Ph.D. Thesis

Adaptivity in Learning Management Systems Focussing on Learning Styles

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Abstract

Learning management systems (LMSs) such as WebCT, Blackboard, and Moodle are commonly and successfully used in e-education. While they focus on supporting teachers in creating and holding online courses, they typically do not consider the individual differences of learners. However, learners have different needs and characteristics such as prior knowledge, motivation, cognitive traits, and learning styles. Recently, increasing attention is paid to characteristics such as learning styles, their impact on learning, and how these individual characteristics can be supported by learning systems. These investigations are motivated by educational theories, which argue that providing courses which fit the individual characteristics of students makes learning easier for them and thus, increases their learning progress.

This thesis focuses on extending LMSs to provide adaptivity by incorporating learning styles according to the Felder-Silverman learning style model. An automated approach for identifying learning styles from the behaviour and actions of learners has been designed, implemented, and evaluated, demonstrating that the proposed approach is suitable for identifying learning styles. Based on this approach, a standalone tool for automatic detection of learning styles in LMSs has been implemented.

Furthermore, investigations have been conducted on improving the automatic detection of learning styles by using additional information from cognitive traits. The potential of working memory capacity is investigated. Results of a comprehensive literature review and two comprehensive evaluation studies show that relationships between working memory capacity and learning styles exist and that these relationships can provide additional information for the detection process of learning styles.

Moreover, a concept for extending LMSs by enabling them to automatically generate and present courses that fit the students' learning styles has been developed, implemented, and evaluated, using Moodle as a prototype. Results show that the proposed concept for providing adaptive courses is successful in supporting students in learning.

By extending LMSs with adaptivity, a learning environment is built that supports teachers as well as learners. In such an adaptive LMS, teachers can continue using the advantages of LMSs and learners can additionally benefit from adaptive courses. This research opens ways for advanced learning systems, which are able to learn the needs and characteristics of learners, respond to them immediately, and provide learners with courses where adaptation is frequently improved and updated to the learners' needs.

Kurzfassung

Lernplattformen, wie zum Beispiel WebCT, Blackboard und Moodle, werden heutzutage immer mehr genutzt. Während diese Lernplattformen Lehrende sehr gut im Erstellen und Abhalten von Online-Kursen unterstützen, bieten sie nur wenig bis keine Möglichkeiten, auf die individuellen Bedürfnisse, Fähigkeiten und Eigenschaften der Lernenden, wie zum Beispiel deren Wissensstand, Motivation, kognitive Fähigkeiten und Lernstile, einzugehen. In den letzten Jahren wurde vermehrt der Einfluss von individuellen Eigenschaften der Lernenden, wie beispielsweise deren Lernstile, auf den Lernprozess erforscht sowie Untersuchungen durchgeführt, um diese in e-Learning Systemen zu unterstützen. Diese Untersuchungen basieren auf erziehungswissenschaflichen Theorien, die besagen, dass Lernende einfacher und erfolgreicher Lernen, wenn Kurse an ihre individuellen Eigenschaften angepasst sind.

In dieser Dissertation wird gezeigt, wie Lernstile entsprechend dem Felder-Silverman learning style model in Lernplattformen berücksichtigt werden können. Ein Ansatz zum automatischen Erkennen von Lernstilen, bei welchem die Lernstile vom Verhalten der Lernenden im Online-Kurs hergeleitet werden, wurde entwickelt, implementiert und evaluiert. Die Ergebnisse zeigen, dass der Ansatz zum Erkennen von Lernstilen geeignet ist und Lernstile mit hoher Genauigkeit erkennt. Basierend auf diesem Ansatz wurde ein „stand-alone“ Tool entwickelt, das automatisch Lernstile in Lernplattformen identifiziert.

Des Weiteren wurde untersucht, ob das automatische Erkennen von Lernstilen durch das Einbeziehen von zusätzlicher Information, wie zum Beispiel kognitiven Fähigkeiten, verbessern werden kann. Dafür wurde die Beziehung zwischen Lernstilen und der Kapazität des Kurzzeitgedächtnisses untersucht. Die Ergebnisse einer umfassenden Literaturrecherche sowie zweier umfangreicher Studien zeigen, dass Beziehungen zwischen Lernstilen und der Kapazität des Kurzzeitgedächtnisses bestehen und dass diese Beziehungen zusätzliche Informationen zum Erkennen von Lernstilen liefern.

Darüber hinaus wurde ein Konzept entwickelt, implementiert und evaluiert, welches Lernplattformen dahingehend erweitert, dass sie automatisch adaptive Kurse generieren und präsentieren können. Die in Moodle durchgeführte Evaluierung zeigt, dass das entwickelte Konzept erfolgreich Lernende unterstützt und ihnen das Lernen vereinfacht.

Durch das Erweitern von Lernplattformen mit Adaptivität werden Lernumgebungen geschaffen, in denen sowohl Lehrende als auch Lernende unterstützt werden. In einer solchen adaptiven Lernplattform können Lehrende weiterhin die Vorteile von Lernplattformen nützen und Lernende werden zusätzlich mit adaptiven Kursen unterstützt. Die behandelten Forschungsfragen dieser Dissertation bilden wichtige Grundlagen für die zukünftige Entwicklung von Lernsytemen, welche die Bedürfnisse, Fähigkeiten und Eigenschaften der Studierenden erlernen, darauf umgehend eingehen und Kurse zur Verfügung stellen, in denen Adaptivität laufend verbessert wird und die an die jeweils aktuellen Bedürfnisse der Lernenden angepasst sind.

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Contents

CHAPTER 1
Introduction

In this chapter the motivation and problem statement of this thesis are discussed and the research issues covered in this thesis are introduced. Subsequently, the structure of the thesis is described.

1.1 Motivation and Problem Statement

Nowadays, more and more educational institutions, such as universities, offer e-learning courses. Some of these courses are blended with traditional education, while others are conducted completely online. However, e-learning courses need an environment, where they are managed and organised. In the majority of cases this task is fulfilled by a learning management system (LMS). LMSs provide a variety of features to support teachers in creating, administering, and managing online courses. On the other hand, they typically do not consider individual differences of learners and treat all learners equally regardless of their personal needs and characteristics.

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

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

Considering learning styles, investigations are motivated by educational and psychological theories, which argue that learners have different ways in which they prefer to learn. Furthermore, Felder, for example, pointed out that learners with a strong preference for a specific learning style may have difficulties in learning if the teaching style does not match with their learning style (Felder and Silverman, 1988; Felder and Soloman, 1997). From theoretical point of view, conclusion can be drawn that incorporating learning styles of students in the learning environment makes learning easier for them and increases their learning efficiency. On the other hand, learners whose learning styles are not supported by the learning environment may experience problems in the learning process.

Adaptive educational systems address exactly this issue. They aim at providing learners with courses that fit their individual needs and characteristics such as their learning styles. While supporting adaptivity is a big advantage of these systems, they also have severe limitations. For example, adaptive systems lack integration, supporting only few functions of web-enhanced education, and the content of courses is not available for reuse (Brusilovsky, 2004). Therefore, such systems are only rarely used. One the other hand, LMSs such as Moodle (2007), WebCT (2007), or Blackboard (2007) are commonly and successfully used. They focus on supporting teachers and help to make online teaching as easy as possible. However, although educational and psychological theories suggest incorporating individual differences of learners, LMSs provide only little or, in most cases, no adaptivity for them.

1.2 Research Issues

The aim of this thesis is to combine the advantages of LMSs with those of adaptive systems by extending LMSs with the functionality to incorporate learning styles and provide adaptivity for learners. In order to realise this goal, investigations regarding three research questions have been conducted:

1. *How can learning styles be identified?*

   In order to provide adaptivity, the learning styles of learners need to be known first. In this thesis, an automated approach for identifying learning styles based on the behaviour and actions of learners in online courses using LMSs is proposed. The effectiveness of a data-driven approach and a literature-based approach for inferring learning styles from the behaviour and actions of learners is compared and evaluated. Additionally, more detailed investigations on identifying characteristic preferences within learning style dimensions were performed. Based on the achieved findings, a tool has been developed that allows teachers to identify learning styles of their students while using an LMS.

2. *How can the detection process of learning styles be improved?*

   While the proposed approach for identifying learning styles is based on information from the behaviour and actions of learners, other sources might also have potential in providing information for detecting learning styles. Within this thesis, the relationship between learning styles and cognitive traits, in particular working memory capacity, is investigated. Therefore, a comprehensive literature review, an exploratory study, and a main study were performed, investigating whether a relationship between learning styles and working memory capacity exists.

3. *How can adaptive courses be provided in LMSs?*

   Once learning styles are known, LMSs can be extended in order to enable them to generate and present adaptive courses. Within this thesis, a concept for providing adaptive courses in LMSs based on learning styles is developed. The concept is implemented as an add-on to Moodle and evaluated with respect to its efficiency in supporting learners and making learning easier for them.

Furthermore, two general aims concerning all three parts of research exist. First, research conduced within this thesis aims at proposing concepts and approaches which are suitable for LMSs in general rather than for one specific system. However, the concepts and approaches are implemented and evaluated by using the LMS Moodle, which was selected based on a performed evaluation of LMSs.

Second, since the objective of this thesis is to combine the advantages of LMSs with those of adaptive systems, an adaptive LMS should not lose its simplicity and should still be easy to use for teachers. Therefore, teachers should have as little as possible additional effort when using the proposed adaptive LMS.

1.3 Structure of the Thesis

The thesis is organised in 8 chapters. In the next chapter, an introduction of learning styles is provided, describing common learning style models, implications of learning styles in education, and criticism and challenges in the field of learning styles. Parts of this chapter were published as book chapter (Graf and Kinshuk, in press-c).

Chapter 3 introduces adaptive educational hypermedia systems. General aspects regarding adaptivity are discussed and subsequently, adaptive educational hypermedia systems incorporating learning styles are described.

Chapter 4 deals with learning management systems and their potential to incorporate learning styles. First, an introduction about LMSs is provided. Subsequently, an evaluation of LMSs is presented, aiming at identifying the LMS which is most appropriate for being extended to an adaptive one. Next, the chapter describes the benefits of the Felder-Silverman learning style model, which was selected as most suitable learning style model for the use in LMSs. As a basis for further research regarding incorporating learning styles in LMSs, a study about whether learners with different learning styles really behave differently in an online course in an LMS is introduced. Parts of this chapter were published as book chapter and conference/workshop papers (Graf and Kinshuk, 2006b, in press-a; Graf and List, 2005).

