Chapter 5
Adaptive and Personalized Learning Based on Students' Cognitive Characteristics

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Abstract Working memory capacity (WMC) is a cognitive characteristic that affects students' learning behaviors to perform complex cognitive tasks. However, WMC is very limited and can be easily overloaded in learning activities. Considering students' WMC through personalized learning materials and activities helps in avoiding cognitive overload and therefore positively affects students' learning. However, in order to consider students' WMC in the learning process, an approach is needed to identify students' WMC without any additional efforts from students. To address this problem, we introduce a general approach to automatically identify WMC from students' behavior in a learning system. Our approach is generic and designed to work with different learning systems. Furthermore, by knowing students' WMC, a learning system can provide teachers meaningful recommendations to support students with low and high WMC. Accordingly, we created a recommendation mechanism that provides recommendations based on the guidelines of cognitive load theory. These recommendations are intended to assist in presentation

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of information in order to reduce working memory overload. Information about WMC is also the basis for designing adaptive systems that can automatically provide students with individualized support based on their WMC.

Keywords Adaptive and personalized learning · Cognitive characteristics · Working memory capacity

5.1 Introduction

Working memory capacity (WMC), one of students' cognitive characteristics, is to keep active a limited amount of information for a very brief period of time (Miller 1956; Driscoll 2005). Results of several studies have shown that students with low or high levels of WMC have very different performances on the different attention levels during performing cognitive tasks (Broadway and Engle 2011; Engle 2010; Gathercole and Alloway 2008). Knowing the levels of students' WMC can help in many ways to enhance learning and teaching in learning systems. First, teachers can use this information to provide meaningful recommendations to their students. Furthermore, information about students' WMC can be used as input for adaptive systems to provide students with customized learning content and activities to suit their individual WMC. This chapter focuses on two main questions: how to identify students' WMC from their learning behaviors in learning systems and how to provide teachers with recommendations to support students based on their individual WMC.

Deficiencies in student's WMC result in varying performances on a variety of tasks. Traditionally, WMC can be measured by a variety of memory span tasks including counting span, operation span, and reading span tasks which are related to the complex cognitive tasks (Broadway and Engle 2011; Carretti et al. 2009; Unsworth et al. 2012). However, the main disadvantage of these measured tasks is that students have to do them in addition to their learning. Therefore, our research aims at enabling typical learning systems to automatically identify different levels (high/low) of students' WMC without any distractions while students learn. An approach is proposed to profile student behaviors from the log data available in a learning system's database. These behaviors are then analyzed and used as basis to calculate and identify students' WMC.

WMC is very limited and can be easily overloaded in learning activities that require complex cognitive tasks. Other related studies have also indicated that cognitive load can affect students' performance of cognitive tasks in online learning (Gathercole and Alloway 2008; Sweller et al. 1998). These studies argued that if the sum of the cognitive loads exceeds the students' WMC, learning will be impaired. In other words, if the students' cognitive load is too high, it will affect them in learning effectively in learning environment. According to the cognitive load theory, the load of working memory may be affected by the intrinsic nature of the learning materials, by the presentation of those materials and by the learning activities students should do (Sweller et al. 1998). The second aim of our research is, therefore, to present meaningful recommendations and suggestions for teachers in order to avoid overload of students' WMC and to enhance the instructional design in learning systems. The recommendations aim at assisting teachers to provide individual support for students based on their WMC.

The next two sections present an overview of students' cognitive characteristics, in particular WMC, and related works on adaptive and personalized technologies. In the fourth section, an approach for identifying WMC in learning systems is introduced, including explanations on the preprocessing steps, the relevant behavior patterns for WMC detection, and the calculation of individual WMC from these patterns. In the fifth section, a recommendation mechanism to provide recommendations to teachers based on students' different levels of WMC is introduced. The final section concludes the chapter and discusses future works.

5.2 Cognitive Characteristics—Working Memory Capacity

Humans have a limited working memory in both capacity and duration to deal with cognitive activities. From the aspect of capacity, working memory is capable of holding only about seven (minus/plus two) elements (or chunks) of information for a brief period of time (Miller 1956). From the aspect of duration, Driscoll (2005) found that new information retained in working memory without rehearsal is forgotten after a very short time. Several studies have highlighted the importance of WMC for learning and investigated the relations between WMC and different aspects, such as reading comprehension, academic achievement, and attention control (Carretti et al. 2009; Woehrle and Magliano 2012). Carretti et al. (2009) concluded that individuals with poor reading comprehension seem to be impaired in their WMC to actively maintain relevant information, inhibiting off-goal information or to update their memory content. In terms of attention control, individuals with high WMC are better in maintaining attentional focus on a cognitive task, especially when faced with distractions (Woehrle and Magliano 2012). The findings of Alloway and Alloway (2010) showed that a five-year-old child's working memory is a better predicator of academic achievement than IQ. These studies suggest that working memory may be a core cognitive ability that underlies and constrains our ability to process information across cognitive domains. WMC is also crucial to many learning activities in online learning because students have to hold information in their minds while engaging in an online learning activity. Traditionally, WMC can be measured by a variety of memory span tasks. Such tasks are used to measure the amount of information that can be held accessible in the working memory. For example, such tasks look at how many words or digits a person can retain and recall in a brief period of time. However, an obvious disadvantage is that students have to take this kind of task additionally to their learning activities. Another disadvantage is that students' WMC is detected at one point of time and any distractions or lack of motivation to conduct this task would seriously and permanently affect the result.

