

IMPROVING STUDENT MODELING: THE RELATIONSHIP BETWEEN LEARNING STYLES AND COGNITIVE TRAITS*

Sabine Graf

*Women's Postgraduate College for Internet Technologies
Vienna University of Technology
Vienna, Austria
Tel: +43 1 58801 18817
Fax: +43 1 58801 18895
graf@wit.tuwien.ac.at*

Taiyu Lin

*Department of Information Systems, Massey University
Palmerston North, New Zealand
Tel: +64 6 350 5799 ext 7643
Fax: +64 6 350 5725
t.lin@massey.ac.nz*

Kinshuk

*Department of Information Systems, Massey University
Palmerston North, New Zealand
Tel: +64 6 350 5799 ext 2090
Fax: +64 6 350 5725
kinshuk@ieee.org*

ABSTRACT

A challenge of student modeling in adaptive virtual learning environments is to get enough information about the learner. Information about the learner such as the domain competence, the learning style or the cognitive traits of a learner is very important for an adaptive environment to achieve its main aim, namely to adapt to the learners' needs. In this paper we investigate the interaction between learning styles, in particular the Felder-Silverman learning style model, and working memory capacity, a cognitive trait. As a result we demonstrate some relationships between learners with high working memory capacity and a reflective, intuitive, and sequential learning style whereas learners with low working memory capacity tend to prefer an active, sensing, visual, and global learning style. These interactions make it possible to improve student models.

KEYWORDS

Felder-Silverman learning style model, cognitive trait model, working memory capacity, student model

1. INTRODUCTION

Student models (for explanation, see Brusilovsky, 1994) are essential to any adaptive virtual learning environments. They store information about learners and use this information to adapt to the learners' needs. For example, student models can include personal data, domain competence, learning style, and/or cognitive traits of a learner. The simplest approach to fill a student model is to ask the student about the required data.

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But this approach is not very suitable for identifying accurate information for various components of student model, such as cognitive traits, domain competence and learning style. For example, the estimation of domain competence is subjective and for stating the cognitive traits and the learning style, comprehensive tests or questionnaires have to be performed. A more meaningful approach is to track the students' behavior and infer the required information from this behavior. The challenge of this approach is to get out enough information from the learners' behavior.

The aim of this paper is to demonstrate the relationship between the learning style and the cognitive traits of a learner. This relationship can be used to improve the identification process of both, the learning style and the cognitive traits, in an adaptive virtual learning environment.

To exemplify this relationship, we investigate the interaction of working memory capacity, one cognitive trait included in the cognitive trait model (Lin, Kinshuk, and Patel, 2003), with Felder-Silverman learning style model (Felder and Silverman, 1988). Both models are described in the next section in more detail. In Section 3 we present the mapping between the Felder-Silverman learning style model and working memory capacity and Section 4 concludes the paper.

2. BACKGROUND

Before presenting the relationship between the dimensions of Felder-Silverman learning style model (FSLSM) and the cognitive trait model, both models are introduced briefly. The description of FSLSM focuses on the different dimensions and the characteristic behavior and preferences of learners for each dimension. The presentation of the cognitive trait model delivers – beside an introduction in cognitive traits – an insight of how cognitive traits can be identified in virtual learning environments.

2.1 Felder-Silverman Learning Style Model

The Felder-Silverman learning style model (Felder and Silverman, 1988) characterizes each learner according to four dimensions. The first dimension distinguishes between an active and a reflective way of processing information. Active learners learn best by working active with the learning material, e.g. working in groups, discussing about the material, or applying it. In contrast reflective learners prefer to think about and reflect the material.

The second dimension covers sensing versus intuitive learning. Learners who prefer a sensing learning style like to learn facts and concrete learning material. They tend to be more patient with details and also more practical as intuitive learners and like to relate the learned material to the real world. Intuitive learners prefer to learn abstract learning material, such as theories and their underlying meanings. They like to discover possibilities and relationships and tend to be more innovative and creative than sensing learners. Therefore, they score better in open-ended tests than in tests with a single answer to a problem. This dimension differs from the active-reflective dimension in an important way: sensing-intuitive dimension deals with preferred source of information whereas active-reflective dimension covers the process of transforming the perceived information into knowledge.