Chapter 5 presents investigations regarding the first research question, namely how to identify learning styles. Parts of this chapter were published as journal paper, book chapter, and conference papers (Graf and Kinshuk, 2006a, 2006c, in press-b; Graf, Viola, and Kinshuk, 2007; Graf et al., 2006b, 2007).

Chapter 6 deals with the second research question and shows how the detection process of learning styles can be improved by using information from cognitive traits. Parts of this chapter were published as journal and conference papers (Graf et al., 2006a; Graf, Lin, and Kinshuk, 2005, 2007, in press).

Chapter 7 focuses on the third research question and deals with how to extend LMSs in order to enable them to provide adaptive courses. Parts of this chapter were published as journal paper, book chapter and conference papers (Graf, 2005; Graf and Kinshuk, 2007, in press-b; Wen et al., 2007a, 2007b).

Chapter 8 concludes the thesis by highlighting its contributions and discussing limitations and future directions.

CHAPTER 2
Learning Styles

The field of learning styles is complex and affected by several aspects, leading to different concepts and views. Many learning style models exist in literature, each proposing different descriptions and classifications of learning types. Coffield et al. (2004b) identified 71 models of learning styles and categorised 13 of them as major models with respect to their theoretical importance in the field, their widespread use, and their influence on other learning style models. Furthermore, a lot of research has been done in the last 30 years with respect to different aspects of these learning style models. For example, as stated by Coffield et al. (2004b), about 2000 articles have been written related to the Myers-Briggs Type Indicator (Briggs Myers, 1962) between 1985 and 1995 and more than 1000 publications have been written about the Kolb learning style model (Kolb, 1984) as well as the Dunn and Dunn learning style model (Dunn and Dunn, 1974). Although much research has been conducted in the field of learning styles, several important questions are still open and under discussion, as described in detail in Section 2.3.

To date, no single definition of the term learning style has been identified. Honey and Mumford (1992, p. 1), for example, defined learning styles as “a description of the attitudes and behaviours which determine an individual’s preferred way of learning”. Felder (1996, p. 18) defined learning styles as “characteristic strengths and preferences in the ways they [learners] take in and process information”. James and Gardner (1995, p. 20) defined learning styles 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”.

Depending on the ideas and aspects of the meaning of learning styles, other terms such as learning strategy and cognitive style are often used in a similar context or even interchangeable to the term learning style. In the following paragraphs, definitions of the terms learning strategies and cognitive styles are introduced and the difference to learning styles is described.

Learning strategies can be seen as short term methods that students apply in a particular situation. These strategies can change with the time, teacher, subject, and situation. When learning strategies are frequently used by students, learning styles can be derived from these strategies (Pask, 1976b). Based on Pask’s work, Entwistle, Hanley, and Hounsell (1979, p. 368) define a learning strategy as “the way a student chooses to tackle a specific learning task in the light of its perceived demands” and learning style “as a broader characterisation of a student’s preferred way of tackling learning tasks generally”. Furthermore, they argued that distinct learning styles underlie learning strategies.

According to Jonassen and Grabowski (1993), learning styles can also be seen as applied cognitive styles in the domain of learning, removed one more level from pure processing ability. As evidence of this removal, learning styles are usually based on self-reported learning preferences. For measuring them, instruments are used that ask learners about their preferences. In contrast, cognitive styles are identified by task-relevant measures, which test the actual ability or skill.

The next subsection introduces several commonly used learning style models. Subsequently, the implications of learning styles for education as well as criticism and challenges of the field of learning styles are discussed.

2.1 Common Models of Learning Styles

As mentioned before, a high number of learning style models exists in literature. Coffield et al. (2004b) classified learning style models into 5 families which are based on some overarching ideas behind the models, attempting to reflect the views of the main theorists of learning styles. The first family relies on the idea that learning styles and preferences are largely constitutionally based including the four modalities: visual, auditory, kinaesthetic, and tactile. The second family deals with the idea that learning styles reflect deep-seated features of the cognitive structure, including patterns of abilities. A third category refers to learning styles as one component of a relatively stable personality type. In the fourth family, learning styles are seen as flexibly stable learning preferences. The last category moves on from learning styles to learning approaches, strategies, orientations and conceptions of learning.

Table 2.1: Summary of described learning style models

Learning styles as relatively stable personality type	**Learning styles related to approaches and strategies**	**Constitutionally-based learning styles**	**'Flexibly stable' learning styles**
Myers-Briggs	Pask	Dunn and Dunn	Kolb
	Entwistle	Gregorc	Honey and Mumford
	Grasha-Riechmann		Herrmann
			Felder and Silverman

This section describes 10 commonly used learning style models. The selection of these models is based on Coffield's review (Coffield et al., 2004a), including the theoretical importance in the field, their widespread use, and their influence on other learning style models. Additionally, the applicability of the learning style models in technology enhanced learning was considered as important criterion, including the application of learning style models in already existing systems as well as their potential to be used in a system. Since this thesis focuses on learning styles rather than on cognitive styles, models that measure the cognitive abilities and skills rather than self-reported learning preferences were excluded. Therefore, no models of the second family were described, where learning styles are seen as features of the cognitive structure. Table 2.1 shows the selected learning style models grouped according to the classification by Coffield et al. (2004b) and ordered according to the dependencies of the models among each other.

2.1.1 Personality Types as defined by Myers-Briggs

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, MBTI includes important aspects for learning. Besides, 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 extrovert and introvert dimension refers to the orientation of a person. 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 preferences on the four dimensions 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.

The standard version of the MBTI is the 93-item Form M (Myers and McCaulley, 1998). The previous version is the Form G (Myers and McCaulley, 1985), which includes 126 items, and there exist also an abbreviate version with 50 items. The instruments include a series of forced-choice questions, related to the four bipolar scales, and calculate the personality type based on the answers.

2.1.2 Pask's Serialist/Holist/Versatilist Model

During the development of the conversation theory (Pask, 1972, 1976a, 1976b), Pask studied patterns of conversations between individuals to identify various styles of learning and thinking. A critical method according to the conversation theory is the "teachback" approach, where students teach their peers. Different patterns for designing, planning, and organising of thought as well as for selecting and representing information were investigated, resulting in the identification of three types of learners (Pask, 1976b). *Serialist* students use a serial learning strategy. They tend to concentrate more narrowly on details and procedures before conceptualising an overall picture. They typically work from the bottom up, learn step-by-step in a linear sequence and concentrate on well-defined and sequentially ordered chunks of information. According to Pask, serial learners tend to ignore relevant connections between topics, which can be seen as their learning deficit. In contrast, *holists* use a holistic learning strategy. They tend to concentrate on building broad descriptions and use a top-down approach. They focus on several aspects of the subject at the same time and use complex links to relate multileveled information. While they are good in building interconnections between theoretical, practical, and personal aspects of a topic, holistic learners do not focus on enough details, which can be seen as their learning deficit. *Versatile* learners employ both, serial and holistic learning strategies. They engage in global and detailed approaches and succeed in achieving a full and deep understanding. Therefore, versatile learners are proficient at learning from most or all modes of instruction.

Pask developed some tests such as the Spy Ring History Test (Pask and Scott, 1973) and the Clobbits Test (Pask, 1975) as measure for serial, holistic and versatile thinking. Some years later, Entwistle (1981; 1998) and Ford (1985) developed self-report inventories for identifying a preference for serial, holistic, and versatile learning styles. The Study Preference Questionnaire developed by Ford (1985) provided students with pairs of two statements (one on the left side and one on the right side) and asked them to indicate their degree of agreement with either statements, or to indicate no preference, using a 5 point scale. Entwistle's learning style model (described in the next section) is based on Pask's work. With respect to his model, Entwistle designed inventories to tap into a number of dimensions of study attitudes and behaviours, including also the serial/holistic/versatile dimension (Entwistle, 1981, 1998).

2.1.3 Entwistle's Deep, Surface and Strategic Learning Approach

The research conduced by Entwistle and his colleagues (Entwistle, 1981, 1998; Entwistle, McCune, and Walker, 2001) deals with the involvement of students' intentions, goals and motivation in their learning approach. Entwistle argued that the students' orientations to and conceptions of learning lead to and are affected by the student's typical approaches to learning. The model is based on research by Pask (1976b), Marton (1976), and Biggs (1979) and distinguishes between three approaches for learning and studying (Entwistle, McCune, and Walker, 2001): learners applying a *deep learning approach* are intrinsically motivated and have the intention to understand the ideas for themselves. They learn by relating ideas to previous knowledge and experiences, looking for patterns and underlying principles, and checking evidence and relating it to conclusions. They examine logic and arguments cautiously and critically, develop an understanding of the topic, and become actively interested in the course content. In contrast, learners who apply a *surface learning approach* are extrinsically motivated and aim merely at meeting the requirements of the course. They treat the course content as unrelated bits of knowledge, try to identify those elements of a course that are likely to be assessed and focus on memorising these details. They carry out procedures routinely and find difficulty in making sense of new ideas presented. They see little value or meaning in either courses or tasks set, study without reflecting on either purpose or strategy, and feel undue pressure and worry about their work. In the *strategic learning approach*, students combine the deep and surface approach in order to achieve the best possible outcome in terms of marks. Students who adopt the strategic approach put consistent effort into studying, manage time and effort effectively, find the right conditions and materials for studying, and monitor the effectiveness of ways of studying. They are alert to assessment requirements and criteria and gear work to the perceived preferences of teachers.

For measuring the adopted approach of learning and studying of students, several versions of a questionnaire have been evolved such as the Approaches to Studying Inventory (ASI) (Ramsden and Entwistle, 1981), the Course Perception Questionnaire (CPQ) (Ramsden and Entwistle, 1981), the Revised Approaches to Studying Inventory (RASI) (Entwistle and Tait, 1995), the Approaches and Study Skills Inventory for Students (ASSIST) (Entwistle and Tait, 1996), and the Approaches to Learning and Studying Inventory (ALSI) (Tyler and Entwistle, 2003). Since Entwistle's model is based on Pask's serial and holistic learning strategy, this concept is also included in the questionnaires. For example, in the ASSIST, the currently most often used instrument, the serial and holistic learning strategy is included as subcategory of the deep learning approach.

2.1.4 Grasha-Riechmann Learning Style Model

The Grasha-Riechmann learning style model (Grasha and Riechmann, 1975; Riechmann and Grasha, 1974) focuses on the students' social interaction with their teachers and fellow students in the classroom environment. Grasha and Riechmann identified three bipolar dimensions in order to understand the students' behaviour with respect to their social interaction: the participant/avoidant, collaborative/competitive, and dependent/independent dimension.

