Computers in Human Behavior 25 (2009) 1280–1289

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Learning styles and cognitive traits – Their relationship and its benefits in web-based educational systems

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ARTICLE INFO

Article history:
Available online 5 August 2009

Keywords:
Adaptivity
Cognitive traits
Learning styles
Felder–Silverman learning style model
Student modelling
Working memory capacity

ABSTRACT

Different learners have different needs; they differ, for example, in their learning goals, their prior knowledge, their learning styles, and their cognitive abilities. Adaptive web-based educational systems aim to cater individual learners by customizing courses to suit their needs. In this paper, we investigate the benefits of incorporating learning styles and cognitive traits in web-based educational systems. Adaptivity aspects based on cognitive traits and learning styles enrich each other, enabling systems to provide learners with courses which fit their needs more accurately. Furthermore, consideration of learning styles and cognitive traits can contribute to more accurate student modelling. In this paper, the relationship between learning styles, in particular the Felder–Silverman learning style model (FSLSM), and working memory capacity, a cognitive trait, is investigated. For adaptive educational systems that consider either only learning styles or only cognitive traits, the additional information can be used to provide more holistic adaptivity. For systems that already incorporate both learning styles and cognitive traits, the relationship can be used to improve the detection process of both by including the additional information of learning style into the detection process of cognitive traits and vice versa. This leads to a more reliable student model.

1. Introduction

Different learners have different knowledge about the domain, aim at different goals, have different learning styles, and also have different cognitive abilities. In traditional education, teaching in a way that the needs of all students are met is difficult, especially in classes with a high number of students. In web-based educational systems, lots of research works have been conducted in the area of adaptive instruction (Brusilovsky, 1996). Adaptive systems have been developed which aim at providing courses that fit the needs of learners.

Adaptivity can be provided in different ways. Adaptation techniques can be distinguished between adaptive presentation support and adaptive navigation support (Brusilovsky, 1996). Adaptive presentation includes adaptation features based on content such as adaptive multimedia presentation and adaptive text presentation, whereas adaptive navigation is based on links and includes features such as direct guidance as well as adaptive sorting, hiding and annotating of links. Furthermore, adaptivity can be provided based on different characteristics of learners such as their prior knowledge, motivation, learning styles, and cognitive traits.

This paper focuses on the consideration of learning styles and cognitive traits in adaptive web-based educational systems. Several educational theories and studies agree that learners learn easier when their learning styles match with the teaching style (e.g., Bajraktarevic, Hall, & Fullick, 2003; Felder & Silverman, 1988; Graf, Lan, Liu, & Kinshuk, 2009; Hayes & Allinson, 1996). Felder and Silverman (1988) pointed out that learners with a strong preference for a specific learning style have difficulty in learning when this learning style is not supported by the teaching environment. Such mismatches lead to poor student performance. Based on these arguments, adaptive systems such as AHA! (Stash, Cristea, & de Bra, 2006), CS383 (Carver, Howard, & Lane, 1999), IDEAL (Shang, Shi, & Chen, 2001), MAS-PLANG (Peña, Marzo, & de la Rosa, 2004), TANGOW (Paredes & Rodríguez, 2004), as well as an add-on for the learning management system Moodle (Graf & Kinshuk, 2007) has been developed, which provide courses that match the learning style of learners.

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0747-5632/$ - see front matter
doi:10.1016/j.chb.2009.06.005

Like learning styles, cognitive traits influence the learning process. Research on working memory (Anderson, 1983; Byrne, 1996; Case, 1995; Huai, 2000; Salthouse & Babcock, 1991; Scandura, 1973) showed the fact 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 in a negative way and leads to poor student performance.

For learning styles and cognitive traits, different kinds of adaptivity can be provided. A system that incorporates only learning styles provides different adaptive features than a system that incorporates adaptivity for cognitive traits. Combining adaptivity for both learning styles and cognitive traits allows a system to provide better adaptivity than a system that provides adaptivity for only one of them.

However, a requirement for providing adaptivity in web-based educational systems is to know the characteristics of learners. Therefore, student models are essential to any adaptive educational system (Brusilovsky, 1994). Student models contain information about the learners. For example, they can include demographic data, domain competence, learning goals, learning style, and/or cognitive traits. Student modelling is the process of building and updating the student model. Brusilovsky (1996) distinguished between two different ways of student modelling: collaborative and automatic. In the former, the learners are asked to provide explicitly information for building and updating the student model. For instance, the learners can provide data such as answering explicitly whether a page was relevant for their learning goals, filling out questionnaires in order to identify their learning styles or performing tasks to detect their cognitive traits. In the automatic student modelling approach, the process of building and updating the student model is done automatically based on the actions of the learners when they are using the learning system. A challenge of this approach is to get enough reliable information to build a robust student model. As a solution, the use of additional sources can help to get more information about the learners (Brusilovsky, 1996).

In this paper, focus is placed on the Felder–Silverman learning style model (FSLSM) (Felder & Silverman, 1988), and working memory capacity (WMC), a cognitive trait included in the Cognitive Trait Model (CTM) (Kinshuk & Lin, 2003; Lin & Kinshuk, 2005). Both models are introduced in Section 2. The aim of the paper is to demonstrate the benefits of incorporating both, learning styles and cognitive traits, in adaptive web-based educational systems. On one hand, considering learning styles and cognitive traits allows suiting courses more accurately to the students' characteristics by providing adaptivity based on learning styles as well as cognitive traits. Furthermore, by incorporating learning styles and cognitive traits in an adaptive educational system, more information about the learner is available which can be used to improve student modelling. In order to use this information as an additional source in the detection process of learners' characteristics, investigations about the relationship between FSLSM and WMC were conducted and are presented in Section 3. First, existing studies were investigated and indirect relationships could be derived. Afterwards, an experiment was performed where the direct relationship between FSLSM and WMC was analysed. Discussion about the benefits from the identified relationship for improving student modelling and therefore adaptivity is provided. Section 4 concludes the paper.

2. Learning style model and Cognitive Trait Model

In this section, the Felder–Silverman learning styles model and the Cognitive Trait Model are introduced in order to provide background information for current investigations. Description about the two models is provided and student modelling and adaptivity issues are discussed.

2.1. 1 Felder–Silverman learning style model

Several learning style theories exist in literature, for example, the learning style model by Kolb (1984), Honey and Mumford (1982), Dunn and Dunn (1974), Pask (1976), and Felder and Silverman (1988). While most learning style models classify learners as belonging to a few groups, the Felder–Silverman learning style model (FSLSM) describes the learning style of a learner in more detail, distinguishing between preferences on four dimensions and therefore enabling adaptive learning systems to provide courses which are better tailored to the learners' preferences. Moreover, FSLSM is based on tendencies, indicating that learners with a high preference for a certain behaviour can act sometimes differently, enabling the learning style model to considers exceptional behaviour. Another important reason for selecting the FSLSM for this research work was that it is widely used in adaptive educational systems focusing on learning styles, which therefore makes this research widely applicable.

2.1.1. Description of the Felder–Silverman learning style model

FSLSM characterises each learner according to four dimensions: sensing/intuitive, active/reflective, visual/verbal, and sequential/global.

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 than 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 tend to score better in open-ended tests than in tests with a single answer to a problem.