5.3 Adaptive and Personalized Learning Technology

An adaptive learning system offers students with personalized content, presentation, and navigation supports in a learning environment (Park and Lee 2003). Such systems are able to consider relevant students' characteristics (Park and Lee 2003). The student model is the basis for personalization in such adaptive learning systems (Chrysafiadi and Virvou 2012) and is responsible for storing students' characteristics such as intellectual ability, cognitive abilities, learning styles, prior knowledge, achievement motivation, self-efficacy, and abilities to solve problems and making decisions (Park and Lee 2003; Chrysafiadi and Virvou 2012). By knowing the characteristics of students, an adaptive learning system can offer personalized learning spaces (adaptive courses and materials) and support (such as adaptive annotations, navigation, and recommendations).

Building and updating a student model is called student modeling. Two different student modeling approaches exist for identifying students' characteristics, preferences, and needs in learning systems: collaborative and automatic (Brusilovsky 1996). In the collaborative approach, the student provides explicit information (e.g., learning goals, preferences, etc.) for the student modeling mechanism (Brusilovsky 1996). In this approach, the adaptive learning system gets the required information about students by collaborating with the students in collecting the information. An example of such collaborative student modeling approach is WebOSPAN (Lin 2007), where students perform a sequence of memory and calculation tasks based on which their WMC is identified. The automatic student modeling approach refers to building and updating the student model automatically based on the behaviors and actions of students in learning systems. Conati and Maclaren (2009) used an automatic approach to analyze students' browsing data recorded in the log file of a web-based learning system and concluded that students' cognitive style (field dependence and independence) and learning behaviors are related. Cognitive trait model (CTM) is another example for an automatic student modeling approach that profiles students according to their three cognitive traits: WMC, inductive reasoning ability, and associative learning skills (Lin 2003). In CTM, the students' behaviors in a course are used to infer those three cognitive traits. The results of an evaluation of the CTM (Lin 2007) showed a significant correlation between the results of WMC obtained from CTM and the scores from WebOSPAN task. Lin's study (Lin 2007) provides a practical validation to CTM as well as proves the effectiveness of the selected behaviors to determine WMC. The CTM is very much related to our work. While the concept of CTM could be generalized, its implementation has not been that way. In our work, we particularly focus on using behavior patterns that can be identified in any learning system and course, and integrate this concept into a detection tool that can be applicable for learning systems in general. In the following section, we will introduce an approach for automatically detecting students' WMC based on their continuous behavior in learning systems.

5.4 Approach of Detecting WMC in Learning Systems

This section focuses on how to enable typical learning systems to automatically identify different levels (high/low) of students' WMC from their learning behavior and actions in learning systems. A student modeling approach is introduced and a detection tool, DeLeS (Graf et al. 2009a, b), is extended to identify students' WMC from their activity log data of learning systems. In the following subsections, a detailed explanation is provided about each step of this approach.

5.4.1 Preprocessing of Data

In order to analyze students' behavior and detect relevant behavior patterns, some preprocessing of behavior data and course data in learning systems is required. The preprocessing includes (1) the identification of learning sessions, (2) filtering out activities that are not dedicated to learning as well as activities where students visit a learning activity only for very short time, and (3) building a Learning Sequence Table called LSEQ table that includes the structure of the course in terms of the predefined sequence of learning activities/objects in a course.

5.4.2 Relevant Behavior for WMC Detection

In learning situations, there are several behavior patterns known in the literature that give indications for a student's WMC. Six patterns are considered and explained subsequently. Since most of these patterns are based on students' navigational behavior, types of navigational behavior are described by a relation function, *R (preLO, currLO)*. This function relates two learning objects (LOs): the source (*preLO*) and the destination (*currLO*).

1. **Linear navigation pattern**: Linear navigation means that students learn the materials linearly and follow the learning sequence of the course defined by teachers. Huai (2000) performed an experiment to investigate the relationship between WMC, long-term memory, and a serial/holistic learning style. To draw conclusions about the relationship between WMC and a serial/holistic learning style, linear and nonlinear navigational behavior of students was investigated. As a result, Huai also found that students with high WMC tend to focus on linear navigation and students with low WMC tend to use nonlinear navigation.