The *participant/avoidant* dimension indicates how much a student wishes to become involved in the classroom environment. Students who adopt a participant style desire to learn the course content and enjoy attending the class. They take responsibility for their own learning and enjoy participating in the learning activities. In contrast, students who adopt an avoidant style do not like to learn and do not enjoy attending the class. They also do not take responsibility for their learning and avoid taking part in the course activities.

The *collaborative/competitive* dimension measures the motivation behind a student's interactions with others. Collaborative learners are characterised as learners who are cooperative, enjoy working with others, and see the classroom as a place for learning and interacting with others. On the other hand, competitive learners see their fellow students as competitors. They have the motivation to do better than others, enjoy competing, and see the classroom as a win-lose situation.

The *dependent/independent* dimension measures attitudes toward teachers and how much the students desire freedom and control in the learning environment. Dependent students see the teacher as the source of information and structure. They want to be told what to do by authorities and learn only what is required. Independent learners are characterised as confident and curious learners. They prefer to think for themselves and work on their own.

For measuring the preference of students with respect to the six learning styles, a 90-item self-report inventory called Student Learning Styles Scale (SLSS) (Grasha and Riechmann, 1975) was developed. The questionnaire is created in particular for college and high school students. It is divided in six subcategories, each for one learning style. Each subcategory consists of 15 questions. Students are asked to rate their agreement or disagreement to these questions on a 5-point Likert scale. Considering the issue that the styles may change from class to class for each student, two different forms are designed, one that assesses a general class, and the second that relates to a specific course.

2.1.5 Dunn and Dunn Learning Style Model

The Dunn and Dunn learning style model (Dunn and Dunn, 1974; Dunn and Griggs, 2003) was originally proposed in 1974 and then refined and extended over the years. The model distinguishes between adults and children and includes five variables where each variable consists of several factors.

The *environmental* variable includes sound, temperature, light, and seating/furniture design. The *sociological* variable incorporates factors dealing with the preference for learning alone, in a pair, in a small group, as part of a team, with an authority, or in varied approaches (as opposite to in patterns). For children, additionally the motivation from parents/teachers is included as factor. The *emotional* variable consists of the factors motivation, conformity/responsibility, persistence, and need for structure. The *physical* variable is comprised of factors regarding perception/modality preferences (visual, auditory, tactile/kinaesthetic external, kinaesthetic internal), food and drink intake, time of day and mobility. The *psychological* variable was added later to the model and includes factors referring to global/analytic preferences, right or left hemisphericity, and impulsive/reflective preferences.

For detecting the learning style preferences according to the Dunn and Dunn learning style model, different versions of questionnaires were developed. The Learning Styles Inventory (Dunn, Dunn, and Price, 1996) was developed for children and exists in three versions (kindergarten to grade 2, grade 3 and 4, grade 5-12). This inventory consists of 104 questions which employ a 3-choice or 5-choice Likert scale. The Building Excellence Inventory (Rundle and Dunn, 2000) is the current version for adults. It includes 118 questions and employs a 5-point Likert scale. As a result, a high or low preference for each factor is identified.

2.1.6 Gregorc's Mind Styles Model

Gregorc's mind style model (Gregorc, 1982a; Gregorc, 1982b; Gregorc, 1985) is based on two dimensions dealing with the preferences for *perception* and *ordering*. Regarding perception, people can prefer an abstract or concrete way of perception, or some combination of both. Abstract perception refers to the ability to process information through reason and intuition, often invisible to our physical senses. In contrast, concrete perception emphasises the physical senses and refers to the ability to process information through these senses. The ordering dimension deals with the way a learner is arranging, prioritising, and using information in either a sequential or random order, or in a combination of both. While a sequential style pertains to use a linear, step-by-step organisational scheme, a random order style refers to the use of a network-like format which relates data to each other in a variety of ways. The perceptual and ordering preferences can be combined into four basic mediation channels which lead to four types of learners.

The *concrete sequential* learners prefer to use their five senses for processing information and are considered as orderly, logical, and sequential. These learners look for authority and guidance in a learning environment and prefer to extract information from hands-on experiences.

The *concrete random* learners are characterised by the need to experiment with ideas and concepts and will employ trial-and-error in learning. They like to explore the learning environment, are considered as insightful, can easily move from facts to theory, and do not like authoritative interventions.

The *abstract sequential* learners have their strengths in the area of decoding written, verbal, and image symbols. They prefer rational and sequential presentations and are good in synthesising ideas and producing new concepts or outcomes to new conclusions. They will defer to authority and has a low tolerance for distractions.

The *abstract random* learners are characterised by a keen awareness of human behaviour and an ability to evaluate and interpret atmosphere and mood. They prefer an unstructured learning environment and collaborations with others, are good in seeing relationships, tend to be reflective and need time to process data before reacting to it.

A more detailed description about the characteristics and preferences of the four types of learners is provided by Gregorc (1982a; 1982b).

The Gregorc Style Delineator (Gregorc, 1982b; Gregorc, 1985) is a self-report instrument to detect learners' preferences for the two dimensions and therefore their preferred channels. The instrument presents the students with 40 words arranged in 10 columns of four items each. The learners are then asked to rank the four words relative to how they fit to themselves (1 for being least and 4 for being most like themselves). Scores for each of the four learner types can range from 10 to 40, calculated by summing up the ranks of the respective words for each channel.

2.1.7 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 generalisations, 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. 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 organising 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 conceptualisation 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 strengths 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 characterised as risk-takers and as people who excel in situations that call for adaptation to specific immediate circumstances.

For identifying learning styles based on Kolb's learning style model, the Learning Style Inventory (LSI) was developed (Kolb, 1976) and revised several times. The current version of LSI (Kolb and Kolb, 2005) uses a forced-choice ranking method to assess an individual's preferred modes of learning (Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation). Individuals are asked to complete 12 sentences about their preferred way of learning. Each sentence has four endings and the individuals are asked to rank the endings according to what best describes how they learn (4 = most like you; 1 = least like you). The results of the LSI indicate the individuals' preferences for the four modes. Furthermore, their score for the active/reflective and concrete/abstract dimensions can be derived from the preferred modes, which again lead to the preferred type of learning style.

2.1.8 Honey and Mumford's Learning Style Model

The learning style model by Honey and Mumford (1982) is based on Kolb's Experiential Learning Theory (for example, Kolb, 1984) and is developed further on the four types of Kolb's learning style model (Kolb, 1984). The active/reflective and concrete/abstract 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 and 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. For Reflectors, learning occurs mainly by observing and analysing the observed experiences.

The Learning Style Questionnaire (LSQ), a self-report inventory for identifying learning styles based on the Honey and Mumford learning style model, as well as its manual was initially developed in 1982 (Honey and Mumford, 1982), revised in 1992 (Honey and Mumford, 1992) and then replaced in 2000 (Honey and Mumford, 2000) and again revised in 2006 (Honey and Mumford, 2006). Currently, two versions of the LSQ exist, one with 80 items and one with 40 items.

2.1.9 Herrmann "Whole Brain" Model

The Herrmann "Whole Brain" model (Herrmann, 1989) is based on the split-brain research carried out by Roger Sperry (1964), separating the brain in the *left and right cerebral hemispheres*. In addition, the Herrmann "Whole Brain" model considers, following MacLean (1952), the hypothesised functions of the brain's limbic system. Accordingly, individuals are modelled with respect to how they process information using either a *cerebral mode*, by thinking about the problem, or a *limbic mode*, which is a more active approach based on experimentation.

The Herrmann "Whole Brain" model distinguishes between four modes or quadrants. Learners who have a primary preference for quadrant A (*left hemisphere, cerebral*) prefer logical, analytical, mathematical, technical thinking and can be considered as quantitative, factual, and critical. Learners with a primary preference for quadrant B (*left hemisphere, limbic*) tend to be sequential and organised, like details, structure and plans and have a structured, organisational and controlled thinking style. Learners with a primary preference for the quadrant C (*right hemisphere, limbic*) are characterised as emotional, interpersonal, sensory, kinaesthetic, and musical. Learners who have a primary preference for quadrant D (*right hemisphere, cerebral*) tend to be visual, holistic, and innovative and prefer conceptual, synthesising, and imaginative thinking.

For identifying the preferred quadrant, the Herrmann Brain Dominance Instrument (HBDI) was developed (Herrmann, 1989). The HBDI is a self-report inventory, containing 120 questions. As a result of the HBDI, a brain dominance profile is calculated, which shows the primary, secondary and tertiary preferences.

2.1.10 Felder-Silverman Learning Style Model

In Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988), learners are characterised by values on four dimensions. These dimensions are based on major dimensions in the field of learning styles and can be viewed independently from each other. They show how learners prefer to process (active/reflective), perceive (sensing/intuitive), receive (verbal/visual), and understand (sequential/global) information. While these dimensions are not new in the field of learning styles, the way in which they describe a learning style of a student can be seen as new. While most learning style models, which include two or more dimensions, derive statistically prevalent learner types from these dimensions, such as the models by Myers-Briggs (Briggs Myers, 1962), Gregorc (1982a), Kolb (1984), and Honey and Mumford (1982), Felder and Silverman describe the learning styles by using scales from +11 to -11 for each dimension (including only odd values). Therefore, the learning style of each learner is characterised by four values between +11 and -11, one for each dimension. These scales facilitate describing the learning style preferences in more detail, whereas building learner types does not allow distinguishing between the strength of the preference. Additionally, the usage of scales allows expressing balanced preferences, indicating that a learner does not have a specific preference for one of the two poles of a dimension. Furthermore, Felder and Silverman consider the resulting preferences as tendencies, meaning that even a learner with a strong preference for a particular learning style can act sometimes differently.

The *active/reflective* dimension is analogous to the respective dimension in Kolb's model (1984). 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 communicating 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 or in a small group together with one good friend.

The *sensing/intuitive* dimension is taken from the Myers-Briggs Type Indicator (Briggs Myers, 1962) and has also similarities to the sensing/intuitive dimension in Kolb's model (Kolb, 1984). Learners with a sensing learning style like to learn facts and concrete learning material, using their sensory experiences of particular instances as a primary source. They like to solve problems with standard approaches and also tend to be more patient with details. Furthermore, sensing learners are considered as more realistic and sensible; they tend to be more practical than intuitive learners and like to relate the learned material to the real world. In contrast, intuitive learners prefer to learn abstract learning material, such as theories and their underlying meanings, with general principles rather than concrete instances being a preferred source of information. They like to discover possibilities and relationships and tend to be more innovative and creative than sensing learners. Therefore, they score better in open-ended tests than in tests with a single answer to a problem. This dimension differs from the active/reflective dimension in an important way: the sensing/intuitive dimension deals with the preferred source of information whereas the active/reflective dimension covers the process of transforming the perceived information into knowledge.