The active/reflective dimension distinguishes between an active and a reflective way of processing information. Active learners learn best by working actively with the learning material, by applying the material, and by trying things out. Furthermore, they tend to be more interested in communication with others and prefer to learn by working in groups where they can discuss about the learned material. In contrast, reflective learners prefer to think about and reflect on the material. Regarding communication, they prefer to work alone.

The visual/verbal dimension differentiates learners who remember best what they have seen, such as pictures, diagrams and flow-charts, and learners who get more out of textual representation, regardless whether they are written or spoken.

In the fourth dimension, the 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 a 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 a strong preference for active learning, whereas the value −11 states that a learner has a strong preference for reflective learning.

2.1.2. Student modelling based on the Felder–Silverman learning style model

In order to identify learning styles according to the FSLSM, the Index of Learning Styles (ILS) has been developed (Felder & Soloman, 1997). Furthermore, recent research work has been done on identifying learning styles with respect to the FSLSM automatically from the behaviour of students in learning systems as well as their performance on specific tasks (e.g., Cha, Kim, Park, Yoon, Jung, & Lee, 2006; García, Amandi, Schiaffino, & Campo, 2007; Graf, Kinshuk, & Liu, 2008). While García et al., 2007 used Bayesian networks in order to build a model for calculating learning styles based on data about patterns from students' behaviour and performance, Cha et al. (2006) investigated to usage of Hidden Markov Models and Decision Trees. Graf et al. (2008) applied a rule-based method in order to calculate learning styles from the data of students' behaviour and performance.

A central component of all approaches are the patterns of behaviour, which represent either how students behave in the course or which performance they achieved on specific tasks in the course. The approaches for detecting learning styles are depending on the time span for gathering data about the patterns of behaviour and respectively that data from diverse patterns are available. The more information is available, the more accurate the learning styles can be identified.

2.1.3. Adaptivity based on the Felder–Silverman learning style model

Felder and Silverman (1988) have given several examples on how to address the different needs of learners with respect to their learning styles in traditional education. Most of these suggestions can also be applied in online learning. In the following paragraphs, two examples are given, showing how adaptivity can be provided for active and reflective as well as for sequential and global learning styles in typical learning systems.

A main characteristic of an active learning style is a preference for learning by doing. For this purpose, active learners can use exercises, where some practical questions/tasks are provided. On the other hand, reflective learners get more out from examples, observing how something can be done rather than doing it actively. One way to provide adaptivity for active and reflective learners is to vary the number of questions in an exercise and the number of examples, providing more questions or more comprehensive exercises for active learners and providing more examples for reflective learners.

A main characteristic of learners with global preferences is that they do not learn in incremental steps. Usually, they need a lot of time and much information until they get the "big picture" of a topic. Since these learners find it difficult to take any affirmative action without a complete picture, it is more suitable for them to first learn more about the whole topic, and do exercises and tests only after all information is learned and when they can see the "big picture". Therefore, one possibility to adapt to the needs of global and sequential learners in web-based educational systems is to provide two different recommended sequences of learning. For sequential learners, it is suitable to learn a chapter, do exercises about this chapter, and then get tested on it. For global learners it is more suitable to separate the exercises and tests from learning concepts and provide them after all concepts have been learned.

2.2. Cognitive Trait Model

The Cognitive Trait Model (CTM) (Kinshuk & Lin, 2003; Lin & Kinshuk, 2005) is a student model that profiles learners according to their cognitive traits. The CTM includes cognitive traits that are important for learning. Four cognitive traits, working memory capacity, inductive reasoning ability, information processing speed, and associative learning skills are included in CTM so far. In the current investigation between the CTM and the learning style model, only working memory capacity (WMC) is covered, and hence discussed below.

2.2.1. Working memory capacity

In earlier times, working memory was also referred as short-term memory. Richards-Ward (1996) named it the Short-Term Store (STS) to emphasise its role of temporal storage of recently perceived information. The working memory allows us to keep active a limited amount of information (roughly $7 + -2$ items) for a brief period of time (Miller, 1956). Baddeley (1986) tried to study and understand the working memory by decomposing it into components. The structure of working memory was described as a control-slave system comprised of the Central Executive (controlling component), Phonological Loop (slave component for verbal information), and a Visual-Spatial Sketch-Pad (slave component for graphical information). The Central Executive takes the role to control, monitor the output of the two slave-systems and select what is relevant for potential processing (Richards-Ward, 1996).

While Baddeley (1986) defined working memory structurally, others defined it as a process (Salthouse, Mitcheel, Skovronek, & Babcock, 1989). Salthouse et al. (1989) proposed that working memory consists of (a) a storage capacity sensitive to the number of items presented, and (b) an operational capacity sensitive to the number of operations performed on items. A further study of the operational efficiency of working memory showed that it was not the operational capacity (number of operations allowed) contributing the most to the efficiency of working memory, but it was actually the speed of execution (e.g., comparison speed) that determined the performance of the overall system of working memory (Salthouse & Babcock, 1991). Even though these two different points of view do not agree on a common structure of working memory, they both agree that working memory consists of both storage and operational sub-systems (Richards-Ward, 1996).

2.2.2. Student modelling in the Cognitive Trait Model

The proposition of the CTM changes the traditional idea of the student model that is thought of as just a database sitting on the server which is full of numbers for only a particular task. The CTM offers the role of a '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, Whiteman, Starr, Whalley, & Fox, 2004).

Similar to the detection process of learning styles, the CTM gathers data from the students' behaviour and performance in a learning system. Certain learner behaviours, called Manifestation of Traits (MOTs), can be used to infer about the cognitive capacity. Examples of such MOTS are navigational linearity, reverse navigation, and performing simultaneous tasks. 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 WMC). 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 (ITN) (Lin & Kinshuk, 2004). Each ITN represents a particular cognitive trait (e.g., WMC) of the learner. Each node in the ITN has a weight and corresponds to an MOT. Once an 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 saved as cognitive traits in the Cognitive Trait Model.

2.2.3. Adaptivity based on working memory capacity

Kinshuk and Lin (2003) described adaptive techniques to incorporate the cognitive load of learners in adaptive educational systems. They focused on three cognitive abilities included in the CTM, namely working memory capacity, inductive reasoning skills, and associative learning skills, and pointed out recommendations how to support learners with low and high abilities. These recommendations affect the number and relevance of links, the amount/detail, concreteness, and structureness of content, as well as the number of information resources. The following paragraphs give an example regarding two of these control elements, the amount/detail of content and the relevance of links, and how they can be used for providing adaptivity in typical learning systems.

The amount or detail of content affects the volume of the presentation and the granularity of the presented content. For example, learners with high WMC do well with highly detailed content, but presenting too much content to learners with low WMC can overload their cognitive capacity and therefore lead to negative effects in learning. For this reason, it is appropriate to vary the amount of content. The content of the courses can be divided into obligatory content which has to be learned by all learners and auxiliary content which facilitates the understanding of the obligatory content or might provide some additional information but need not necessarily be presented. Providing a low amount of content means that some auxiliary content is not recommended.

Kinshuk, Oppermann, Patel, and Kashihara (1999) identified six types of navigational links and also pointed out the relevance to the domain of each kind of these links. Direct successor links lead to the successive domain concepts and are most relevant to the domain. Next in the order of relevance are fine-grained links which lead to detailed explanations of the current concept. Afterwards, there are glossary links, providing a definition of domain concepts or terms, followed by problem links, leading to problems or exercises. Next, there are parallel concept links, leading to analogous concepts that are related to the domain concepts. Lastly, there are excursion links that lead to related learning concepts that are usually outside of the current context. The relevance of links is a control element that provides information about which kinds of links should be presented. For example, for learners with low WMC the course should focus on relevant links so that the learners get the important information. For learners with high WMC, the relevance should decrease to enlarge the exploration and domain space of the learning process so that more information is available to the learners.

