CHAPTER 27: TECHNOLOGIES LINKING LEARNING, COGNITION AND INSTRUCTION*

Sabine Graf

Vienna University of Technology

Women's Postgraduate College for Internet Technologies

graf@wit.tuwien.ac.at

Kinshuk

Athabasca University

School of Computing and Information Systems

kinshuk@ieee.org

ABSTRACT

There are many different ways in which people prefer to learn. Furthermore, people have different cognitive abilities that influence the way effective learning takes place. Incorporating individual differences such as learning styles and cognitive abilities into education makes learning easier and increases the learner's performance. In contrast, learners whose needs are not supported by the learning environment experience problems in the learning process. In this chapter we introduce some cognitive traits that are important for learning and also discuss how to incorporate different abilities in

* This research has been partly funded by the Austrian Federal Ministry for Education, Science, and Culture, and the European Social Fund (ESF) under grant 31.963/46-VII/9/2002.

educational systems. In regard to learning styles, some major approaches as well as possible strategies for involving learning styles in online courses are presented. In the next section, recent research dealing with identifying learning styles and cognitive traits based on the behaviour of students during a course is presented. This information is necessary to provide adaptive courses. Finally, the relationship between cognitive traits and learning styles is discussed. This relationship leads to additional information and therefore to a more reliable student model.

Keywords and definitions:

Cognitive abilities: Abilities to perform any of the functions involved in cognition whereby cognition can be defined as the mental process of knowing, including aspects such as awareness, perception, reasoning, and judgment.

Learning styles: There is no single agreed definition of learning styles. A general definition is provided by Honey and Mumford (1992) saying that a learning style is a description of the attitudes and behaviours which determine an individual's preferred way of learning.

Student modelling: Student models store information about students including domain competence and individual domain-independent characteristics. Student modelling is the process of building and updating the student model.

27.1 INTRODUCTION

Individual learners play a central role in a technology enhanced learning environment. Each learner has individual characteristics such as different cognitive abilities, learning style preferences, prior knowledge, motivation, and so on. These individual differences affect the learning process and are the reason why some students find it easy to learn in a particular course whereas others find the same course difficult (Jonassen & Grabowski, 1993).

The context in which learning takes place also plays an important role. This learning context includes learning objectives, learning activities, learning assessments, the used technology or tools, information resources, and teachers, tutors or assistants. The learner with his/her individual differences as well as the mentioned aspects of the learning context can be seen as components of a learning system. Each of these components and especially the interaction between these components influences the learning process.

For example, Gagné (1985) argued that an interaction between the learning objectives and the learning activities exists and that different conditions on the structure and kind of learning activities are necessary for different types of learning objectives. He identified five categories of learning, namely verbal information, intellectual skills, cognitive strategies, motor skills, and attitudes. For learning attitudes, persuasive arguments or a kind of role model are necessary. In contrast, to learn motor skills, an important condition of learning is to practise these skills. On the other hand, when learning verbal information like facts, no practices, arguments or role models are necessary.

Another example is the interaction between information resources and the individual differences of learning styles. The information resources can be presented in different forms such as text, images, animations, simulations, graphs, and so on, and therefore matches or mismatches with each learner’s preferred way of receiving information. The better these aspects match, the better learning can take place. Furthermore, the information might be comprised of concrete material such as facts and data or the information might deal about more abstract material like concepts and theories. Again, matching or mismatching influence the learning process.

Many other links between the above mentioned components are investigated and influences on learning are elaborated. In this chapter, we focus on research dealing with the link between aspects of individual learners, in particular cognitive abilities and learning styles, how instruction can be designed in order to match or mismatch with these needs, and how these instructions can be supported by technology.

Concerning individual differences, a lot of research has been done about prior knowledge and its influence on learning. Jonassen and Grabowski summarized that prior knowledge is one of the strongest and consistent individual difference predictors of achievement (Jonassen & Grabowski, 1993). Although prior knowledge seems to account for more variance in learning than other individual differences, more recently educational researchers have focused on aspects of cognitive abilities and learning styles, their influence on learning, and also how they can be incorporated in technology enhanced learning.

Cognitive abilities and learning styles play an important role in education. For example, cognitive overload may hinder the process of learning and yield to poor performance. Regarding learning styles, Felder pointed out that learners with strong preference for a specific learning style may have difficulties in learning if the teaching style did not match with their learning style (Felder & Silverman, 1988; Felder & Soloman, 1997). From theoretical point of view, we can therefore argue that incorporating the cognitive abilities and learning style of students makes learning easier and increases the learning efficiency of the students. On the other hand, learners who are not supported by the learning environment may experience problems in the learning process.

