Exploring the Usage of an Adaptive Learning System for Elementary School Math Classes

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Abstract. *In this paper, we present the preliminary results of testing an adaptive learning system on tablet computers developed for mathematics classes in the lower grades of primary school.*
The developed system consists of two parts: the mobile application for repetition and revision of math exercises, and an administrative interface, through which teachers can create new tasks, monitor students' progress, and analyse the results of each student.
The adaptivity algorithm, based on various available information, assesses the current knowledge level of each student and populates a list of next tasks with ones of appropriate difficulty.
The preliminary study was conducted with a small class of third-grade students, and the results show that the adaptivity algorithm generally successfully assessed the students' knowledge level (the level which coincides with the teacher's assessment). Exceptions and border case issues are analysed in detail, and improvements to the algorithm are suggested.

Keywords. adaptive learning, adaptive systems, technology-enhanced learning, primary education

1 Introduction

Adaptive learning systems (ALSs) are software applications that monitor student behaviour and learning characteristics continuously dynamically adjusting the process in order to improve the learning experience of each student.
The adaptive educational systems were rapidly evolving in recent years since they greatly rely on computer science, programming, and technology advancement, which are the fields that have experienced fast and immense progress in the last 30 years (V. Shute et al., 2021; V. J. Shute & D, 2012; Van Schoors et al., 2021).
As stated in a paper by Knutov et al. (Knutov et al., 2009), there are three basic forms of adaptation: content adaptation, adaptive navigation, and adaptive presentation, which are supported by a number of different technologies and approaches, like data mining, context awareness or grouping. Park and Lee recognized and described several adaptive instructional models, with macro and micro-adaptive instructional models as the two most common types of learning adaptation today (Park & Lee, 2003). Similarly, Alshammari et. Al. (Alshammari et al., 2014) analyse three main perspectives (learner, domain and adaptation), while Paramythis and S. Loidl-Reisinger (Paramythis & Loidl-reisinger, 2004) look at the adaptive environments from 4 different perspectives: domain, learner, group, and adaptive model perspective, with each system implementing one or more of these models creating different levels of personalized experiences. On the basis of Paramythis and S. Loidl-Reisinger's work, Jianu and Vasilateanu proposed their adaptive gamified e-learning system, using adaptive questions and rewards in the form of levels and points (Jianu & Vasilateanu, 2017).
One of the learning activities often being adapted are task repetitions and practice, especially in subjects like Mathematics or Chemistry, where solving a large number of numerical tasks is a common way to gain knowledge and experience.
Solving tasks and practicing with the use of technology, e.g. with mobile applications could be more interesting to students than solving tasks with a pen and paper or in a workbook (Carruthers, 2015; Mendez et al., 2018). The students could take it more like a game and fun than a school obligation. On the other hand, solving tasks with the help of the software application offers many benefits. The application could, and indeed often does automatically check for validity and accuracy of the answer, and students get immediate feedback. If the task was solved incorrectly, the correct answer or a hint could be displayed. By showing the tasks one by one, students could keep a better focus, fixating only on the current task instead of a whole paper or workbook page with tens of similar tasks. Finally, the tasks in the workbooks are pre-written and cannot be adapted to different students and their needs. Some students need more time and practice to master the material, and others less. For students who know the material better, solving easy tasks could become boring and monotonous, while those with less knowledge could be discouraged by difficult tasks. For

this reason, we designed and developed an application that uses an adaptivity algorithm to estimate the current knowledge level of each student and adapt new set of tasks accordingly, so that the tasks are always challenging enough for all the students in the classroom.

2 Related Work

The field of Mathematics, especially the repetitions and task practicing, is often a target for the implementation of different adaptive learning systems. Recently, several authors have experimented in the area, designing and developing different adaptivity algorithms and computer systems that could have a potential to improve learning. Very recently Bang, Li, and Flynn (Bang et al., 2022) conducted a study to measure learning outcomes and engagement improvement of students using the adaptive learning application compared to students who did not use it. They noticed significant learning gains and skill improvement in students using their application, while teachers praised the application as a helpful learning resource and supplement to existing lessons and curricula. Rosen et al. (Rosen et al., 2018) implemented an adaptive learning system inside an existing MOOC. and found out that the adaptivity increased the learning gains, especially if the student was offered the topics in which the lowest level of mastery was shown. Jagušt et al. (Jagušt et al., 2018) conducted a study with different gamified learning activities, including an adaptive one. They measured improved performance levels in students using the adaptive application, which could lead to better learning outcomes, especially combined with improved interest and motivation, which has been achieved with added gamification elements. Zlatović, Balaban and Hutinski (Zlatović et al., 2022) created an online knowledge assessment system for university students, with adaptivity and personalization elements. The system proved to be efficient for achieving individual learning results.