Adaptivity based on cognitive traits affects in general the whole structure of a course whereas adaptivity based on learning styles, in general, focuses more on the details of the course. Using adaptivity based on cognitive traits as a basis and enriching it with adaptivity based on learning styles enables a system to provide more holistic adaptivity, which leads to a better support of the learners by considering their cognitive abilities as well as their learning styles.

3. The relationship between Felder–Silverman learning style model and working memory capacity

In order to provide adaptivity, the learning styles and cognitive traits of students need to be known. This section focuses on the benefits of incorporating learning styles and cognitive traits in order to improve the student modelling process, which is a crucial part in adaptive educational systems. A challenge for student modelling, especially automatic student modelling, is to get enough reliable information. When incorporating learning styles and cognitive traits, more information about a learner is available which can be used as additional source to improve the detection process.

In this section, investigations about the relationship between WMC, a cognitive trait which is important for learning, and each of the four dimensions of the Felder–Silverman learning style model, which is one of the most often used learning style models in adaptive learning systems, are shown. In the next subsection, investigations about the relationship between FSLSM and WMC based on existing studies from literature are presented. Subsequently, an experiment with real data is presented, where learners filled out a questionnaire about learning styles and performed a task in order to identify their WMC. Results of the experiment as well as its benefits for web-based educational systems are discussed.

3.1. Indirect relationships between Felder–Silverman learning style model and working memory capacity

For investigating the relationship between learning styles based on the FSLSM and WMC, existing studies that deal with the interaction of learning styles, cognitive styles, and cognitive traits were investigated. From these studies, indirect relationships between the dimensions of FSLSM and WMC can be concluded.

For the sensing/intuitive dimension, a relationship towards convergence/divergence, as introduced by Hudson (1966), was identified based on similarities in their characteristics. Furthermore, Bahar and Hansell (2000) found a relationship between convergence/divergence and WMC, which therefore provides indications for a relationship between WMC and the sensing/intuitive dimension. In addition, a similarity between the sensing/intuitive dimension and field-dependency/independency (Witkin, Moore, Goodenough, & Cox, 1977) with respect to a preference for abstractness and concreteness can be seen in their definitions and was also identified, for example, by studies by Ford and Chen (2000) and Davis (1991). Field-dependency/independency is also related to WMC, as argued, for example, by Al Naeme (1991), Bahar and Hansell (2000), El-Banna (1987), and Pascual-Leone (1970), supporting again the relationship between WMC and the sensing/intuitive dimension. Furthermore, an association can be found between WMC and concreteness/abstractness in structural learning theory (Scandura, 1973). All these indications point to a relationship between WMC and the sensing/intuitive dimension of the FSLSM, where learners with high WMC tend to have an intuitive learning style and learners with low WMC tend to have a sensing learning style.

The learning style model by Kolb (1984) includes also convergency and divergency, using it in relation to the preference of "doing" versus "watching" and therefore indicating a link to the active/reflective dimension. Furthermore, the characteristics of field-dependency/independency (Witkin et al., 1977) includes preferences regarding social orientation, which were also confirmed, for example, by a study by Summerville (1999) and therefore show again a relation to the active/reflective dimension which also incorporates social orientation. Since both, convergency/divegency and field-dependency/independency are related with WMC, these findings provide conclusions for a relationship between WMC and the active/reflective dimension of FSLSM. In addition, Hadwin, Kirby, and Woodhouse (1999) provided a link between the active/reflective dimension and WMC by investigating the impact of note-taking versus providing notes by the lecturer on performance considering students' WMC. Furthermore, Beacham, Szumko, and Alty's (2003) provided relevant information for the relationship between WMC and an active/reflective learning style by identifying the learning styles of dyslexic learners, who are known to have impaired WMC (e.g., Simmons & Singleton, 2000). From the evidence of all studies above, postulation about the relationships can be made between active learning style and low WMC, and between reflective learning style and high WMC.

Wey and Waugh (1993) investigated the relationship between field-dependency/independency and the students' performance when working either with text-only based instructions or instructions with text and graphics, allowing to infer a link between a visual/verbal learning style, field-dependency/independency, and therefore WMC. Furthermore, Beacham et al.'s (2003) study contributes to the relationship between visual/verbal learning style and WMC. Both studies demonstrate that learners with low WMC (and either a field-dependent cognitive style or dyslexia) benefit from visual material and therefore prefer a more visual learning style. However, no evidence was found for a bi-directional relationship and therefore no conclusions can be drawn about the WMC of learners with a visual learning style.

Regarding the sequential/global dimension, Huai (2000) investigated the relationship between WMC, long-term memory capacities, and a serial/holistic learning style, which is very similar to the sequential/global dimension and therefore links WMC with this dimension. Furthermore, the relationship between the sequential/global dimension and WMC is strengthen by the similarities in the characteristics of field-dependency/independency and the sequential/global dimension with respect to the learners' need for context when learning a topic and their preference for analytical/holistic behaviour, confirmed also by a study by Liu and Reed (1994). In addition, a relationship between field-dependency/independency and holistic/serial biases is supported, for example, by Ford and Chen's (2000) study, again supporting a relationship between WMC and the sequential/global dimension of FSLSM. Another support for this relationship is given by the study by Beacham et al. (2003), investigating the learning styles according to FSLSM of dyslexic learners. Concluding from the findings of the studies mentioned above, all sources are pointing to the link between high WMC and sequential learners, and low WMC and global learners.

3.2. Experiment

From literature, evidence is given that a relationship between learning styles and WMC exists. Indications were found that learners with a high WMC tend to prefer a reflective, intuitive, and sequential learning style. On the other hand, learners with a low WMC tend to have an active, sensing, and global learning style. For the visual/verbal dimension, only a one-directional relationship was identified rather than a bi-directional correlation as for the other dimensions. Learners with low WMC tend to prefer a visual learning style but learners with high WMC might have visual or verbal preferences. Accordingly, learners with verbal learning style tend to have a high WMC but learners with a visual learning style might have high or low WMC.

While the conclusions from literature are based only on indirect relationships, an experiment was performed that investigates the direct relationship between the four learning style dimensions of FSLSM and WMC. In the following subsections, this experiment is described, including a description about how learning styles and WMC were identified, an explanation about the used method, and the presentation of the results.

3.2.1. Materials

In the experiment, 297 undergraduate students, studying Computer Science or Information Systems at a university in Austria, participated. For analysing the relationship between learning styles and WMC, these characteristics of the students had to be detected.

In order to identify learning styles, the Index of Learning Styles questionnaire (ILS) (Felder & Soloman, 1997) was used, which aims at detecting learning styles based on the FSLSM. The ILS questionnaire is an often used instrument and consists of 44 questions, 11 for each dimension. As mentioned earlier, according to FSLSM each learner has a personal preference for each of the four dimensions which is indicated by values between +11 and −11, in steps of +/−2.