The third, *visual/verbal* dimension deals with the preferred input mode. The dimension differentiates learners who remember best what they have seen (e.g., pictures, diagrams, flow-charts and so on), from learners who get more out of textual representations, regardless of the fact whether they are written or spoken.

In the fourth dimension, learners are distinguished between a *sequential and global* way of understanding. This dimension is based on the learning style model by Pask (1976b), where sequential learners refer to serial learners and global learners refer to holistic learners. 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. Because the whole picture is important for global learners, they tend to be more interested in overviews and in a broad knowledge, whereas sequential learners are more interested in details.

For identifying learning styles based on the FSLSM, Felder and Soloman developed the Index of Learning Styles (ILS) (Felder and Soloman, 1997), a 44-item questionnaire. As mentioned earlier, each learner has a personal preference for each dimension. These preferences are expressed with values between +11 to -11 per dimension, with steps +/-2. This range comes from the 11 questions that are posed for each dimension.

2.2 Implications of Learning Styles in Education

Many educational theorists and researchers consider learning styles as an important factor in the learning process and agree that incorporating them in education has potential to make learning easier for students. Furthermore, Felder, for example, argued that learners with a strong preference for a specific learning style might have difficulties in learning if their learning style is not supported by the teaching environment (Felder and Silverman, 1988; Felder and Soloman, 1997). Thus, from theoretical point of view, it can be argued that incorporating the learning styles of students makes learning easier for them and increases their learning efficiency. On the other hand, learners who are not supported by the learning environment may experience problems in the learning process.

Learning styles can be considered in different ways in education. A first step is to make learners aware of their learning styles and show them their individual strengths and weaknesses. The knowledge about their learning styles helps students to understand why learning is sometimes difficult for them and is the basis for developing their weaknesses.

Furthermore, students can be supported by matching the teaching style with the learning styles of the students. Due to the nature of learning styles, providing students with learning material and activities that fit their preferred ways of learning seems to have high potential to make learning easier for them. However, the matching approach aims at a short-term goal, namely to make learning as easy as possible at the time students are learning. Looking at long-term goals, educational theorists such as Messick (1976), Kolb (1984) and Grasha (1984) suggested that learners should also train their not-preferred skills and preferences. Messick argued that when learners acquire more educational experience, they are required to adapt to a variety of instructional methods and styles. The ability to adapt to different instructional styles will prepare them with important life skills. For example, providing verbal learners with only visual forms of instruction forces them to develop and use visual skills. For Grasha, the mismatching approach is relevant in order to make learning interesting and challenging for students and Kolb argued that the educational objectives for mismatching are personal growth and creativity. However, in Gregorc's model, learning styles are seen as stable, and therefore he argued that a mismatched approach can harm students (Gregorc, 2002). Felder advises against the unintentional, permanent mismatch of teaching styles and learning styles, where teachers are unaware of their own learning styles and may, as a result, teach only according to this style, thus favouring certain students and disadvantages others (Felder, 1993). Summarising these aspects, conclusion can be drawn that the mismatching approach should be applied intentionally and depending on the adopted learning style model as well as on the learners' needs. In an environment, where students get their individual learning material and activities, the matching and the mismatching approaches can be applied in a controlled manner, depending on specific conditions such as the current learning goal, the experience of the learner in a particular subject, their motivation and so on.

A less intensive approach for teachers is to support their learners by including learning material and activities in their courses that address different learning styles rather than teaching in a way that accommodate only one learning style. For example, if the learning material consists mainly of abstract material, teachers can include some concrete examples to support a sensing/concrete learning style or if the teacher is mainly lecturing in the course, he/she can include some group work activities in order to support active learners. By addressing different learning styles, some activities match with the students' strengths and some with their weaknesses. However, the composition is not controlled since the course is the same for all students.

2.3 Criticism and Challenges of Learning Styles

The field of learning style is complex and although lot of research has been conducted, several important questions are still open and controversial issues are under discussion. The main challenge is to clarify these controversies, answer the open questions and provide a clear understanding of the field.

At current stage, plenty of learning style models exists, each integrating some aspects of learning, and some overlapping each other. This high number of learning style models leads to criticism and the question on how to incorporate all different dimensions of learning styles in education, or from a more practical view, which learning style model is most relevant and shall be used. Furthermore, the similarities and relationship between these different learning style models and dimensions are mostly not elaborated. Therefore, a challenge of the field of learning styles is to conduct research that involves all learning style models and dimensions, bring clarity in its relationships to each other as well as to other relevant factors of learning (e.g., cognitive styles and cognitive abilities), evaluate them in order to identify major learning style models/dimensions, and develop a holistic model that integrates all relevant aspects of learning styles.

Furthermore, controversial issues such as the question whether learning styles are stable or not over time, subject and environment should be clarified. Depending on the basic ideas behind the learning style models, theorists make different claims for the degree of stability within their learning style models. On the one extreme of this continuum, theorists define learning styles similar to learning strategies and therefore as flexible and changeable from context to context and even from task to task. Some theorists see learning styles as “flexibly stable”, arguing that previous learning experiences and other environmental factors form the learning styles of students. Others relate learning styles strongly to cognitive styles and abilities and argue that they are stable over a long period of time or even see them as God-given and not changeable. However, based on the incorporation of particular dimensions in different models with different ideas about the stability, controversial issues occur. For example, the serial and holistic learning style by Pask (1976b) is related to the sequential and random style by Gregorc (1982a). However, Pask considers the dimension as relatively flexible while Gregorc claims that the learning styles are not changeable. Therefore, future research is needed in order to clarify the stability of specific dimensions as well as learning style models.

Another issue of criticism deals with the implications of learning styles in education. While the effectiveness of the matching approach seems to be intuitive and is one of the most popular recommendations, 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 learning styles. So far, no substantial, uncontested and hard empirical evidence exist that the matching approach has a significant positive effect on the students’ achievement (Coffield et al., 2004b). As Jonassen and Grabowski (1993) summarised, 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, specialised aptitude constructs or standardised tests, and a lack of conceptual or theoretical linkage between aptitudes and the information-processing requirements of the treatment” (Jonassen and Grabowski, 1993, p. 28). This conclusion shows that more high-quality research is necessary to get a clear picture about the effect of specific learning styles and other factors on achievement.

However, the main criticism regarding the matching approach is that it is simply "unrealistic, given the demands of flexibility it would make on teachers and trainers" (Reynolds, 1997, p. 121). In traditional learning, teachers would have to routinely change their teaching style to accommodate the different learning styles in a class. Therefore, the feasibility of the matching approach is depending on the number of students and on the adopted learning style model. Pask (1976b), for example, distinguishes between three learning styles, Honey and Mumford (1982) propose four types of learners, the Myers-Briggs Type Indicator (Briggs Myers, 1962) includes 16 different types and in the Felder-Silverman learning style model (Felder and Silverman, 1988), learners can have up to 625 ($=5^4$) different learning styles when arranging each of the four dimensions into five groups (e.g., strong active, moderate active, balanced, moderate reflective, strong reflective). Therefore, teachers might not have the capacity to provide each learner with an individual combination of learning material and activities as soon as the number of students and the number of different learning styles increase. However, in technology enhanced learning, changing the teaching styles for each student and therefore tailoring courses to the individual needs of students is possible, even for a high number of different learning styles and almost independent on the number of students. Lot of research is done in the area of adaptive educational systems, and recently more and more research deals with personal characteristics of learners, such as learning styles. In Chapter 3, a description on adaptive educational systems incorporating learning styles is provided and in Chapter 7, an approach for enabling learning management systems to provide adaptive courses with respect to the Felder-Silverman learning style model is introduced.

Additionally, further research is necessary regarding mismatching teaching styles and learning styles, its effect on learning, and the conditions when such a mismatch is beneficial in terms of either to support learners and make learning more interesting for them or to achieve long-term goals by forcing them to train their weaknesses.

Another point of criticism is the method for measuring learning styles. Most learning style models provide a questionnaire, where students are asked about their preferences with respect to the learning style model. These questionnaires raise several problems. Questionnaires, in general, have to deal with the problem that the given answers might not correspond to the real behaviour the questions aim to investigate (Draper, 1996; Paredes and Rodríguez, 2004). The use of questionnaires in general and as an instrument for identifying learning styles is based on several assumptions. Firstly, the assumption is made that students are motivated to fill out the questionnaire properly and to the best of their knowledge about their preferences. Secondly, filling out a questionnaire about the preferred way of learning requires that the students are aware of their preferred way of learning. However, Stash, Cristea, and de Bra (2006), for example, identified that the Masters students participating in their study about adaptation to learning styles had only little meta-knowledge on their learning preferences, and Merrill (2002), for example, even argued that most students are unaware of their learning styles. Thirdly, social and psychological aspects such as the students' beliefs about how people should behave can influence their answers on the questionnaire. Additionally, using questionnaires for identifying learning styles underlies the assumption that the learning styles are stable for a long period of time. However, as discussed before, the stability of learning styles is still a controversial issue. As soon as learning styles change, the results of the questionnaires are not valid any more and students would have to do it again in order to identify their new learning styles. However, this approach would raise new issues, dealing with how to identify when a learning style changed and how to motivate students to fill out the questionnaire several times.

Another issue is the validity and reliability of the questionnaires themselves. According to Coffield et al. (2004b), four criteria have to be fulfilled as a minimum standard for any instrument which is to be used to redesign pedagogy: construct validity, predictive validity, internal consistency reliability, and test-retest reliability. Construct validity means that the instrument actually measures the theoretical construct or trait that it purports to measure. Predictive validity refers to whether the range of behaviour can be seen to have an impact on task performance. The internal consistency reliability refers to the homogeneity of the items intended to measure the same quantity that is the extent to which responses to the items are correlated. The test-retest reliability measures the extent to which an individual achieves the same result when performing the questionnaire twice within a specific period (e.g., one month). However, this test is based on the assumption that learning styles are stable, at least during the test period. Most learning style questionnaires are tested according to these criteria. However, instruments often lack one or several of these criteria, researchers achieve inconsistent results or even identify latent dimensions. Coffield et al. (2004b, p. 56) argued that from the 13 major learning style models they have identified and studied, only three of the models "could be said to come close to meeting these criteria".

From all these argumentations about questionnaires, the conclusion can be drawn that questionnaires have to deal with several problems and restrictions. People who are using such questionnaires for identifying learning styles should therefore be aware of these problems and restrictions as well as consider the limitations of the questionnaires when interpreting the results. Since the proper identification of learning styles is a crucial issue, challenge is to develop an approach that measures learning styles more accurately and reliably, minimizing the extent to be affected or restricted by other factors. In Chapter 5, an alternative approach to questionnaires is introduced, which aims at overcoming the above mentioned problems and restrictions of questionnaires. In this approach, learning styles are identified automatically from the students' behaviour and actions during a course.

