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An Online Mathematics Learning Platform for Thai Student Based on a 5-levels Math Problem Difficulty Model

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Abstract: Thai students often struggle on international assessments, even though mathematics problem-solving is a critical component of the curriculum and is studied extensively. This paper proposes an online mathematics learning platform based on a 5-level problem difficulty model to provide adaptive learning for Grade 8 and 9 students. An experiment involving 50 students demonstrated that those using the platform achieved statistically significant improvement based on paired-sample T-test ($p < 0.001$) compared to a control group. These findings suggest that adaptive learning tools can enhance mathematics proficiency and engagement.

Keywords: Personalized Learning, Online learning, Mathematics

1. Introduction

Thailand's persistent underperformance in PISA (OECD, 2019), ranking 58th out of 81 countries in 2022, highlights a gap between educational practices and essential skill development. Thai students struggle with mathematical literacy, reflecting an overemphasis on rote memorization rather than analytical thinking. This raises a crucial question: how can Artificial Intelligence (AI) be integrated into mathematics education to enhance analytical skills? Potential solutions include AI-driven adaptive learning, intelligent tutoring systems, visualization tools, and real-time feedback to strengthen critical problem-solving.

There are several implemented tools with the idea of adaptive learning in mathematics including the adaptive scheduling model to assign educational activities at scale in an online course (Bassen et al., 2020) focusing on adaptive educational activities using reinforcement learning models and real-time evaluation during learning. A game-based learning environment was proposed to improve elementary school students' performance by integrating mathematics content into the game (Yeh et al., 2019). Adaptive dynamic assessment for individualized instruction based on the knowledge structure of the problem was proposed and tested (Wu et al., 2017). An e-learning system using a model based on learning theories was proposed on an open-source platform (Ahn & Edwin, 2018). Math quiz recommender system was proposed (Dai et al., 2022) with quiz difficulty based on probability that students will give a wrong answer and mastery level of each concept based on the performance of the quiz the learner had attempted.

From our research, we found that no prior work has demonstrated the use of math problems (MP) as a tool to create a level-based model of the difficulty of each MP using a definite indicator for student classification.

Thus, in this paper, we aim to study the use of MP as a tool to assess students' level by analyzing students' decisions in math problems. This work focuses on Grade 8 and 9 students in Thailand. This study investigates the effect of learning by analyzing examples and the improvement achieved using our tool.

The rest of the paper is organized as follows. Section 2 explains the design of the model. Section 3 provides an experimental setting. Section 4 provides a result. Last, Section 5 gives a summary of the paper and a future plan for the research.

2. System Design

To construct a math problem difficulty model, we have to start with the foundational knowledge of when learners first encounter MP. First, from the example in textbooks, where the MP uses a basic concept, they learned in the chapter and can be solved easily. Then, when they further their study, the MP becomes more complex by having more numbers and cannot be calculated easily. Next, the applied MP requires multiple basic concepts to solve.

From this ideology, we created five levels of difficulty of MP as shown in Table 1. The model is based on the difficulty of MP. The student levels up when they can do a higher-level problem. The difficulty model is inspired by a system in Thai textbook that classifies math problem difficulty levels into several difficulty levels: basic, intermediate, and advanced levels for high school admission and an Olympiad level.

Table 1. *5-levels of Math Problem Difficulty Model*

Level	Indicator	Example
1	• Use 1 basic concept to solve • Can be calculated quickly	How many possible ways to make a total of 100 baht using 10-baht coins, 5-baht coins, and 1-baht coins, using all three types of coins?
2	• Use 1 basic concept to solve • Cannot be calculated quickly	If x and y are countable number with the following condition (1) $GCD(x,y) = 6$ (2) $x^2 + xy = 288$ then what is value of x + y?
3	• Use 2–3 basic concepts to solve • Can be calculated quickly	If the product of four distinct positive integers is 60, what is the maximum possible value of the sum of these four integers?
4	• Use 2–3 basic concepts to solve • Cannot be calculated quickly	If m, n and p are distinct positive integer that satisfy the equation, $(m-3)\ (n-3)\ (p-3) = 4$; then what is value of $m+n+p$?
5	• Required advanced concepts to solve	If a, b and c are real numbers such that $a + b + c = a^2 + b^2 + c^2 = a^3 + b^3 + c^3 = 5$ then what is the value of $a^5 + b^5 + c^5$?

To apply the model, we developed Optimal Mathematics Learning (OML) as an online mathematics learning platform as a web application. The web application is developed using the Django framework. The tool is used to provide an adaptive learning path from the level of MP the learner can solve. Specifically, it is used to recommend MP with a similar difficulty level to the one that learners can solve. To do that, we collected MP for classification with our models from online resources. Finally, teaching documents and videos are created as a learning resource in the system for each level.

3. Experiment

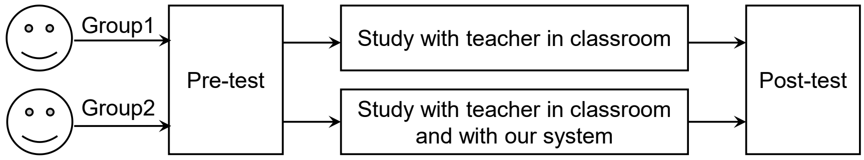

Figure 1. Experiment Processes

For an overview of this experiment, we aimed to study the effect of the tool in a real environment. The experiments were to find improvement in learners' mathematics levels. The flow of the experiment is shown in Figure 1.

