Adaptive Recommendations to Students Based on Working Memory Capacity*

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***Abstract*—An adaptive learning system is able to consider students' cognitive characteristics and then provide them with personalized content, presentation, and navigation supports. Working memory capacity (WMC) is one of the important cognitive characteristics to keep active a limited amount of information for a very brief period of time. Students might forget the important information or the learning guidelines from their limited working memory among all the information available in learning systems. Therefore, this paper proposes a mechanism to provide students with suitable and timely recommendations in learning systems based on individual student's WMC. Six types of adaptive recommendations are used to remind and suggest additional learning activities to students based on their WMC. In this mechanism, we also consider different types of objects in different situations to suit different learning scenarios.**

Keywords-working memory capacity, adaptive learning system, recommendation mechanism

I. INTRODUCTION

Adaptive learning systems provide students personalized content, presentation and navigation supports, based on their individual characteristics [1], such as learning styles, cognitive abilities, learning goals, and goal orientation [2]. Many researchers have tried to map the influence of those characteristics on the learning process and outcomes in adaptive learning systems [3][4]. For example, our previous study proposed a student modelling approach for identifying one of students' individual characteristics, namely working memory capacity (WMC), from their activity log information in learning systems [5]. As a consequence, adaptive learning systems can use students' WMC information as an input to provide them with personalized learning contents and suitable activities to fit their WMC. We also proposed a recommendation mechanism in learning systems for providing teachers with recommendations for designing and improving adaptive learning contents and learning presentation based on students' WMC [6].

In this paper, we will introduce another recommendation mechanism which is also based on students' WMC and provides them with different types of recommendations in different quantities in learning systems. The aim of this mechanism is to provide adaptivity with meaningful recommendations for students in order to suggest them additional learning activities on the basis of their individual WMC. Furthermore, the mechanism assigns the recommendations to different learning objects in such a way that they remain meaningful and within appropriate limits to ensure usefulness and avoid frequent distraction from learning process.

The next section situates this research by providing context of existing efforts on adaptivity based on students' cognitive characteristics and the inference of their WMC in cognitive tasks. Section 3 then discusses the recommendation mechanism for providing suggestions to students in learning systems based on their individual levels of WMC. Section 4 concludes the paper by discussing the strengths and weaknesses of the proposed approach and identifying future research directions.

II. RELATED WORKS

Adaptive learning systems generally focus on providing adaptivity based on students' characteristics such as intellectual abilities, cognitive abilities, learning styles, prior knowledge, achievement motivation, self-efficacy, and abilities to solve problems and making decisions [2][7]. By knowing students' characteristics, an adaptive learning system can offer personalized learning spaces (adaptive courses and materials) and support (such as adaptive annotations, navigation, and recommendations) [1]. Some e-learning systems have been implemented to recommend which learning objects should the students learn next [8][9]. Researchers have also developed a variety of adaptive systems to use different recommendation techniques in order to suggest appropriate adaptivity to students, based on their preferences, knowledge, and the behaviours of other students with similar characteristics [4][10]. The student model is the basis for personalization in such adaptive learning systems [7]. Building and updating a student model is called student modelling. Our previous research work has applied a student modelling approach to enable learning systems to detect students' characteristics from their behavior in online courses [5]. In this research, we extend that work by focusing on identifying one of students' characteristics, working memory capacity (WMC).