Summarising this section, it can be concluded that several controversies and unsolved problems still exist in the field of learning styles. It seems that we are still far way from a holistic model of learning styles that integrates all relevant aspects of learning styles and provides a clear understanding, for example, about the stability of learning styles/dimensions and their effects on learning. However, the controversies in and criticism of learning styles show challenges in the field. This thesis tackles some of the challenges and introduces new approaches which contribute to getting closer to solve some of the mentioned problems.

CHAPTER 3
Adaptive Educational Hypermedia Systems

Ted Nelson was one of the pioneers of hypertext and defined it as a combination of natural language text with the computer's capability for interactive branches (Conklin, 1987). In other words, hypertext can be seen as non-sequential text, which is connected by hyperlinks. Hypermedia extends the concept of hypertext by media elements such as graphics, audio, and video, rather than text-only presentations.

The aim of adaptive hypermedia systems is to provide hypermedia content that fits to the individual needs of the users. Adaptive hypertext/hypermedia systems can be defined as "hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible aspects of the system to the user. In other words, the system should satisfy three criteria: it should be a hypertext or hypermedia system, it should have a user model, and it should be able to adapt the hypermedia using this model" (Brusilovsky, 1996, p. 88). Considering the definition from the viewpoint of an adaptive educational hypermedia system (AEHS), the adaptation process in such a system consists of two parts: first, a model of the learner has to be built (and updated) which includes all necessary information about the learner to provide adaptivity and second, this information has to be used in order to generate adapted courses.

In the following subsection, discussion is provided on general aspects of AEHS, including how relevant information about the student can be gathered and which techniques exist to provide adaptive content. Subsequently, several AEHS are introduced which incorporate the individual learning styles of students to provide adapted content.

3.1 General Aspects regarding Adaptivity

The spectrum of adaptation in systems ranges from adaptive systems to adaptable systems (Oppermann, Rashev, and Kinshuk, 1997). *Adaptable systems* allow the user to change certain parameters and adapt the systems' behaviour accordingly. In contrast, *adaptive systems* adapt to the users automatically based on the system's assumptions about the users' needs (Oppermann, 1994). Since this thesis focuses on adaptivity, discussion is provided only regarding adaptive systems.

Additionally, the term *intelligent tutoring (or educational) systems* is widely used in the educational domain. Intelligent tutoring systems focus on the use of techniques from the field of artificial intelligence to provide broader and better support for the learners. In contrast, adaptive educational systems stress the aim to be different for different learners or groups of learners (Brusilovsky and Peylo, 2003). However, many systems can be considered as intelligent and adaptive educational systems.

As proposed for intelligent tutoring systems (Brusilovsky, 1994), four modules are necessary to provide personalized content for learners. The *student module* is responsible for building and updating the student model which includes all relevant data about the learner. The *expert (or expertise) module* is responsible for the domain knowledge (e.g. the facts and rules of a particular domain), which is stored in the expert model, and for the internal representation of the domain knowledge in the system. The *tutoring module* provides information about how the learning material, available from the expert model, can be presented in a proper way considering the individual needs of the student, accessed through the student model. The *interface module* is responsible for presenting the content determined by the tutoring module and controls the communication and interaction of students with the system.

Besides the proposed structure, reference models such as the AHAM (de Bra, Houben, and Wu, 1999) and the Munich model (Koch and Wirsing, 2002) provide a more general description of the architecture of a typical adaptive hypermedia system. However, these models are not specifically designed for the educational domain and therefore not described in detail here.

The next subchapters deal with the two steps in the adaptation process of AEHS, describing how information about the learners can be gathered and how this information can be used to provide adaptivity. The description focuses on the classification of approaches for student modelling and providing adaptivity.

3.1.1 Student Modelling

The student model plays a crucial role in AEHS. It includes all relevant information that the system has gathered about the learner. This information is then used as a basis for providing suitable adaptivity. The process of building and updating the student model is called student modelling. While Self (1994) provided a comprehensive description of student modelling from a point of view of the formal techniques, Brusilovsky (1994, 1996) classified student models and techniques for student modelling based on existing systems.

Brusilovsky (1996) distinguished between two different ways of student modelling: collaborative and automatic student modelling. In the collaborative student modelling approach, the learners provide explicit feedback which can be used to build or update the student model. For instance, the learner can provide data for the student modelling mechanism such as stating explicitly whether a page was relevant for his/her learning goal. Another option is to let the learner do the adaptation by himself/herself and therefore show directly what he/she expects from the system. For example, the order of links on a page can be changed by the learner, showing the preferred order to the system. Another possibility is that the learner is allowed to directly update the information of the student model. With respect to learning styles, an often used technique is to let students fill out a questionnaire in order to get information about their learning styles. On the other hand, in the automatic student modelling approach, the process of building and updating the student model is done automatically based on the behaviour and actions of the learners when they are using the system for learning. While this approach allows students to focus only on learning rather than additionally providing explicit feedback about their preferences, the main problem with the approach is to get enough reliable information to build a robust student model. According to Brusilovsky (1996), a solution to this problem might be the use of additional, more reliable sources such as the results of tests in the student modelling process.

Furthermore, student modelling can be done statically or dynamically. Static student modelling refers to an approach where the student model is initialized only once (mostly when the students are registering in the course). In contrast, a dynamic student modelling approach frequently updates the information in the student model.

In a student model, different kinds of information can be included. Brusilovsky (1994) distinguished two major groups, namely models of course knowledge and models of individual subject-independent characteristics. Both are different in terms of the form of representation of the model as well as the methods used in its construction and application. While first investigations about student modelling were focused on models about the course knowledge, more and more research is now done on modelling individual characteristics of learners such as learning styles.

3.1.2 Providing Adaptivity

Once information about the learners is available from the student model, adaptivity can be provided. Different aspects have to be considered when aiming at providing students with adapted courses.

One dimension refers to *what* can be adapted in a system. Different methods exist for providing students with adapted courses. These methods determine which features of the system are different for different learners. Adaptation features can be classified regarding their aim into two groups, namely for *adaptive presentation* and *adaptive navigation support* (Brusilovsky, 2001). Adaptive navigation support is based on links and includes features such as direct guidance, map adaptation, as well as adaptive sorting, hiding, annotating and generating of links. Adaptive presentation includes adaptation features based on content such as adaptive multimedia presentation, adaptive text presentation, and adaptation of modality. Adaptive text presentation can be further distinguished between natural language adaptation and canned text adaptation. The latter includes inserting/removing of fragments by displaying or hiding them, altering fragments by changing text within a fragment, sorting fragments by changing their order, dimming fragments by making them less visible, for example, by using gray font, and stretchtext where items or paragraphs are initially displayed or hidden by the system but can be opened or closed by the learner.

Another dimension incorporates what kind of information about the learner is used as a source for the adaptation. Adaptivity can be provided based on different characteristics and needs of learners. For instance, a system can provide adaptivity to the prior knowledge, the learning goals, the cognitive abilities, and the learning styles of students.

For providing adaptivity based on preferences and skills, especially in the context of learning styles, another dimension exists. This dimension deals with the goal of providing adaptivity (Jonassen and Grabowski, 1993). The most often used approach is to match the instructions to the preferences or skills of the learners and teach according to the learners' strengths. This approach aims at a short-term goal namely to make learning as easy as possible at the time learners are using the system. Looking at long-term goals, researchers such as Messick (1976) and Felder and Spurlin (2005) suggested that learners should also train their not-preferred skills and preferences. Messick argued that when learners acquire more educational experience, they are required to adapt to a variety of instructional methods and styles. The ability to adapt to different instructional styles will prepare them with important life skills. For example, providing verbal learners with only visual forms of instruction forces them to develop and use visual skills.

3.2 Adaptive Educational Hypermedia Systems Incorporating Learning Styles

In this section, adaptive educational hypermedia systems are introduced which provide adaptivity according to learning styles. The description of the systems focuses on both above introduced issues, namely on how the systems gather information about the learners and which adaptation features they are using in order to provide adaptivity.

3.2.1 CS383

CS383 (Carver, Howard, and Lane, 1999) was the first adaptive educational hypermedia system that incorporated Felder-Silverman learning style model. The system provided adaptivity based on the sensing/intuitive, visual/verbal, and sequential/global dimensions of FSLSM. Regarding the active/reflective dimension, Carver et al. (1999) argued that the nature of hypermedia systems inherently supports both active and reflective learning. These systems force students to make choices and therefore actively involve them in the learning process, which facilitates active learning. On the other hand, reflective learning is supported since students have the possibility to reflect and think about the material at any point in their studies.

The developed course included a comprehensive collection of media objects which include slide shows, hypertext, lesson objectives, a response system, a digital library, and media clips. Based on the identified learning styles, the system offered students the option to order these objects in accordance with how well the multimedia objects fit to their individual learning styles. The ranking of the multimedia objects was based on a coarse media granularity. Therefore, each media type received a ranking rather than ranking each single object.

For identifying the learning styles of students, the Inventory of Learning Styles (Soloman, 1992), the first version of a questionnaire for identifying learning styles based on FSLSM, was used at the beginning of the course. The learning styles of the students were calculated based on their answers to 28 questions and were stored in the student model.

3.2.2 MANIC

Multimedia Asynchronous Networked Individualized Courseware (MANIC) (Stern et al., 1997; Stern, Woolf, and Kurose, 1997) provided lecture-based material in terms of slides and audio material. The slides were constructed dynamically based on the students' level of understanding and their learning preferences. The system did not explicitly support a specific learning style model but incorporated different aspects from different learning style models such as the Felder-Silverman learning style model.

The concept for providing adaptivity (described in more detail in Stern and Woolf, 2000) was based on the stretchtext technique. Accordingly, basic learning material was presented to all learners. This material could be enriched by supplementary learning material, allowing graphics as well as text. Adaptive features included the media type (graphic or text), the instruction type (explanation, example, description, definition, analogy), the abstractness (abstract, concrete), and the place of the supplementary learning material within the topic and the concept. According to the students' preferences, specific types of supplementary learning material were presented or hidden. However, students always had the possibility to hide supplementary learning material which was shown, and ask for showing material that was hidden.

For detecting the students' learning preferences, a Naïve Bayes Classifier was used. Information about the learners' preferences was gathered from their interaction with the system, when asking for showing hidden material or hiding presented material. This information was used by the Naïve Bayes Classifier to learn the students' preferences. To improve the accuracy of this technique, population data were considered additionally.

