2010 Workshops on Database and Expert Systems Applications

Using Cognitive Traits for Improving the Detection of Learning Styles

Sabine Graf and Kinshuk
School of Computing and Information Systems
Athabasca University, Canada
sabineg@athabascau.ca; kinshuk@athabascau.ca

***Abstract*—While providing online courses that fit students' learning styles has high potential to make learning easier for students, it requires knowing students' learning styles first. This paper demonstrates how the consideration of cognitive traits such as working memory capacity (WMC) can help in detecting learning styles. Previous studies have identified a relationship between learning styles and cognitive traits. In this paper, the practical application of this relationship is described and its potential to improve the detection of learning styles by additionally including data from cognitive traits in the calculation process is discussed. An extended approach and architecture for identifying learning styles which consider cognitive traits is also introduced. Furthermore, an experiment has been conducted that shows the positive effect of considering WMC in the detection process of learning styles for two out of three learning style dimensions, leading to higher precision of the results and therefore more accurate identification of learning styles which in turn lead to more accurate adaptivity for students.**

Keywords-adaptivity in learning systems, cognitive traits, working memory capacity, learning styles

I. INTRODUCTION

Providing e-learning or online courses as well as courses that are delivered in a blended format becomes more and more popular in today's education. However, in most cases, such courses lack adaptivity and do not consider the individual characteristics and needs of students. But students differ, for example, with respect to their background knowledge, motivation, interest in the subject, learning styles, and cognitive traits. Considering the students' individual differences can make learning easier for them and lead to a more satisfying learning experience as well as to more effective learning.

In recent years, more and more research has been conducted on incorporating students' cognitive characteristics such as learning styles and cognitive traits into online courses by providing courses that match the students' cognitive characteristics. With respect to learning styles, several educational theories and studies argue that learners learn easier when their learning styles match with the teaching style (e.g., [1, 2, 3, 4]). Similarly, cognitive traits influence the learning process. Research on working memory (e.g., [5, 6, 7, 8, 9, 10]) has shown that the speed of learning, the memorisation of learned concepts, effectiveness of skill acquisition, and many other learning abilities are all affected by the capacity of working memory. Providing content that exceeds the cognitive abilities of a student affects the learning progress negatively and leads to poor student performance.

Based on these arguments and studies, several learning systems have been developed in recent years, aiming at providing adaptive courses based on students' cognitive characteristics. Examples of such systems include CS383 [11], LSAS [2], INSPIRE [12], TANGOW [13], AHA! [14, 15], TSAL [16], WELSA [17], and the add-on to a learning management system [18]. Evaluations of such systems demonstrated the possible benefits and positive effects of adaptivity based on cognitive characteristics, including higher learning satisfaction, less time required for learning, and/or better grades (e.g., [2, 16, 17, 18]).

For providing adaptivity in online courses, students' characteristics have to be known first. With respect to technology enhanced learning, Brusilovsky [19] distinguished between two different ways for getting information about the learners' characteristics: the *collaborative* and the *automatic* student modelling approach. In the former, the students explicitly provide information about themselves (e.g., filling out a questionnaire that helps to identify their learning styles or performing a task in order to identify their cognitive traits), whereas in the latter, the system automatically infers the characteristics from the behaviour and actions of students while they are working/learning in the system. The automatic approach has several advantages. Since information is gathered automatically from students' behaviour, no additional effort from students is required, such as answering questions of a questionnaire or performing a task to provide information about their cognitive traits. Furthermore, the automatic approach uses data from a time span rather than from a specific point of time. This makes an automatic approach more accurate and less error-prone, enabling the system to learn characteristics of students over time as well as consider exceptional behaviour of students in the identification process. However, a problem with the automatic approach is to get enough reliable information to build a robust student model. As a solution, Brusilovsky [19] recommended the use of additional sources of information. Hence, it is beneficial to find mechanisms that use whatever information about the learner is already available to get as much reliable information to build a more robust student model.