For detecting WMC, the Web-OSPAN task (available at http://kinshuk.athabascau.ca/webospan/) was used. Web-OSPAN is a web-based version of the operation word span task (OSPAN) (Turner & Engle, 1989). According to de Neys, d'Ydewalle, Schaeken, and Vos (2002), the operation word span task has become one of the most popular tasks to measure WMC. In the task, subjects are required to perform simple arithmetical operations such as $(2 * 3) + 4 = 10$ and answer whether this operation is true or false. After each operation, a word is presented. The subjects are asked to perform 2–6 arithmetic operations and at the end are asked to recall the words presented after each operation in the correct order. As proposed by Turner and Engle (1989), the total number of correct calculations (referred to as process measure, ranged from 0 to 60), the total number of correct recalled words (referred to as WMC values, ranged from 0 to 60), the maximum set size the subject had the words recalled correctly (referred to as set size memory span, ranged from 0 to 6), and the mean response latency are recorded and the total number of correctly recalled words is used as a measure of WMC. Web-OSPAN follows OSPAN (Turner & Engle, 1989) in recording these measures. Additionally, Web-OSPAN records a partial correct memory span (ranged from 0 to 60), which counts words as correct even when the order of words is not correct.

3.2.2. Method for statistical data analysis

Data of students, who had more than 15 mistakes in the calculations of Web-OSPAN or spent less than 5 min in ILS, were discarded because they were considered as not reliable enough for inclusion in the experiment. Data from 225 students were finally used for analyses.

Furthermore, the reliability of ILS (measured by Cronbach's alpha) was improved through removing weak reliable questions. This modification resulted in a reliability of 0.524 for the active/reflective dimension by removing one question, 0.687 for the sensing/intuitive dimension by removing one question, 0.691 for the visual/verbal dimension by removing three questions, and 0.595 for the sequential/global dimension by removing two questions. While these alpha values are still low, Tuckman (1999) argued that values greater than 0.5 are acceptable for attitude assessments such as ILS and therefore all ILS dimensions can be assumed as reliable.

Data analysis was done by a general and an in-depth analysis. In both, outliers were excluded for the analysed dimension. General analysis dealt with correlation analysis between values of the ILS dimensions and WMC values by using rank correlation (Kendall's tau and Spearman's rho). Additionally, the recorded measures gathered from Web-OSPAN were analysed by correlating them with the WMC values in order to show how significant they are related to working memory capacity. According to the structure of analysed values, Pearson's correlation or rank correlation was applied.

For the in-depth analysis, learning style values were divided into three groups, distinguishing, for example, between an active, balanced, and reflective preference. The groups were built based on recommendations by Felder and colleagues (Felder & Silverman, 1988; Felder & Spurlin, 2005) and with respect to the performed reduction of questions for increasing reliability. Since maximum three questions were removed due to reliability reasons, the recommended thresholds from Felder are still reasonable. Therefore, values greater or equal than +4 indicate a preference for one pole, values smaller or equal to −4 indicate a preference for the other pole and values between +3 and −3 indicate a balanced learning style.

Then, chi-square test was used to identify differences between the groups. If significant differences were detected, further analyses were performed to identify the kind of relation between the groups. These further analyses included correlation analysis between WMC values and the absolute values of ILS in order to identify a correlation between WMC and the strength of preference. Moreover, the dataset was split into two sub-datasets S_x and S_y in in-depth analysis. S_x covers only data with an ILS value greater than or equal to −3, representing a balanced preference and a preference for the positive pole of each dimension, and S_y covers only data with an ILS value smaller than or equal to +3, representing a balanced preference and a preference of the negative pole of each dimension.

For each sub-dataset, correlation analysis was performed. Additionally, group comparison methods were conducted by applying *t*-test if data were normally distributed or Mann–Whitney-*U* test if data were not normally distributed. Comparison was performed in two directions, once by grouping the WMC values in two categories and using ILS values as variables and once by grouping ILS values in two categories and using WMC values as variables. Former aims at identifying differences between learners with low and high WMC on the ILS values, whereas the latter looks for differences between learners with a balanced learning style and a preference for the investigated pole with respect to the WMC values.

For the visual/verbal dimension, the identified indirect relationship to WMC indicated a one-directional rather than a bi-directional relationship. In order to prove one-directional relationships, data were separated into two sub-datasets F_{vis} and F_{ver}, where F_{vis} includes only data from visual learners and F_{ver} includes only data from verbal learners. Then, for each sub-dataset, the number of learners in WMC groups (grouped by steps of 5) was calculated and rank correlation analysis was performed in order to find a correlation between the frequencies of learners with, for example, a verbal learning style (F_{ver}) and their WMC. Afterwards, results for F_{vis} and F_{ver} were compared. The same was done for the two sub-datasets including learners with only high WMC (F_{high}) and only low WMC (F_{low}). Due to the high difference in variance in the variables, Kendall's tau can be considered as more robust than Spearman's rho and is therefore applied for these analyses.

3.2.3. Results

In the following subsections, the results of the conducted analyses for the measures of Web-OSPAN as well as for each learning style dimension are presented and discussed.

3.2.3.1. Measures of Web-OSPAN. The conducted correlation analysis, calculated by Pearson's *r*, Kendall's tau or Spearman's rho respectively, shows that all other measures gathered from Web-OSPAN are highly significantly ($p < 0.001$) correlated with the WMC values. The set size memory span (tau = 0.649, rho = 0.757) and the partial correct memory span (tau = 0.741, rho = 0.883) show a strong positive correlation to the WMC values. Interesting is that the mean response time is negatively correlated ($r = -0.361$), which indicates that learners who answered quickly answered correctly more often. The values of the process measure show only a low positive correlation (tau = 0.191, rho = 0.258). Table 1 summarizes the results.

3.2.3.2. Working memory capacity and the sensing/intuitive dimension. The results of the correlation analysis of the sensing/intuitive values and all measures of the Web-OSPAN task show a significant but weak negative correlation between the sensing/intuitive values and the size set memory span (tau = −0.113, $p = 0.046$; rho = −0.137, $p = 0.045$). This result gives an indication for an indirect relationship between WMC and the sensing/intuitive dimension since the WMC values are highly correlated with the size set memory span, as previously shown. This indirect relationship links a sensing learning style with low WMC and an intuitive learning style with high WMC. The results of the chi-square test ($\chi^2 = 8.628$, $p = 0.013$) show that the three groups (sensing, balanced, and intuitive) are significantly different from each other. Since the correlation of WMC values and absolute sensing/intuitive values is not significant, this is another indication for a linear correlation between a sensing/intuitive preference and WMC.

Looking at the sub-dataset $S_{sen/bal}$, a significant but weak negative correlation between the sensing/balanced values and the set size memory span (tau = −0.132, $p = 0.041$; rho = −0.157, $p = 0.041$) was found, which again hints at an indirect relation to WMC. Accordingly, a sensing learning style is associated with a low WMC and a balanced learning style is associated with a high WMC. This is also supported by the results of the group comparison in both directions. The highly significant result ($U = 2263$, $p = 0.005$) from the Mann–Whitney-*U* test between groups of WMC shows that learners with low WMC tend to have a significantly higher preference for a sensing learning style than learners with high WMC. Looking in the other direction, the conducted *t*-test ($T = -1.976$, $p = 0.050$) shows that learners with a sensing learning style tend to have significantly lower WMC than learners with a balanced learning style.