Working memory plays a critical role in the learning process [11]. Students use their limited WMC to process instructional information for performing learning activities. Information is lost from working memory when students are distracted for some reason, such as by irrelevant information or amount of learning materials [11][12]. Experimental studies have also shown that students' preferences are affected by attentional control and working memory load during complex cognitive tasks [13]. In classroom learning, students with low WMC are easily and frequently

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overloaded in structured learning activities, leading to failure in following instructions, and difficulties in performing complex tasks that combine remembering tasks and demanding mental tasks [11]. The principles of the working memory intervention in classroom learning suggested for students with low WMC are to avoid working memory failures in order to prevent the student's learning from being delayed and impaired [11]. The warning signs of working memory overload include incomplete recall, failure to follow instructions, place-keeping errors (such as missing out letters or words in a sentence or writing a word twice successively), and task abandonment. These principles also enable teachers to be able to monitor the students' working memory loads and then use some strategies to reduce their loads when necessary, such as repeating important information, encouraging the use of memory aids, and developing ways for individual students to support memory. For the aspect of online learning, there are a number of strategies used to allow students to perceive and attend to the information so that it can be transferred to working memory [14]. For instance, information should be presented in different modes and students should be required to apply, analyze, and synthesize.

III. Recommendation Mechanism for Students Based on Their WMC

In order to provide students with meaningful recommendations based on adaptivity in learning systems, a recommendation mechanism is developed in this study. This mechanism considers when to present a recommendation, what adaptive recommendations should be presented, and how to assign an adaptive recommendation for certain type of learning objects based on different levels of students' WMC.

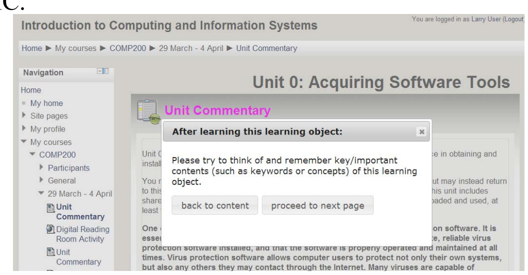

Figure 1. The snapshop of providing an adaptive recommendation after learning a learning object

A. *Recommendation in Learning System*

Each recommended learning object determined is assigned only one recommendation by our mechanism depending on different priority orders of different situations. Fig. 1 shows the snapshot of an adaptive recommendation presented in learning system after a student has learnt a learning object. This action is triggered when the student clicks on the next learning object. Once an adaptive recommendation is presented, she/he can either chose to remain in the content of the current learning object or proceed to the next object. A detailed description of the methods of this mechanism, the adaptive recommendations, and the priority orders of different situations is provided in the following subsections.

B. *Methods of Recommendation Mechanism*

The mechanism uses two methods, time-based and probability-based, to determine which learning object should be assigned a recommendation at a certain point in time in the learning process. These two methods are based on student's learning time and their WMC values. In time-based method, each learning object has its minimum learning time defined by teacher/instructor. Students are expected to spend at least the specified minimum learning time on each learning object. If the learning time of a student on a learning object is less than its minimum learning time, she/he probably did not spend enough time to gather enough information of this learning object. In this situation, the time-based method is activated to adaptively recommend her/him additional activities in accordance to her/his WMC. Different situations are considered and described in the section of priority order below based on the activation of time-based method.

On the other hand, probability-based method considers the WMC value within the scale of 0 (LOW) to 1 (HIGH). Each student's WMC is classified within that scale as follows: Strong LOW ($0 \leq WMC < 0.15$), Moderate LOW ($0.15 \leq WMC \leq 0.35$), Weak LOW ($0.15 \leq WMC \leq 0.35$), Balance ($WMC=0.5$), Weak HIGH ($0.5 < x < 0.65$), Moderate HIGH ($0.65 \leq x \leq 0.85$), and Strong HIGH ($0.85 < x \leq 1$). Each degree of WMC has its corresponding probability value to determine the number of learning objects for which recommendations need to be assigned in a particular week/section of a course. In every week/section, the first learning object must be determined to assign a recommendation. The other objects are determined randomly and different number of recommendations according to the probability value of a student's WMC value. Students with low WMC could lose the crucial information or forget the guidance of ongoing learning activities [11]. This means low WMC students may frequently make errors on these activities and fail to complete them. Therefore, students are provided with appropriate number of recommendations based on different degrees of WMC in order to remind them about and help them concentrate on learning certain types of learning objects. The corresponding probability values of seven WMC degrees are as follows: Strong LOW (90% of learning objects in week/section), Moderate LOW (70%), Weak LOW (50%), Balance (40%), Weak HIGH (30%), Moderate HIGH (10%), and Strong HIGH (only the first object in every week/section). For example, if there are ten learning objects in a week/section, a student who has Moderate LOW WMC will need more recommendations (say, 70% of learning objects) to remind her/him in order to support her/his low WMC. Therefore, the system will identify seven objects randomly out of those ten objects and assign adaptive recommendations to them. Based on different probabilities, only a few of the learning objects are assigned adaptive recommendations in order not to interrupt too much and hence annoy students in their learning progress. Based on the above description of two methods, the probability-based method is used to identify certain number of learning objects in every section/week and the time-based method is applied for defining different situations. However, the time-based method does not need to be considered in all types of recommendations because while some of the activities will need students to spend sufficient time in order to complete them, others will not.