Although these hypotheses seem to be intuitive and supported by educational theories, inconsistent results are obtained by studies dealing with investigating the effects on achievement when providing matched and mismatched instructions for learners with different abilities and preferences. As Jonassen and Grabowski (1993, p. 28ff) summarized, several reasons for such inconsistent results are known in the field of aptitude-treatment interaction (ATI) research. Limitations might include “small samples size, abbreviated treatments, specialized aptitude constructs or standardized tests, and a lack of conceptual or theoretical linkage between aptitudes and the information-processing requirements of the treatment”.

An example for a supporting study is the study performed by Bajraktarevic, Hall, and Fullick (2003) showing that students attending an online course that matches with their preferred learning style (either sequential or global) achieved significantly better results than those who received a mismatched course. Another supporting example is the study by Ford and Chen (2001) where they investigated the performance of students attending a course that either matches or mismatches with their cognitive style (field-dependency or field-independency). Also in this case, students who undertook the matched course achieved significantly better results than those who attended the mismatched course. In contrast, the study by Brown, Brailsford, Fisher, Moore and Ashman (2006) focused on the visual and verbal preference of learners. As a result they concluded that “it did not seem to matter whether a student was a visual or bimodal learner, nor if they were presented with visual, verbal or mixed representations of data” (Brown et al., 2006, p. 333). Another example for a study that did not yield significant results was described in Tillema (1982) and dealt with the serial and holistic cognitive style. These inconsistent results show that more future work is necessary.

However, a lot of recent research has been done dealing with aspects of incorporating cognitive abilities and learning styles in technology enhanced learning systems. This chapter aims at providing an overview on these aspects. First, an introduction into cognitive traits and learning styles is provided, taking also into account instructional strategies to support specific cognitive traits and learning styles of students in educational systems. The next section discusses and gives examples of how cognitive traits and learning styles can be identified. Subsequently, the relationship between cognitive traits and learning style is discussed.

27.2 COGNITIVE TRAITS

Humans typically have a number of cognitive abilities. In this section, we focus on cognitive abilities which are important for learning. For these abilities we discuss how instruction is related with these cognitive abilities and how to support learners with low and high cognitive abilities in educational systems.

27.2.1 Working Memory Capacity

Working memory allows us to keep active a limited amount of information (roughly 7+-2 items) for a brief period of time (Miller, 1956). In earlier times, working memory was also referred as short-term memory. While there are different views on the structure of the working memory, researchers now agree that it consists of both storage and operational sub-systems (Richards-Ward, 1996). Deficiencies in working memory capacity result in different performances on a variety of tasks. Examples of affected tasks include natural language use (comprehension, production, etc.), recognition of declarative memory, skill acquisition and so on (Byrne, 1996).

The dual-code hypothesis is based on the assumption that the working memory consists of two separate components, one concerned with verbal materials and one concerned with nonverbal materials (Clark & Paivio, 1991). According to this hypothesis, cognitive load is reduced when both channels (verbal and nonverbal) are attracted and thus, better learning can take place. A supporting example is the study conducted by Moreno and Valdez (2005) where students were presented with diagrams (nonverbal information) with an explaining text (verbal information), only diagrams or only the explaining text. As a result, students who got both types of information achieved best results in tests about retention as well as transfer of knowledge. Another supporting study of the dual-code hypothesis was performed by Wey and Waugh (1993). They found out that field-dependent learners, who tend to have low working memory capacity (e.g. Al Naeme, 1991; Bahar & Hansell, 2000), have difficulties in learning text-only material and benefit from material that contains text and graphics.

However, some conditions exist for the positive effect of dual code presentation. According to Mayer (1997) and Kalyuga, Chandler, and Sweller (1999), information should not be redundant and should be integrated so that students are not forced to split their attention. For example, presenting a text in written format as well as in audio format imposes an additional cognitive load and therefore has negative effects on learning. Furthermore, it seems to be important to incorporate the domain experience of the learners. As Kalyuga, Chandler, and Sweller (2000) found out in their study, the effectiveness of presenting information in dual-code decreases with the increasing learner experience. While novice learners achieve better results when learning from diagrams with audio text than with diagrams only, more experienced learners yield better results from diagrams only, resulting from the reduced cognitive load imposed from the diagram only presentation.

Based on the Exploration Space Control elements (Kashihara, Kinshuk, Oppermann, Rashev, & Simm, 2000) different versions of courses can be created that suit different needs. These elements include the number and relevance of paths, the amount, concreteness and structure of content, as well as the number of information resources. The instructional design in learning systems should assist learners by considering their abilities and avoiding cognitive overload. For learners with low working memory capacity, this can be achieved by decreasing the number and increasing the relevance of paths in a course. Furthermore, less but more concrete content should be presented. Moreover, the number of available media resources should increase. In contrast, for learners with high working memory capacity, less relevant paths can be presented with the amount of content as well as its abstractness being increased (Kinshuk & Lin, 2003).

