Development of an Adaptive E-Learning Model for Students with Disabilities: Mathematics Learning as an Example

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Abstract – This research developed an innovative adaptive learning model by using multi-source of personalization information, that is, personal cognitive strengths and weaknesses, thinking style, learning style, and prior knowledge. Based on the innovative adaptive e-learning model, a multi-characteristic-based adaptive learning system has been developed. Finally, implications for practice and future research were discussed.

Keywords: Special Education, e-Learning, Adaptive Learning

1 Introduction

Based on the educational concept of “No Child Left Behind,” improving the educational system for children with mild disabilities is a key focus of educational reforms.

With advancements in information technologies and the ever-increasing popularity of the Internet, e-learning models that integrate the Internet and information technologies have become a newly emerging learning trend in addition to educational upgrades and reforms[1].

Experts of special education expect information technologies to increase the competence of students with disabilities, compensating for their underperformance or insufficient abilities [2].

The physical, mental, and learning characteristics of students with disabilities differ from those of non-disabled students and include a lack of concentration, poor short-term memory, weak abstract reasoning, and slow learning abilities. Because of these characteristics, they experience greater difficulty learning, their learning performance is lower, and they are less able to learn in a traditional manner compared to non-disabled students. An e-learning environment differs from traditional classrooms and can reduce the learning difficulties encountered by students with disabilities, enabling them to learn more effectively.

According to the current studies, although e-learning development and applications have been diversified, e-learning are insufficient for special education in elementary schools. Few online learning materials are specially designed to accommodate the needs of different students [3]. Additionally, most current online learning systems only provide remedies after students have encountered learning errors and do not provide measures to prevent mistakes and reduce their frustration with examinations. Therefore, considering the personalities of students with disabilities from a procedural perspective, providing an adaptive learning experience and preventing potential errors can improve their e-learning performance.

Mathematics is an essential skill for resolving daily issues and is the foundation for learning science subjects. Studies have shown that approximately 6% to 7% of non-disabled students experience difficulties learning mathematics[4]. The percentage is even higher among students with disabilities.

For students with disabilities, we designed an adaptive mathematics e-learning model according to their existing knowledge and characteristics, such as their learning and thinking styles, strengths, and weaknesses. This model provides students with adaptive learning procedures, content, presentation methods, error prevention strategies, tests, and remedial methods to enable them to learn effectively. Then, using this model, we developed an e-learning platform and implemented supporting technologies. Additionally, we also verified the validity of this model through experiments.

2 Model Design

Based on the learning theories discussed previously, adaptive e-learning, and e-learning for students with disabilities, we propose an adaptive e-learning model for disabled students in this section (Fig. 1). We use this model to design the structure of an e-learning system structure (Fig. 2) to be used as a reference for mechanism and technological developments in the future, as explained below.

(1) Pretest and Student Model Construction: Students must complete the pretest the first time they enter the learning platform. The computerized adaptive test assesses students’ mathematics abilities and constructs a knowledge model for students based on the test results. The scales for learning and thinking styles are then employed to assess students’ learning and thinking styles.

(2) Adaptive Learning and Supporting Mechanisms: After students begin the learning process, the learning path planning mechanism is used to determine a learning path for students. Adaptive learning materials are provided according to students’ strengths, weaknesses, and thinking
and learning styles. Potential errors for students during concept learning are predicted and learning error prevention strategies are applied.

(3) Concept Testing and Computerized Adaptive Testing: After each concept learning process is completed, students receive a computerized adaptive test that presents questions that match students’ abilities and determine their learning status.

(4) Remedial Learning and Learning Error Adaption: Students’ answers reflect their learning status. If they provide the correct answers in the test, they continue onto step 1 for the next learning unit; otherwise, the learning error is identified based on the items selected by students, and the appropriate remedial learning strategy is provided to the student.