Also, some commercially available applications offer different levels and types of adaptivity. For example, Knowji[1], a language learning platform, monitors the progress in word learning, and shows more often the words that are not yet mastered. It also tries to predict when a particular word will be forgotten and invites the user to repeat it. Drillster[2] learns about users from the answers and generates questions according to the area in which it considers the user to be weaker, encouraging them to practice weaker tasks more often.

On the other hand, some researchers reported negative or neutral results. For example, Jansen et al. (Jansen et al., 2016) researched the possibilities of task difficulty adaptation in math practice. They allowed students to set their estimated success rate and based on that provided tasks of different difficulty. The approach didn't show any benefit in the terms of skills improvement or self-belief, possibly because the whole process was not automatic, and students could be giving the wrong estimation on purpose, to gain more points later in the gamified application. Similarly, Papoušek and Pelánek (Papoušek & Pelánek, 2017) developed a system where users could adapt the question difficulty, and found only a small effect of student self-adjustments in their geography class experiment. In the end, they suggest and give some advice on how to automatically estimate student knowledge levels.

3 Methodology

In this case study, an adaptive system for the practice of mathematics tasks was designed, developed, and tested with a small group (N=12, 6 boys and 6 girls) of 3rd-grade lower primary school students.

3.1 The application

The developed learning system consists of a mobile application and a corresponding server that contains pre-prepared lessons. Each lesson contains one or more task groups, which in turn contain tasks the students have to solve. Task groups have the function of grouping tasks by certain similarities. There were three types of tasks - multiple-choice including four possible answers, true-false questions, and tasks that required input of the numerical solution. Each task has an estimated difficulty level, which can range from 1 to 3 (1 - easy, 2 - medium, 3 - hard). The difficulty levels were estimated by teachers (Figure 1).

Figure 1. Student solving an ABC question on a tablet computer

When a student starts an application, starting screen of the app interface offers a list of existing lessons.

[1] https://www.knowji.com/

[2] https://drillster.com/

After the student selects a lesson, the adaptivity algorithm selects a set of 15 tasks for solving. Tasks are displayed one by one on the screen. After the student enters a numeric answer or selects one of the offered answers, the answer is logged on the server, the correctness is checked, and the feedback is displayed to the student. If the student answered incorrectly, the correct answer is displayed.

After the student has solved all 15 tasks, the success of solving the lesson is evaluated. Users receive feedback in a form of a simple 1-5 grade, calculated as a number of correct answers multiplied by the difficulty level of each task, then divided by a maximum possible score, and finally scaled to the 1-5 interval.

3.2. The adaptivity algorithm

Based on the existing data from the system log, and similar to studies described in (Balaban, 2015; Zlatović et al., 2022), to the built-in adaptivity algorithm estimates the student's knowledge of the selected lesson, to make it easier for students to master and permanently adopt the learning material. Based on the estimated knowledge level, the algorithm selects future tasks (in sets of 15 tasks) for each student. The more the students answer correctly, the adaptivity algorithm will generate more and more difficult tasks, and, in this way, students will gradually improve their knowledge. The algorithm will more often choose tasks that student had problems with solving in the past (or similar ones) for the student to eventually master. Also, over the time people tend to forget the learned material, and if they don't refresh their knowledge regularly, the level of knowledge may fall. In this case, after the algorithm detects a knowledge drop, a set of easier tasks is generated for student, to refresh the material as soon as possible.

In the beginning, while there is no recorded log data, the algorithm does not have information about the student's knowledge. In that case, it selects a set of tasks consisting of 5 tasks of each difficulty level. It selects tasks from different task groups to make the generated set of tasks as diverse as possible. After the student solved the lesson for the first time, the algorithm has some data to work on and can assess the knowledge level of that student.