27.2.2 Reasoning Ability

With respect to reasoning abilities, we can distinguish between inductive, deductive and abductive reasoning. In the following discussion, we will focus on inductive reasoning, since this ability is the most important one regarding learning. We shall also provide some discussion on deductive reasoning.

Inductive reasoning skills relate to the ability to construct concepts from examples. When a student faces a complicated problem, he/she looks for known patterns, and uses them to construct a temporary internal hypotheses or schema in which to work (Bower & Hilgard, 1981). It is easier for students who possess better inductive reasoning skill to recognize a previously known pattern and generalize higher-order rules. As a result, the load on working memory is reduced, and the learning process is more efficient. In other words, the higher the inductive reasoning ability, the easier it is to build up the mental model of the information learned. According to Harverty, Koedinger, Klahr, & Alibali (2000) inductive reasoning ability is the best predictor for academic performance.

For simulation based discovery learning, students are asked to infer characteristics of a model through experimentations by using a computer simulation and thus are asked to use their inductive reasoning skills. According to Veermans and van Joolingen (1998) simulation based discovery learning results in deeper rooting of the knowledge, enhanced transfer, the acquisition of regulatory skills, and would yield better motivation. However, discovery learning does not always yield to better learning results. One of the reasons is that students have difficulties in performing the required processes. To improve the learning progress and support learners with low inductive reasoning abilities, Veermans and van Joolingen have designed a mechanism that provides advices based on the performed experiments in the simulation. This mechanism is integrated in SimQuest, an authoring system for simulation based discovery (van Joolingen & de Jong, 2003).

Considering again exploratory learning and the Exploration Space Control elements, for learners with low inductive reasoning skills, many opportunities for observation should be provided. Therefore, learning systems can support these learners by providing a high amount of well-structured and concrete information with many paths. For learners with high inductive reasoning skills, the amount of information and paths should decrease to reduce the complexity of the hyperspace and hence enable the learners to grasp the concepts quicker. Moreover, information can be presented in a more abstract way (Kinshuk & Lin, 2003).

Deduction is defined as drawing logical consequences from premises. An application for deductive reasoning is, for instance, naturalistic decision making (Zsambok & Klein, 1997), which deals with examining what people do in real world situations. It has been observed that experienced decision makers recognize the situation and associate an appropriate solution whereas unexperienced decision makers perform an unorganized and almost random search of alternatives. When it comes to complex situations, humans often fail in finding appropriate solutions. According to Dörner (1997) several reasons exist for such failures, for example, humans tend to oversimplify the mental model of the complex system, tend to be slow in thinking when it comes to conscious thoughts, or tend to ignore the possibility of side-effects. However, Dörner's experiments showed that leaders from business and industry tend to make more effective decisions in complex situations. Therefore, he argued that the necessary behaviour and skills can be acquired and learnt.

27.2.3 Information Processing Speed

Information processing speed determines how fast the learners acquire the information correctly. Instructional designers should take into account the consideration of learner's information processing speed. For example, a learner may have such a slow reading speed that he/she is unable to hold enough details in working memory to permit decoding of the overall meaning (Bell, 2001).

Based on the Exploration Space Control elements, for learners with low information processing speed, only the important points should be presented. Therefore, the number of paths and information should decrease and the relevance of paths should increase. Additionally, the structure of the information should increase in order to speed up the learning process. In contrast, for learners with high information processing speed the information space can be enlarged by providing a high amount of information and paths (Kinshuk & Lin, 2003).

27.2.4 Associative Learning Skills

The associative learning skills link new knowledge to existing knowledge. The association process requires pattern-matching to discover the space of existing information, analysis of the relationships between the existing and new knowledge, and finally retention of the new knowledge in long-term memory (or more specifically to maintain links to the new knowledge).

In order to assist the association processes during the student's learning, the instruction needs to assist the recall (revisit) of learned information, clearly show the relationships of concepts (new to existing), and facilitate new or creative association/insight formation by providing information of the related domain area. High amount of information, different media resources, and many relevant paths help a learner with low associative learning skills to associate one concept to another. Furthermore, well-structured information makes linkage between concepts easier. In contrast, for learners with high associative learning skills less structure of information allows them to navigate more freely and hence enhances the learning speed. Additionally, the relevance of the paths should decrease to enlarge the information space (Kinshuk & Lin, 2003).

27.2.5 Metacognition

The concept of metacognition was introduced by John Flavell (1976). Several definitions for metacognition exist, for instance, according to Flavell (1976, p. 232) "Metacognition refers to one's knowledge concerning one's own cognitive processes and products or anything related to them". Panaoura and Philippou (2005) define metacognition as the awareness and monitoring of one's own cognitive system and its functioning. Metacognition consists of several dimensions, however, self-representation (the knowledge about cognition) and self-regulation (the regulation of cognition) are the main dimensions. Recent research points out that metacognition plays an important role in the learning process (Alexander, Fabricius, Fleming, Zwahr, & Brown, 2003; Mayer, 1998; Panaoura & Philippou, 2004). For instance, it is known that learners with high metacognitive abilities perform better in problem solving tasks (Lester, Garofalo, & Lambdin-Kroll, 1989; Mayer, 1998).