Considering the intuitive/balanced part, only a significant negative correlation between the intuitive/balanced values and the mean response latency (tau = −0.149, $p = 0.032$; rho = −0.205, $p = 0.029$) was found. According to the previously described results of the Web-OSPAN measures, only a weak correlation exists between the WMC values and the mean response latency, which seems to be not reliable enough to conclude for an indirect relationship. Also from group comparison, no significant relations were found.

Table 1
Results of the correlation between WMC values and other measures of Web-OSPAN.

Measure of Web-OSPAN	Correlation coefficients	Significance
Set size memory span	tau = 0.649, rho = 0.757	$p < 0.001$
Process measure	tau = 0.191, rho = 0.258	$p < 0.001$
Mean response time	$r = -0.361$	$p < 0.001$
Partial correct memory span	tau = 0.741, rho = 0.883	$p < 0.001$

Table 2
Results from statistical analysis of the sensing/intuitive dimension and WMC values. (Significant results are presented in bold; results from other measures of the Web-OSPAN task are only stated if they provide indications for the investigated relationship.)

Statistical approach	Coefficient	Significance
General		
Correlation	tau = −0.037	$p = 0.451$
	rho = −0.055	$p = 0.425$
In-depth (all data)		
Chi-square test	$\boldsymbol{\chi^2 = 8.628}$	**p = 0.013**
Correlation (absolute ILS values)	tau = −0.036	$p = 0.465$
	rho = −0.051	$p = 0.449$
Correlations to other relevant measures		
Set size memory span	**tau = 0.113**	***p* = 0.046**
	rho = 0.137	***p* = 0.045**
In-depth (only sen/bal)		
Correlation	tau = −0.077	$p = 0.174$
	rho = −0.105	$p = 0.176$
Correlations to other measures		
Set size memory span	**tau = −0.132**	***p* = 0.041**
	rho = −0.157	***p* = 0.041**
WMC categories: *u*-test	***U* = 2263**	***p* = 0.005**
ILS categories: *t*-test	***T* = −1.976**	***p* = 0.050**
In-depth (only int/bal)		
Correlation	tau = 0.092	$p = 0.182$
	rho = 0.121	$p = 0.193$
WMC categories: *u*-test	$U = 1041.5$	$p = 0.055$
ILS categories: *t*-test	$T = -0.839$	$p = 0.403$

From these results (summarized in Table 2), conclusions can be drawn that a sensing learning style is associated with low WMC and the more balanced the learning style becomes, the higher WMC tends to be. For the second part of the relationship concerning ILS values indicating a balanced learning style towards an intuitive learning style, no evidence in data was found. This might be attributed to the few learners with a strong intuitive preference in the data set, since only seven learners had an ILS values smaller or equal to −8.

3.2.3.3. Working memory capacity and the active/reflective dimension. In the general analysis, no significant correlations were found between WMC and the active/reflective values. However, according to the in-depth analysis, the significant result of the chi-square test (χ^2 = 7.889, p = 0.019) indicated that the three groups (active, balanced, and reflective) were different to each other. A significant but weak negative correlation between the absolute active/reflective values and the WMC values (tau = −0.169, p = 0.001; rho = −0.222, p = 0.001), the set size memory span (tau = −0.140, p = 0.015; rho = −0.161, p = 0.015), and the partial correct memory span (tau = −0.167, p = 0.002; rho = −0.216, p = 0.003) was found. These correlations indicate that learners with a balanced learning style tend to have high WMC, whereas learners with either a very active or a very reflective learning style tend to have low WMC. This hypothesis is furthermore supported by the results of the analysis of the sub-dataset $S_{\text{act/bal}}$ and $S_{\text{ref/bal}}$.

Looking at the sub-dataset $S_{\text{act/bal}}$, which includes only data indicating an active or balanced preference, the correlation analysis resulted in a significant negative correlation between the active/balanced values and WMC values (tau = −0.173, p = 0.002; rho = −0.226, p = 0.003), set size memory span (tau = −0.162, p = 0.014; rho = −0.191, p = 0.013), partial correct memory span (tau = −0.142, p = 0.022; rho = −0.188, p = 0.023), and process measure (tau = −0.138, p = 0.019; rho = −0.177, p = 0.021). These correlations indicate that active learners tend to have low WMC and balanced learners tend to have high WMC (and vice versa). This is further supported by a significant result of the Mann–Whitney-U test (U = 2324.5, p = 0.008), comparing the high WMC group and low WMC group over the active/balanced values and indicating that learners with low WMC have a significantly more active learning style than learners with high WMC.

On the other hand, looking at $S_{\text{ref/bal}}$, the reflective/balanced part of data, a significant but weak positive correlation between the WMC values and the reflective/balanced values according to Spearman's rho (rho = 0.163, p = 0.045) was found. However, this relation is supported by the highly significant result of the t-test (T = -3.094, p = 0.002), comparing the reflective and balanced group over the WMC values and showing that reflective learners have significantly lower WMC than balanced learners.

From all these evidences (summarized in Table 3), conclusion can be drawn that a significant relationship between the active/reflective dimension and WMC exists. This relationship shows that the more balanced the learning style is, the higher WMC the learners tend to have. On the other hand, the stronger the preference for either an active or a reflective learning style is, the lower WMC the learners tend to have. Regarding an active learning preference, the results of the experiment are in agreement with the conclusions from the indirect relationship, since both associate low WMC with an active learning preference. However, regarding a reflective preference, conclusions from the indirect relationship argued for high WMC. According to the results from the experiment, active and reflective preferences are associated with low WMC, whereas a balanced learning style is related to high WMC.

Table 3
Results from statistical analysis of the active/reflective dimension and WMC values. (Significant results are presented in bold; results from other measures of the Web-OSPAN task are only stated if they provide indications for the investigated relationship.)

Statistical approach	Coefficient	Significance
General		
Correlation	tau = −0.003	p = 0.952
	rho = 0.000	p = 0.998
In-depth (all data)		
Chi-square test	**χ^2 = 7.889**	**p = 0.019**
Correlation (absolute ILS values)	**tau = −0.169**	**p = 0.001**
	rho = −0.222	**p = 0.001**
Correlations to other relevant measures (absolute ILS values)		
Set size memory span	**tau = −0.140**	**p = 0.015**
	rho = −0.161	**p = 0.015**
Partial correct memory span	**tau = −0.167**	**p = 0.002**
	rho = −0.216	**p = 0.003**
In-depth (only act/bal)		
Correlation	**tau = −0.173**	**p = 0.002**
	rho = −0226	**p = 0.003**
Correlations to other relevant measures		
Set size memory span	**tau = −0.162**	**p = 0.014**
	rho = −0.191	**p = 0.013**
Partial correct memory span	**tau = −0.142**	**p = 0.022**
	rho = −0.188	**p = 0.023**
WMC categories: u-test	**U = 2324.5**	**p = 0.008**
ILS categories: t-test	**T = −1.894**	**p = 0.060**
In-depth (only ref/bal)		
Correlation	tau = 0.114	p = 0.061
	rho = 0.163	**p = 0.045**
WMC categories: u-test	U = 2068.5	p = 0.130
ILS categories: t-test	**T = −3.094**	**p = 0.002**

3.2.3.4. Working memory capacity and the visual/verbal dimension. As expected from the indirect relationship, no significant result for a bi-directional relationship between WMC and the visual/verbal dimension was found, either with general analysis or with in-depth analysis. Since a one-directional relationship was detected from existing studies, the analysis focuses on proving one-directional relationships by using correlation of frequencies in sub-datasets.