The visual-verbal dimension differs between learners who remember best what they have seen, e.g. pictures, diagrams, flow-charts, and learners who get more out of words, regardless whether they are written or spoken.

In the fourth dimension learners are characterized according to their understanding. Sequential learners learn in small incremental steps and therefore have a linear learning progress. They tend to follow logical stepwise paths in finding solutions. In contrast, global learners use a holistic thinking process and learn in large leaps. They tend to absorb learning material almost randomly without seeing connections but after they have learned enough material they suddenly get the whole picture. Then they are able to solve complex problems and put things together in novel ways but they have difficulties in explaining how they did it.

Each learner has personal preference for each dimension. These preferences are expressed by values between +11 to -11 per dimension. Using the active-reflective dimension as an example, the value +11 means that a learner has strong preferences for active learning, whereas the value -11 states that a learner has strong preferences for reflective learning. Thus, each learner can be characterized by four values between +11 and -11, each for one dimension.

2.2 Cognitive Trait Model

Cognitive Trait Model (CTM) (Lin, Kinshuk, and Patel, 2003) is a student model that profiles learners according to their cognitive traits. Working memory capacity is an example of cognitive trait. The goal of CTM is to have a student model that can be persistent over a long period of time and consistent across a variety of domains. Thus the CTM is perfectly suitable for those students who aim to proceed on life-long learning.

CTM changes the traditional idea of the student model that is thought as just a database sitting on the server and is full of numbers for only a particular task. The CTM offers the role of ‘learning companion’, which can be consulted by and interacted with different learning environments about a particular learner. The CTM can still be valid after a long period of time due to the more or less persistent nature of cognitive traits of human beings (Deary et al., 2004). When a student encounters a new learning environment, the learning environment can directly use the CTM of the particular student, and doesn’t need to “re-learn the student” from scratch. The CTM can also be saved to portable electronic media, such as a flash drive, and accessed every time the student starts up a learning session. In this sense, the CTM is like a learning companion who even though does not know “what” is to be learned, but knows “how” can the learning content be best presented to the student. The CTM also stands as a cognitive facilitator between the student and the learning management system.

CTM can be implemented in many forms; the structure of a possible embodiment (Figure 1) is discussed in this section to provide the reader an idea of how CTM could be implemented. The learner interface provides a presentation of the learning environment to interact with the learner. In Web-based systems, the learner interface is generally implemented inside a Web browser. Due to the stateless nature of the HTTP protocol used by Web browsers, it is necessary to embed a mechanism that can monitor events created by a learner’s interactions with a learning environment. The mechanism is represented by the Interface Listener Component in Figure 1. Learner interactions are interpreted as a series of learner actions performed on knowledge objects. Actions are then passed on to the Action History Components and are stored in Action History.

The performance-based model is assumed to be independently existed in the virtual learning environment. It represents a learner’s domain competence and models the problem-solving process that the learner undertakes. Certain learner’s behaviours, called Manifestation of Traits (MOTs), can be used to infer about the cognitive capacity. Information of the performance-based model, such as passing or failing a unit, can be useful for detecting MOTs of some cognitive traits, and therefore data in the performance-based model is used as a source by the MOT Detector Component. Different interface should be created to cater for different type of performance-based model.