![Student View](image1)

![System View](image2)

Figure 1. Adaptive e-Learning Model for Students with Disabilities

3 Mechanism and Techniques of e-Learning Platforms

3.1 Student Model Construction

To record each student’s characteristics, knowledge structure, and learning-related information to plan adaptive learning for each student, we designed a student model.

In the e-learning environment, two major standards are used when referencing user information[5], that is, personal and private information (PAPI) presented by IEEE, and learner information packaging (LIP) presented by IMS. These two standards defined the syntax and semantics of a learner model. However, PAPI and LIP have certain common properties; differences only exist in the details of their classification. We incorporate both standards according to the requirements of this study to define the five categories in the student model (Fig. 3): (1) personal information; (2) personal preference; (3) students’ abilities; (4) learning activity; and (5) learning performance. The fields in the circle are data inputted by students. The fields in the oval contain related student information obtained from the pretest. The fields in the rectangle are student learning data obtained during the learning process.

When students first enter the system, student model construction includes two major components, namely, the “student knowledge structure construction” under “student abilities” and the “relevant personal characteristics” under “student preferences.” Construction of the student model involves two major components, that is, the “student knowledge structure construction” and the “personal characteristics test.”

![Student Model](image3)

Figure 3. Student Model
3.1.1 Student Knowledge Structure Construction

Based on the adaptive pretest results and the preconstructed learning knowledge structure, we established a personal knowledge structure for students. For the knowledge-structure-based adaptive test (KSAT) [6], because each concept in mathematics contains numerous test items, we incorporated item response theory (IRT) into the design to achieve a hybrid adaptive test.

(1) KSAT

KSAT can be used to reduce the number of test items effectively. In the example shown in Fig. 4, the students first completed a test for Concept A. If they answered incorrectly, they were required to complete tests for Concepts B and C. If they answered Concept B incorrectly but Concept C correctly, we assumed that they already understood all concepts under Concept C; thus, two questions were skipped. They were only required to complete a test on Concept D afterward. This approach not only reduces testing time but also clearly identifies the student’s misconceptions. Because the participants of this study were students with disabilities who typically had low learning achievements, the adaptive test began with simple questions and gradually increased the difficulty level.

![Knowledge Structure](image)

Figure 4. Knowledge Structure

(2) Item Response Theory

Item response theory is a modern method for selecting test questions, using probability to identify the relationship between a person’s ability to take an examination and the questions in the examination. The selected test items in each examination match the student’s ability. However, the difficulty level cannot meet the requirements of each student regarding their abilities. The optimum test arrangement is to provide each student with a test suitable for their condition and based on their ability. According to the correctness of the student’s answer to the previous question, the system selected the subsequent question. This method constructs a student knowledge model, and is also used in the examination after each concept learning process is complete. The process steps are detailed below.

(a) Estimating Student’s Ability

During this step, test items that are suitable for the student according to their ability are provided to avoid a situation in which randomly selected questions are too difficult and reduce the student’s correctness rate. This study also used the three-parameter logistic model[7], as shown in Eq. (1).

\[
P_i(\theta) = c_i + (1 - c_i) \frac{1}{1 + e^{-a_i(\theta - b_i)}}. \tag{1}
\]

In this equation, \(\theta\) represents the student’s ability, \(b_i\) represents the difficulty parameter of question \(i\), \(a_i\) represents the discrimination parameter of question \(i\), and \(c_i\) represents the guessing parameter of question \(i\).

The maximum likelihood procedure is used to estimate students’ ability. During the test, students’ responses to the questions are scored as zero or one using a dichotomy. The known test item parameters are included in the test item response vector to calculate the student’s ability, as shown in Eq. (2).

\[
\hat{\theta}_{s+1} = \hat{\theta}_s + \frac{\sum_{i=1}^{N} -a_i[u_i - p_i(\hat{\theta}_s)]]}{\sum_{i=1}^{N} a_i^2 p_i(\hat{\theta}_s)Q_i(\hat{\theta}_s)}, \tag{2}
\]

In this equation, \(\hat{\theta}_s\) represents the estimated value of the student’s ability regarding question \(a_1\), where \(I = 1, 2, \ldots, N\). \(u_i\) represents the student’s response to question \(i\), where zero indicates an error and one indicates a correct answer. \(p_i(\hat{\theta}_s)\) represents the probability of answering correctly in the item characteristic curve based on the ability value of \(\hat{\theta}_s\). \(Q_i(\hat{\theta}_s)\) represents the probability of answering incorrectly in the item characteristic curve.