Looking at two datasets separating learners with high and low WMC, correlation between frequencies and visual/verbal preferences shows a highly significant and strong positive correlation for both, learners with low WMC (tau = 0.857, p = 0.002) and learners with high WMC (tau = 0.889, p = 0.001). This was expected since it is known from other studies, summarised by Felder and Spurlin (2005), and can also be seen from the data in our studies that, in general, more learners have a visual than a verbal learning style.

When separating learners with visual and verbal learning preference, correlation analysis of frequencies shows a significant correlation for learners with a verbal learning style (tau = 0.51, p = 0.033). This indicates that in the group of verbal learners, a high frequency is associated with high WMC, whereas few verbal learners have low WMC. In contrast, when looking at learners with a visual learning style, the result of the correlation is not significant (tau = 0.455, p = 0.520).

As a conclusion, our findings (summarized in Table 4) confirm the existence of a one-directional relationship, which indicates that learners with a verbal learning style tend to have high WMC, whereas visual learners have either high or low WMC.

3.2.3.5. Working memory capacity and the sequential/global dimension. According to literature, indications exist for a relationship between a sequential learning style preference and high WMC as well as a global learning style preference and low WMC. Based on the data of this study, no evidence that yields to this conclusion was found. Neither general analysis nor in-depth analysis resulted in

Table 4
Results from statistical analysis of the visual/verbal dimension and WMC values. (Significant results are presented in bold.)

Statistical approach	Coefficient	Significance
General		
Correlation	tau = −0.043	$p = 0.381$
	rho = −0.059	$p = 0.382$
In-depth		
Chi-square test	$\chi^2 = 1.308$	$p = 0.520$
One-directional relationship		
Only for learners with low working memory capacity: correlation between frequencies and vis/ver dimension	**tau = 0.857**	$\boldsymbol{p = 0.002}$
Only for learners with high working memory capacity: correlation between frequencies and vis/ver dimension	**tau = 0.889**	$\boldsymbol{p = 0.001}$
Only for visual learners: Correlation between frequencies and WMC values	tau = 0.455	$p = 0.520$
Only for verbal learners: Correlation between frequencies and WMC values	**tau = 0.51**	$\boldsymbol{p = 0.033}$

Table 5
Results from statistical analysis of the sequential/global dimension and WMC values.

Statistical approach	Coefficient	Significance
General		
Correlation	tau = 0.004	$p = 0.935$
	rho = 0.001	$p = 0.993$
In-depth		
Chi-square test	$\chi^2 = 1344$	$p = 0.511$

a significant relationship as can be seen from Table 5. Therefore, our findings are in disagreement with the indirect relationship found from literature, by indicating that there exist no relationship between the sequential/global learning style dimension and WMC.

3.3. Benefits of the identified relationships for web-based educational systems

Web-based educational systems aim at providing learners with an environment where they can easily learn. In order to achieve this goal, accommodating the needs of learners is an important issue for making these systems useful and effective for learners. Many researchers pointed out the relevance of adaptivity, personalization, and intelligent support in web-based educational systems (e.g., Brusilovsky & Peylo, 2003; de Bra, 2002; Kinshuk & Graf, 2007; Sampson, Karagiannidis, & Kinshuk, 2002). While the first adaptive and intelligent web-based educational systems focused mainly on considering the students' knowledge and learning progress, a broader set of characteristics, needs, and states of learners is investigated and used in current systems.

This study focuses on the consideration of learning styles and cognitive traits in web-based educational systems. ConsideringThe adaptivity based on the cognitive traits, in general, focuses more the structure of the course, including for example adaptations regarding the number and relevance of links within the course and learning material, the amount/detail, concreteness, and structureness of the content and the number of information resources. On the other hand, adaptivity based on learning styles, in general, focuses more on details about specific types of learning objects, including for example the sequence in which different types of learning objects are presented and the number of particular types of learning objects, tasks, and questions presented to learners.

In the following paragraph, some examples for combining adaptivity based on cognitive traits and adaptivity based on learning styles are discussed in order to show how the combination of these two kinds of adaptivity can enrich the overall adaptivity of the web-based educational systems. These are based on the examples given in Sections 2.1.3 and 2.2.3, dealing with active/reflective learning, sequential/global learning, and low/high WMC.

In the given examples, adaptivity based on active and reflective learning is indirectly included in adaptivity based on WMC. Adaptivity for active and reflective learning has an impact on the number of questions which should be presented in an exercise. On the other hand, adaptivity with respect to students' WMC has an influence on whether exercises should be presented or not, based on the suggested amount of content and the relevance of links. But this dependency is only indirect. For example, increasing or decreasing the amount of content concerns all types of learning objects and hence also the number of questions in an exercise. Applying initially the adaptivity based on WMC in order to create the overall structure of the course and adjusting the presentation of particular types of learning objects afterwards based on the preferences for an active or reflective learning style increases adaptivity and makes the courses fit more accurately to students' characteristics. Another example deals with adaptivity based on sequential and global learning, which is independent of the two features for adaptivity based on WMC. Neither the amount of content nor the relevance of links influence whether exercises and tests should be presented at the end of each chapter or at the end of the course. Again, adaptivity based on WMC can be used for generating the structure of the course and subsequently details can be changed based on the preferences for sequential and global learning.

The findings of this study contribute towards providing adaptivity based on cognitive traits and adaptivity based on learning styles. The results of current investigations show that relationships exist between FSLSM and WMC. These relationships show tendencies, indicating, for example, that most of the learners with low WMC tend to have an active learning style.

The identified relationships provide additional information about the learners. This information leads to two benefits for web-based educational systems with respect to enhancing adaptivity. The first benefit is for adaptive educational systems that are able to detect either only learning styles or only cognitive traits. As shown from the example above, a system that supports adaptivity based on cognitive traits and learning styles enhances the overall adaptivity of the system and is able to provide courses that suit the needs of learners better than a system that uses only one kind of adaptivity. But the requirements for providing adaptivity based on learning styles and cognitive traits are to know the learning styles and cognitive traits of the learners. Systems that detect either only learning styles or only cognitive traits can benefit from the identified relationships between learning styles and cognitive traits. For example, a system that is able to detect only learning styles can use the identified relationships to get also some information about the learners' cognitive traits. This information can be used to provide some additional adaptivity based on cognitive traits and therefore improve the overall adaptivity of the system.

The second benefit of the relationship between learning styles and cognitive traits refers to improving the student modelling process of systems that are able to detect both, learning styles and cognitive traits. In the previous case the student model includes information about either only learning styles or only cognitive traits and is extended by information about the other one. In this case, the student model already includes both, learning styles and cognitive traits, and the identified relationship between learning styles and cognitive traits can be used to build a more reliable student model. Detecting learning styles and cognitive traits is a complex process. As mentioned in the introduction, a meaningful approach for detecting them is to track the behaviour of learners during an online course and automatically infer their learning styles and cognitive traits from this behaviour. This process needs a lot of interaction between the learner and the system and therefore takes time to provide a reliable conclusion about their learning styles and cognitive traits. The relationship between learning styles and cognitive traits provides additional information about the learners which can be included in the detection process and hence improve the reliability of the student model.

