

Personalization of Learning Materials for Mathematics Learning Using a Case-Based Reasoning Algorithm

Mona Masood¹, Nur Azlina Mohamed Mokmin²

¹Centre for instructional Technology & Multimedia Universiti Sains Malaysia, 11800 USM, Penang, Malaysia

²Politeknik Balik Pulau, 11000 Balik Pulau, Penang, Malaysia

drmona_usm@yahoo.com

Abstract—Personalization is important to ensure that learning can cater to the needs of individual learners. The Intelligent Tutoring System (ITS) is a technology that can ease the personalization process; one of the most widely used algorithms in ITS is case-based reasoning (CBR). This study measures the ability of the CBR algorithm to give suggestions for the most suitable learning material based on specific information supplied by the user of the system. In order to test the ability of the application to recommend learning material, two versions of the application were created. The first version displayed the most suitable learning material, and the second version displayed the least preferable learning material. The results show that the first version of the application successfully assigns students to the most suitable learning material when compared with the second version.

Index Terms—Algebra; Artificial Intelligent; Case-based Reasoning; Multimedia.

I. INTRODUCTION

In an era when information can be obtained by the touch of a button, the education field faces substantial challenges in coping with the latest trends in technology. As described by [1] in his study, the latest generation of learners has wider learning opportunities than the previous generation in several respects. Thus, the educators of this generation of e-learning must prepare themselves to equip the learning process with the required amount of knowledge to facilitate these learning requirements. One of the tools that have accelerated achievements in e-learning is the personalization technique [2]. Increasing numbers of institutions are expressing a need for technology that can adapt to the changing requirements of students and which can facilitate individual learning. However, the process of personalization is a tedious task if carried out manually, and may require a very large amount of data and time.

Thus, a technology that can mimic the ability of a human teacher to create personalized learning is required to ensure that the personalization process runs smoothly. Studies (such as those by [3] and [4] have suggested the use of artificial intelligence (AI) technology to mimic the ability of a human in creating reasoning in the learning process. This technology is referred to as the intelligent tutoring system (ITS). The process of making a computer system intelligent involves applying an AI algorithm. Although various algorithms have been applied in ITS, such as neural networks and genetic algorithms, case-based reasoning (CBR) is considered to be easier to understand and to construct [5]. The CBR algorithm

has also contributed to the development of various intelligent tutoring systems including UZWEBMAT [6], CBRPROMATH [7], MACBR [8], Domus [9], PLS-ML [10] and STIMTutor [11].

According to [12], in order to make a case-based reasoning application run well, there are four phases of activity which the system must follow. The first is the retrieval phase, in which the most similar case is selected in order to determine the similarity of the new case submitted to the cases stored in the database. The second phase is the revision phase, in which the suggested solution is tested. If the suggested solution is accepted by the system, the solution will be reused. At the end of the cycle, the result of the operation will be retained by the system and referred to again in the next operation.

The unique aspect of the case-based reasoning approach is in the calculation of local and global similarities. Although the standard Euclidean distance calculation and clustering techniques are effective in similarity calculations, this study uses calculations of global and local similarities as proposed by [5]. The CBR algorithm is relatively easy to program and that the retrieval process is effective [13][14]. Therefore, this study attempts to measure the ability of a CBR algorithm to generate personalization of the most suitable learning material based on information constructed from the user.

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

II. METHODOLOGY

The CBR first retrieves the most similar cases from the new cases and the cases stored in the database. The retrieval phase is where similar cases stored in the database are retrieved to identify a solution. This is the phase in which the similarity calculations are carried out by the algorithm; in order to do this, the similarity between the new cases and the stored cases must be calculated. A data set for the retrieving process must be established before the calculation can be started. Thus, a database was created for this study using 25 sets of data from a pilot study that had been carried out previously. This quantity of data is sufficient for the calculation to be carried out [15]. The retrieval process is started by the application when the user selects the 'calculate' button on the application's screen. The information submitted includes the

IDs of the students, their mathematics SPM (national exam) results and learning style preferences.

The information submitted was calculated using the local similarity and global similarity algorithms. These two algorithms are necessary to find the stored data which is most similar to the data submitted to the application. Figure 1 shows a simplified version of the local similarity algorithm, and Figure 2 shows a simplified version of the global similarity algorithm.