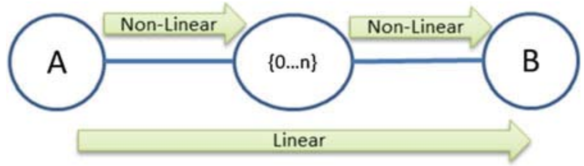

Fig. 5.1 A sample of linear navigational behavior

A sample of linear navigational behavior is shown in Fig. 5.1. When LO B is learned, and the previous LO of LO B (defined in the LSEQ table), LO A, has been learned before, linear navigation is found, no matter whether other LOs are visited between LOs A and B. If this linear navigation is found, it gives an indication for high WMC. Otherwise, nonlinear navigation is found, which gives an indication for low WMC.

2. **Constant reverse navigation pattern**: Reverse navigation means that a student revisits an already visited LO. Constant reverse navigation indicates that a student frequently goes back to an already visited LO. This behavior can be explained by the limited capacity of working memory for students with low WMC (Graf et al. 2009a, b). The process of constant reverse navigation is caused by an insufficient WMC to hold on the materials that have just been visited (Lin et al. 2003). When the learning materials that a student just read on the previous page should be still fresh in his/her working memory, the constant need to navigate backward is a sign of working memory deficiency. The definition of constant reverse navigational behavior is that there are more than two LOs revisited in the same learning session and the navigational relations of these LOs are not defined in the LSEQ table (and therefore not in line with the sequence of LOs in the course structure). Figure 5.2 shows a sample of constant reverse navigational behavior including the following relations of navigation: *R(A, B), R(B, C), R(C, A),* and *R(A, C)*. In these navigational relations, two relations, *R(C, A)* and *R(A, C),* are not defined in the LSEQ table and the two destination LOs, *A* and *C*, are revisited. Thus, the constant reverse navigational behavior is found, which gives an indication for low WMC.
3. **Simultaneous tasks pattern**: The simultaneous tasks pattern is transferred from the ability of attentional control on performing two tasks simultaneously. Previous studies have shown that when performing two tasks simultaneously, low-WMC participants were less accurate than participants with high WMC (Engle 2010; Woehrle and Magliano 2012). For identifying this pattern, overlapping navigational behavior is investigated which indicates that a student tries to

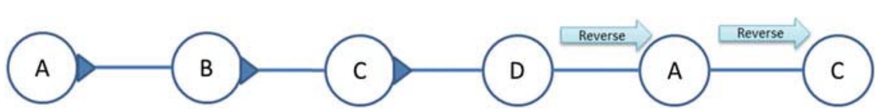

Fig. 5.2 A sample of constant reverse navigational behavior

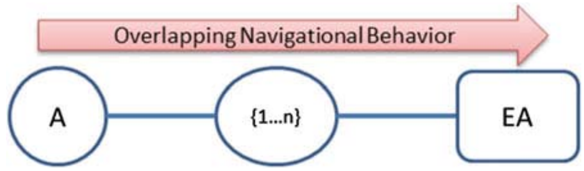

Fig. 5.3 A sample of overlapping navigational behavior

perform two tasks simultaneously. As shown in Fig. 5.3, if a student visits at least one other LO in between LO A and its evaluation, *EA*, overlapping navigational behavior is found. In such situation, the student learns LO A first and then learns other LOs before taking the evaluation of LO A. Therefore, she/he needs to remember the concept of LO A in her/his working memory while learning other LOs. If the student then passes the evaluation of LO A, the simultaneous tasks pattern is found, which gives an indication for high WMC. If she/he fails, the nonsimultaneous tasks pattern is identified, which gives an indication for low WMC.

4. **Recalling learned material pattern**: The recalling learned material pattern is transferred from the relationship between WMC and long-term memory. This pattern is similar to the simultaneous tasks pattern but it is identified within two different learning sessions. Prior works have argued that the individual's ability to retrieve information from long-term memory is determined by their WMC (Unsworth et al. 2012; Engle 2010). As a result, they found that low-WMC participants cannot recall as much information from long-term memory as high-WMC participants since low-WMC individuals do not search the remembered information in their long-term memory as effectively as high-WMC individuals. Figure 5.4 shows a sample of this pattern. This pattern is found if a student visits LO A in one session but does not perform an evaluation of his/her knowledge on LO A in that session. In a different learning session, the student then does not visit LO A but goes directly to the evaluation of LO *A (EA).* If the student then passes the evaluation, it means that she/he could recall the previously visited

