides a statistical comparison of improvement rates between the two methods across the cycles. The PSSO group not only achieved consistently higher mean improvement rates than the even distribution group but also exhibited a greater standard deviation, reflecting more significant and variable gains among individual students - a potential result of the personalized adjustments in study allocation.

TABLE 2. *Comparison of Improvement Rates Between Even Distribution and PSSO Methods Over Three Cycles*

| **Cycle** | **PSSO** | | **Even** | |
|---|---|---|---|---|
| | **Mean** | **Std** | **Mean** | **Std** |
| 1 | 5.21 | 2.00 | 2.79 | 1.28 |
| 2 | 9.88 | 2.70 | 5.17 | 1.91 |
| 3 | 15.76 | 3.89 | 7.80 | 2.14 |

Important insights from Table 2 consist of:

- **Cycle 1**: The PSSO group achieved a mean improvement rate of 5.21 (Std: 2.00), nearly double that of the even distribution group, which had a mean rate of 2.79 (Std: 1.28). This early gap suggests that the PSSO method's initial adjustments provide a stronger foundation for proficiency enhancement.

- **Cycle 2**: The advantage of the PSSO method became more pronounced, with a mean improvement rate of 9.88 (Std: 2.70), compared to 5.17 (Std: 1.91) for the even distribution group. This increase signifies the cumulative impact of adaptive learning, as students continued to benefit from adjustments based on their Cycle 1 test results.

- **Cycle 3**: By the final cycle, the PSSO group reached a substantial mean improvement rate of 15.76 (Std: 3.89), while the even distribution group maintained a mean rate of 7.80 (Std: 2.14). The widening gap at this stage reflects the long-term advantage of personalized optimization, as PSSO continues to refine study allocations to capitalize on individual strengths and areas for improvement.

To assess the reliability of the experimental results, statistical tests were conducted to evaluate consistency across different student groups. The results were validated using standard deviation analysis, which showed that performance improvements followed a stable trend across multiple cycles. Additionally, paired t-tests were applied to compare the pre- and post-experiment proficiency scores, confirming that the observed gains were statistically significant. The consistency of the findings was further reinforced by the relatively low variance in improvement rates, indicating that the adaptive allocation method led to robust and repeatable learning gains. Future studies could explore larger sample sizes and cross-institutional validation to further strengthen the generalizability of these results.

In a real classroom setting, an instructor implementing the PSSO framework can use periodic assessments to guide adaptive study time allocation. For instance, at the start of a semester, students take a diagnostic test to assess their proficiency in listening, speaking, reading, and writing. Based on the results, the system assigns individualized study plans, prioritizing weaker skills. During biweekly assessments, students' progress is recorded, and the PSSO algorithm dynamically adjusts study time. For example, a student initially struggling with speaking but improving rapidly in reading will have more time allocated to speaking while reducing reading practice. This ensures that class time and self-study hours are utilized efficiently. Over the course of the semester, the instructor can review aggregated data to refine teaching strategies, making the adaptive learning process more effective.

## 6. Conclusion.

This study has examined the application of a Particle Swarm Optimization-based approach, PSSO, to optimize study time allocation across four key English language skills—listening, speaking, reading, and writing. By utilizing the Learning Curve model to inform the dynamic adjustment of time distribution, the PSSO method provided a personalized study plan tailored to the specific proficiency levels of individual students. The experiment was structured over three cycles, allowing for continuous re-evaluation and adaptation of study time allocations, based on periodic assessments of student progress. The findings of this study highlight significant advantages of the PSSO approach over a traditional even distribution of study time. Students in the PSSO group consistently achieved higher overall proficiency scores and improvement rates across all cycles compared to those in the control group, who followed a fixed allocation strategy. This improvement was particularly noticeable in later cycles, where the adaptive adjustments provided by PSSO led to sustained and amplified gains in skill development. Statistical analysis confirmed the significance of the differences in performance between the two groups, underscoring the effectiveness of adaptive learning frameworks in language acquisition.

The findings highlight the effectiveness of adaptive learning in optimizing study time allocation, with the PSSO framework demonstrating significant improvements in skill proficiency compared to static methods. The increasing performance gap between the experimental and control groups across cycles suggests that real-time adjustments lead to more sustained learning gains. However, the study also presents certain limitations. First, while the adaptive model is effective, its implementation requires continuous performance tracking, which may pose logistical challenges in large classrooms. Second, the study was conducted over a six-month period, and long-term effects of adaptive learning require further investigation. Lastly, while PSO-based optimization was found to be efficient, exploring alternative models such as reinforcement learning could provide additional insights. Future research should address these aspects to refine and expand the applicability of adaptive learning frameworks.

The PSSO model demonstrates substantial promise for enhancing English language education by optimizing study schedules according to learners' unique proficiency trajectories. This approach offers an efficient, data-driven alternative to conventional fixed-time allocation methods, enabling educators to maximize student progress through targeted interventions. Future work could explore the integration of other optimization algorithms and investigate the model's applicability to other subject areas, further advancing personalized learning strategies in educational settings.

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