(b) Maximum Information Item Selection

We adopted the method of maximum information item selection commonly used in IRT for selecting the questions in the test. This method can provide examinees with test items that have maximal information based on their abilities. Previous studies [8] have proposed an equation for maximum information item selection that is applicable to the three-parameter logistic model, as shown in Eq. (3).

\[
I_i(\theta) = \frac{a_i^2(1 - c_i)}{[c_i + e^{a_i(\theta - b_i)}][1 + e^{-a_i(\theta - b_i)}]^2}. \tag{3}
\]

In this equation, \(\theta\) represents the student’s ability, \(b_i\) represents the difficulty parameter of question \(i\), \(a_i\) represents the discrimination parameter of question \(i\), \(c_i\) represents the guessing parameter of question \(i\), \(e\) represents the natural logarithm, which is 2.71828, and \(I_i(\theta)\) represents the maximal information that question \(i\) provides to the student whose ability value is \(\theta\).

3.1.2 Personality and Characteristics Construction

The preferences in the student model include the student’s personality, such as their learning and thinking styles, strengths, and weaknesses. This information can be obtained from relevant scales. Learning style refers to the psychological experiences of awareness, memory, and thought achieved when a student participates in learning activities, and the habitual characteristics of thinking, sentiment, and physiology evinced in external behavior through. thinking style refers to the way an individual uses and exerts their talent and intellect. The strengths and weaknesses of students were assessed and analyzed using WISC-III measures.
3.2 Learning Path Planning

Before planning a learning path for a student using the student knowledge structure diagram, the conceptual learning disability and misconception of the student must be identified. It also enables further planning of the student’s learning process.

(1) Identify Learning Disability

Because students do not complete all conceptual tests in the KSAT computerized adaptive pretest, the student’s stopping point when the KSAT test was finished was used to identify the student’s learning disability.

(2) Generate a Personalized Learning Path

The student’s stopping point in the mathematics pretest is the concept node that the student answered incorrectly, which was defined as the disability node. Therefore, a method must be provided to the student to remedy their learning disability for a concept and plan to learn a new concept. As shown in Fig. 5.

```
Void Main() {
    Call Find_Remedial_Instruction_Path(k,Cj);
    //Cj as the disability node, Ch as the less difficulty of Cj parent-concept
    Call Learn_New_Concept(Cj,Ch);
    //Ch as a new concept
}
Procedure Find_Remedial_Instruction_Path(k,Cj){
    If(Cj== disability node) {
        Push Cj;
        W=Max[|Weicj[| i<=i<=n]);//Find the weight of the largest node of Cj with the parent concept
    }
    While(Ci != Root Concept)  //when Ci is not Root Node
        Push Ci base on W;
    While Stack is not empty
        RIP=Find_Remedial_Instruction_Path(LPop());
    //RIP:Remedial Instruction Path
}End Procedure
Procedure Learn_New_Concept(Cj,Ch){
    M=Max[|Wcijch[| i<=i<=n]);//Find the largest weight of node of Cj sub-concept.
}End Procedure
```

Figure 5. Learning Path Planning Algorithm

3.3 Learning Error Prevention

Learning error prevention is used to predict students' learning errors according to their learning and thinking styles. The goal is to increase the precision of this prediction. First, the common mathematical errors of students with disabilities must be compiled, and the errors must be classified into different categories. The dimensions of learning style and thinking style are seen as the potential features of learning errors. Potential errors in the learning process are predicted using the document classification method, and the preventative strategy is provided to the student. In this section, we describe the construction of an error prediction classifier, including (1) features selection, (2) classification model training, and (3) correctness assessment.

