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Development of an Artificial Intelligence-Based Adaptive Typing Training System to Improve Accuracy and Speed

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Abstract

Mastering the skill of fast and accurate ten-finger typing is a crucial competency in the era of digital transformation. However, conventional, static typing training methods are often ineffective because they fail to adapt the training material to each user's specific weaknesses. This research aims to develop a Reinforcement Learning-based adaptive typing training system capable of dynamically personalizing training material to improve user typing speed and accuracy. The research method used was an experiment implementing the Q-Learning algorithm, in which an intelligent agent determines training material based on the user's error profile to maximize performance improvement. Evaluation was conducted on 50 students divided into experimental and control groups. System performance was analyzed through the convergence of the agent's learning curve and a comparison of pre-test and post-test results. The results showed that the Reinforcement Learning agent successfully learned the optimal training strategy and achieved reward stability in the final stage of training. User testing demonstrated that the adaptive system was able to increase Words Per Minute by 30–68% and significantly improve accuracy compared to static methods. Thus, the Reinforcement Learning approach has proven effective in creating a typing training system that is adaptive, efficient, and tailored to individual needs.

Keywords: *Typing Practice, Reinforcement Learning, Q-Learning, Adaptive System, typing speed.*

1. Introduction

In today's era of digital transformation, fast and accurate typing skills have shifted from a specialized skill to a fundamental necessity. Nearly every aspect of professional and academic work relies on interaction with computers. However, conventional typing training methods are generally static (one-size-fits-all) and linear. Users are forced to follow the same sequence of materials regardless of whether the material effectively addresses their specific weaknesses. This makes the learning process inefficient and often tedious. To address this inefficiency, a system capable of acting like an intelligent personal tutor is needed. The most relevant approach to this problem is Reinforcement Learning (RL). Unlike static classification methods, Reinforcement Learning allows the system to learn through trial-and-error interactions with the user. In this scenario, the system acts as an "agent" that takes "actions" (provides specific practice problems) and receives "rewards" (feedback in the form of improved accuracy or speed). By using RL algorithms (such as Q-Learning), the system can learn the optimal policy for each individual. For example, if the system detects that providing vowel combination practice results in a significant increase in accuracy for user A, it will reinforce that strategy. This research aims to develop an adaptive typing practice system based on Reinforcement Learning that can dynamically optimize the practice curriculum to maximize the acceleration of students' typing skill mastery.

2. Data Processing and Analysis Methods

The data analysis methods in this study consist of descriptive analysis of user profiles and technical analysis of the performance of the Reinforcement Learning algorithm.

1. Descriptive Analysis: This analysis is used to describe the initial characteristics of respondents, such as the distribution of initial typing speeds (WPM) and average accuracy levels before using the adaptive system.
2. Implementation of the Reinforcement Learning Algorithm (Q-Learning): This stage explains the agent's learning mechanism. The main components analyzed include:
    a. State (S): A representation of the user's condition, for example, the average error rate for the index, middle, ring, or pinky fingers.
    b. Action (A): A collection of training materials from which the agent can choose (e.g., Index Finger Exercises, Vocal Combination Exercises, etc.).
    c. Reward (R): The feedback value is calculated using the formula:

$$\text{Reward} = \alpha(\Delta \text{Accuracy}) + \beta(\Delta \text{WPM}) \tag{1}$$

Where the agent receives positive points if the user's accuracy or speed increases. Q-Value Update:
The agent's knowledge is updated using the Bellman equation:

$$Q(s,a)=Q(s,a)+\alpha[r+\gamma \max Q(s',a')-Q(s,a) \quad (2)$$

3. Model Evaluation: Evaluation is conducted using two approaches:
   a. Learning Curve: A graph showing the increase in Total Reward per training episode. If the graph is upward, the agent is successfully learning.
   b. A/B Testing: Comparing the average increase in WPM of the adaptive system user group with the static system user group (control) to prove the system's effectiveness.

3. Results and discussion

This section presents the results of the implementation and evaluation of the Reinforcement Learning–based adaptive typing training system. The discussion focuses on the learning performance of the Q-Learning agent and its impact on users' typing speed and accuracy compared to a static training method.