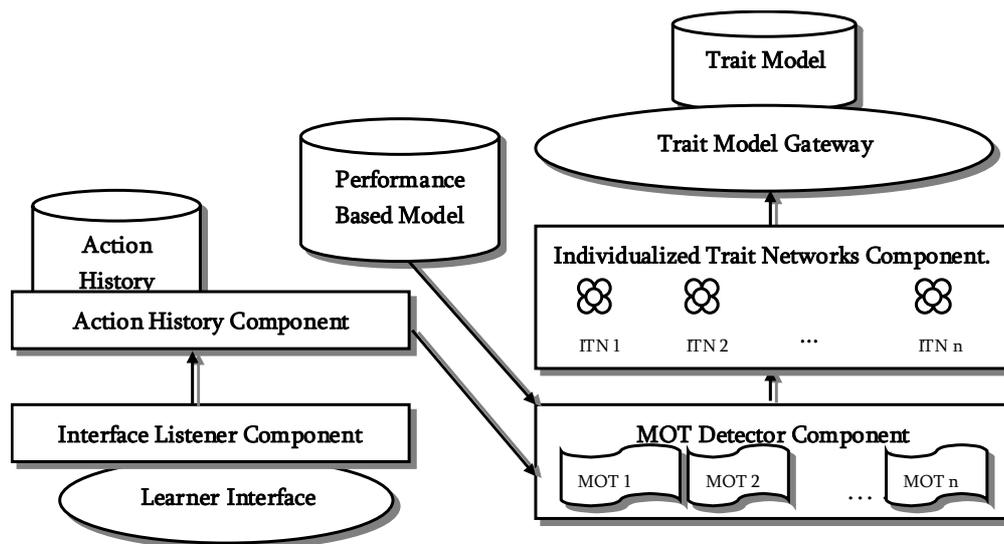


Figure 1. Structural View of Cognitive Trait Model

Various MOTs are defined for each cognitive trait. Each MOT is a piece of an interaction pattern that manifests a learner's characteristic (e.g. low inductive reasoning ability). The MOT Detector Component has knowledge of a number of MOTs and detects those MOTs within a series of actions that are requested from the Action History Component. Each MOT belongs to one of the two groups (low or high) of a particular cognitive trait, and each MOT belongs to only one particular Individualised Temperament Network.

The Individualised Temperament Network (ITN) Component in Figure 1 can have more than one Individualised Temperament Network (Lin and Kinshuk, 2005). Each ITN represents a particular cognitive trait (e.g. inductive reasoning ability) of the learner. Each node in the ITN has a weight and corresponds to a MOT. Once a MOT is detected from the learner's actions, the corresponding node is activated. The result of the execution of an ITN determines how the nodes in the ITN should be updated. The results of the execution of the ITNs are then sent to the trait model gateway, which is responsible for all the transactions to the trait model, and then saved to Trait Model.

3. MAPPING OF LEARNING STYLE MODEL TO COGNITIVE TRAIT MODEL

In this section we describe the interaction between one cognitive trait, namely working memory capacity, and each of the dimensions of the Felder-Silverman learning style model. This interaction can be used to support the identification process of both, learning styles and cognitive traits.

In our investigations we also incorporated cognitive styles. There exist several studies showing that field-dependent students generally have low working memory capacity and field-independent students have high working memory capacity (Al-Naeme, 1991; Bahar and Hansell, 2000; El-Banna, 1987; Pascual-Leone, 1970). Furthermore, there are some relations between the field-dependent/field-independent dimension and dimensions of FSLSM. Thus, we additionally use this interaction to make indirect relationships.

Bahar and Hansell (2000) investigated the interaction between convergence/divergence and working memory capacity. The result of their study shows a significant positive correlation between students' convergence/divergence test results and the results of the working memory capacity test. According to this, divergent students tend to have a high working memory capacity and convergent students tend to have a low working memory capacity. In the study, convergent students are defined according to Hudson (1966) as high IQ learners who score better in intelligence test. Divergent students are defined as highly creative learners who score better in open-ended tests.

An important link of working memory and learning style can be found through literatures of dyslexia. The term dyslexia refers to specific learning difficulty regarding written language (Jeffries and Everatt, 2004). Simmons and Singleton (2000) studied a group of dyslexic university students, compared their reading comprehension ability with non-dyslexic students, and found that "*dyslexic students were specifically impaired in constructing inferences when processing complex text*". No difference was found between the dyslexic and non-dyslexic group when literal question, which only requires information that was explicitly stated in the text, were given. However, significant difference was found when inferential questions, which required the students to integrate more than one piece of information or use their prior knowledge to interpret an ambiguous statement. Dyslexic students had done very poor in inferential questions. Working memory deficiency was identified as a cognitive cause of the result found (Simmons and Singleton, 2000). Beacham, Szumko, and Alty (2003) pointed out that dyslexics have also weakness in other cognitive abilities including short-term memory, sound processing, co-ordination and motor skill and visual processing. Calvo's (2001) experiment of the reading-span task also provided evidence that working memory is essential for elaborative inference during reading by taking an important role in text-integration process. The inferential ability takes the role of bridging the gap between the necessary semantics and thus it is called bridging inferential (Calvo, 2001).