Previous research [20, 21, 22] has investigated the relationship between learning styles, in particular the Felder-Silverman learning styles model (FSLSM) [3], and cognitive traits, in particular working memory capacity (WMC). The results of those studies showed that a relationship between learning styles and cognitive traits exists. The aim of the

1529-4188/10 $26.00 © 2010 IEEE
DOI 10.1109/DEXA.2010.35

IEEE computer society

study in this paper is to show how this relationship can be applied in practice to improve student modelling of learning styles. It is demonstrated how the additional information about students' cognitive traits can be incorporated in the identification process of learning styles. Furthermore, a study has been conducted with 63 students to demonstrate the positive effect of considering information from students' cognitive traits in the identification process of learning styles.

The next section provides background information about learning styles, cognitive traits, as well as the summary of previous studies regarding the relationship between learning styles and cognitive traits. Section III introduces an approach and tool for identifying learning styles and shows how cognitive traits can be included in the identification process. Section IV presents an experiment that compares the results of the tool for identifying learning styles when considering only information from students' behaviour and when considering information about students' behaviour and their cognitive traits. Discussion about the results is also provided. Section V discusses the conclusions of our research.

II. Background

Several different learning style models exist in literature, and while looking at adaptive educational systems which incorporate learning styles, FSLSM is found to be one of the most often used models in recent times and some researchers even argue that it is the most appropriate model [11, 23].

According to FSLSM, each learner is characterised according to four dimensions: active/reflective dimension where *active* learners learn by trying things out and working with others and *reflective* learners learn by thinking things through and working alone; sensing/intuitive dimension, where *sensing* learners like to learn concrete material and tend to be practical and *intuitive* learners prefer to learn abstract material such as theories and their meanings and tend to be more innovative than sensing learners; visual/verbal dimension, where *visual* learners remember best what they have seen and *verbal* learners get more out of words, regardless of the fact whether they are spoken or written; and sequential/global dimension, where *sequential* learners learn in linear steps and prefer to follow linear stepwise paths and *global* learners learn in large leaps and are characterized as holistic.

Regarding cognitive traits, WMC is an important factor for learning [5, 6, 7, 8, 9, 10]. In earlier times, working memory was also referred to as short-term memory. Richards-Ward [24] named it the Short-Term Store to emphasise its role of temporal storage of recently perceived information. Working memory enables people to keep active a limited amount of information (roughly 7+-2 items) for a brief period of time [25].

In a comprehensive literature review [20], the relationship between the four learning style dimensions of FSLSM and WMC has been investigated by looking at studies that deal with the interaction of learning styles, cognitive styles, and cognitive traits. From these studies, indirect relationships between the dimensions of FSLSM and WMC have been concluded. Based on these indirect relationships, an exploratory study with 39 students was conducted [21], where students were asked to fill out the Index of Learning Styles (ILS) questionnaire [26], a commonly used questionnaire for identifying learning styles based on the FSLSM. Furthermore, students were asked to undertake the Web-OSPAN task for identifying their WMC [22, 27]. The data from both instruments were analysed and again relationships between the learning style dimensions and WMC were found. Due to the promising results of this exploratory study, a main study was then conducted with 297 students [22], using the same instruments as described for the exploratory study in order to identify students' learning styles and WMC. The in-depth analysis of the gathered data showed again that relationships between learning styles and WMC exists. For the active/reflective dimension, a non-linear relationship was found, indicating that learners with either strong active or strong reflective learning style tend to have low WMC, and the more balanced the learning style is the higher WMC students tend to have. For the sensing/intuitive dimension, statistically significant results were found indicating that learners with a sensing learning style tend to have low WMC, and the more balanced the learning style becomes the higher students' WMC tend to be. Regarding the visual/verbal dimension, evidence for a one-directional relationship was found, where learners with a verbal learning style tend to have high WMC but learners with high WMC might have either a visual or a verbal learning style. For the sequential/global learning style dimension, no significant relationship was found.

Comparing the results of the main study with the results of the exploratory study and the literature review, two inconsistencies can be seen: the first deals with the sequential/global dimension, where a relationship is found by literature but not by studies [21, 22] and the second one refers to the reflective learning style preference, which is associated once with low WMC and once with high WMC.

Since the results of the main study are based on in-depth analysis with data from a high number of participants and the study investigated the direct relationship between the dimensions of FSLSM and WMC, the results of this study are used for including cognitive traits into the detection process of learning styles.