1. Get the user's input
2. Find the maximum value of learning style
3. Find the maximum value of SPM mathematics results from previous cases and the new case.
4. Find the maximum value of the Math Learning Style from previous cases and the new case.
5. Find the range of maximum and minimum value for SPM Math and Learning Style
6. Find the absolute value of the new case minus all the cases in the database
7. Calculate local similarity values for each math learning style and SPM math result

Figure 1: Local similarity algorithm

1. For every global similarity value, find the percentage of the similarity.
2. Find the maximum global similarity value

Figure 2: Global similarity algorithm

The second phase is the reuse process, which uses solutions from the cases that are found to be similar to the new case. The third phase is the revision process, in which the selected solution is tested. This is important to ensure that the recommendation actually fits the requirements. For this study, students needed to answer the post-test at the end of every lesson, so that the result could be compared with the result from the pre-test. The learning gain (LGS) used in this study is calculated by subtracting the pre-test from the post-test. The retaining phase is the last phase of the CBR cycle, in which the information that has been calculated and evaluated is stored in the database for the next iteration of the CBR cycle. In order to evaluate the effectiveness of the algorithm in calculating the similarity score, an application called Case-Based Reasoning Intelligent Tutoring for Algebra Learning (CRISTAL) was developed with two versions. The first version is PLM (Personalized Learning Material), which recommends the most suitable learning material based on the profile submitted. The second version is NPLM (Non-Personalized Learning Material) which assigns the students to learning material that is not mapped to the students' profile. The algebraic fraction is selected as the learning domain, based on the recommendation of the subject lecturers and the students' test results.

When the users (the students) start the application, they first have to answer a pre-test consisting of 10 algebraic fraction questions; the students need to simplify the fractions given to them. Following this, they are asked to enter their ID, to answer a set of math learning style inventory questions and then to enter information about their mathematics SPM result. This information is constructed into a set of learning profiles to be calculated by the CBR engine using the CBR algorithm. The students are then asked to answer the post-test questions. The materials developed for this study were based on four different learning styles proposed by [16]. The first learning material, Mastery Learning Material (MLM) applied a learning strategy with graduated difficulty. This strategy is developed for students with a 'mastery' learning style, who prefer learning in a procedural manner. The learning material

is designed in the form of a mini-library, where the notes are arranged at three levels: beginner, intermediate and expert. Students can choose the level of learning they are most comfortable with. A detailed description of the development process of this learning material is discussed by [17], and a snapshot is shown in Figure 3.



Figure 3: Mastery learning material

The second learning material, Understanding Learning Material (ULM), applied a Concept Attainment learning strategy, prepared for students with an 'understanding' learning style preference. The learning materials are designed in the form of a map with eight checkpoints. At each checkpoint, the students are given eight questions; for each question, there is one correct and one wrong questions concept, and the students are asked to determine which is wrong and which is right. A detailed description of the learning material is given by [18] and a snapshot is shown in Figure 4.

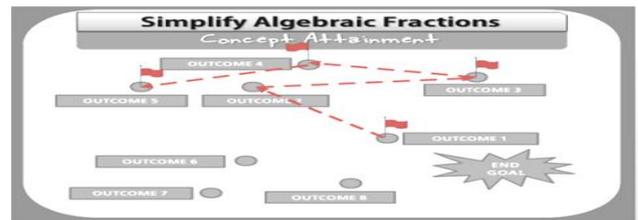


Figure 4: Understanding learning material

The third learning material, Self-Expressive Learning Material (SLM), is developed for students who prefer the 'self-expressive' learning style. The learning material developed for this study applied an inductive learning strategy, in which the students are asked to create the concept on their own by exploring the scenarios given to them in the learning material. This learning strategy is discussed by [19] and Figure 5 shows a snapshot of the learning material. The last learning material, Interpersonal Learning Material (ILM), was developed for students with an 'interpersonal' learning style preference. Students with this learning style tend to enjoy solving questions and learning using notes that relate to their real lives. The learning material applied a real-life application learning strategy, and all concepts were presented with notes relating to their daily life. A detailed description is given by [4] and a snapshot is displayed in Figure 6.