C. Types of Adaptive Recommendations

There are six types of adaptive recommendations (R1, R2, R3, R4, R5, R6) developed in our recommendation mechanism. Table I and subsequent descriptions explain the details of those recommendations, including when should they be presented (before/after learning object) and which method should be adopted to assign a recommendation. These recommendations have been designed according to the literature, for developing students' own learning strategies that allow them to prevent or overcome working memory overload problems [11][14].

Regarding the use of two methods, the probability-based method can be applied for all types of recommendations for determining different quantities of learning objects to which recommendations should be assigned. Only three types of recommendations require consideration of the time-based method because the learning activities suggested by these three recommendations require sufficient learning time by the students for performing those activities.

TABLE I. SIX TYPES OF ADAPTIVE RECOMMENDATIONS

No	Asking student	When	Method
R1	In order to improve your learning, you can try to take some notes when you learn this learning object.	Before	Probability
R2	If you have any questions about this learning object, you can post your questions in the discussion forum or ask your tutor via email to get some help.	After	Time Probability
R3	Please try to post your ideas, thoughts, or reflections about what you learnt in this learning object in the discussion forum.	After	Probability
R4	Can you summarize in your own words what you learnt about this learning object?	After	Time Probability
R5	You can try to do a rehearsal of the content of this learning object in order to improve your memory.	After	Time Probability
R6	Please try to think of and remember important contents (such as keywords or concepts) of this learning object.	After	Probability

1) R1: taking the notes: Students should be recommended to take notes in order to facilitate their learning [15]. Cary and Carlson also argued that the taking of notes helps students ease the load on the working memory and resolve complex problems [16]. R1 is about recommending students to take notes before they start a learning object. However, time-based method cannot be applied in R1 since no learning time can be gathered when students start to learn. Hence, this recommendation only considers the probability-based method and is only provided before learning.

2) R2: asking for the help: Students should be recommended to ask for the assistance in online courses [14]. Unsworth and Engle argued that low WMC individuals may encounter more problems compared to high WMC individuals when they are learning new information [17]. Therefore, R2 is about recommending students to pose their questions to their teacher/instructor frequently via discussion or email after learning a learning object. Students should spend enouth time to think about how to ask the quesions if they need proper help from their teacher/instructor after learning [11]. As a consequecne, this recommendation is provided while finishing the learning and both methods can be applied for this recommendation.

3) R3: developing the knowledge: Students should be encouraged to develop their own thinking by transferring their knowledge into the long-term memory [18]. High WMC individuals have better ability of using different strategies to transfer the knowledge into their long-term memory effectively [13]. R3 is about suggesting students to post their own ideas, thoughts and reflections in order to think about how to apply the learned knowledge. This adaptive recommendation is assigned after learning a learning object. Whenever studnets learn some cruical information from learning obejcts, they may need to disscus it immediately with other students or teacher/instractor [11]. Thereby, this recommendation is provided after learning but is not restricted by the time-based method.