III. Identification of Learning Styles

In this section, an approach and tool for identifying learning styles are introduced which have been successfully evaluated with 127 students [28]. Subsequently, the extension of this approach and tool are shown in order to consider the relationship between learning styles and cognitive traits as identified by the in-depth analysis of the study summarised in the previous section [22].

A. An Approach for Identifying Learning Styles from Students' Behaviour in Online Courses

In the proposed approach [28], detecting learning styles is done by detecting patterns of behaviour that give indications about students' learning styles. Since FSLSM is based on learning in general, for detecting learning styles in learning systems the general behaviour proposed by FSLSM has been mapped to behaviour in learning systems.

In order to make the approach applicable for learning systems in general, only commonly used types of learning objects in such systems were selected to be the basis for patterns. These types of learning objects include: content objects, outlines, examples, self assessment tests, exercises, and discussion forums. Furthermore, the navigation behaviour of students in the course was considered.

Overall, 27 patterns of behaviour were considered for the four learning style dimensions. Patterns mainly dealt with how often a student visited particular types of learning objects, how much time a student spent on particular types of learning objects as well as how well a student performed on questions of particular types in self-assessment tests and exercises (e.g., questions that require overview knowledge or question about details).

Data about students' behaviour can be used to calculate hints for specific learning style preferences. For example, if a learner often visited exercises, this gives us a hint that the learner prefers an active learning style. Hints are stated by four values: 3 indicates that the student's behaviour gives a strong indication for the respective learning style, 2 indicates that the student's behaviour is average and therefore does not provide a specific hint, 1 indicates that the student's behaviour is in disagreement with the respective learning style, and 0 indicates that no information about the student's behaviour is available. In order to classify the behaviour of students into these four groups, thresholds from literature are used as basis, considering additionally the characteristics of the respective course.

By summing up all hints and dividing them by the number of patterns that include available information, a measure for the respective learning style is calculated.

This approach considers that not all learning systems might be able to track data about all patterns and excludes the patterns for which no information is available. However, the more data can be tracked and patterns are included in the calculation process, the more reliable the results are.

The approach has been implemented as a tool, consisting of two components. The *data extraction component* is responsible for extracting the relevant data from the learning system's database. Therefore, it requires information about which types of learning objects and patterns of behaviour need to be extracted. Because the tool is generated for learning systems in general rather than for only one specific system, heterogeneity of database schemata needs to be considered. The data extraction component delivers raw data which represent the behaviour of the learners regarding the determined patterns. These raw data are then passed to the *calculation component*, which is responsible for using these data to calculate learning style preferences based on the approach described above.

B. Considering Cognitive Traits for Identifying Learning Styles

While the approach described in the previous subsection is based on behaviour of students only, this subsection demonstrates how the approach and tool can be extended so that other sources can be additionally considered, such as cognitive traits, in order to include more information in the calculation process of learning styles and therefore build a more robust student model.

In this extended approach, the calculation of learning styles is based on two inputs: data about students' behaviour and data about students' cognitive traits. Data about cognitive traits can provide, similar to data about students' behaviour, indications for students' learning styles. Based on the findings of the study about the relationship between the four learning style dimensions of FSLSM and WMC [22], the following indications are considered in the calculation process of learning styles.

For the active/reflective dimension, it is assumed that high WMC gives an indication for a balanced learning style. For learners with low WMC, no indication is added in the calculation process since low WMC can be related to either a strong active or a strong reflective learning style preference. For the sensing/intuitive dimension, a low WMC gives an indication for a sensing learning style while a high WMC is not considered to give any indication based on the results in [22]. For the visual/verbal dimension, low WMC gives an indication for a visual learning style and high WMC gives no indication that can be considered in the calculation process. The sequential/global dimension has not been included in this extended approach since no relationship between WMC and this dimension has been identified.

Figure 1 shows the extended architecture of the tool pointing out the two different sources of data for calculating learning styles.