If the student previously solved the selected lesson, the recorded information is used when the algorithm generates a set of new tasks, with special emphasis on the tasks from the last attempt. Based on the result (scaled to 0 – 3 interval) of the last attempt, the number of future tasks with each difficulty level is calculated, as shown in table 1. The generated set always contains the tasks of all difficulty levels, to minimise the possibility of wrong student knowledge level assessment by the algorithm. With each new result saved in the data log, the algorithm adjusts students' score, which in turn, changes a list of future tasks (Table 1).

Table 1. Number of selected tasks with each difficulty level based on the calculated student knowledge level

Knowledge level	Easy (1)	Medium (2)	Hard (3)
[0,1]	8	5	2
<1,2]	4	7	4
<2,3]	2	5	8

After determining the number of tasks of each difficulty level, the algorithm selects them randomly from appropriate task groups, giving priority to the tasks that the student didn't try to solve yet, or didn't solve correctly. For each task that was solved incorrectly in the previous attempt, an equivalent is found by taking a task of the same difficulty from the same group of tasks (similar tasks are in the same group of tasks).

4 Results

To test the algorithm and detect possible issues or anomalies, the experiment with a group of 3rd-grade students was conducted, and application usage data was collected in the server log, and analysed.

The future tasks for each student are selected based on several criteria like the accuracy of task solving, assumed level of knowledge, task characteristics etc. When selecting tasks with certain characteristics (task difficulty and group of tasks), priority is given to tasks that the student has not yet solved, and then the tasks that the student solved incorrectly. The described behaviour of choosing tasks that have less accuracy of solving can be seen in Figure 2. The results are presented for a specific student and the tasks from one lesson - the algorithm more frequently selects tasks that the student has not yet mastered.

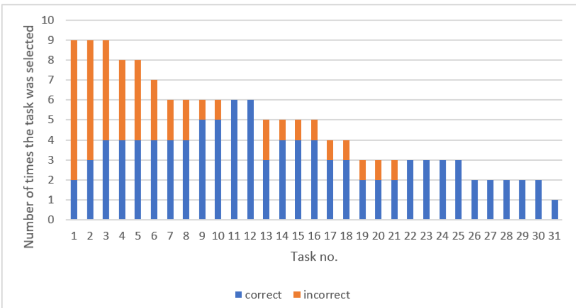

Figure 2. The frequency of selection of individual tasks in relation to the correctness

When observing the adaptability of the algorithm, we will first observe one student and his attempts to solve a specific lesson because the adaptivity algorithm evaluates students' knowledge for each lesson separately and generates sets of tasks based on the assessed knowledge. We observed the same student and the same lesson as in the previous example, but this behaviour is also manifested in other students and lessons (Figure 3).

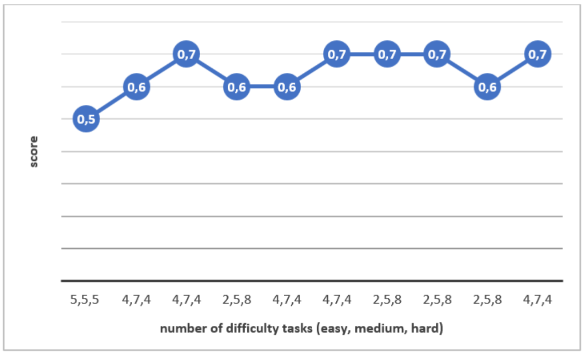

Figure 3. The change in the generated task list as a result of student knowledge level change

The x-axis shows a number of tasks of individual difficulty that have been selected for student at the beginning of each round. The first value on the x-axis represents the very first attempt of the student to solve the lesson. At that point, the algorithm has no information of the student's knowledge for the selected lesson, so it generates an equal number of tasks of each difficulty. The student solved the selected tasks with a score of 0.5. Taking this result into account, the next set of tasks is generated for him (4 easy, 7 medium, and 4 hard tasks). From the picture, one can notice that the algorithm is constantly adapting the list of future tasks. If the student has solved the previous set of tasks well, the algorithm picks more difficult tasks for the next round, and vice versa.