3.3.1 Error Prediction Classification Model Construction

(a) Initialize Personality Dimensions

Through numerical calculations of students’ personality dimensions, we obtained the following correlation series:

\[ \omega_0 = (\omega_0(1), \omega_0(2), \omega_0(3), \ldots, \omega_0(k)) \]
\[ \omega_1 = (\omega_1(1), \omega_1(2), \omega_1(3), \ldots, \omega_1(k)) \]
\[ \ldots \]
\[ \omega_{m} = (\omega_{m}(1), \omega_{m}(2), \omega_{m}(3), \ldots, \omega_{m}(k)) \]

In the set, \( i = 0, \ldots, m; k = 1, \ldots, n \), \( \omega_i \) represents the student information series in the \( i \)th personality dimension or the correctness rate. \( \omega_{i}(1) \) represents the first student’s information in the \( i \)th personality dimension.

The information series is then included in Eq. (3) for initialization, as shown in the following equation.

\[ x_i(k) = \frac{\omega_i(k)}{\omega_{i}(1)}, \forall k \in \{1,2,\ldots,n\} \quad i \in \{0,\ldots,m\}. \]  (3)

Here, \( x_i(k) \) is the transformation series of \( \omega_i(k) \). \( \omega_i(k) \) is the information of the \( k \)th student in the \( i \)th personality dimension.

(b) Calculate the Difference Series for Each Personality

All series obtained in Step (a) are considered comparison series. The correctness rate \( x_m(k) \) is used as the reference series. As shown below, Eq. (4) is used to calculate the difference series for obtaining the measurement of a distance space.

\[ \Delta_{m}(k) = |x_{m}(k) - x_{i}(k)| \forall k \in \{1,2,\ldots,n\} \quad i \in \{0,\ldots,m\}. \]  (4)

In this equation, \( x_{m}(k) \) represents the transformation series of the correctness rate and \( x_{i}(k) \) represents the transformation series of personality.

(c) Calculate the Grey Relational Coefficient for Personality

The difference series obtained in Step (b) is included in Eq. (5) to calculate the grey relational coefficient for personality. Because the comparison series intersects with the reference series, we typically have \( \Delta_{mn} = 0 \).

\[ \gamma(x_0(k), x_i(k)) = \frac{\min_{k} \min_{l} \Delta_{l}(k) + \rho \max_{l} \max_{k} \Delta_{l}(k)}{\Delta_{l}(k) + \rho \max_{l} \max_{k} \Delta_{l}(k)}. \]  (5)
In this equation, \( \min_k \min_i \Delta_i(k) \) is the absolute minimal difference value among all series, \( \max_k \max_i \Delta_i(k) \) is the absolute maximal difference value, and \( p \) is the discrimination coefficient, which indicates the loss of information or distortion caused by over reducing the absolute maximal difference value; the scale is zero to one.

(d) Calculate the Weight of the Grey Relational Coefficient for Each Personality

The grey relational coefficient obtained in Step (c) is averaged using Eq. (6) to obtain the relational weight for each personality dimension. The equation is shown below.

\[
y(x_0, x_i) = \frac{1}{n} \sum_{k=1}^{n} \gamma(x_0(k), x_i(k))
\]

Here, \( x_0(k) \) is the transformation series of the correctness rate, \( x_i(k) \) is the transformation series of personality, and \( \gamma(x_0(x), x_i(x)) \) is the relational coefficient between the correctness rate and the \( i \)th personality dimension for the \( k \)th student.

(2) Classifier Training

We used the support vector machine (SVM), which was proposed by Vapnik in 1995 and is based on statistics theory. This is a linear binary classifier with a linearly separable hyperplane. SVM provides numerous advantages for resolving nonlinear, high-dimensional model differentiation problems with minimal samples. Two sets of data were prelabeled with the classification values (1 or -1) and trained using a linear function until the optimal decision function of the two sets of data were obtained. Through the optimal decision function, we identified the optimal classification hyperplane that causes the maximum margin between the two sets of data.