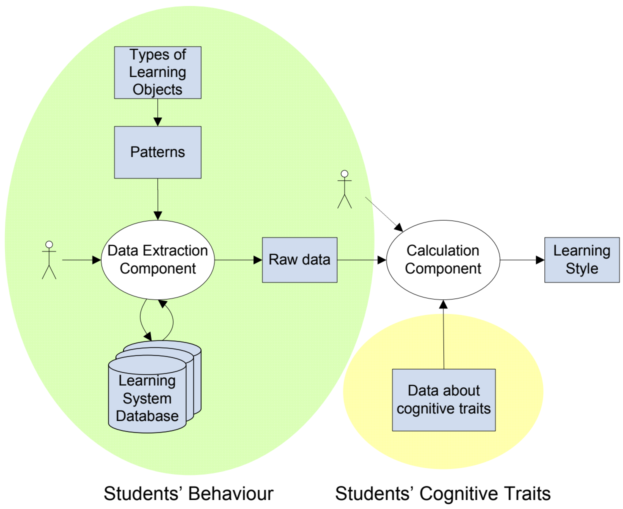

Figure 1. Extended architecture for identifying learning styles

IV. Experiment

In order to demonstrate the practical usage of the identified relationship between learning styles and cognitive traits, the proposed extension has been implemented for considering cognitive traits in the detection process of learning styles as described in the previous section and an experiment has been conducted for demonstrating the effects of including data about students' WMC in the calculation process of learning styles. In the following subsections, the experiment design, method and results are described.

A. Experiment Design and Method

In this experiment, 63 students at a university in Austria participated. The students were asked to fill out the ILS questionnaire [26] and conduct the Web-OSPAN task [22, 27] in order to identify their learning styles and WMC. Furthermore, the students attended an online course about object oriented modelling, where data about students' behaviour in the course was tracked.

In order to identify learning styles automatically, the tool introduced in Section III was used. The tool aims at detecting learning styles for each dimension of the FSLSM on a 3-item scale, distinguishing, for example, between an active, balanced, and reflective learning style. Therefore, the tool uses thresholds of 0.25 and 0.75 in order to create such a 3-item scale from the results of the calculation process, represented as normalized values between 0 and 1. Similarly, results of the ILS questionnaire, four values between +11 and -11, were divided into three groups. The result of the Web-OSPAN task are values between 0 and 60, where 60 indicates a very high WMC and 0 indicates a very low WMC. In order to distinguish between a high WMC and low WMC, a threshold of 30 was used.

The goal of this experiment is to demonstrate the positive effect of incorporating cognitive traits, in particular WMC, in the calculation process of learning styles. Therefore, the tool was first used by including data only from students' behaviour as input values. Then the results of the tool were compared with the results of the ILS questionnaire by using the following measure (as used originally by García et al. [29]):

$$\text{Precision} = \frac{\sum_{i=1}^{n} Sim(LS_{predicted}, LS_{ILS})}{n} \cdot 100 \quad , \qquad (1)$$

where $LS_{predicted}$ refers to the learning style predicted by the tool, using a 3-item scale, LS_{ILS} represents the learning style from the ILS questionnaire, using a 3-item scale, and n is the number of students. The function *Sim* compares its two parameters $LS_{predicted}$ and LS_{ILS} and returns 1 if both are equal, 0.5 if one represents a balanced learning style and the other represents a preference for one of the two poles of the dimension, and 0 if they are opposite.

Subsequently, the tool was used by including data from students' behaviour and cognitive traits as input data and the results were compared with the results of the ILS questionnaire by using formula 1 again. It was assumed that the weight of data about behaviour and the weight of data about cognitive traits are both 0.5.

B. Results and Discussion

Table I shows the results of this experiment. The first row presents the results of formula 1 when using the tool with behaviour data only and comparing these results with the ILS questionnaire results. The second line shows the result of formula 1 when using the tool with behaviour data and data about students' WMC and comparing these results with the ILS questionnaire results.

As can be seen in Table I, the inclusion of cognitive traits does not lead to a difference in the precision measure for the active/reflective dimension in this test group. However, for the sensing/intuitive dimension, the precision measure increased from 74.60% to 76.19%. Furthermore, for the visual/verbal dimension the precision measure increased from 76.19% to 79.36%. Although the increases are relatively small, they represent promising results since single patterns or traits provide only hints and the calculation process of learning styles is based on the idea that many such hints lead to reliable conclusions about students' learning styles. While students' behaviour is represented by data from many patterns, the cognitive traits of students are currently only represented by WMC. Therefore, having increases in the precision of the results of the detection process with only one trait is a promising result and encourages research about including also other cognitive traits in the calculation process of learning styles.

	act/ref	sen/int	vis/ver
only behaviour	79.37	74.60	76.19
behaviour and cognitive traits	79.37	76.19	79.37

TABLE I. RESULTS OF PRECISION MEASURES

Overall, the results show that considering the relationship between cognitive traits, such as WMC, and learning styles can help in improving the precision of detecting learning styles and can contribute valuable information for identifying learning styles with higher precision.