3.2.3 IDEAL

Intelligent Distributed Environment for Active Learning (IDEAL) (Shang, Shi, and Chen, 2001) was an adaptive and intelligent agent-assisted system to support active learning. Learning material was adapted to the students in terms of selecting, organizing, and presenting it depending on background knowledge, learning styles, language, and accessibility (Rodriguez et al., 2002). Regarding learning styles, the concept of providing adaptivity and the student modelling techniques were open to any major learning style model.

IDEAL allowed content as well as navigation adaptation features. Based on the architecture of IDEAL, possible adaptation features regarding learning style included the ordering of examples, general rules, and summary concepts, the inclusion of optional/enrichment material, the selection of visual metaphors and icons, and text to speech conversion selection. These adaptation features had to be specified with respect to the applied learning style model.

While the knowledge of learners was frequently updated based on their performance and reviewed topics, learning style, language, and accessibility acted as long-term traits and were modelled statically. For determining the learning style, the use of a suitable questionnaire for the respective learning style model was intended when the learners registered for a course. Learners could retake the questionnaire if they wanted, and they could decide whether the results of the questionnaire were taken for all courses or only for the currently registered one. Furthermore, when taking the course, learners had the possibility to switch to any of the available learning style adaptations on the fly.

3.2.4 MASPLANG

MASPLANG (Peña, 2004; Peña, Marzo, and de la Rosa, 2002) was a multi-agent system which was developed to enrich the intelligent tutoring system USD (Fabregat, Marzo, and Peña, 2000) with adaptivity regarding learning styles and the students' state of knowledge. USD was an adaptable platform which provides users the possibility to adapt courses to their needs by themselves. MASPLANG extended USD in terms of providing adaptivity which means that the system was able to adapt courses automatically according to the knowledge and learning style of the students. Regarding learning styles, the Felder-Silverman learning style model was applied.

Adaptivity based on learning styles was provided in terms of choosing the relevant media formats, instructional strategies, and navigation tools. The adaptation features were based on the techniques used in CS383 (Carver, Howard, and Lane, 1999) and the possibilities of the USD platform. For providing suitable instructional strategies, the use of lesson objectives, case studies, lectures, knowledge nucleus, conceptual maps, and synthesis was adapted according to the individual learning styles. Regarding the relevant media format, for specific learning styles slideshows (text and/or multimedia), media clips (graphics, digital movies, and/or audio files), and linear text were considered. Moreover, the navigation tools were adapted to the learning styles. This included the use of back and forward arrows, printings, online-help, general vision maps, and filters. Also collaborative tools like chat, forum, and e-mail were considered.

In order to identify students' learning styles, the ILS questionnaire (Felder and Soloman, 1997) was used as a basis. Later on, the students' profile was fine-tuned through a case-based reasoning process (Habitat-ProEnvironment, 2001) which used students' behaviour and actions as source.

3.2.5 LSAS

Learning Style Adaptive System (LSAS) (Bajraktarevic, Hall, and Fullick, 2003) incorporated the sequential/global dimension of FSLSM. For getting information about the students' learning styles, the ILS questionnaire (Felder and Soloman, 1997) was used.

Adaptivity was provided by two different user interface templates. For sequential learners, each page contained small chunks of information, which included only text rather than other links. The only links included in the pages were the 'forward' and 'back' buttons which provided the learners with a linear learning path. On the other hand, global learners had more navigational freedom. Pages comprised elements such as a table of contents, a summary at the end of the page, an overview of the pages, a section with supplemental links, and related links within the text. These elements provided learners with an overview about the topic and gave them the opportunity to navigate freely through the course.

In order to evaluate the effectiveness of the system and the provided adaptivity, an experiment with 21 students was conducted. Students were asked to use the system to learn two subjects. While for the first subject, the system presented a course that matched with the detected learning styles of the students, for the second subject the system presented a course that did not match with their learning styles. According to the conduced pre-test and post-test for each subject, it could be seen that learners performed significantly better when the teaching style matched with the learning style.

3.2.6 iWeaver

The architecture of iWeaver (Wolf, 2003) was based on the Dunn and Dunn learning style model (Dunn and Dunn, 1974; Dunn and Griggs, 2003). iWeaver incorporated several aspects of this learning style model and aimed at keeping a balance between the cognitive load of a learner, the accessible navigation option, and the learning content. iWeaver was developed to teach the programming language Java. The system was based on two concepts: media experiences which referred to the presentation modes and learning tools which were related to the psychological domain of the Dunn and Dunn learning style model.

iWeaver supported different learning styles by four types of media experience. For visual text learners, the content was presented in a rich text format. Visual picture learners were presented with text enriched by illustrations, diagrams and animations. For tactile kinaesthetic learners, an interactive version of the content was shown and auditory learners were supported by audio files where additionally the key concepts were shown in bullet-point style. The learning tools supported global learners by providing them with mind maps, reflective and visual text learners were supported by a content-aware note-taking tool, impulsive learners were provided with the option to try out their acquired knowledge by accessing a Java compiler, and internal kinaesthetic learners had the possibility to see additional examples. For the presentation modes and the learning tools, adaptive link ordering as well as adaptive link hiding was used. Therefore, only suitable presentation modes and learning tools were shown to the learners but the learners had access to hidden presentation modes and learning tools. Furthermore, the content navigation menu was generated dynamically depending on the progress of the learners.

When learners used the system the first time, they had to fill out the “Building Excellence Inventory” (Rundle and Dunn, 2000) for assessing their learning styles according to the Dunn and Dunn learning style model. Based on the answers, the initial student model was built. Additionally, after each unit learners had to give feedback about the effectiveness, progress and satisfaction with the learning material. An extension of iWeaver was planned which aimed at updating the student model based on the behaviour of the learners in the course, their feedback, and the feedback of learners with a similar profile.

3.2.7 INSPIRE

Intelligent System for Personalized Instruction in a Remote Environment (INSPIRE) (Papanikolaou et al., 2003) lets learners select their learning goal and accordingly generates lessons that correspond to specific learning outcomes, accommodating learners’ knowledge level, progress, and learning style. Learners have the possibility to intervene in the lesson generation process as well as make changes in their student model. Therefore, INSPIRE can act as an adaptive and adaptable system. INSPIRE combines two traditional instructional design theories, the Elaboration Theory (Reigeluth and Stein, 1983) and the Component Display Theory (Merrill, 1983), with the learning style model by Honey and Mumford (1992).

Adaptivity is provided in terms of curriculum sequencing, adaptive navigation support, and adaptive presentation. While curriculum sequencing and adaptive navigation support is performed based on the learners’ goals, their progress and their knowledge level, adaptive presentation is based on the learning styles of the learners. For the four types of learning styles (Activist, Theorist, Pragmatist, and Reflector), the learning material is adapted in terms of the method and the order of the presentation.

Although the behaviour and actions of the learners are tracked by the system, this information is not used for the detection of learning styles. Instead, a questionnaire developed by Honey and Mumford (1992) is applied and has to be filled out by the learners when they log in the first time. Alternatively, learners have the possibility to initialize or update their learning style in the student model.

In order to evaluate the adaptive and adaptable functionality of INSPIRE, a study with 23 students was performed. Results indicated that most students appreciated the functionality of the system and the support offered by it.

3.2.8 TANGOW

Task-based Adaptive learNer Guidance On the Web (TANGOW) (Carro, Pulido, and Rodriguez, 2001) is a system designed for building web-based courses on the basis of teaching tasks and rules. The content of a course is defined as a list of media elements associated to a teaching task. In order to provide adaptivity, TANGOW incorporates two dimensions of FSLSM, namely the sensing/intuitive and the sequential/global dimensions (Paredes and Rodríguez, 2004).

Adaptation is realised by modifying the order of tasks and the order of elements within the tasks. Course designers can build the default order of tasks using AND, ANY, OR, and XOR rules. For a sequential learning style, all ANY rules were replaced by AND rules in order to provide a more structured path through the learning material. In contrast, for a global learning style, all AND rules were changed to ANY rules. Regarding the sensing and intuitive learning style dimension, the order within the tasks is modified. For sensing learners, the example is presented first, followed by the explanation. On the other hand, for intuitive learners, the explanation is shown first, followed by the example.

The student modelling process is based on a mixed approach (Paredes and Rodríguez, 2004). When students log in the first time, they are asked to fill out the ILS questionnaire (Felder and Soloman, 1997). The result is then mapped to a 3-level scale for each dimension, distinguishing between, for example, a strong sensing learning style, a balanced learning style, and a strong intuitive learning style. For learners with a balanced learning style, the default order defined by the designer is presented, and for others, adaptivity is provided. After initializing the student model, it is automatically updated by observing the learners' actions in the course. When learners behave contrary to the determined learning style preference stored in the student model, this information is revised.

TANGOW's functionality has been improved recently by additionally incorporating learning styles into collaborative aspects with respect to student group formation (Alfonseca et al., 2006; Paredes and Rodriguez, 2006).

3.2.9 AHA!

Similar to IDEAL, Adaptive Hypermedia for All (AHA!) (AHA! 2007; de Bra and Calvi, 1998; Stash, Cristea, and de Bra, 2006) lets authors decide about the learning style model they want to implement in their course. Therefore, an authoring tool (de Bra, Aerts, and Rousseau, 2002) and a generic adaptation language for learning styles called LAG-XLS (Stash, Cristea, and de Bra, 2005) were developed.

The adaptation language allows three types of adaptive behaviour: selection of items to present, ordering information, and creating different navigation paths (Stash, Cristea, and de Bra, 2005). The authors can create their own instructional strategies, which define how the adaptation is performed based on the three types of adaptive behaviour, or reuse existing instructional strategies. Stash, Cristea and de Bra (2006) introduced predefined instructional strategies for an active versus reflective learning style, Verbalizer versus Imagers, holist (global) versus analytic style, and field-dependent versus field-independent style.

Currently, AHA! does not provide any questionnaire to identify the learning styles. Instead, a registration form is provided where the incorporated learning styles are described and students can manually state their learning style preferences. For updating or revising the predefined learning styles, authors can define instructional meta-strategies, which define how the learning style preferences can be inferred from the students' browsing behaviour. Two predefined instructional meta-strategies are introduced, one for textual and pictorial information and one for the navigation in breadth-first or depth-first order. If the information in the student model does not match with the gathered information by the meta-strategy, the learner is asked to change the instructional strategy. Furthermore, learners always have the possibility to change the information in the student model and therefore choose another instructional strategy. (Stash, Cristea, and de Bra, 2004, 2006)

Stash, Cristea and de Bra (2006) conducted an evaluation of the usage as well as the authoring process in AHA! with 34 students from computer science and business information systems. Two conclusions can be drawn from this evaluation. Firstly, significant differences were found when comparing the stated learning styles from the registration form with the results from ILS questionnaire. It can be concluded that students might possess only little meta-knowledge on their learning style preferences and therefore the student model might be filled with incorrect data. Secondly, when students were asked to act as authors and create new instructional strategies and meta-strategies, they stated that they had difficulties. This result underlines that for the creation of new strategies a lot of psychological and/or pedagogical knowledge as well as specific knowledge about learning styles are required.