27.3 LEARNING STYLES

Several different learning style models exist in the literature, each proposing different descriptions and classifications of learning types. To date, no single definition of learning style has been identified. For example, Honey and Mumford (1992, p. 1) defined learning styles as “a description of the attitudes and behaviours which determine an individual’s preferred way of learning”. James and Gardner (1995, p. 20) defined it more precisely by saying that learning style is the “complex manner in which, and conditions under which, learners most efficiently and most effectively perceive, process, store, and recall what they are attempting to learn”.

Furthermore, researchers do not agree on whether learning styles are stable over time. In some studies, learning style changed quite quickly (e.g. Clariana, 1997) whereas some other researchers argue that learning styles are stable over a long period of time (Felder & Spurlin, 2005; Keefe, 1979; Kolb, 1981).

In this section, we introduce some of the most common classifications of learning styles, namely Myers-Briggs Type Indicator (Briggs Myers, 1962), Kolb's learning style model (Kolb, 1984), Honey and Mumford's learning style model (Honey & Mumford, 1982), and Felder-Silverman learning style model (Felder & Silverman, 1988). Focusing on the last one, we also discuss possible teaching strategies, which can be used to support learners with different learning styles in educational systems.

27.3.1 Myers-Briggs Type Indicator

Myers-Briggs Type Indicator (MBTI) (Briggs Myers, 1962) is a personality test and is not focused specifically on learning. Nevertheless, the personality of a learner influences his/her way of learning and therefore, other learning style models are based on considerations of MBTI.

Based on Jung's theory of psychological types (Jung, 1923), the MBTI distinguishes a person's type according to four dichotomies: extroversion/introversion, sensing/intuition, thinking/feeling, and judging/perceiving. All possible combinations can occur, which result in a total number of 16 types.

The terms extrovert and introvert refer to how a person orients and receives his/her energy. The preferred focus of people with an extrovert attitude is on the surroundings such as other people and things, whereas an introvert's preferred focus is on his/her own thoughts and ideas. Sensing and intuition deal with the way people prefer to perceive data. While sensing people prefer to perceive data from their five senses, intuitive people use their intuition and prefer to perceive data from the unconscious. The judgment based on the perceived data can be distinguished between thinking and feeling. Thinking means that the judgment is based on logical connections such as “true or false” and “if-then” while feeling refers to “more-less” and “better-worse” evaluations. However, judgment and decisions are in both cases based on rational considerations. The last dichotomy describes whether a person is more extroverted in his/her stronger judgment function (thinking or feeling) or in the perceiving function (sensing or intuition). Judging people prefer step-by-step approaches and structure as well as coming to a quick closure. Perceiving people have a preference for keeping all options open and tend to be more flexible and spontaneous.

The four preferences interact with each other rather then being independent, and for a complete description of a person’s type, the combination of all four preferences needs to be considered.

27.3.2 Kolb’s Learning Style Model

The learning style theory by Kolb (1984) is based on the Experiential Learning Theory (for example, Kolb, 1984), which models the learning process and incorporates the important role of experience in this process. Following this theory, learning is conceived as a four-stage cycle. *Concrete experience* is the basis for *observations and reflections*. These observations are used to *form abstract concepts and generalizations*, which again act as basis for *testing implementations of concepts* in new situations. Testing implementations results in concrete experience, which closes the learning cycle. According to this theory, learners need four abilities for effective learning: a Concrete Experience abilities,

b) Reflective Observation abilities, c) Abstract Conceptualization abilities, and d) Active Experimentation abilities. On closer examination, there are two polar opposite dimensions: concrete-abstract and active-reflective. Kolb (1981) described that "as a result of our hereditary equipment, our particular past life experience, and the demands of our present environment, most of us develop learning styles that emphasize some learning abilities over others". Based on this assumption, Kolb identified four statistically prevalent types of learning styles.

Convergers' dominant abilities are abstract conceptualization and active experimentation and therefore their strengths lie in the practical applications of ideas. The name "Convergers" is based on Hudson's theory of thinking styles (Hudson, 1966), where convergent thinkers are people who are good in gathering information and facts and putting them together to find a single correct answer to a specific problem.

In contrast, *Divergers* excel in the opposite poles of the two dimensions, namely concrete experimentation and reflective observation. They are good in viewing concrete situations in many different perspectives and in organizing relationships to a meaningful shape. According to Hudson, a dominant strength of Divergers is to generate ideas and therefore, Divergers tend to be more creative.