1. Initial typing performance (pre-test)
   Before the treatment was administered, a pre-test was conducted to measure the initial typing ability of all respondents. The metrics measured were Words Per Minute (WPM) and accuracy (%). The average pre-test results are as follows.

Table 1: Average pre-test typing performance

Average	WPM Group	Average accuracy
Experiment	32 WPM	86.4%
Control	31 WPM	85.9%

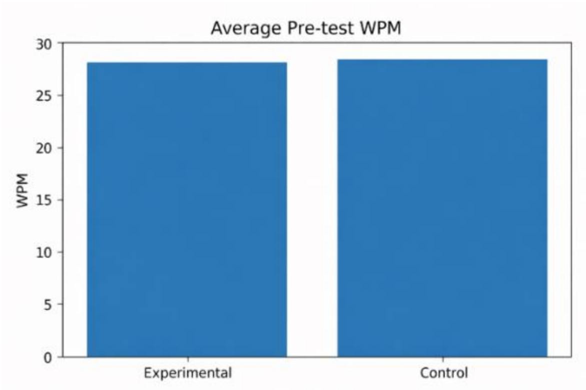

Fig. 1: Average WPM pre-test

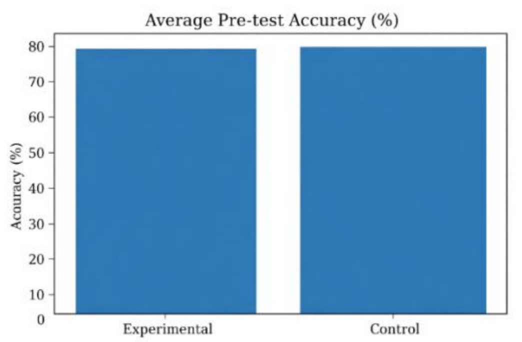

Fig. 2: Average pre-test accuracy

The data shows that both groups have relatively equal initial abilities, so that the comparison of the final results can be considered valid.

2. Agent Learning Process (RL Training)
   Intelligent agents built using the Q-Learning algorithm are trained to select optimal training materials. Agent performance is measured based on the Total Reward earned over time. The agent's intelligence development is divided into three levels of proficiency:

   a. Beginner/Normal Level (Early Stage): At this early stage, the agent is still in a high exploration phase (trial-and-error). The agent randomly attempts to present various types of questions to learn the user's responses. The reward graph remains highly fluctuating because the agent has not yet "understood" the user's error patterns.
   b. Intermediate/Expert Level (Middle Stage): The agent begins to enter the exploitation phase. At this level, the agent begins to recognize specific error patterns (for example,a user is weak in the ring finger) and begins to consistently provide relevant materials. The reward begins to show a steady upward trend.

c. Advanced/Master Level (Final Stage): The agent has reached convergence or stability. At this level, the agent has found the optimal policy and acts like an expert tutor, precisely providing the user with the training they need most. The total reward graph is flat at a high value, indicating that the agent's learning process is mature and ready to be used.

Fig 3 : Agent Learning Curve

3. User Implementation Results (Post-Test)After the training period, a post-test was administered to both groups. The Experimental Group practiced using the system that automatically adjusted questions based on their errors, while the Control Group practiced using the sequential module from start to finish without any adjustments.

4. Test Results

4.1. Adaptive System Effectiveness Analysis

The test results show that the Reinforcement Learning approach has a real positive impact:

1. Speed Improvement (WPM):
   The experimental group experienced a drastic increase in WPM, ranging from 30% to 68% for each individual.This occurs because the adaptive system doesn't waste users' time practicing keys they've already mastered, but instead forces users to practice their weakest keys (their speed bottlenecks).