3.2.10 Summary of Adaptive Educational Hypermedia Systems

From the systems introduced in this chapter, it can be seen that many ways exist to incorporate learning styles in adaptive educational hypermedia systems. Table 3.1 summarises the systems with respect to their applied learning style models (or aspects of these models), the used student modelling approach and the way they provide adaptive courses.

Table 3.1: Adaptive educational hypermedia systems considering learning styles

System	Developed	Learning style model	Student modelling approach	Methods for providing adaptivity
CS383	1999	Sensing/intuitive, visual/verbal, and sequential/global dimension of FSLSM	Inventory of Learning Styles questionnaire	Ordering of multimedia objects
MANIC	2000	Combination of learning preferences	Automatic approach by using a Naïve Bayes Classifier and population data	Use of stretchtext (hiding and presenting additional content)
IDEAL	2002	Determined by the teacher	Questionnaire of the considered learning style model	Ordering, inclusion and selection of learning material
MASPLANG	2002	FSLSM	Index of Learning Styles questionnaire for initializing and a case-based reasoning process for fine-tuning	Adaptation in terms of choosing the relevant media formats, instructional strategies, and navigation tools
LSAS	2003	Sequential/global dimension of FSLSM	Index of Learning Styles questionnaire	Hiding/presenting additional links and course elements
iWeaver	2003	Presentation preferences and psychological preferences with respect to the Dunn and Dunn learning style model	Building Excellence Inventory; automatic approach is planned	Link ordering and link hiding for selecting different presentation modes and learning tools
INSPIRE	2003	Honey and Mumford learning style model	Questionnaire by Honey and Mumford or initializing/updating the student model manually	Method and order of the content presentation
TANGOW	2004	Sensing/intuitive and sequential/global dimension of FSLSM	Index of Learning Styles for initializing and an automatic student modelling approach for revising the information in the student model	Order of tasks and order of elements within the tasks
AHA!	2005/ 2006	Determined by the teacher	Manually initialized and updated by determined instructional meta-strategies	Adaptation in terms of selection of items to present, ordering information, and creating different navigation paths

CHAPTER 4

Learning Management Systems and their Potential for Incorporating Learning Styles

The previous chapter introduced adaptive educational hypermedia systems. These systems focus on supporting learners by providing courses that fit to their needs and characteristics. However, these systems typically lack support for fulfilling the needs of teachers and administrators. When applying adaptive systems in real teaching situations, some limitations arise (Brusilovsky, 2004). For example, adaptive systems lack integration and they support only few functions of web-enhanced education. Brusilovsky (2004, p. 104) pointed out that "while AWBES [adaptive web-based educational systems] as a class can support every aspect of Web-enhanced education better than LMS [learning management systems], each particular system can typically support only one of these functions". Furthermore, content that was created for one adaptive system cannot be reused for another. As a consequence, adaptive systems are not that often used by educational institutions.

On the other hand, learning management systems (LMSs) such as Moodle (2007), Blackboard (2007), and WebCT (2007) focus on supporting teachers and administrators in creating, administering, and managing online courses. LMSs provide a great variety of features which can be included in the courses such as learning material, quizzes, forums, chats, assignments, wikis, and so on. As such, they have become very successful in technology enhanced learning and are commonly used by educational institutions, but they provide very little or, in most cases, no adaptivity.

The aim of this thesis is to extend LMSs by incorporating learning styles, including investigations about how to automatically identify learning styles and how to provide courses that fit the learning styles of students. In this chapter, an overview of LMSs and investigations about their potential to incorporate learning styles is presented. In the next subsection, a brief introduction of LMSs is provided. Subsequently, an evaluation of LMSs is described, aiming on one hand to identify the functionalities and features of LMSs and on the other hand to find the LMS which is most suitable for using as a prototype to be extended in order to incorporate learning styles. The next subsection deals with the selected learning style model and points out its benefits over other learning style models with respect to incorporating learning styles in LMSs. The last subsection presents a study, which investigated the behaviour of students in an online course using an LMS with respect to their learning styles based on the selected learning styles model. This study can be seen as the basis for further investigations since it analyses whether students with different learning styles also behave differently in an online course of an LMS. Different behaviour in a course can be interpreted as different needs, which again leads to the conclusion that adaptivity can support these learners. Furthermore, the study investigates whether learning styles and behaviour are correlated, which can be seen as basis for investigations towards automatic student modelling.

4.1 Introduction in Learning Management Systems

Besides the term *learning management system*, many other terms exist with similar or equal meaning, such as *course management system* or *e-learning platform.* According to Alias and Zainuddin (2005, p. 28), a learning management system can be defined as "a software application or Web-based technology used to plan, implement, and assess a specific learning process". Another definition is provided by Baumgartner, Häfele, and Maier-Häfele (2002) stating that an e-learning platform (or in the context of this thesis, a learning management system) is a server-side installed software, which assists in teaching of any learning material via the internet and supports the organisation of the necessary processes. Furthermore, Baumgartner, Häfele, and Maier-Häfele (2002) point out five main areas of operations of e-learning platforms. Accordingly, teachers can use them to present content, provide students with communication tools such as discussion forums, chat, and video conferencing, create assignments and quizzes, evaluate and assess students' performance, and be supported in administration issues regarding content, courses, students, progress of students and so on.

In literature, also the term *learning content management system (LCMS)* exists. In some works, learning management systems are used as synonym for learning content management systems. However, some works distinguish between LMSs and LCMSs, defining LMSs as systems which provide support only on course level, considering a course as the smallest entity. In contrast, LCMSs incorporate the concept of (reusable) learning objects and support teachers in creating, storing, and managing of learning objects. In this thesis, we do not distinguish between LMSs and LCMSs and assume that LMSs also consider the concept of learning objects.

LMSs can be seen as "empty" environments which are developed for teachers to create and manage their courses and fill them with content. However, developers of LMSs decide on how learning can take place in the LMS and build the LMS based on pedagogical strategies. Such pedagogical strategies can be, for example, based on concepts of learning theories such as behaviourism, cognitivism, and constructivism. Another example is that LMSs can emphasise a more learner-centered approach or teacher-centered approach. Each LMS follows some pedagogical strategy regardless of whether developers used it intentionally or not. However, only few LMSs seem to be built intentionally based on a specific pedagogical strategy. One of these systems is Moodle whose design and development is guided by a social constructionist pedagogy, which is based on four concepts (Dougiamas, 2007): *Constructivism* points to the view that learning is an active process in which learners construct new knowledge based on their current/past knowledge as they interact with their environment. *Constructionism* refers to the concept that learning is particularly effective when constructing something for others to experience. *Social constructivism* extends the ideas of constructivism by the social aspects that arise when working in groups. *Connected and separated behaviour* deals with the motivation of students within a discussion. While separated behaviour in discussions is based on objective and factual arguments, defending one's own ideas, connected behaviour refers to the aim of understanding other points of view and accepting subjectivity.

The applied pedagogical strategies in LMSs focus mainly on how to teach learners from a general point of view, without considering the individual needs of learners. In this thesis, the incorporation of individual needs, in particular learning styles, in LMSs is addressed. In the next section, an evaluation of LMSs is presented, showing the functionality and features of LMSs as well as the degree to which adaptation issues are considered so far.

4.2 An Evaluation of Learning Management Systems Stressing Adaptation Issues

In this section, an evaluation of learning management systems is described. The evaluation aims, on one hand, at finding out how good LMSs support general functions and features as well as adaptation issues and on the other hand, at finding the LMS that is most suitable for using as a prototype and extending it to an adaptive LMS. Only open source systems were considered in the evaluation since they can be more easily extended and combined with other products/tools than commercial systems.

Nowadays, a lot of LMSs, open source and commercial ones, with different functionalities, features, and limitations exist in the market. Some evaluations of LMSs are available in the literature. For example, Colace, de Santo, and Vento (2003) conducted a general purpose evaluation, assessing 15 commercial LMSs. The evaluation covered two main parts: services required for online training and course management functionalities. Only a limited number of criteria were analysed and the evaluation was based on a numerical evaluation approach. Another example is the in-depth assessment of 10 commercial LMSs, performed by O'Droma, Ganchev, and McDonnell (2003). The evaluation drew attention on a virtual university information system to be realised with the selected system. The evaluation was based on demo versions and a numerical evaluation approach. Another comprehensive evaluation of 1 open source and 15 commercial LMSs was conducted by Baumgartner, Häfele, and Maier-Häfele (2002). The evaluation was conducted with the focus on the Austrian education system. An extended qualitative weight and sum approach of evaluating the systems was applied.

Most evaluations have focussed on commercial LMSs. In contrast, our evaluation is focused on open source products. Furthermore, our evaluation aims at assessing two issues, on one hand, the general functionality and usage of LMSs and on the other hand, their ability to be extended in order to incorporate different needs and characteristics of learners such as their learning styles and be able to provide adaptive courses.

In the following subsection, an introduction of two well-established evaluation approaches is given. Subsequently, the evaluation process as well as the applied categories for evaluating LMSs is introduced. The next subsection focuses on the adaptation category, explaining in detail which aspects were evaluated as well as presenting the results of the investigated LMSs regarding the adaptation category. Subsequently, the results of the overall evaluation are presented and discussed.

4.2.1 Evaluation Approaches

An evaluation determines the merit or significance of artefacts and therefore, requires a profound evaluation approach (Scriven, 1991). There are two well-established approaches for the evaluation of software products, the numerical weight and sum approach, and the qualitative weight and sum approach. Both are described in the following subsections.

4.2.1.1 Numerical Weight and Sum Approach

The numerical weight and sum (NWS) approach (Scriven, 1991, 1997) weights the criteria of merit on a scale (e.g., 1-5 or 1-10). Furthermore, the performance scores are normalised to a scale (e.g., 1-10 or 1-100). Then the performance scores are multiplied by the weights and summed up for each candidate. The final result is a single number. The winner is the one with the largest score. While this approach is very attractive due to its simplicity, it can yield to an invalid and completely wrong answer. One of the reasons for such an error is the assumption that one can use a single numerical scale for weights, performance, and number of criteria, as well as that it is possible to calculate with these scales. High performing criteria can therefore balance those having a poor performance and strengths and limitations of systems are hidden by a single number.