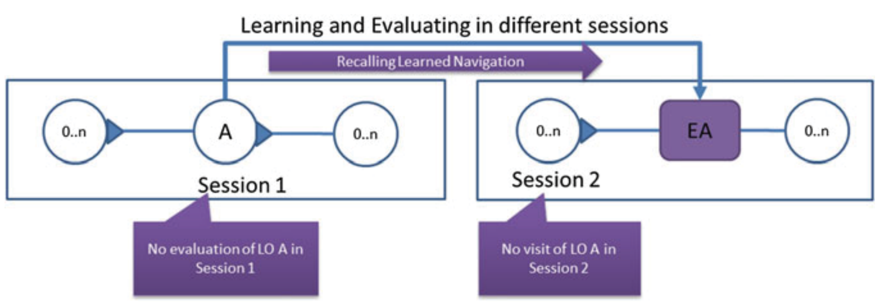

Fig. 5.4 A sample of recalling navigational behavior

information from LO A from her/his long-term memory and the recalling learned material pattern is found, which gives an indication for high WMC. If she/he fails the evaluation, the non-recalling learned material pattern is identified which gives an indication for low WMC.

5. **Revisiting passed learning object pattern**: Similar to the previous pattern, the revisiting passed learning object pattern is transferred from the ability of using WMC to retrieve information from long-term memory. As mentioned in the previous sections, several studies have argued that individuals with low WMC cannot recall as much information from long-term memory as individuals with high WMC (Engle 2010; Unsworth et al. 2012). This pattern considers a situation where a student visited LO A and successfully completed its evaluation (EA) in the same session but then revisits LO A afterward in a different learning session, as shown as a sample in Fig. 5.5. In such case, the student seems to have problems recalling information from his/her long-term memory and wants to reread some of the already learned information. The more time the student spends on LO A during such revisit, the more problems the student seems to have in recalling the respective information from the long-term memory and therefore, the stronger the indication for low WMC is. In order to calculate this pattern, we consider the time the student i spent on LO A in order to pass the evaluation as base value b_i, and the time that the student spent when he/she revisits LO A as value v_i. Furthermore, let r_i be the ratio v_i/b_i, representing how much time a student spent on revisiting LO A in relation to how much time he/she spent to learn this LO. Let r_{avg} be the average ratio of all students, calculated based on formula 1 and representing how much time on average each student spent on revisiting LO A in relation to how much time he/she spent to learn this LO.

$$r_{\text{avg}} = \frac{\sum_{i=1}^{n} r_i}{n}, \tag{5.1}$$

where n is the overall number of students. This average ratio r_{avg} is then used as threshold and compared to a student's r_i value. If r_i is greater than r_{avg}, the time the student took for reading and recalling already learned information is above average and therefore indicates low WMC. On the other hand, if r_i is smaller

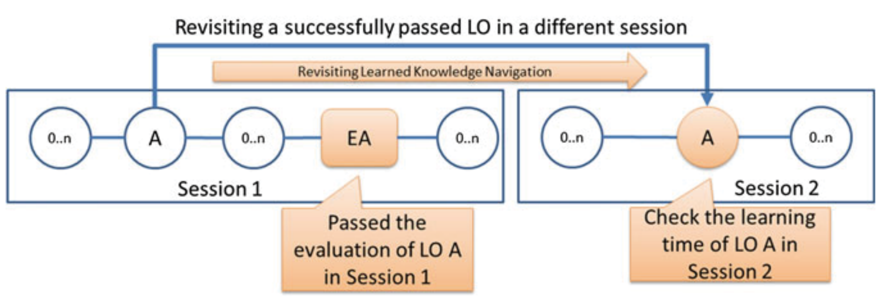

Fig. 5.5 A sample of revisiting navigational behavior

than r_{avg} the time the student took for reading and recalling already learned information is below average and therefore indicates high WMC. If r_i is equal to r_{avg}, an indication for average WMC is given.

6. Learning style pattern: The learning style pattern is based on the relationship between learning styles and WMC. Graf et al. (2009) investigated the direct relationship between WMC and the four learning style dimensions of the Felder-Silverman learning style model (FSLSM) (Felder and Silverman 1988), namely the active/reflective, sensing/intuitive, visual/verbal, and sequential/global dimensions. The results of the study showed that students with a reflective or intuitive learning style tend to have high WMC and students with an active or sensing learning style tend to have low WMC. For the visual/verbal dimension, the study found only a one-directional relationship, namely that learners with a verbal learning style tend to have high WMC, whereas visual learners have either high or low WMC. No relationship for the sequential/global dimension was found. The learning style pattern considers these relationships. Accordingly, if a student has an active or sensing learning style, this gives an indication for a low WMC. On the other hand, a reflective, intuitive, or verbal learning style gives an indication for a high WMC. An average value of all indications from a student's learning styles is calculated and this value represents the overall indication of WMC for this learning style pattern.