When classifying data into two groups during the training stage, the SVM classifier calculates the distance among vectors for training sample \( S \) and finds an equation for a straight line that can separate the training data, as shown in Eq. (7).

\[
\text{Training Data: } S = \{x_i, y_i\}, i = 1, ..., n, x_i \in \mathbb{R}^d, y_i \in \{-1, 1\}
\]

\[
\text{Subject to } y_i (w \cdot x_i - b) - 1 \geq 1, \forall y \min \frac{1}{2} \|w\|^2.
\]

In this equation, \( x_i \) is the \( i \)th data, \( y_i \) is the data type of the \( i \)th data, which is either a positive (1) or negative type (-1). \( w \) is the normal vector for \( x_i \) corresponding to the line, and \( b \) is the amount of displacement for this straight line. Which of these two sets this point belongs to is determined based on the sign of the point. All points with \( y_i = -1 \) belong to the set \( f(x) < 0 \), and all points with \( y_i = +1 \) belong to the set \( f(x) > 0 \). Thus, we can determine which set data belongs to according to the sign of \( f(x) \). During this step, the thinking style and learning style features were used as training data to obtain the cut-off function between the two classified groups. The boundary of the two classified groups was expanded its the maximum along the vertical plane of the hyperplane, until it reached a certain group. This method separates the two types of data with the longest distance to the classification plane and generates a definite classification function.

### 3.3.2 Variables for Prevention Strategy Determination

Because prediction may have duplicate results, we designed a discriminant equation to determine whether to provide a prevention strategy. The method is explained below.

(a) Discriminant Equation

\[
\begin{cases}
e_i^k = 1 & \text{provide} \\
e_i^k = 0 & \text{do not provide}
\end{cases}
\]

\[\forall \ e_i^k \in S: i = 1, 2, ..., n, k = 1, 2, ..., m.\]

In this equation, \( e_i^k \) represents the given determinant variable of the \( i \)th error type in the remedial learning strategy for the \( k \)th student. The default value is always one.

(b) Variable Adjustment

\[
\begin{cases}
e_i^k = -1 & \text{if } s_i = 1 \\
e_i^k = \text{others} & \text{if } s_i \neq 1
\end{cases}
\]

\[\forall \ s_i \in S: i = 1, 2, ..., n, k = 1, 2, ..., m.\]

In this equation, \( e_i^k \) represents the given determinant variable of the \( i \)th error type in the remedial learning strategy for the \( k \)th student. The default value is always one. \( s_i \) indicates whether a prevention strategy is provided on this occasion; one means a strategy is provided and zero means a strategy is not provided.

### 3.4 Adaptive Material Providing

This module provides adaptive materials to students according to their learning and cognition style, strengths, and weaknesses as recorded by the student model.

(1) Learning Style Adaptation

Learning style adaptation comprises the six dimensions proposed by[10], namely, motivation, persistence, responsibility, structure, visual types, and auditory types. Each dimension ranges from 0 to 16. The adaptive strategy for each personality dimension is listed in Table (1).

| Table 1. Adaptive teaching strategies for learning styles |
|---|---|---|
| Dimension | Strategy | Adaptive Presentation Method |
| Motivation | <10 | Different kinds of encouragement are given for the correct answer in each step |
| Persistence | <10 | Emphasizes important messages |
| Responsibility | <10 | Displays the percentage of completion |
| Visual | >Auditory | Digital voiceover |
| Auditory | >Visual | Supplements pictures with text descriptions |

(2) Thinking Style Adaptation

For this study, we investigated three functional thinking styles: legislative, administrative, and judicial. These three dimensions ranged from 0 to 25. The dimension that scored the highest of the three was used as the student’s thinking style. Methods for adaptation are shown in Table (2).
identify the potential learning difficulties of these students, followed by remedial learning. Adaptive learning content must meet the requirement of each student. Based on the collected literature, experiments, and the analysis and compilation based on expert instructors, we used the common error types as distracters for the standard question answers. Preprocessing for this method is relatively complicated. However, it aids analysis of online error types if the common errors are analyzed accurately.