In this experiment, students in the basic education program from normal classes and gifted educated program (GEP) classes of a high school in Thailand participated and tested subjects. Our experiment had 50 students voluntarily participating, including 36 students from grade 8 and 14 students from grade 9. There are 22 and 6 students in Grades 8 and 9 participating, respectively. Total of 28 GEP students. In normal classes, 14 and 8 students of Grades 8 and 9 are participating, respectively. The students in each classroom are divided into two groups of 25 students each. For all groups, study in the classroom normally with the teacher. Additionally, two groups were assigned with different learning processes as follows: Group1: Study without OML as an assistant, Group2: Study with OML as an assistant.

Math concepts in the experiment for each grade are different according to the current topic that the school is teaching, which in Grade 8 is Statistics 2 and Grade 9 is Trigonometry. Then, we selected 50 problems from our database in each concept to create a pretest and post-test, each test consisting of 25 problems. Each problem is select 4 choice answer type. Difficulty in the grade 8 pre-test and post-test are 3.24 and 3.12, respectively. The difficulty in grade 9 pre-test and post-test are 3.12 and 3.04, respectively.

The pre-test and post-test were conducted in our system by asking students to select math problems to do 10 from 25 items. This is to obtain data on the problems that students choose to work on. The problem order is random every time a student opens the test. We set a deadline for students to submit their answers to 2 days after the system opened to students. After the pre-test, Group2 are allowed to use our system to study with individuals' recommended content according to their level evaluated in the pre-test. The post-test then was conducted after the end of the pre-test for 21 days. As a restriction, the post-test is not repeated with pre-test problems. The difference in post-test and pre-test scores is a measure of improvement.

4. Result

Table 2. *Improvement result separated by groups and classrooms*

Group	Normal Grade 8	GEP Grade 8	Normal Grade 9	GEP Grade 9	Overall Normal	Overall GEP	All
1	1.71	0.89	2.33	1.00	2.00	0.91	1.48
2	4.29	3.69	3.50	1.25	4.11	3.12	3.56

Table 3. *Improvement results between Group1 and Group2 with paired-sample t-test*

Group	Mean	σ	Differences Mean	Differences σ	t	p
1	3.5600	2.8296	2.0800	1.1581	9.0290	< .001
2	1.4800	2.8301				

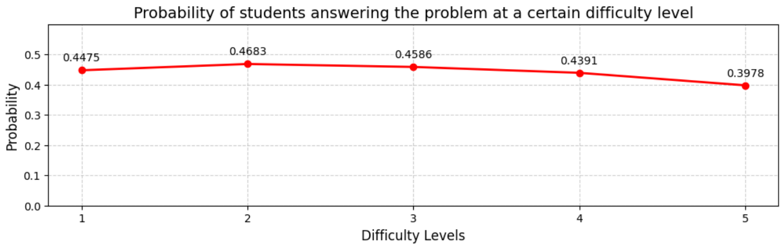

Figure 2. Probability of students answering the problem at a certain difficulty level

The improvement results between two groups from Table 2 and Table 3 all indicated that the group using the tool (Group2) improves better than the group without the tool (Group1) in every class. Specifically, there was a significant difference in the improvement after learning

Especially in regular class, where the difference improvement score of Group2 is higher in every class. In addition, Group2 of students in the GEP class in Grade 8 differed the most from Group1, unexpectedly. We consider GEP students as students at the basic and advanced levels. By applying the OML system to these students, they can release their potential effectively.

In Figure 2, the probability at each level is calculated from the average probability of solving the problems across all tests. Most students' complete problems at levels 1 through 4, although a few manage to do level 5. Since students can skip harder problems in favor of easier ones, this highlights the significance of our difficulty model, as it aligns problem selection behavior with the indicators defined in our difficulty model.

After the experiments, students were asked for opinions regarding learning. Most of the students gave remarks that 'The test is hard' as well as suggestions from Group2 to improve the learning material in the system.

5. Conclusion, Discussion, and Future Works

In this paper, we proposed a 5-levels of the math problem (MP) difficulty model to classify student levels based on the level of MP they can do. Next, we developed an Optimal Mathematics Learning (OML) as an online mathematics learning platform for deploying our model and providing an adaptive learning path for students from the difficulty level of MP they can do.

Based on the experimental results, it can be concluded that students using the tool have statistically significant improvements than the group that is not using the tool. Moreover, the results of improvement showed that the tool works best for regular class students in Grade 8 who have lower levels of mathematics, while it was less effective for students in gifted classes, especially in Grade 9.

To improve our work, we plan to apply the tool to students in other grades, as well as develop an extension of the model to make problems at the same level comparable. Increasing the functionality of the system and deeper sub-units of the chapter recommendation are to be considered. Furthermore, more experiments on other grades and knowledge backgrounds will be conducted to study the effect of the learning steps from our system.

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