3.1 Working Memory Capacity & Sensing-Intuitive Dimension

According to the definition of Hudson (1966), divergent students are very similar to intuitive students. Both tend to be creative and score better in open-end tests than in tests where only a single answer is asked. In contrast, divergent students have strong similarities with intuitive students. Based on these similarities and on

Bahar and Hansell's results according to the interaction between convergence/divergence and working memory capacity, we can conclude that sensing learners tend to have a low working memory capacity whereas intuitive learners tend to have a high working memory capacity.

Another main feature of the sensing-intuitive dimension is the concrete-ness (as opposed to abstract-ness) of preferred learning material. Like field-dependent learners, sensing learners prefer concrete material, whereas intuitive learners, like field-independent learners, prefer to learn abstract material (Ford and Chen, 2000; Davis, 1991). An association can be found between field-(in)dependency and working memory capacity in structural learning theory (Scandura, 1973). Structural learning theory postulates that the information learned are rules. In order to identify and learn low-order (fundamental) rules, representative problem samples of the low-order rules have to be presented and the corresponding solutions available to learners prior to that of the high-order (advanced) rules. The number of representative problem samples should increase for learners with low working memory capacity so that they can grasp low-order rules first and use them to generate high-order rules (Kinshuk and Lin, 2005). From the line of inference in accordance to the structural learning theory, learners with low working memory capacity and with sensing learners can be similarly categorized by having preference of learning with examples and tendency to be field-dependent; learners with high memory capacity and intuitive learners can also be categorized to have preference of learning with abstract concepts and tendency to be field-independent.

The investigations above have shown a relationship between working memory capacity and the sensing-intuitive dimension of FSLSM. Learners with high memory capacity tend to have an intuitive learning style whereas learners with low memory capacity tend to prefer a sensing learning style.

3.2 Working Memory Capacity & Active-Reflective Dimension

Hudson (1966) and Kolb (1984) both used the terms of divergent and convergent learners. Although Hudson distinguishes them as thinking styles whereas Kolb examined them as learning styles, there is a strong relationship between both. In both Hudson's (1966) and Kolb's (1984) studies, divergent learners are defined by as creative, and convergent learners do best when there is only a single answer to a problem. Additionally, Kolb's learning style model relates the four learner types (Diverger, Converger, Assimilator, and Accommodator) to the dimension of doing versus watching as well as to the dimension of feeling versus thinking. Convergers are related to active experimentations (doing) and Divergers are related to reflective observations (watching). Therefore, Divergers and Convergers refer not only to the sensing-intuitive dimension of FSLSM but also to the active-reflective dimension. Because Convergers are found to have a low working memory capacity and Divergers high working memory capacity (Bahar and Hansell, 2000), a relationship between an active-reflective learning style and working memory capacity can thus be established.

This relationship is further substantiated by the characteristics of field-dependent and field-independent learners. According to Witkin et al. (1977), field-dependent learners prefer interaction and communication with others in groups. Field-dependent and field independent learners are classified in the low-working memory capacity and high working memory capacity group respectively in the discussion above.

Beacham, Szumko, and Alty's (2003) study were also in agreement to our line of speculation by showing that 73% of the dyslexic learners (low working memory capacity) have the active learning style and 27% have the reflective learning style.

From all evidences above, postulation about the relationships can be made from active learning style to low working memory capacity, and from reflective learning style to high working memory capacity.

3.3 Working Memory Capacity & Verbal-Visual Dimension

It has to be acknowledged that several views suggested that working memory consists of separate components for verbal and nonverbal information (Paivio, 1986; Baddeley, 1986). However, there are also studies that does not emphasize the structural view of working memory: Salthouse and Babcock (1991) as well as Daneman and Carpenter (1980) viewed working memory as a process; Atkinson and Shiffrin (1968) defined working memory functionally as the gateway allowing information to be transferred to the long-term memory. For the study from Beacham, Szumko, and Alty (2003) quoted in the discussion below, working memory is viewed as a whole instead of divided components.