5.5 From Learning Patterns to WMC

After preprocessing the data, these data are used to calculate the students' WMC based on the five navigational behavior patterns and the learning style pattern. If a navigational behavior pattern is detected in a relation between two LOs, this relation is considered as an activated relation for the particular pattern. In each learning session, a value p is calculated for each of the five navigational behavior patterns based on the number of activated and non-activated relations in this session. This value p shows how strongly the student's behavior represents the respective pattern. Subsequently, the value p for each pattern is transferred to its indication for WMC (e.g., a high p value for linear navigation provides an indication for high WMC). Then, the indications from the five navigational behavior patterns and the indication based on the learning style pattern are summed up and divided by the number of activated patterns (where the learning style pattern is considered as activated as soon as the learning styles of the student are known). The result of this calculation represents the indication for WMC of the respective learning session. Although the learning style pattern is not dependent on learning sessions, we decided to add the indication from this pattern in each session in order to ensure that this pattern has the same impact in the detection process as all other navigational behavior patterns. Each learning session also contains a weight, which determines the influence of each session on the overall value of WMC and is calculated based on the number of activated relations in a session for all patterns. In order to calculate the student's WMC, the WMC indication of each session is multiplied by the weight of the respective session. Subsequently, the results for all sessions are summed up and divided by the number of sessions. The resulting value is the identified WMC for the respective student.

5.6 Recommendation Mechanism for Teachers to Support Learners with Different WMC

While the previous section presented an approach to automatically identify students' WMC, in this section, a recommendation mechanism is introduced that uses the information about students' WMC to present meaningful and personalized recommendations for teachers in order to avoid overloading particular students' WMC as well as to enhance the instructional design in their courses. Students in an online course exhibit different performance in different learning sessions and one reason can be different levels of WMC. The recommendations provided by this mechanism are therefore considering the level of WMC at which a student performs in the learning sessions and provide teachers with suggestions on how to support a particular student according to cognitive load theory (Sweller 2005; Watson and Gable 2013) and the features of working memory (Miller 1956; Driscoll 2005). For example, if a student with high WMC exhibits signs of low WMC in a particular learning session, the teacher is made aware of this mismatch and provided with recommendations on how to support the student to successfully learn in the respective learning session.

Two types of WMC results of a student are considered in the recommendation mechanism: the WMC identified in one session (called session WMC) and the total WMC from all sessions. Both of these types of WMC results can be automatically detected as described in the previous section. If the session WMC and the total WMC match, it means that the student is acting with the same performance in that session as the overall performance from all sessions. The recommendation mechanism does not take any action in that situation and does not present any information to the teacher. On the other hand, if the results do not match, it means that the student has probably faced some problems or distractions in that session. When a mismatch is found, further information and recommendations based on the student's WMC are displayed to the teacher. If a student has high total WMC but her/his session WMC is low, the recommended information for high WMC will be displayed. On the contrary, if a student has low total WMC but her/his session WMC is high, the recommended information for low WMC will be presented to the teacher. Figure 5.6 shows a screenshot of a student who has low WMC but exhibits high WMC in a session.

The recommendations based on WMC consist of general and recommended information. The general information provides further details on those sessions in which the WMC results are mismatched. The recommended information presents guidelines and suggestions for supporting the respective student based on her/his WMC.

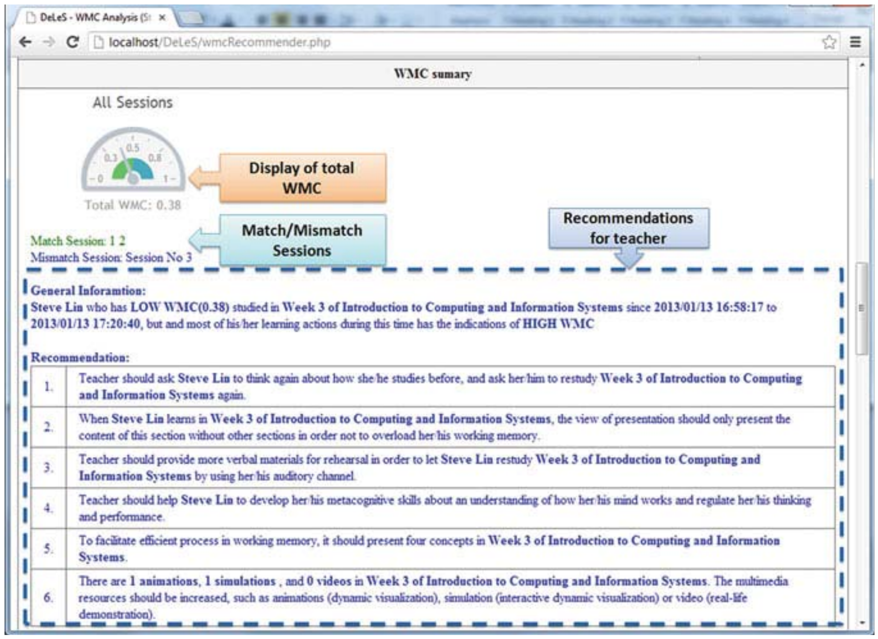

Fig. 5.6 Information and recommendations for a learner with low WMC

General Information: General information presented to the teachers consists of student, course, and session information. This information enables teachers to know who, where, and when a student might have problems. The teachers can then conduct investigations for improving their instruction materials. The mechanism presents overviews of student and course information to teachers, showing them a list of students who have a mismatch in their session WMC and total WMC, as well as the number of mismatches that each student and each session/course has. For a single student, the format of general information is as follows:

> {StudentName} who has {TotalWMC} studied in {SectionTitle} of {CourseTitle} since {BeginTime} to {EndTime}, but most of his/her learning actions during this time indicate {SessionWMC}.

Recommended Information: The following paragraphs describe the recommendations based on different levels of WMC, including a brief discussion on the features of recommendations, the relationship with cognitive load as well as concrete suggestions for each feature.

- **Recommendations for high WMC**: Students with high WMC have high capacity in their working memory to process information. Accordingly, the recommendations for high-WMC individuals (described in the following paragraphs in more detail) focus on how to guide them effectively to use their working memory.

1. **Increasing learning space**
   Unsworth and Engle (2007) suggested that individuals with high WMC are better at discriminating relevant and irrelevant information in their search set. They also mentioned that high-WMC individuals have poorer performance than low-WMC individuals if they use constrained search set. Increasing the learning space can lead to extending the search set and therefore, can be helpful for high-WMC students. The view of presented information will then be increased to allow the students to get the most out of the domain (Kinshuk and Lin 2003). The recommendation for this feature is:

When {StudentName} learns {SectionTitle}, the other sections of {CourseTitle} should also be presented to her/him in order to extend her/his available learning space.

2. **Promoting deep processes**
   Anderson (2008) suggested that real-life applications should be used in online learning to help transfer information to students' long-term memory by promoting their deep processes. High-WMC individuals have a better ability of using different strategies to transfer the knowledge into their long-term memory effectively (Unsworth et al. 2012). In cognitive load theory, the variability effect also encourages students to develop knowledge structure that aids in transfer of training to similar situations in the real world (Sweller 2005). Therefore, teachers should encourage high-WMC students to engage in deeper thinking by transferring their knowledge to real-life applications. The recommendation for this feature is:

{StudentName} should think about how to apply the learned knowledge of {SectionTitle} of {CourseTitle} in real life. This activity can help her/him in processing information to her/his long-term memory and encourages deeper thinking.

3. **Attending learning activity**
   Anderson (2008) 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. Unsworth and Engle (2007) pointed out that high-WMC individuals could maintain the task goal better compared to low-WMC individuals when they are learning new information. Therefore, in a situation where students with high WMC have shown signs of low-WMC behavior, they could be suggested to use additional tools such as mind maps or concept tools to help them connect their new and already learned information. Also, the hierarchical organization of information presented as mind map or concept map provides a high degree of structure, which would facilitate connection of new knowledge with already learned knowledge and reduce the cognitive load for learning new information (Watson and Gable 2013). The recommendation for this feature is:

{StudentName} should be encouraged to attend a summary activity (such as creation of mind map or concept map) after learning {SectionTitle} of {CourseTitle}. This hierarchical map will help her/him to connect the main concepts (ideas) of this section to already learned knowledge.

4. **Using metacognitive skills**
   Students should be given more opportunities to use their metacognitive skills and should be encouraged to participate in activities that use their metacognitive skills actively (Anderson 2008). Whitebread (1999) argued that high-WMC individuals have better metacognitive skills about how to learn new knowledge than low-WMC individuals. Therefore, teachers should encourage high-WMC students to use their metacognitive skills when they have difficulties. The recommendation for this feature is:

{StudentName} should be encouraged to rethink how she/he studied before and compare the differences between her/his learning in {SectionTitle} of {CourseTitle} and previous sections. This will help {StudentName} to use her/his own metacognitive skills to find out what difficulties she/he encountered in {SectionTitle} of {CourseTitle}.

- **Recommendations for low WMC**: For students with low WMC, their capacity of working memory can be exceeded easily. Accordingly, recommendations for students with low WMC (described in the following paragraphs in more detail) focus on how to reduce their cognitive load.

1. **Decreasing learning space**
   Previous studies have argued that low-WMC individuals are poorer than high-WMC individuals at searching information in a larger search set (Unsworth et al. 2012; Unsworth and Engle 2007). In order to protect the students from overloading the working memory with complex hyperspace structure, the number of navigational path should be decreased (Gathercole and Alloway 2008; Kinshuk and Liu 2003). Thus, decreasing the learning space into particular parts would reduce the intrinsic load by presenting less information at a time. The recommendation for this feature is:

When {StudentName} learns {SectionTitle} of {CourseTitle}, the view of presentation should only present the content of this section and no other sections in order to avoid overloading her/his working memory.