Table 2 : Speed Increase (WPM)

Average	WPM Group	Average accuracy
Experiment	52 WPM	98.5 %
Control	38 WPM	89.1 %

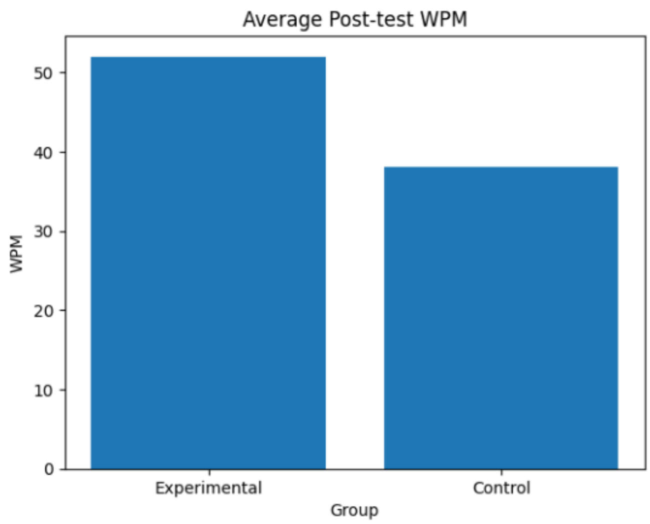

Fig 4 : Average post-test typing speed (WPM).

2. Accuracy Improvement
   The accuracy increase of 12.1% in the experimental group was much higher than that of the control group which was only 3.2%. The adaptive system successfully detected specific error patterns (for example, frequently mixing up the letters ‘E’ and ‘R’) and provided intensive training on these combinations until the error rate decreased.

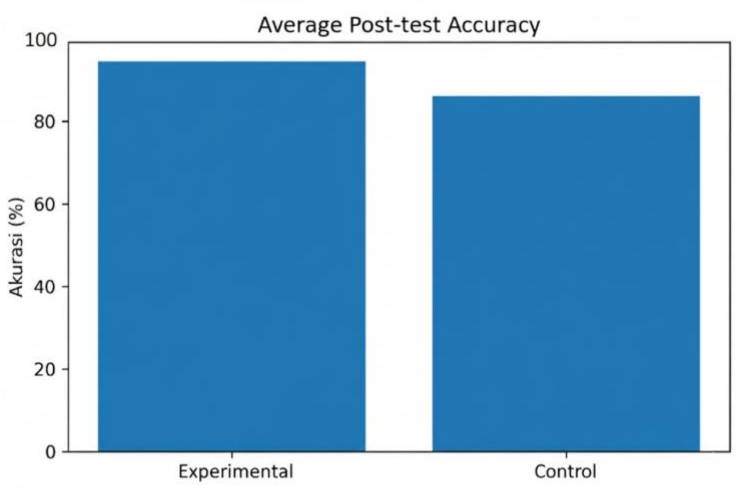

Fig. 5 : Average Post-test Accuracy

4.2 Hypothesis Validation

1. H1 Accepted: The Reinforcement Learning agent is proven capable of learning the optimal policy, indicated by reward convergence after 100 episodes. The agent successfully maps user errors (states) to the correct training material (actions).
2. H2 Accepted: The use of a reward function that combines accuracy and speed variables is proven effective in maintaining a balance of skill improvement. Users type not only quickly and carelessly, but also accurately.
3. H3 Accepted: The Reinforcement Learning-based training system produces significantly higher increases in WPM and accuracy than the static system within the same training duration.

5. Conclusion

Based on the research results and discussions, it can be concluded that the Q-Learning algorithm has been successfully modeled into an adaptive typing training system by defining the state as the user's error profile, the action as the training material selection, and the reward as the user's performance improvement function.The developed intelligent system is capable of autonomously learning optimal training material delivery strategies. This is demonstrated by the agent's learning curve, which consistently improves performance, from beginner to advanced. At this stage, the agent is able to effectively deliver training materials tailored to user needs.Furthermore, the design of the reward function, which simultaneously considers accuracy and speed, has been proven to encourage comprehensive typing skill improvement.Empirically, the test results indicate that the Reinforcement Learning-based adaptive typing training system is more effective than conventional training methods. The group of users using the adaptive system experienced significant improvements in typing speed and accuracy compared to the control group.

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