As an example, the additional information about learning styles can improve the detection process of WMC in the CTM. As discussed previously, different researchers have looked at WMC differently; it is analogous to different observers perceiving different portrayals of an object from different angles. In the study of cognitive trait, Lin, Kinshuk, and Patel (2003) listed a number of manifestation of trait (MOTs), the patterns of behaviour that give indication to the capacity of the cognitive trait. An example of MOTs is navigational linearity: experimental results of Huai's study (Huai, 2000) showed that students with higher WMC tend to navigate linearly and students with lower WMC navigate non-linearly. Other MOTs of working memory include frequency of reverse navigation, ability to perform tasks simultaneously, comparison speed, and so on.

In close scrutiny, each of the MOTs holds a certain degree of truth about the characteristics of working memory. Taking any one of them and discarding the rest means taking a great risk of losing the accuracy desired. With the regarded difficulty to understand mysteries of the mind (Blackmore, 2003), not a single MOT could include a complete and all-embracing description of how working memory works. Therefore, the more MOTs are included in the analysis, the more likely it is to get accurate representation of the cognitive trait.

The four dimensions of FSLSM can therefore provide additional MOTs given the relationships between WMC and the learning style model. This addition can greatly enhance the accuracy of what Cognitive Trait Model can estimate about WMC.

4. Conclusion

This paper discussed the relationship between learning styles and cognitive traits as well as the benefits of considering learning styles and cognitive traits in web-based educational systems. Accommodating learners' needs and providing them with adaptive courses and learning experiences is an important issue for web-based educational systems. The general aim of incorporating learning styles and cognitive traits in such systems is to provide more holistic and accurate adaptivity. Adaptivity based on cognitive traits affects the course in a more general way than adaptivity based on learning styles. Both kinds of adaptivity enrich each other and combining them leads to courses that provide more adaptivity, considering cognitive traits as well as learning styles of a learner.

Adaptivity can only be provided if the needs of learners are known by the system. To improve student modelling, relationships between learning styles and working memory capacity (WMC) were investigated and identified. In current investigations, Felder–Silverman learning style model (FSLSM) is mapped with WMC, one trait of the Cognitive Trait Model. After deriving indirect relationships between the FSLSM and WMC from literature, an experiment with 297 students was performed. The results showed a relationship for the active/reflective, the sensing/intuitive, and the visual/verbal dimension, whereas no relationship was found for the sequential/global dimension.

The interaction between cognitive traits and learning styles can be used to improve the student model of an adaptive educational system and therefore to provide more holistic and accurate adaptivity. A system that is able to detect either only learning styles or only cognitive traits can use the relationship to get some information about the other, not detected feature. According to this additional information, the system can provide more adaptivity. For systems that already consider both, learning styles and cognitive traits, the relationship can be used to improve automatic student modelling and build a more robust student model.

In this paper, the existence of a relationship between learning styles and cognitive traits is shown. Future work will deal with using the additional information gathered from the relationship and demonstrate the benefits by the use of real data. On the one hand, we plan to incorporate the information about learning styles in the detection process of CTM in order to improve the inference process of modelling WMC in CTM. On the other hand, we plan to build a learning style student model using the additional information about cognitive traits in order to improve the automatic student modelling approach. Furthermore, we plan to extend the research to include additional cognitive traits such as inductive reasoning skill, and associative learning skill.

Acknowledgements

The authors acknowledge the support of Austrian Science Fund (FWF) under Grant J2831-N13, National Science Council of the Republic of China, Taiwan, under Contract No. NSC 96-2520-S-008-007-MY2, NSC 097-2811-S-008-001-, and NSC 97-2631-S-008-003-, iCORE, Xerox, and the research related gift funding by Mr. A. Markin.

References

Al Naeme, F. F. A. (1991). *The influence of various learning styles on practical problem-solving in chemistry in Scottish Secondary Schools.* University of Glasgow.

Anderson, J. R. (1983). *The architecture of cognition*. Cambridge, MA: Harvard University Press.

Baddeley, A. D. (1986). *Working memory*. Oxford: Oxford University Press.

Bahar, M., & Hansell, M. H. (2000). The relationship between some psychological factors and their effect on the performance of grid questions and word association tests. *Educational Psychology, 20*(3), 349–364.

Bajraktarevic, N., Hall, W., & Fullick, P. (2003). Incorporating learning styles in hypermedia environment: empirical evaluation. In P. de Bra, H. C. Davis, J. Kay & M. Schraefel (Eds.), *Proceedings of the workshop on adaptive hypermedia and adaptive web-based systems* (pp. 41–52). Nottingham, UK: Eindhoven University.

Beacham, N., Szumko, J., & Alty, J. (2003). *An initial study of computer based media effects on learners who have dyslexia* (final report). Loughborough University.

Blackmore, S. (2003). The case of the mysterious mind. *New Scientists, 2425*, 36–39.

Brusilovsky, P. (1994). The construction and application of student models in intelligent tutoring systems. *Journal of Computer and Systems Sciences International, 32*(1), 70–89.

Brusilovsky, P. (1996). Methods and techniques of adaptive hypermedia. *User Modeling and User-Adapted Interaction, 6*(2–3), 87–129.

Brusilovsky, P., & Peylo, C. (2003). Adaptive and intelligent web-based educational systems. *International Journal of Artificial Intelligence in Education, 13*, 156–169.

Byrne, M. D. (1996). A computational theory of working memory. Retrieved 28 May, 2007, from http://www.acm.org/sigchi/chi96/proceedings/doctoral/Byrne/mdb_txt.htm.

Carver, C. A., Howard, R. A., & Lane, W. D. (1999). Addressing different learning styles through course hypermedia. *IEEE Transactions on Education, 42*(1), 33–38.

Case, R. (1995). Capacity-based explanations of working memory growth: A brief history and reevaluation. In F. E. Weinert & W. Schneider (Eds.), *Memory performance and competencies: issues in growth and development* (pp. 23–24). Mahwah, NJ: Erlbaum.

Cha, H. J., Kim, Y. S., Park, S. H., Yoon, T. B., Jung, Y.M., & Lee, J. -H. (2006). Learning style diagnosis based on user interface behavior for the customization of learning interfaces in an intelligent tutoring system. In M. Ikeda, K. D. Ashley & T. -W. Chan (Eds.), *Proceedings of the 8th international conference on intelligent tutoring systems, lecture notes in computer science* (pp. 513–524, vol. 4053). Berlin, Heidelberg: Springer.

Davis, J. K. (1991). Educational implications of field dependence–independence. In S. Wapner & J. Demick (Eds.), *Field dependence–independence: Cognitive style across the life span* (pp. 149–175). Hillsdale, NJ: Lawrence Erlbaum Associates.

de Bra, P. (2002). Adaptive educational hypermedia on the web. *Communications of the ACM, 45*(5), 60–61.

de Neys, W., d'Ydewalle, G., Schaeken, W., & Vos, G. (2002). A Dutch, computerized, and group administrable adaptation of the operation span test. *Psychologica Belgica, 42*, 177–190.

Deary, I. J., Whiteman, M. C., Starr, J. M., Whalley, L. J., & Fox, H. C. (2004). The impact of childhood intelligence on later life: following up the scottish mental surveys of 1932 and 1947. *Journal of Personality and Social Psychology, 86*(1), 130–147.

Dunn, R., & Dunn, K. (1974). Learning style as a criterion for placement in alternative programs. *Phi Delta Kappan, 56*(4), 275–278.