4) R4: summarizing the learned content: Students should be encouraged to engage in a summary activity after learning [11]. Anderson also suggested that students should use the strategies or tools to construct a memory connection between the novel information and learned knowledge already stored in long-term memory [14]. Therefore, R4 is about suggesting students the summary activity in order to help them connect their new and already learned information. However, a summary activity can only be done after students have spent a sufficient time on leaning. Therefore, this adaptive recommendation is assigned after learning and adopts both methods.

5) R5: doing the rehearsal: When learning novel information, students without rehearsal typically forget the new knowledge within a very short time [19]. Low WMC individuals are not able to keep information in their working memory as long as their high WMC counterparts can [17]. Rehearsal would be an effective way to help students remember and transfer the learned information from their working memory to the long-term memory [11]. R5 is about suggesting students to rehearse after learning for a long enough learning time in order to improve their memory. Therefore, this recommendation considers both time-based and probability-based methods after students finish an object.

6) R6: remembering the key/important information: Students with limited working memory are likely to forget the key information after a brief period of time [19]. Low WMC individuals are more likely to have their attention captured by distraction compared to high WMC individuals and thus are also more susceptible to losing access to the task goal [13]. R6 is about encouraging those students to rethink or remember the key or important content after learning. This recommendation cannot be limited by how much time students take in learning a learning object. This kind of activity can also not be done when students start to learn an object. Therefore, students are not restricted by the time-based method after they learn a learning object.

D. Priority Order of Different Situations

Only one recommendation for each learning object is presented to students according to the availability of different learning object types and the priority rules of different situations. The availability represents the available adaptive recommendations for a type of learning object. The considered types of learning objects, based on our previous study [20], are as follows: Commentary, Content, Conclusion, Additional Reading Material, Reflection Quiz, Self-Assessment, Animation, Exercise, Example, Real-Life Application, and Discussion Forum Activity. However, these objects cannot be applied with all types of adaptive recommendations. For example, students cannot take a note when they undertake a quiz, learn with an animation, or post in the forum. Table II shows the availability of recommendations for each type of learning object.

TABLE II. AVAILABILITY OF LEARNING OBJECT

Learning object Type	Adaptive Recommendation No.					
	R1	*R2*	*R3*	*R4*	*R5*	*R6*
Commentary		√				√
Content	√	√	√	√	√	√
Conclusion		√			√	√
Additional Reading Material	√	√	√	√	√	√
Reflect Quiz		√				
Self-Assessment		√				
Animation		√	√		√	
Exercise		√				
Example	√	√	√	√	√	√
Real Life Application	√	√	√	√	√	√
Discussion Forum Activity		√				

The priority rules consider two conditions: whether the time-based method is activated or not as well as whether the next learning object is a Discussion Forum Activity or not. For the first condition, if the time-based method is activated, it means that if student's learning time is less than the minimum learning time, it is not enough to think deeply or remember too much information. If time-based method is activated, as shown in Table I, three recommendations (R1, R3, and R6) about posting and remembering will not be assigned. For the second condition, we consider whether the next object is a Discussion Forum Activity or not. It means that students can discuss with teacher/instructor and other students or can post their thoughts/ideas at the next object, which is a Discussion Forum Activity.. Therefore, two recommendations (R2 and R3) about using forum will be assigned earlier. According to the literature about preventing working memory problems in classroom and online learning [11][14][18], we have designed the recommended sequence as a priority order for different types of learning objects in different situations. Four situations are based on these priority rules. Each situation has its own priority order table as shown in Tables III, IV, V and VI. The first two situations consider activation of time-based method. Situation 1 represents where time-based method is ACTIVATED and the next learning object is NOT a Discussion Forum Activity. Situation 2 represents where time-based method is ACTIVATED and the next object is a Discussion Forum Activity. On the other hand, the time-based method is not activated for the other two situations. The Situation 3 means that time-based method is NOT ACTIVATED and the next learning object is NOT a Discussion Forum Activity. The Situation 4 means that time-based method is NOT ACTIVATED and the next object is a Discussion Forum Activity.