Assimilators excel in abstract conceptualization and reflective observation. Their greatest strength lies in creating theoretical models. They are good in inductive reasoning and in assimilating disparate observations into an integrated explanation.

Accommodators have the opposite strength to Assimilators. Their dominant abilities are concrete experience and active experimentation. Their strengths lie in doing things actively, carrying out plans and experiments, and becoming involved in new experiences. They are also characterized as risk-takers and as people who excel in situations that call for adaptation to specific immediate circumstances.

27.3.3 Honey and Mumford’s Learning Style Model

The learning style model by Honey and Mumford (1982) is based on Kolb’s Experiential Learning Theory and is developed further on the four types of Kolb’s learning style model. The active-reflective and sensing-intuitive dimensions are strongly involved in the defined types as well. Furthermore, Honey and Mumford stated that “the similarities between his model [Kolb’s model] and ours are greater than the differences” (Honey & Mumford, 1992).

In Honey and Mumford’s learning style model the types are called: Activist (similar to Accommodator), Theorist (similar to Assimilator), Pragmatist (similar to Converger), and Reflector (similar to Diverger). Activists involve themselves fully in new experiences, are enthusiastic about anything new, and learn best by doing something actively. Theorists excel in adapting and integrating observations into theories. They need models, concepts, and facts in order to engage in the learning process. Pragmatists are interested in real world applications of the learned material. They like to try out and experiment on ideas, theories, and techniques to see if they work in practice. Reflectors are people who like to observe other people and their experiences from many different perspectives and reflect about them thoroughly before coming to a conclusion. Also, learning occurs for these people by observing and analyzing the observed experiences.

27.3.4 Felder-Silverman Learning Styles Model

While Honey and Mumford's as well as Kolb's learning style models focus on few statistically prevalent types, in Felder and Silverman learning style model (Felder & Silverman, 1988) learners are characterized by values on four dimensions. These dimensions can be viewed independently and they show how learners prefer to process (active/reflective), perceive (sensing/intuitive), receive (verbal/visual), and understand (sequential/global) information. Because the range of each dimension in Felder and Silverman learning style model reaches from +11 to -11, a balanced preference can also be expressed. These values represent tendencies, saying that even a learner with a strong positive or negative value can act sometimes differently.

The active/reflective dimension is analogous to the respective dimension in Kolb's model, saying that active learners learn best by working actively with the learning material, e.g. working in groups, discussing about the material, or applying it. To support these learners in technology enhanced educational systems, exercises, interactive animations, and group work tasks can be provided to allow them to deal with the subject actively. In contrast, reflective learners prefer to think about and reflect the material. Therefore, they need enough time for doing so. Learning systems support this by allowing learners to learn in their own pace.

The sensing/intuitive dimension is taken from the Myers-Briggs Type Indicator and has also similarities to the sensing/intuitive dimension in Kolb's model. 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 score better in open-ended tests than in tests with a single answer to a problem. While intuitive learners are good at learning from abstract concepts and theories, for sensing learners a high number of examples and all kinds of media resources addressing their senses such as audio or video objects are required to support their learning process.

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 of whether they are written or spoken. Accordingly, visual learners can be assisted by including visual elements such as pictures or diagrams in the learning material. For verbal learners, communication tools such as forum or chat are helpful.

In the fourth dimension, learners are distinguished between a sequential and global way of 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; however, they have difficulties in explaining how they did it. For sequential learners it is important to provide a well structured path through the course material and not overextend them by providing too many links. In contrast, global learners prefer to go their own way through the course. To help global learners to get the whole picture of the course, overviews should be presented.

27.4 IDENTIFYING COGNITIVE TRAITS AND LEARNING STYLES

To incorporate cognitive traits and/or learning styles in educational systems, information about cognitive traits and learning styles need to be first collected. One approach is to let students perform comprehensive tests or questionnaires to find out the cognitive traits or learning styles. Such an approach; however, has potential to suffer from the biases and indecisiveness of the learners. A more meaningful approach is to track the students' behaviour and infer the required information from their behaviour. Cognitive Trait Model (Kinshuk & Lin, 2004; Lin & Kinshuk, 2005) uses this approach to profile learners according to their cognitive traits. For the identification of learning styles, approaches for detecting the dimensions of Felder-Silverman learning style model are introduced.

27.4.1 Identification of Cognitive Traits

Cognitive Trait Model (CTM) is a student model that profiles learners according to their cognitive traits. Four cognitive traits, working memory capacity, inductive reasoning ability, processing speed, and associative learning skills are included in CTM so far. 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, 2004). When a student encounters a new learning environment, the learning environment can directly use the CTM of the particular student, and does not need to "re-learn the student".