Finding no improvements in the precision measure for the active/reflective dimension can be explained by the different results of the literature review [20], exploratory study [21] and main study [22] for the active/reflective dimension. In the literature review, a linear correlation was found arguing that learners with an active learning style tend to have low WMC and learners with a reflective learning style tend to have high WMC. In the exploratory study only a general analysis aiming at finding linear correlations was performed and as a result, no relationship was found for the active/reflective dimension. In the main study, a more detailed analysis was conducted and a non-linear relationship was discovered, indicating that learners with a strong active or strong reflective preference tend to have low WMC and the more balanced the learning style becomes the higher WMC tend to be. In this experiment, the results from the main study were used because this study analysed the relationship between learning styles and WMC in more detail than the other two studies. However, since no improvements in the precision measures were found, further investigations are required in order to find out more about the relationship between WMC and active/reflective dimension of the FSLSM.

V. Conclusions and Future Work

This paper showed how the relationship between learning styles, in particular the FSLSM, and cognitive traits, in particular working memory capacity (WMC), can be used for identifying learning styles. First, we presented how to extend an already available approach for identifying learning styles from the behaviour of students by additionally considering students' WMC. Second, an experiment was conducted that successfully demonstrated that considering the relationship between learning styles and WMC in the detection process of learning styles can help in improving the precision of the identified learning styles.

This paper shows that considering other sources such as cognitive traits in the detection process of learning styles can improve student modelling, leading to higher precision of the resulting learning style preferences and thus to more accurate adaptivity for students.

Currently, only one cognitive trait, namely WMC, has been considered. However, the promising results encourage investigations about the relationships between learning styles and other cognitive traits such as inductive reasoning ability and associative learning skills. Furthermore, future research will deal with more detailed investigations regarding the active/reflective dimension and its relationship to WMC.

Acknowledgments

Authors acknowledge the support of NSERC, iCORE, Xerox, and the research related gift funding by Mr. A. Markin.

References

[1] S. Graf, C. H. Lan, T.-C. Liu, and Kinshuk, "Investigations about the effects and effectiveness of adaptivity for students with different learning styles," Proceedings of the IEEE International Conference on Advanced Learning Technologies (ICALT 2009), IEEE Computer Society, 2009, pp. 415-419.

[2] N. Bajraktarevic, W. Hall, and P. Fullick, "Incorporating learning styles in hypermedia environment: Empirical evaluation," Proceedings of the Workshop on Adaptive Hypermedia and Adaptive Web-Based Systems, Eindhoven University, 2003, pp. 41-52.

[3] R. M. Felder and L. K. Silverman, "Learning and teaching styles in engineering education," Engineering Education, vol. 78, no. 7, 1988, pp. 674–681.

[4] J. Hayes and C. W. Allinson, "The implications of learning styles for training and development: A discussion of the matching hypothesis," British Journal of Management, vol. 7, 1996, pp. 63-73.

[5] J. R. Anderson, The architecture of cognition. Cambridge, MA: Harvard University Press, 1983.

[6] M. D. Byrne, A computational theory of working memory, 1996. Available: http://www.acm.org/sigchi/chi96/proceedings/doctoral/Byrne/mdb_txt.htm [Accessed: 6 June, 2010]

[7] R. Case, "Capacity-based explanations of working memory growth: A brief history and reevaluation," in Memory performance and competencies: Issues in growth and development, Erlbaum, 1995, pp. 23-24.

[8] H. Huai, Cognitive style and memory capacity: Effects of concept mapping as a learning method, Ph.D. thesis, Twente University, The Netherlands, 2000.

[9] T. A. Salthouse and R. L. Babcock, "Decomposing adult age differences in working memory," Developmental Psychology, vol. 27, no. 5, 1991, pp. 763-776.