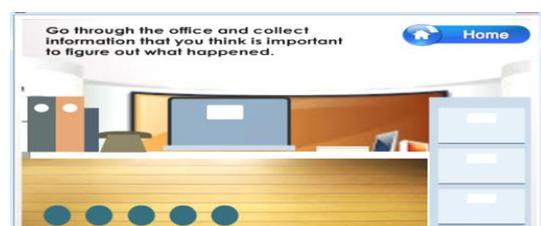


Figure 5: Self-Expressive learning material



Figure 6: Interpersonal Learning Material

III. RESULT

In order to evaluate the ability of the application to recommend the most suitable learning material, 309 polytechnic students were selected for this study. The students were in the first semester of their diploma study and in the first week of the semester. A total of 168 students were assigned by the application to the first version (Personalized Learning Material-PLM) and 141 students were assigned to the second version (Non-personalized Learning Material-NPLM). The distribution of the students according to the learning materials was as displayed in Table 1.

Table 1
Number of Students from Each Learning Material

Learning Material	Number of Students
Mastery Learning Material	142
Understanding Learning Material	40
Self-Expressive Learning Material	87
Interpersonal Learning Material	40
Total	309

This distribution was solely based on the calculation by the CBR algorithm. The learning performance is calculated using the Case-based Similarity Score (CSS). The analysis showed that the data was not normally distributed; therefore, the Mann-Whitney U test was used to replace the t-test as the statistical test. The test hypothesis was: "There is no significant difference between PLM and NPLM in CBR Similarity Score." These two learning treatments (PLM and NPLM) were the independent variables, and the dependent variable was the CSS. The analysis shows that the students in the PLM group had a higher mean than those in the NPLM group. The PLM group scored 97.08 in CSS value, while the NPLM mean score was 48.97. Based on the visual observation of the data distribution, only the mean rank between the two groups can be inferred. The test showed that the mean rank of PLM (mean rank = 225.01) is higher than that of NPLM (mean rank = 71.59). The test has the values of $U = 83$, $z = -15.47$ and $p\text{-value} = .001$. The result shows that there is a significant difference between the means of the two groups, the PLM group scoring better than the NPLM group. This result proved that the application has been able to recommend the most suitable learning material based on the students' profiles. The recommendation of the best learning material is important to ensure the students were presented with the learning materials that are suitable for their learning preferences.

IV. CONCLUSION

The study objective is to measure the accuracy of the application in giving suitable recommendations of learning materials. The application, which is one of the products of

ITS technology, is intended to facilitate the process of personalizing students' learning. The AI algorithm has the ability to overcome the drawbacks that exist in applying the personalization technique in traditional classrooms [20]. Thus, it is observable in the results that the group that was presented with PLM has higher CS value than the group with NPLM. As [21] pointed in their research, the effectiveness of an application that utilizes a CBR algorithm depends on three main factors. The first factor is the case representation that is crucial in CBR algorithms. The data from the students' ID, mathematics results, and mathematics learning style preferences were transformed into variables for the retrieval process in the CBR engine. The accurate variable representation has contributed to the correct calculation by the application [22]. The case representation is the crucial process of the student model and is responsible for ensuring the effectiveness of the CBR application [23].

The second factor is the calculation of the similarity values using the information from the student profile. This study used the local similarity and global similarity algorithm calculation as proposed by [24]. The similarity calculation method was easier to program and effective [13]. An accurate calculation is important to prevent errors in an ITS application in order for the application to personalize the learning material effectively. However, more research is needed to test the effectiveness of the algorithm with other parameters such as students' learning path and students' psychological state. The last factor that determined the effectiveness of the CBR application in recommending learning materials is the retrieval process of the algorithm. The CBR algorithm must be able to retrieve from the stored cases the most similar case with the new case submitted to the application.

As stated by [25], there are four ITS components, Domain Model, Tutoring Model, Student Model and User Interface Model. The function of the CBR algorithm is in the Student Model as part of the ITS component. Most importantly, as regards to ITS, is the ability of the technology to integrate all the components in the process of providing good tutoring to the students. Thus, it can be concluded that this study has discussed the application of the CBR algorithm in determining the most suitable learning material for the Malaysian polytechnic students in learning algebra. The study of the most effective methods and technologies for learning mathematics is important to produce competent engineering workers from technical and vocational institutions [26]. It is hoped that the results and discussion derived from this study can give added value to the field of instructional technology and multimedia

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