The identification of the cognitive traits is based on the behaviour of learners in the system. Various patterns, called Manifests of Traits (MOT), are defined for each cognitive trait. Each MOT is a piece of an interaction pattern that manifests a learner's characteristics. A neural network (Lin & Kinshuk, 2004) is responsible for calculating the cognitive traits of the learners based on the information of the MOTs.

27.4.2 Identification of Learning Styles

There are a number of adaptive systems available in the literature incorporating learning styles. For example, CS383 (Carver, Howard, & Lane, 1999) was the first adaptive hypermedia system that was based on Felder-Silverman learning style model (FSLSM). The course conducted in the system included comprehensive collection of media objects. The system offered students the option to order these objects in accordance with how well they fit to the learning style of the student. Also MAS-PLANG (Peña, Marzo, & de la Rosa, 2002), a multi-agent system which has been developed to enrich the intelligent tutoring system USD (Fabregat, Marzo, & Peña, 2000) with adaptivity with respect to learning styles is based on FSLSM. Another example is INSPIRE (Papanikolaou & Grigoriadou, 2003) that is based on Honey and Mumford's learning style theory. In all these systems and in most other systems which incorporate learning styles, the learning style is identified based on a questionnaire that needs to be filled out by learners before using the system. These questionnaires are based on the assumption that learners are aware of how they learn. Jonassen and Grabowski (1993, p. 234) pointed out that "because learning styles are based on self-reported measures, rather than ability tests, validity is one of their most significant problems".

García, Amandi, Schiaffino, and Campo (2006) studied the use of Bayesian networks (Jensen, 1996) to detect students' learning styles based on their behaviour in the educational system SAVER. Based on the Felder-Silverman learning style model, they determined patterns of behaviour, which are representative for the respective dimensions, as well as the different states these variables/patterns can take. Because SAVER does not incorporate the visual/verbal dimension, this dimension is left out from investigations.

While the above approaches are developed for specific systems, Graf and Kinshuk (2006) proposed an approach to detect learning styles in learning management systems (LMS) in general. Equal to the approach by Garcia et al. (2006), the

Felder-Silverman learning style model is used as the basis but in this case all four dimensions are incorporated. The patterns of behaviour are derived from commonly used features in LMS such as forums and exercises. Regarding the calculation of the learning styles, the approach used in the Index of Learning Styles (Felder & Soloman, 1997), a questionnaire for identifying the learning style according to Felder-Silverman learning style model, is applied.

27.5 THE RELATIONSHIP BETWEEN LEARNING STYLES AND COGNITIVE TRAITS

So far, cognitive traits and learning styles were discussed separately. Consideration of their relationship with each other makes it possible to get additional information about the learner. In educational systems that consider either only learning styles or only cognitive traits, the relationship leads to more information. This additional information can be used to provide more adaptivity, namely for learning styles and cognitive traits instead of only for one of them. In systems that incorporate learning styles as well as cognitive traits, the interaction can be used to improve the detection process of the counterpart. This leads to a more reliable student model.

Graf, Lin, and Kinshuk (2005) investigated the relationship between the Felder-Silverman learning style model and one cognitive trait, namely working memory capacity. Based on the literature, a relationship between high working memory capacity and a reflective, intuitive, and sequential learning style can be identified. In contrast, learners with low working memory capacity tend to prefer an active, sensing, and global learning style. Regarding the visual-verbal dimension, it can be concluded that learners with low working memory capacity tend to prefer a visual learning style but learners with a visual learning style do not necessarily have low working memory capacity. To verify the proposed relationship, an exploratory study with 39 students was conducted (Graf, Lin, Jeffrey, & Kinshuk, 2006). The results show that the identified relationship between working memory capacity and two of the four dimensions of the learning style model – the sensing-intuitive and the visual-verbal dimension – is significantly supported. For the two remaining dimensions only tendencies but no significant correlations were found and therefore, a further study with a larger sample size is planned.

27.7 CONCLUSION

Incorporating cognitive traits and learning styles in technology enhanced educational systems supports learners and makes learning easier for them. Nevertheless, only few systems consider these needs so far. While there is at least some attention in adaptive systems, learning management systems which are commonly used in e-education nowadays, do not incorporate personal needs, such as learning styles or cognitive traits, at all.

This chapter focused on three issues: (a) introducing cognitive traits which are important for learning and major learning style theories as well as pointing out strategies to incorporate both of them in educational systems, (b) approaches to identify cognitive traits and learning style as a requirement to adapt to them, and (c) the relationship between cognitive traits and learning styles to get additional information and therefore improve student modelling.

As a conclusion, linking learning style and cognitive traits with instruction and incorporating them in educational systems is an important and beneficial issue for students. Obviously, more research work on learning styles and especially on cognitive traits is necessary to further establish their importance in e-education.

REFERENCES

Al Naeme, F. F. A. (1991). *The influence of various learning styles on practical problem-solving in chemistry in Scottish secondary schools*. Ph.D. Dissertation, University of Glasgow.