The priority orders in each table are used as recommending sequence to assign one adaptive recommendation for a learning object; for example, the priority order of Content in Situation 4 is R1->R3->R2->R4->R5->R6. If a recommendation assigned is same as the previous recommendation, then the next assigned recommendation has to be changed to next adaptive recommendation in its priority order. As shown in the same example, if R3 has been assigned previously, the next recommendation will be R2. Furthermore, if R6, the last recommendation, was assigned to the previous object, the next recommended object will be assigned with R1 which goes back to the first recommendation in the order. This mechanism can decide one adaptive recommendation for a particular object in order to avoid presenting duplicate recommendations to students.

TABLE III. PRIORITY ORDER TABLE OF SITUATION 1

Learning object Type	Adaptive Recommendation No.					
	R1	*R2*	*R3*	*R4*	*R5*	*R6*
Commentary		2				1
Content		3		1	2	
Conclusion		3			2	1
Additional Reading Material		3		1	2	
Reflect Quiz		1				
Self-Assessment		1				
Animation		1			2	
Exercise		1				
Example		3		1	2	
Real Life Application		3		1	2	
Discussion Forum Activity		1				

TABLE IV. PRIORITY ORDER TABLE OF SITUATION 2

Learning object Type	Adaptive Recommendation No.					
	R1	*R2*	*R3*	*R4*	*R5*	*R6*
Commentary		1				2
Content		1		2	3	
Conclusion		1			2	3
Additional Reading Material		1		2	3	
Reflect Quiz		1				
Self-Assessment		1				
Animation		1			2	
Exercise		1				
Example		1		2	3	
Real Life Application		1		2	3	
Discussion Forum Activity		1				

TABLE V. PRIORITY ORDER TABLE OF SITUATION 3

Learning object Type	Adaptive Recommendation No.					
	R1	***R2***	***R3***	***R4***	***R5***	***R6***
Commentary		1				2
Content	1	6	5	2	3	4
Conclusion		1			2	3
Additional Reading Material	1	6	5	2	3	4
Reflect Quiz		1				
Self-Assessment		1				
Animation		1	2		3	
Exercise		1				
Example	1	6	5	2	3	4
Real Life Application	1	6	5	2	3	4
Discussion Forum Activity		1				

TABLE VI. PRIORITY ORDER TABLE OF SITUATION 4

Learning object Type	Adaptive Recommendation No.					
	R1	***R2***	***R3***	***R4***	***R5***	***R6***
Commentary		1				2
Content	1	3	2	4	5	6
Conclusion		1			2	3
Additional Reading Material	1	3	2	4	5	6
Reflect Quiz		1				
Self-Assessment		1				
Animation		1	2		3	
Exercise		1				
Example	1	3	2	4	5	6
Real Life Application	1	3	2	4	5	6
Discussion Forum Activity		1				

IV. CONCLUSIONS AND FUTURE WORK

Previous studies have pointed out the effects of students' cognitive characteristics on the need of adaptivity in learning systems [3][4]. Several studies have also shown that individual differences in WMC affect students' performances of cognitive tasks [11][13][17]. This paper has proposed a recommendation mechanism that provides students with meaningful recommendations and suggestions based on different levels of their WMC in learning systems. Four different situations are considered through priority ordering to determine appropriate learning activities from six types of adaptive recommendations. Students can then adopt the recommendations with different qualities and in different timing to develop their own learning strategies while learning. This proposed mechanism only uses students' WMC as input for adaptive learning system to provide students automatically personalized recommendations. Therefore, the mechanism can be applied in any learning systems once students' WMC is identified in the systems. Our future work will consider additional suggestions and activities as adaptive recommendations in order to provide more meaningful and individualized support.

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