2. **Rehearsing learned information**
   Low-WMC individuals are not able to keep information in their working memory as long as high-WMC individuals can (Unsworth and Engle 2007). Rehearsal would be an effective way to help students remember and transfer the learned information from her/his working memory to the long-term memory (Gathercole and Alloway 2008). Driscoll (2005) argued that novel information in human cognitive system is lost within a very short time without rehearsal. The recommendation for this feature is:

{StudentName} should be encouraged to rehearse {SectionTitle} of {CourseTitle} in order to help her/him to retain important information.

3. **Training metacognitive skills**
   As mentioned in Anderson's article (Anderson 2008), teachers should provide students more opportunities to use their metacognitive skills. However, students with low WMC may have difficulty concentrating and may frequently lose their task goal when learning information (Unsworth and Engle 2007). Previous studies have suggested that training of metacognitive skills may help students with low WMC in developing an understanding of how to learn and how to think when learning new information (Watson and Gable 2013). The recommendation for this feature is:

{StudentName} needs some help in developing her/his metacognitive skills about how her/his mind works and regulate her/his thinking and performance. {StudentName} should be encouraged to rethink how she/he learns in general and how she/he thinks when she/he learned in previous Sects.

4. **Preventing overload**
   Miller proposed a "magical number seven" to give the earliest quantification of the capacity limit associated with working memory (Miller 1956). Watson and Gable suggested that up to four facts about a learning object are more easily handled in working memory (Watson and Gable 2013). If the number of facts (such as concepts or ideas) increases, the natural complexity of information increases and the intrinsic cognitive load thus is high. The recommendation for this feature is:

To facilitate efficient processing in working memory, {SectionTitle} of {CourseTitle} should present maximum four concepts/ideas.

5. **Using multimedia resources**
   Previous studies have suggested that the number of multimedia resources should increase for low-WMC students so that they could be provided with multimedia resources that work best for their WMC (Broadway and Engle 2011). In cognitive load theory, the modality effect suggests that multiple recourses of information are essential for understanding and learning (Sweller 2005). The recommendation for this feature is:

There are {NumofAnimation} animations and {NumofSimulation} simulations in {SectionTitle} of {CourseTitle}. More animations (dynamic visualization or video demonstration) and more simulations (interactive dynamic visualization) could help {StudentName} to better understand and learn this Sect.

6. **Attracting attention**
   Low-WMC individuals are more likely to have their attention captured by distractions compared to high-WMC individuals and thus are also more susceptible to losing access to the task goal (Unsworth et al. 2012). Therefore, in order to attract student attention, the important and critical information should be highlighted and be explained with additional explanations. In cognitive load theory (Sweller 2005) the split attention effect occurs when attention is split between multiple sources of visual information that are all essential for understanding. Thus, the extraneous cognitive load is reduced

by integrating multiple sources of information (Sweller 2005). The recommendation for this feature is:

{StudentName} would benefit from having pointed out the important information in {SectionTitle} of {CourseTitle} again or using different explanations in order to gain her/his attention and help in remembering the information.

In conclusion, this section introduced a mechanism that provides teachers with various recommendations and suggestions based on different levels of students' WMC. The mechanism presents general and recommended information about students' performance to the teachers once it identifies that a student's behavior in a particular session does not correspond with her/his WMC. Teachers can then use this information to provide appropriate materials and personalized suggestions for students based on their WMC levels.

5.7 Integration and Visualization of WMC Information and Recommendations in Learning Systems

Both, the detection tool for identifying students' WMC based on their behavior as well as the recommendation mechanism to provide teachers with recommendations on how to support students with different WMC, are designed to be integrated into