3.6.2. Strategy to the Problem Matching

Based on a survey completed by expert instructors and review of relevant studies, we identified the common mathematical error types and the corresponding strategies for students with disabilities. We present nine common error types and several corresponding solution strategies for each error.

3.6.3. Problem Solving Strategies Selecting

We used the concept of collaborative filtering to select strategies for problem solving. This method was first realized in the Tapestry mail system[11]. The purpose is to recommend information of interest to users based on the preferences of a group with common interests and experiences. Through a collaborative mechanism, each participant responds and records the filtered target to enable other participants to screen information. This method allows concepts that are difficult to describe to be filtered out (for example, personal preference), and enables other users to learn rapidly from the feedback. This method is further explained below.

(1) Collect User Information

Use students’ learning and thinking style in the student model as user information.

(2) Nearest Neighbor Search (NNS)

Calculate the similarity between two users. Divide the system users into N groups with high similarity using Pearson’s correlation analysis, as shown in Eq. (10).

$$
\text{sim}(a,b) = \text{corr}_{ab} = \frac{\sum_{j=1}^{M}(P_{ai} - \bar{P}_a)(P_{bi} - \bar{P}_b)}{\sqrt{\sum_{j=1}^{M}(P_{ai} - \bar{P}_a)^2 \sum_{j=1}^{M}(P_{bi} - \bar{P}_b)^2}}.
$$

Here, $P_{ai}$ is the score of $i^{th}$ learning style of Student $A$, $P_{bi}$ is the score of $i^{th}$ learning style of Student $B$, $\bar{P}_a$ is the average score of all learning styles of Student $A$, $\bar{P}_b$ is the average score of all learning styles of Student $B$, and $\text{sim}(a,b)$ is the Pearson’s correlation coefficient.

(3) Generate Recommendations

We employed the news recommendation method using collaborative filtering[12] and considered the preferred strategies of each student to calculate the weight of each solution, as shown in Eq. (11).

$$
P_{sc} = \left(1 + \frac{R_c}{R_{all}}\right) \times \left(1 + \frac{P_{sc}}{\sum_{c=1}^{N} R_{ac}}\right) \times \left(1 + \frac{R_{se}}{\sum_{e=1}^{N} R_{se}}\right). \quad (11)
$$

### Table 2. Adaptive teaching strategies for thinking styles

<table>
<thead>
<tr>
<th>Thinking style</th>
<th>Strategy</th>
<th>Adaptive Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Legislative</td>
<td>Structured</td>
<td>Display step-by-step solutions</td>
</tr>
<tr>
<td>Administrative</td>
<td>Guidance</td>
<td>Display three solution strategies and ask the student to select the correct one</td>
</tr>
<tr>
<td>Judicial</td>
<td>Inductive</td>
<td>Provide minimal hints initially, increasing hints as the error rate increases</td>
</tr>
</tbody>
</table>

(3) Strengths and Weaknesses Adaptation

Students’ strengths and weaknesses were assessed in advance using the WISC-III intelligence test. The adaptive teaching strategies are shown in Table (3).