Table 1. Mapping of Felder-Silverman learning style dimensions and working memory capacity

	High Working Memory Capacity	Low Working Memory Capacity
Felder-Silverman Learning Style Dimensions	Reflective	Active
	Beacham, Szumko, and Alty (2003) Kolb (1984) Witkin et al. (1977)	
	Intuitive	Sensing
	Bahar and Hansell (2000) Davis (1991) Ford and Chen (2000) Kinshuk and Lin (2005) Scandura (1973)	
Cognitive Styles	Verbal or Visual	Visual
	Beacham, Szumko, and Alty (2003) Simmons and Singleton (2000)	
	Sequential	Global
	Beacham, Szumko, and Alty (2003) Huai (2000) Mortimore (2003)	
Cognitive Styles	Field-independent	Field-dependent
	Al-Naeme (1991) Bahar and Hansell (2000) El-Banna (1987) Pascual-Leone (1970)	
	Divergent	Convergent
	Bahar and Hansell (2000)	

Beacham, Szumko, and Alty (2003) in their study found that 97% of the dyslexic learners are visual learners and the remaining 3% sat also just in the mild-verbal range. They further stated that “*this was to be expected since dyslexic people do tend to be talented in the areas of creativity and visual thinking*” (Beacham, Szumko, and Alty 2003, p23 quoting West 1997; Mortimore, 2003) to support their finding.

Beacham, Szumko, and Alty (2003, p16) further quoted McLoughlin’s (2001) work, which stated “An inefficient working memory will clearly undermine skill acquisition and learning. Describing dyslexia ... [as a working memory deficit] ... can help explain both the persisting writing language difficulties”, as a rationale to explain why low working memory would cause problem in reading comprehension. This rationale is in agreement to Simmons and Singleton’s (2000) view that the cause of inability to solve inferential problems (and thus dyslexia) is due to insufficient working memory capacity. Comprehension of text would certainly be undermined by insufficient capacity to buffer what was read before. It is thus fair to argue that learners with sever deficiency in working memory would have problem in reading, meaning dyslexia, and thus would prefer visual learning as the result of Beacham, Szumko, and Alty’s (2003) study.

3.4 Working Memory Capacity & Sequential-Global Dimension

An empirical study by Huai (2000) showed that learners with holistic learning style have significantly smaller working memory than learners with serial learning style (highly capable to follow and remember sequentially fixed information). The difference between holistic (described in Huai, 2000) and global learning style (described in Felder and Silverman, 1988) is only nominal. The same applies to serial and sequential learning styles.

Beacham, Szumko, and Alty's (2003) had also recorded higher preference (14% higher) of global learning style to sequential learning style among dyslexic learners (low working memory capacity). They quoted another supportive finding from Mortimore (2003) saying that "*dyslexic learners are inclined to focus more successfully upon of any topic rather than its details and sequences of information*" (Beacham, Szumko, and Alty, 2003).

All sources are pointing to the link from high working memory capacity to sequential learners and low working memory capacity to global learners. Table 1 summarises the discussed relationships of working memory capacity and learning styles.

4. CONCLUSION & FUTURE WORK

The aim of this paper is to identify interactions between learning styles and cognitive traits. Considering the learning style, we based our investigations on the Felder-Silverman learning style model. As an example for cognitive traits, working memory capacity was applied. As a result, interactions between these the dimensions of the learning model and the working memory capacity he been identified. Learners with low working memory capacity tend to prefer an active, sensing, visual, and global learning style. On the other hand, learners with high working memory capacity tend to be reflective, intuitive, and sequential.

The results of the paper show that the identification process of both, learning styles and cognitive traits, can be supported by each other. If the learning style of a learner is already detected, it gives indications of cognitive traits and if cognitive traits of a learner are available, we can draw conclusions to his/her learning style. Therefore, these interactions can be used to improve the process of student modeling.

Future work includes further investigations concerning other cognitive traits, such as inductive reasoning skills, associative learning skills, and information processing speed. Another open issue is the question how strong each cognitive trait influences each learning style dimension and the other way around. Therefore, a study will be performed where learners are tested for their learning style and cognitive traits. Analyzing these test results will deliver a detailed insight into the interrelations of cognitive traits and learning styles. Additionally, it is planned to show the advantages of this relationship by using a web-based educational system which incorporates the relationship.

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