Alexander, J., Fabricius, W., Fleming, V., Zwahr, M., & Brown, S. (2003). The development of metacognitive causal explanations. *Learning and Individual Differences*, 13, 227-238.

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 *Proceedings of the Workshop on Adaptive Hypermedia and Adaptive Web-Based Systems* (pp. 41-52). Nottingham, UK.

Bell, T. (2001). Extensive reading: Speed and comprehension. *The Reading Matrix*, *1*(1).

Bower, G. H., & Hilgard, E. R. (1981). *Theories of learning*. Englewood Cliffs: Prentice Hall.

* Briggs Myers, I. (1962). *Manual: The Myers-Briggs Type Indicator*. Palo Alto, CA: Consulting Psychologists Press.

Brown, E., Brailsford, T., Fisher, T., Moore, A., & Ashman, H. (2006). Reappraising cognitive styles in adaptive web applications. In *Proccedings of the International World Wide Web Conference* (pp. 327-335). ACM Press.

Byrne, M. D. (1996). *A computational theory of working memory*. Paper presented at the Doctoral Consortium of CHI'96 Human Factors in Computing Systems Conference, Vancouver, Canada, ACM Press, 31-32. Retrieved April 28, 2006, 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.

Clariana, R. B. (1997). Colloquium: Considering learning style in computer-assisted learning. *British Journal of Educational Technology*, 28(1), 66-68.

Clark, J. M., & Paivio, A. (1991). Dual coding theory and education. *Educational Psychology Review*, 3, 149-210.

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.

Dörner, D. (1996). *The logic of failure: Why things go wrong and what we can do to make them right* (R. Kimber, & R. Kimber, Trans.). New York: Metropolitan Books.

Fabregat, R., Marzo, J. L., & Peña, C. I. (2000). Teaching support units. In M. Ortega & J. Bravo (Ed.), *Computers and education in the 21st century* (pp. 163-174). Dordrecht, The Netherlands: Kluwer Academic Publishers.

* Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Engineering Education, 78*(7), 674–681. Preceded by a preface in 2002: http://www.ncsu.edu/felderpublic/Papers/LS-1988.pdf (retrieved July 23, 2005).

* Felder, R. M., & Soloman, B. A. (1997). *Index of Learning Styles questionnaire*. Retrieved April 30, 2006, from http://www.engr.ncsu.edu/learningstyles/ilsweb.html

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.

Flavell, J. (1976). Metacognitive aspects of problem solving. In L. B. Resnick (Ed.), *The nature of intelligence* (pp. 231-235). Hillsdale, New Jersey: Lawrence Erlbaum Associates.

Ford, N., & Chen, S. Y. (2001). Matching/mismatching revisited: An empirical study of learning and teaching styles. *British Journal of Educational Technology, 32*(1), 5-22.

Gagné, R. (1985). *The conditions of learning* (4th ed.). New York: Holt, Rinehart & Winston.

* García, P., Amandi, A., Schiaffino, S., & Campo, M. (in press). Evaluating Bayesian networks' precision for detecting students' learning styles. *Computers & Education*.

Graf, S., & Kinshuk. (2006). An approach for detecting learning styles in learning management systems. In *Proceedings of the International Conference on Advanced Learning Technologies* (pp. 161-163). Alamitos, CA: IEEE Computer Science.

Graf, S., Lin, T., Jeffrey, L., & Kinshuk. (2006). An exploratory study of the relationship between learning styles and cognitive traits. In *Proceedings of the European Conference of Technology Enhanced Learning*, Lecture Notes in Computer Science, Vol. 4227 (pp. 470-475). Heidelberg: Springer Verlag.

* Graf, S., Lin, T., & Kinshuk. (2005). Improving student modeling: The relationship between learning styles and cognitive traits. In *Proceedings of the IADIS International Conference on Cognition and Exploratory Learning in Digital Age* (pp. 37-44). Lisbon, Portugal: IADIS Press.

Harverty, L. A., Koedinger, K. R., Klahr, D., & Alibali, M. W. (2000). Solving inductive reasoning problems in mathematics: No-so-trivial pursuit. *Cognitive Science*, 24(2), 249-298.

Honey, P., & Mumford, A. (1982). *The manual of learning styles* (1st ed.). Maidenhead: Peter Honey.

* Honey, P., & Mumford, A. (1992). *The manual of learning styles* (3rd ed.). Maidenhead: Peter Honey.

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

James, W. B., & Gardner, D. L. (1995). Learning styles: Implications for distance learning. *New Directions for Adult and Continuing Education, 67*, 19-31.

Jensen, F. (1996). *An introduction to Bayesian networks.* New York: Springer Verlag.

* Jung, C. (1923). *Psychological types*. London: Pantheon Books.