### Table 3. Adaptive teaching strategies for strengths and weaknesses

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Strategy</th>
<th>Adaptive Presentation Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual</td>
<td>Strong</td>
<td>Supplement pictures for text descriptions</td>
</tr>
<tr>
<td></td>
<td>Weak</td>
<td>Digital voiceover</td>
</tr>
<tr>
<td>Auditory</td>
<td>Strong</td>
<td>Digital voiceover</td>
</tr>
<tr>
<td></td>
<td>Weak</td>
<td>Supplement pictures for text descriptions</td>
</tr>
<tr>
<td>Concentration and attentiveness</td>
<td>Weak</td>
<td>Increase font size and circle important messages</td>
</tr>
<tr>
<td>Processing speed</td>
<td>Weak</td>
<td>Display the multiplication table</td>
</tr>
<tr>
<td>Sequential processing</td>
<td>Strong</td>
<td>Display step-by-step solutions</td>
</tr>
<tr>
<td></td>
<td>Weak</td>
<td>Display all solution steps simultaneously</td>
</tr>
<tr>
<td>Parallel processing</td>
<td>Strong</td>
<td>Display all solution steps simultaneously</td>
</tr>
<tr>
<td></td>
<td>Weak</td>
<td>Display step-by-step solutions</td>
</tr>
</tbody>
</table>

3.5 Computerized Adaptive Testing

After each concept is learned, the system provides a computerized adaptive test based on IRT. The most suitable questions are selected according to the student’s ability. The IRT adaptive test was explained in Section 3.1.1.

3.6 Learning Error Adaptation

This module provides necessary remedial learning when students encounter learning difficulties. We used the concept of formative evaluation to understand students’ learning status and responded with appropriate strategies to resolve problems using collaborative filtering. The steps in this module are learning problem detection, matching strategies to a problem, and strategy selection for problem solving.

3.6.1. Learning Problem Detection

The first step in adaptation is the identification of students who require remedial learning using screening or assessments. Official measurement is then conducted to
Here, $R_C$ is the number of times Strategy C was read by all students, $R_{all}$ is the total number of times that all strategies are read by all students, $R_{sc}$ is the number of times Strategy C was read by Student a, and $R_{sc}$ is the number of times Strategy c was read by students in the same group as Student a.

4 Experiment

Participants were 68 elementary school students with mild disabilities. To verify the impact of this adaptive design on their learning performance, we used the pretest and posttest results and the difference in learning performance between these two groups to assess the effectiveness of the system. Table 4. shows the mean scores of 68 students for both the pre-test and post-test are 26.0294 and 56.4706, respectively. Table 5. shows the comparison results of the paired samples t-test of the pre-test and post-test scores. This study found that the difference of the mean scores between the pre-test and post-test score is 30.441, the result reach the significant level under a degree of freedom of 67. In other words, after using the proposed adaptive e-learning model, the promotion of student learning performances is significant.

Table 4. Paired samples statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>The number of samples</th>
<th>Std. deviation</th>
<th>Std. error mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-test</td>
<td>26.0294</td>
<td>68</td>
<td>31.39254</td>
<td>3.8069</td>
</tr>
<tr>
<td>Post-test</td>
<td>56.4706</td>
<td>68</td>
<td>25.72905</td>
<td>3.12011</td>
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</tbody>
</table>

Table 5. Paired samples test

<table>
<thead>
<tr>
<th>Paired differences</th>
<th>Mean</th>
<th>Std. deviation</th>
<th>Std. error mean</th>
<th>95% confidence interval of the difference</th>
<th>t</th>
<th>df</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-test</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>30.441</td>
<td>20.106</td>
<td>2.438</td>
<td>25.574</td>
<td>35.308</td>
<td>12.485</td>
<td>67</td>
</tr>
</tbody>
</table>

5 Conclusions and Future Research

This study developed an adaptive mathematics learning model for students with disabilities. Using the student model, instructors can plan a learning path and learning material for each student that meets their unique instructional needs. Using the computerized adaptive test, learning errors caused by mismatching question difficulty level with the student’s ability can be avoided. Adaptive strategies for learning difficulties enable students to resolve the learning error and avoid repeating the mistake. In the studies conducted in the last decade, emotion has been shown to be an critical factor in e-learning [13]. In future studies, we aim to incorporate an emotional identification design into our system, which can enable us to determine whether students’ poor performance is caused by inadequate material or design procedures, or because of the student’s emotional state.

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