El-Banna, H. (1987). *The development of a predictive theory of science education based upon information processing theory*. University of Glasgow.

Felder, R. M., & Soloman, B. A. (1997). Index of learning styles questionnaire. Retrieved 15 January, 2009, from http://www.engr.ncsu.edu/learningstyles/ilsweb.html.

Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Engineering Education, 78*(7), 674–681.

Felder, R. M., & Spurlin, J. (2005). Applications, reliability and validity of the index of learning styles. *International Journal on Engineering Education, 21*(1), 103–112.

Ford, N., & Chen, S. Y. (2000). Individual differences, hypermedia navigation and learning: An empirical study. *Journal of Educational Multimedia and Hypermedia, 9*(4), 281–311.

García, P., Amandi, A., Schiaffino, S., & Campo, M. (2007). Evaluating Bayesian networks' precision for detecting students' learning styles. *Computers & Education, 49*(3), 794–808.

Graf, S., Lan, C. H., Liu, T. -C., & Kinshuk (2009). Investigations about the effects and effectiveness of adaptivity for students with different learning styles. In *Proceedings of the IEEE international conference on advanced learning technologies* (pp. 415–419). Riga, Latvia: IEEE Computer Science.

Graf, S., & Kinshuk (2007). Providing adaptive courses in learning management systems with respect to learning styles. In G. Richards (Ed.), *Proceedings of the world conference on E-learning in corporate, government, healthcare, and higher education (E-learn)* (pp. 2576–2583). Chesapeake, VA: AACE Press.

Graf, S., Kinshuk, & Liu, T. -C. (2008). Identifying learning styles in learning management systems by using indications from Students' behaviour. In P. Diaz, Kinshuk, I. Aedo, & E. Mora (Eds.), *Proceedings of the international conference on advanced learning technologies* (pp. 482–486). Santander, Spain: IEEE Computer Science.

Hadwin, A. F., Kirby, J. R., & Woodhouse, R. A. (1999). Individual differences in notetaking, summarization, and learning from lectures. *Alberta Journal of Educational Research, 45*(1), 1–17.

Hayes, J., & Allinson, C. W. (1996). The implications of learning styles for training and development: A discussion of the matching hypothesis. *British Journal of Management, 7*, 63–73.

Honey, P., & Mumford, A. (1982). *The manual of learning styles*. Maidenhead: Peter Honey.

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

Hudson, L. (1966). *Contrary imaginations*. London: Penguin Books.

Kinshuk, & Graf, S. (2007). Considering cognitive traits and learning styles to open web-based learning to a larger student community. In *Proceedings of the international conference on information and communication technology and accessibility* (pp. 21–26).

Kinshuk, Oppermann, R., Patel, A., & Kashihara, A. (1999). Multiple representation approach in multimedia based intelligent educational systems. In S. P. Lajoie & M. Vivet (Eds.), *Proceedings of the international conference on artificial intelligence in education* (pp. 259–266). Amsterdam: IOS Press.

Kinshuk & Lin, T. (2003). User exploration based adaptation in adaptive learning systems. *International Journal of Information Systems in Education, 1*(1), 22–31.

Kolb, D. A. (1984). *Experiential learning: experience as the source of learning and development*. Englewood Cliffs, New Jersey: Prentice-Hall.

Lin, T., & Kinshuk (2004). Dichotomic node network and cognitive trait model. In *Proceedings of IEEE international conference on advanced learning technologies* (pp. 702–704). Los Alamitos, CA: IEEE Computer Science.

Lin, T., & Kinshuk (2005). Cognitive profiling in life-long learning. In C. Howard, J. V. Boettcher, L. Justice, K. Schenk, P. L. Rogers & G. A. Berg (Eds.), *Encyclopedia of international computer-based learning* (pp. 245–255). Hershey, PA, USA: Idea Group Inc.

Lin, T., Kinshuk, & Patel, A. (2003). Cognitive trait model - a supplement to performance based student models. In K. T. Lee & K. Mitchell (Eds.), *Proceedings of the international conference on computers in education* (pp. 629–632). Norfolk, VA, USA: AACE

Liu, M., & Reed, W. M. (1994). The relationship between the learning strategies and learning styles in a hypermedia environment. *Computers in Human Behavior, 10*(4), 419–434.

Miller, G. A. (1956). The magic number seven, plus or minus two: Some limit of our capacity for processing information. *Psychology Review, 63*(2), 81–96.

Paredes, P., & Rodríguez, P. (2004). A mixed approach to modelling learning styles in adaptive educational hypermedia. *Advanced Technology for Learning, 1*(4), 210–215.

Pascual-Leone, J. (1970). A mathematical model for the transition rule in Piaget's development stages. *Acta Psychologica, 32*, 301–345.

Pask, G. (1976). Styles and strategies of learning. *British Journal of Educational Psychology, 46*, 128–148.

Peña, C. -I., Marzo, J. -L., & de la Rosa, J. -L. (2004). Curriculum sequencing for an E-learning system based on learning styles. In *Proceedings of the fifth international conference on information technology based higher education and training* (pp. 167–172). IEEE Press.

Richards-Ward, L. A. (1996). 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

Salthouse, T. A., & Babcock, R. L. (1991). Decomposing adult age differences in working memory. *Developmental Psychology, 27*(5), 763–776.

Salthouse, T. A., Mitcheel, D. R. D., Skovronek, E., & Babcock, R. L. (1989). Effects of adult age and working memory on reasoning abilities. *Journal of Experiemental Psychology: Learning, Memory, and Cognition, 15*, 507–516.

Sampson, D. G., Karagiannidis, C., & Kinshuk (2002). Personalised learning: educational, technological and standardisation perspective. *Interactive Educational Multimedia, 4*, 24–39.

Scandura, J. M. (1973). *Structural learning I: Theory and research*. London, UK: Gordon & Breach.

Shang, Y., Shi, H., & Chen, S.-S. (2001). An intelligent distributed environment for active learning. *ACM Journal of Educational Resources in Computing, 1*(2), 1–17.

Simmons, F. R., & Singleton, C. H. (2000). The reading comprehension abilities of dyslexic students in higher education. *Dyslexia, 6*(3), 178–192.

Stash, N., Cristea, A., & de Bra, P. (2006). Adaptation to learning styles in e-learning: approach evaluation. In T. Reeves & S. Yamashita (Eds.), Proceedings of world conference on E-learning in corporate, government, healthcare, and higher education (pp. 284–291). Chesapeake, VA: AACE Press.

Summerville, J. B. (1999). Role of awareness of cognitive style in hypermedia. *International Journal of Educational Technology, 1*(1). Retrieved July 22, 2009. Available from http://www.ascilite.org.au/ajet/ijet/v1n1/summerville.

Tuckman, B. W. (1999). *Conducting educational research* (5th ed.). Belmont: Wadsworth Group.

Turner, M. L., & Engle, R. W. (1989). Is Working Memory Capacity Task Dependent? *Journal of Memory and Language, 28*, 127–154.

Wey, P., & Waugh, M. L. (1993). *The effects of different interface presentation modes and users' individual differences on users' hypertext information access performance*. Paper presented at the annual meeting of the American Educational Research Association, Atlanta, GA.

Witkin, H. A., Moore, C. A., Goodenough, D. R., & Cox, P. W. (1977). Field dependent and field independent cognitive styles and their educational implications. *Review of Educational Research, 47*(1), 1–64.