After observing the work of the algorithm individually on students regarding the accuracy of task solving, we wanted to check the global picture of knowledge assessment. We asked the class teacher to rank students according to their assessment of math knowledge. Using the arithmetic mean of the results of all solutions, we calculated how the algorithm evaluates the knowledge of each student individually.

In Table 2, students are ranked within the class according to the assessed knowledge that was calculated by the algorithm, while the last column shows students' rank in a class according to the teacher's assessment. In the second column, the assessed knowledge from algorithm is visible. We can notice that there is a small difference in the assessed knowledge between some students, therefore a small shift in the ranking list with regard to the teacher's assessment should not be a problem.

Generally, students who were rated as "above class average" in math by the teacher were also put in the upper part of the list by the algorithm and vice versa. Nevertheless, there were some deviations. In table 2 the student who was rated 4^{th} by the algorithm was ranked last (12^{th}) by the teacher, which is a "mismatch" of 8 places. A deeper analysis of the log data revealed the reason - that the student was solving only one lesson repeatedly, until solved it perfectly, and did not try to solve any other lesson.

Table 2. Students ordered by their knowledge level by the adaptivity algorithm and by their teacher

Student	knowledge level by the algorithm	Order by algorithm	Order by teacher	Diff.
s1	4.57	1	4	3
s2	4.55	2	2	0
s3	4.50	3	3	0
s4	4.38	4	12	8
s5	4.36	5	1	-4
s6	4.28	6	5	-1
s7	4.21	7	6	-1
s8	3.90	8	10	2
s9	3.71	9	9	0
s10	3.50	10	8	-2
s11	3.50	11	7	-4
s12	3.33	12	11	-1

For that reason, the algorithm, which calculates an arithmetic mean of all task-solving activities for each lesson, calculated the student's score as very high (although, in total it was not high enough for the first place). To improve the application performance in this and similar border cases, some modifications to the algorithm should be done, for example, it could calculate student score differently if student solved only one lesson, or repeatedly solved a small number of lessons in a short period of time. Another option is to take the re-solving of the same task into the calculation with different (smaller) weighting factor, especially if it was done shortly after the student tried to solve that task for the first time. The second biggest mismatch between students' knowledge level and teacher's list, and in the opposite direction, was with student s5, which is, by the teacher, "the best mathematician" in the class. Here the difference between algorithm and teacher is 4 places, and the knowledge level of students in front of him is not much higher than the knowledge level of s5. The log analysis revealed the fact that s5 solved the most tasks in the whole class, which, in turn, could be a reason for somewhat "lower" performance. The student was trying to solve as many tasks as possible in the given time and made more mistakes because of this self-imposed time pressure.

For student s11, although the mismatch was also 4, there is no discussion, because the teacher was not so confident in the order of students in the middle of the list, as she was with top students or the students whose knowledge level is lagging significantly behind the class average.

5 Conclusion and Future Work

In this paper we presented a mobile educational application for math task practice and repetition, that uses the adaptivity to continuously modify a list of tasks that are offered to the student, enhance the quality of learning, improve the amount of learned material and minimise the potential losses by resetting the student's forgetting curve. An experiment conducted on a group of twelve 3rd grade students showed promising results, the system managed to sort the students in a similar way as their teacher, with some anomalies which were discussed in more detail. Also, some improvements to the algorithm were proposed.

This case study adds to the existing corpus of knowledge in the area of adaptive learning systems, giving researchers in the field new implementation case, and teachers another practice example that has a potential to reduce teacher's workload, at the same time improving the personalization and individualization of the teaching process.

There are some noteworthy limitations to this study. Two main issues are a small sample size and only one experiment where the data was collected. Also, the starting task difficulty levels were estimated by teachers, which could introduce some difficulty bias (e.g. teachers could consider some tasks easy, but in reality students could have problems solving them). Although the algorithm included the option to adjust the task difficulty based on the previous student results, since this was the first time the application was used, there was not enough history data to use the difficulty adjustment feature.

In future, we plan to test the application on a much bigger number of students, for a longer period of time, and adjust the task difficulty level on the basis of previous results. This way more usage data will be collected, which would allow more precise student knowledge level assessment.

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