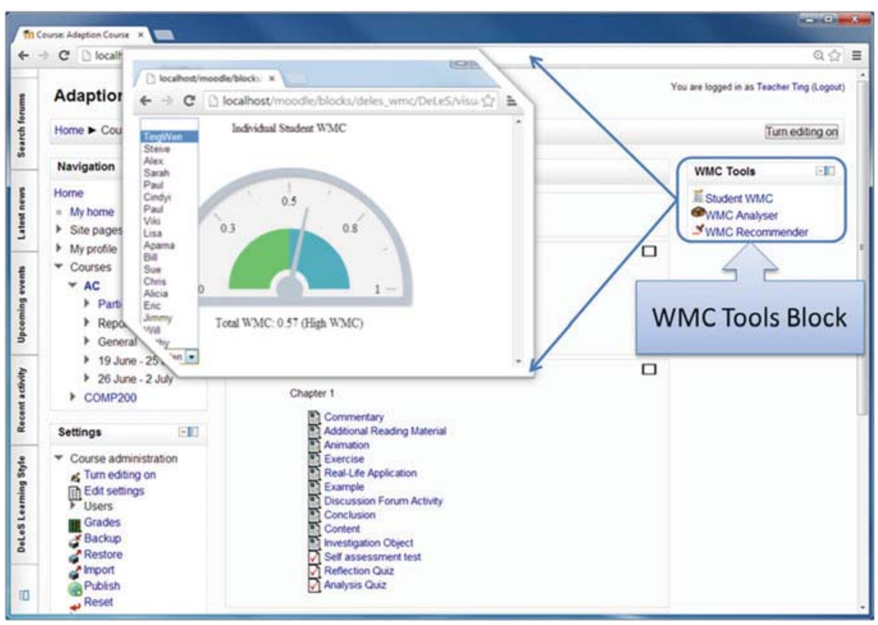

Fig. 5.7 Detection Tool Block in Moodle and Individual Student WMC

existing learning systems. To validate the detection tool and the recommendation mechanism, both have been implemented as plugins for the learning management system Moodle (Moodle 2013) in the form of a block. This block is easily accessible for teachers in a dedicated area at the right side of the learning systems' display (see Fig. 5.7).

The block consists of three links: "Student WMC," "WMC Analyser," and "WMC Recommender." The "Student WMC" link leads to a page that provides teachers with information on their students' WMC. As can be seen in Fig. 5.7, a teacher can select a particular student and can see her/his WMC, which is presented on a scale from 0 to 1, where 0 indicates a very low WMC and 1 indicated a very-high WMC.

The second link ("WMC Analyser") provides more detailed information about students' WMC with respect to each learning session. A teacher can see the students' behavior of each learning session based on the six patterns (LN: Linear Navigation; CR Constant Reverse navigation, ST: Simultaneous Tasks, RC: ReCalling learned materials, RV: ReVisiting passed learning object, and LS: Learning Style), what indication this behavior gives with respect to a student's

Fig. 5.8 WMC Analyzer Interface—LN, CR, ST, RC, RV represents the activated behaviors of respective patterns; nonLN, nonCR, nonST, nonRC, nonRV represents the nonactivated behaviors of those patterns; LS(ref/ins/ver) represents reflective, intuitive, and verbal learning styles; LS(act/sen) represents active and sensing learning styles

WMC as well as the WMC of each session. As shown in Fig. 5.8, the blue bars represent indications for high WMC and the green bars represent indications for low WMC. The WMC of each session is calculated based on the indications from all patterns. For example, Fig. 5.8 shows that the respective student performed more linear navigation behavior than nonlinear in session 6 and therefore, the LN pattern gives an indication value of 0.9 on a scale from 0 to 1 where 0 represents a strong indication for low WMC and 1 represents a strong indication for high WMC. Accordingly, the indication value of 0.9 suggests that the student has high WMC.

The third link ("WMC Recommender") provides teachers with recommendations on how to best support individual student based on their WMC. Once a teacher clicks on this link, the teacher can select for which student she/she wants to get recommendations and subsequently, recommendations are presented as shown in Fig. 5.6.

5.8 Conclusions and Future Works

This chapter proposed an approach for identifying students' WMC from their activity log information in learning systems as well as introduced a mechanism that provides teachers with various recommendations and suggestions based on different levels of students' WMC in learning systems. For detecting students' WMC, six behavior patterns have been identified to be, on one hand, relevant for the identification of WMC as concluded by the literature, and on the other hand, to be domain and learning system independent so that our proposed approach is generic and can be used in different learning systems. As identified in several studies, students' different levels of WMC can affect students' learning performances (Alloway and Alloway 2010; Marengo et al. 2012). The information about students' WMC can be helpful to support students in many ways. For example, by making students and teachers aware of the different WMC levels, teachers can individually support students and provide them with personalized recommendations, while students can better understand their weaknesses and strengths, and use this information to improve their learning.

Accordingly, we proposed a recommendation mechanism to provide teachers with suggestions in order to better support individual students based on their WMC. The proposed recommendation mechanism considers cognitive load theory and the features of working memory to understand students' performances during their learning processes. The mechanism presents general and recommended information about students' learning processes to the teachers once it identifies that a student's behavior in a particular session does not correspond with her/his WMC. Teachers can then use this information to provide appropriate materials and personalized suggestions for students based on their WMC levels.

In addition, information about students' WMC can be used as input for an adaptive learning system to automatically provide students with individualized materials and activities as well as personalized recommendations, considering their level of WMC. Furthermore, since there are other cognitive abilities that affect the learning process, our future work will focus on extending the proposed mechanism to additionally consider those other cognitive abilities, such as inductive reasoning skill, associative skill, and information processing speed.

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