[10] J. M. Scandura, Structural learning I: Theory and research. London, UK: Gordon & Breach, 1973.

[11] C. A. Carver, R. A. Howard, and W. D. Lane, "Addressing different learning styles through course hypermedia," IEEE Transactions on Education, vol. 42, no. 1, 1999, pp. 33-38.

[12] K. A. Papanikolaou, M. Grigoriadou, H. Kornilakis, and G. D. Magoulas, "Personalizing the interaction in a web-based educational hypermedia system: the case of INSPIRE," User-Modeling and User-Adapted Interaction, vol. 13, no. 3, 2003, pp. 213-267.

[13] P. Paredes and P. Rodríguez, "A mixed approach to modelling learning styles in adaptive educational hypermedia," Advanced Technology for Learning, vol. 1, no. 4, 2004, pp. 210-215.

[14] N. Stash, A. Cristea, and P. de Bra, "Adaptation to learning styles in e-learning: Approach evaluation," Proceedings of World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education, AACE Press, 2006, pp. 284-291.

[15] AHA!, 2010. Available: http://aha.win.tue.nl/ [Accessed: 6 June, 2010]

[16] J. C. R. Tseng, H.-C. Chu, G.-J. Hwang, and C.-C. Tsai, "Development of an adaptive learning system with two sources of personalization information," Computers & Education, vol. 51, no. 2, 2008, pp. 776–786.

[17] E. Popescu, Dynamic adaptive hypermedia systems for e-learning, PhD thesis, Université de Craiova, Romania, 2008.

[18] S. Graf and Kinshuk, "Providing adaptive courses in learning management systems with respect to learning styles," Proceedings of the world conference on e-learning in corporate, government, healthcare, and higher education (e-Learn 2007), AACE Press, 2007, pp. 2576-2583.

[19] P. Brusilovsky, "Methods and techniques of adaptive hypermedia," User Modeling and User-Adapted Interaction, vol. 6, no. 2-3, 1996, pp. 87-129.

[20] S. Graf, T. Lin, and Kinshuk, "The relationship between learning styles and cognitive traits - getting additional information for improving student modelling," International Journal on Computers in Human Behavior, vol. 24, no. 2, 2008, pp. 122-137.

[21] S. Graf, T. Lin, L. Jeffrey, and Kinshuk, "An exploratory study of the relationship between learning styles and cognitive traits," Proceedings of the European Conference of Technology Enhanced Learning (EC-TEL 2006), Springer Verlag, 2006, pp. 470-475.

[22] S. Graf, T.-C. Liu, Kinshuk, N.-S. Chen, and S. J. H. Yang, "Learning styles and cognitive traits – Their relationship and its benefits in web-based educational systems," Computers in Human Behavior, vol. 25, no. 6, 2009, pp. 1280-1289.

[23] J. Kuljis and F. Liu, "A comparison of learning style theories on the suitability for elearning," Proceedings of the IASTED Conference on Web Technologies, Applications, and Services, ACTA Press, 2005, pp. 191-197.

[24] L. A. Richards-Ward, Investigating the relationship between two approaches to verbal information processing in working memory: An examination of the construct of working memory coupled with an investigation of meta-working memory, PhD thesis, Massey University, Palmerston North, New Zealand, 1996.

[25] G. A. Miller, "The magic number seven, plus or minus two: Some limit of our capacity for processing information," Psychology Review, vol. 63, no. 2, 1956, pp. 81-96.

[26] R. M. Felder and B. A. Soloman. Index of Learning Styles questionnaire, 1997. Available: http://www.engr.ncsu.edu/learningstyles/ilsweb.html [Accessed: 6 June, 2010]

[27] Web-OSPAN, 2010. Available: http://kinshuk.athabascau.ca/webospan [Accessed: 6 June, 2010]

[28] S. Graf, Kinshuk, and T.-C. Liu, "Supporting teachers in identifying students' learning styles in learning management Ssystems: An automatic student modelling approach," Educational Technology & Society, vol. 12, no. 4, 2009, pp. 3-14.

[29] P. García, A. Amandi, S. Schiaffino, and M. Campo, "Evaluating Bayesian networks' precision for detecting students' learning styles," Computers & Education, vol. 49, no. 3, 2007, pp. 794-808.