* Jonassen, D. H., & Grabowski, B. L. (1993). *Handbook of individual differences, learning, and instruction*. Hillsdale, New Jersey: Lawrence Erlbaum Associates.

Kalyuga, S., Chandler, P., & Sweller, J. (1999). Managing split-attention and redundancy in multimedia instruction. *Applied Cognitive Psychology*, 13, 351-371.

Kalyuga, S., Chandler, P., & Sweller, J. (2000). Incorporating learner experience into the design of multimedia instruction. *Journal of Educational Psychology*, 92, 126-136.

Kashihara, A., Kinshuk, Oppermann, R., Rashev, R., & Simm, H. (2000). A cognitive load reduction approach to exploratory learning and its application to an interactive simulation-based learning system. *Journal of Educational Multimedia and Hypermedia, 9*(3), 253-276.

Keefe, J. W. (1979). Learning style: An overview. In J. W. Keefe (Ed.), *Student learning styles: Diagnosing and prescribing programs* (pp. 1-17). Reston, VA: National Association of Secondary School Principals.

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

* Kinshuk, & Lin, T. (2004). Cognitive profiling towards formal adaptive technologies in web-based learning communities. *International Journal of WWW-based Communities, 1*(1), 103-108.

Kolb, D. A. (1981). Learning styles and disciplinary differences. In A. W. Chickering (Ed.), *The modern American college: Responding to the new realties of diverse students and a changing society* (pp. 232-255). San Francisco: Jossey-Bass.

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

Lester, F., Garofalo, J., & Lambdin-Kroll, D. (1989). Self-confidence, interest, beliefs and metacognition: Dey influences on problem solving behaviour. In D. B. McLeod & V. M. Adams (Ed.), *Affect and mathematical problem solving* (pp. 75-89). New York: Springer Verlag.

Lin, T., & Kinshuk. (2004). Dichotomic node network and cognitive trait model. In *Proceedings of 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 (Ed.), *Encyclopedia of international computer-based learning* (pp. 245-255). Hershey, PA, USA: Idea Group Inc.

* Mayer, R. E. (1997). Multimedia learning: Are we asking the right questions? *Educational Psychologist*, 32, 1-19.

* Mayer, R. E. (1998). Cognitive, metacognitive and motivational aspects of problem solving. *Instructional Science*, 26, 49-64.

* 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.

* Moreno, R., & Valdez, A. (2005). Cognitive load and learning effects of having students organize pictures and words in multimedia environments: The role of student interactivity and feedback. *Educational Technology Research and Developement,* 53(3), 35-45.

Panaoura, A., & Philippou, G. (2004). Young pupil's metacognitive abilities in mathematics in relation to working memory and processing efficiency. In *Proceedings of the International Biennial SELF Research Conference*. Berlin. Retrieved October 19, 2006, from http://self.uws.edu.au/Conferences/2004_Panaoura_Philippou.pdf.

Panaoura, A., & Philippou, G. (2005). The measurement of young pupils' metacognitive ability in mathematics: The case of self-representation and self evaluation. Paper presented at the *Conference of European Society for Research in Mathematics Education.* Sant Feliu de Guíxols. Retrieved October 19, 2006, from http://cerme4.crm.es/Papers%20definitius/2/panaoura.philippou.pdf.

Papanikolaou, K. A., & Grigoriadou, M. (2003). An Instructional Framework Supporting Personalized Learning on the Web. In *Proceedings of the International Conference on Advanced Learning Technologies* (pp. 120–124). Los Alamitos, CA: IEEE Computer Society.

Peña, C. I., Marzo, J. L., & de la Rosa, J. L. (2002). Intelligent Agents in a Teaching and Learning Environment on the Web. In *Proceedings of the International Conference on Advanced Learning Technologies*. Palmerston North, NZ: IEEE Learning Technology Task Force.

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*. Ph.D. Dissertation. Palmerston North, New Zealand: Massey University.

Tillema, H. (1982). Sequencing of text material in relation to information-processing strategies. *British Journal of Educational Psychology*, 32, 170-178.

* van Joolingen, W. R., & de Jong, T. (2003). SimQuest, authoring educational simulations. In T. Murray, S. Blessing & S. Ainsworth (Ed.), *Authoring tools for advanced technology learning environments: Toward cost-effective adaptive, interactive, and intelligent educational software* (pp. 1-31). Dordrecht: Kluwer.

Veermans, K., & van Joolingen, W. R. (1998). Using induction to generate feedback in simulation based discovery learning environments. In *Proceedings of the 4th International Conference on Intelligent Tutoring Systems*, Lecture Notes in Computer Science, Vol. 1452 (pp. 196-205). London, UK: Springer Verlag.

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.

Zsambok, C. E., & Klein, G. (1997). *Naturalistic decision making*. Mowah, NJ: Lawrence Erlbaum Associates.