4.2.1.2 Qualitative Weight and Sum Approach

The qualitative weight and sum (QWS) approach (Scriven, 1991, 1997) overcomes the previously mentioned methodological shortcomings of the NWS approach. Like NWS, a list of criteria is established and weighted. The difference is that QWS is based on the use of symbols for the weights. For example, six qualitative levels of importance for the weights are used, indicated by frequently symbols such as: E = essential, * = extremely important, # = very important, + = important, | = marginally important and 0 = not important. The weight of a criterion determines the range of values that can be used to measure an evaluand’s performance. For a criterion weighted with #, for example, the evaluand can only be judged #, +, |, or 0, but not *. Therefore, lower-weighted criteria cannot overpower higher-weighted criteria.

To evaluate the results, different symbols given to each evaluand are counted. For example, the result of an evaluand can be 2*, 3#, 3|, indicating that 2 criteria were judged by *, 3 criteria were judged by #, and 3 criteria were judged by |. The evaluands can now be ranked according to these numbers. However, sometimes the ranking is not clear. There is no doubt that 3*, 4#, 2| is better than 2*, 4#, 2| but it is not clear whether it is better than 2*, 6#, 1+. In such a case, the evaluation approach shows that more detailed analysis of the two products is necessary in order to find out which one fits better to the predefined needs. If results of more than two evaluands cannot be clearly ranked, then a pairwise comparison is necessary.

4.2.2 Evaluation Process

For this evaluation, the QWS approach was selected because of its characteristic to highlight the strengths and limitations of the systems and therefore provide more detailed information for obtaining a result. The approach was adapted in a way that the essential criteria were assessed in a pre-evaluation phase, similar to the evaluation conducted by Baumgartner, Häfele and Maier-Häfele (2002). These minimum criteria cover general usage requirements and didactical objectives of LMSs. Three minimum criteria were defined concerning the usage of LMSs: an active community, a stable development status, and a good documentation of the system. An active community shows that the system is supported as well as used by many other people, indirectly indicating a good quality of the system. Furthermore, an active community can provide support in case of problems and questions. An indication for an active community is the number of used systems as well as the activities in user forums, web logs and discussion groups. A stable development status indicates a reliable and not error-prone product, which is executable in an operational environment. The availability of good documentation is crucial for the installation and customisation of the system; otherwise there is a high degree of dependence on the LMS community. The minimum criterion for the didactical objective of the system was that the system's focus has to be on the presentation of content instead of communication functionalities.

At the beginning of the evaluation, 36 open source LMSs were selected and evaluated according to the mentioned minimum criteria. The following nine LMSs met all four criteria:

- *ATutor*, version 1.4.1 (ATutor, 2007; Gray, 2002),
- *Dokeos*, version 1.5.5 (Dokeos, 2007),
- *dotLRN*, version 2.0.3 (dotLRN, 2007), based on *OpenACS*, version 5.1.0 (Calvo, Ghiglione, and Ellis, 2003; OpenACS, 2007),
- *ILIAS*, version 3.2.4 (ILIAS, 2007),
- *LON-CAPA*, version 1.1.3 (LON-CAPA, 2007),

- *Moodle*, version 1.4.1 (Moodle, 2007),
- *OpenUSS*, version 1.4 (OpenUSS, 2007) extended with *Freestyle Learning*, version 3.2 (Freestyle Learning, 2007; vom Brocke, 2001),
- *Sakai*, version 1.0 (Sakai, 2007), and
- *Spaghettilearning*, version 1.1 (Spaghettilearning, 2005), now known as Docebo (Docebo, 2007)

Subsequently, these nine LMSs were tested in detail. An example course, simulating a real life teaching situation by creating courses, managing users, and simulating course activities, was designed and conducted using each system.

Finally, to evaluate the nine LMSs, their characteristics were divided into eight categories, which are described in Table 4.1. These categories act merely as a classification and include several subcategories. The subcategories were then weighted and evaluated based on the experience from the usage of each LMS when conducting the example course. Several attributes were used for measuring the performance of each subcategory. Furthermore, a rule was defined for each subcategory, which determines how the values of the attributes were combined to the performance value of the respective subcategory in the form of the 5 symbols (*, #, +, |, or 0). According to the QWS approach, the symbols for each subcategory were then summarised for each category by counting how often each symbol occurs. The resulting sequence of symbols can be seen as the performance value of the category of the respective LMS. For building the performance value for the LMS, again all symbols of all categories were summarised.

Table 4.1: Evaluation categories for evaluating LMSs

Categories	Description
Communication Tools	Functionality, features, and usability of the following communication tools: forum, chat, messages, announcements, conferences, and collaboration; availability of synchronous and asynchronous communication tools
Learning Objects	Functionality, features, and usability of the authoring tool for creating learning objects such as tests, learning material, exercises, and others; features and options for importing learning objects
Management of User Data	Storage and presentation of user data and user behaviour: tracking, statistics, identification of online users, and personal user profiles
Usability	Quality of user-friendliness, support, documentation, and assistance in the system
Adaptation	Available functions and handling of adaptability, personalisation, extensibility, and adaptivity
Technical Aspects	Technical realisation and requirements: standards, system requirements, security, and scalability
Administration	Functionality and usability of administrational aspects: user management, authorisation management, and setup of the system
Course Management	Functionality and usability of course management aspects: administration of courses, assessment of tests, and organisation of learning objects and communication tools

4.2.3 Adaptation Capabilities

This section presents the adaptable and adaptive features of the evaluated LMSs, and shows how easily the systems can be extended. The focus is on customisable adaptation only, which can be done without programming skills. Four subcategories were used in the adaptation category: adaptability, personalisation, extensibility, and adaptivity. These subcategories are described in more detail in the following paragraphs, pointing out the evaluated attributes. Subsequently, the results of the adaptation category are presented.

Adaptability includes all facilities to customise the system for the educational institutions' needs. One important feature concerns the design of the LMS and the options to change it, for example, by predefined templates or by adapting the design according to the corporate identity of the institution. Another feature is the multi-language functionality that provides the ability to support multiple languages within the same LMS. Additionally, the subcategory assesses whether the system is translated completely into another language or a mixture of English and a second language is presented. Furthermore, the user-friendliness is considered.

Personalisation indicates the facilities of each individual user to customise his/her own view (e.g., the design or the language) of the system.

Extensibility is, in principle, possible for all open source products. Nevertheless, there might be big differences in its realisation. For example, the programming style is a crucial criterion. Also, the availability of documented application programming interfaces (API) can facilitate the extension of the systems. In some communities, detailed guidance for extending the system exists or even templates are available. The basic intention of these forms of assistance is that the extended features can be integrated into subsequent versions of the system. Thus, templates ensure the compatibility of the extension for future versions.

Adaptivity indicates all kinds of automatic adaptation to the individual learners' needs. The list of features in this subcategory is short because at present time there is very little adaptivity available in the existing LMSs. One feature deals with the possibility to adapt the content of courses automatically to the learners' needs. Another feature incorporates personal annotations, for example, annotating learning objects as already visited or as too difficult to visit. Annotations in the area of communication tools are considered as well.

The evaluation results of the adaptation category are presented in Table 4.2. The *maximum values* represent the symbols, which can be achieved at maximum per subcategory. Examining the results from the perspective of subcategories, it can be seen that the adaptability and the personalisation subcategories yield a broad range of results. The majority of the systems were estimated as very good with regard to extensibility. In contrast, adaptivity features are underdeveloped. The majority of LMSs does not consider adaptivity at all.

Table 4.2: Results of the adaptation category

	Adaptability	Personalisation	Extensibility	Adaptivity	Ranking
Maximum values	*	#	*	*	
ATutor	|	#	#	|	3
Dokeos	|	0	*	+	2
dotLRN	+	+	*	0	2
ILIAS	+	#	*	0	2
LON-CAPA	+	#	#	|	2
Moodle	#	+	*	|	1
OpenUSS	#	#	#	0	2
Sakai	0	0	*	0	3
Spaghettilearning	+	#	+	0	3

Looking at the results in a system specific way, it can be seen that it is difficult to achieve an exact ranking from the results of the QWS approach. Therefore, a pairwise comparison of the results of all systems was conducted and systems were divided according to their results in groups.

As a result of the pairwise comparison, Moodle can be seen as the best LMS concerning adaptation issues. Moodle provides an adaptive feature called “lesson” where learners can be routed automatically through pages depending on their answer to a question after each page. Furthermore, the extensibility is supported very well by a documented API, detailed guidelines, and templates for programming. Also, adaptability and personalisation aspects are included in Moodle. Templates for themes are available and can be selected by the administrator. Furthermore, students can choose from more than 40 languages.

OpenUSS is the only system, which obtained a similar estimation to Moodle in this category. Due to the comparisons with other systems, OpenUSS is ranked in the second group, together with Dokeos, dotLRN, ILIAS, and LON-CAPA. ATutor, Sakai, and Spaghettilearning rank last because their evaluation values were in all pairwise comparisons either worse or equal to all other systems.

Stressing the adaptivity feature, Dokeos is the only system which achieved a moderate value. Dokeos provides annotation links for learning objects and shows personal news like the availability of new topics in the forum, new agenda items, or new documents on the course overview pages.

4.2.4 Results of the Overall Evaluation

This section presents the overall evaluation results. Table 4.3 shows the results for each LMS and each subcategory, classified by categories. The best results of each category are highlighted. Moodle dominates the evaluation by achieving the best rating five times. The strengths of Moodle are the realisation of communication tools, the creation and administration of learning objects, the management of user data, usability aspects, and adaptation issues. For management of user data, Spaghettilearning achieved a rating which can be seen as equal to the rating of Moodle. ILIAS obtained the best rating for technical aspects, administration, and course management. The system dotLRN achieved a similar rating as ILIAS for the technical aspects and LON-CAPA obtained a similar rating as ILIAS for the course management.

Table 4.3: Evaluation results for each subcategory of the investigated LMS

<table>
<tr><th></th><th colspan="7">Communication tools</th><th colspan="5">Learning objects</th><th colspan="4">Management of user data</th><th colspan="4">Usability</th><th colspan="4">Adaptation</th><th colspan="4">Technical aspects</th><th colspan="3">Adminis-tration</th><th colspan="3">Course management</th></tr>
<tr><th>Subcategories</th><th>Forum</th><th>Chat</th><th>Mail/Messages</th><th>Announcements</th><th>Conferences</th><th>Collaboration</th><th>Synchronous & asynch. tools</th><th>Tests</th><th>Learning material</th><th>Exercises</th><th>Other creatable LOs</th><th>Importable LOs</th><th>Tracking</th><th>Statistics</th><th>Identification of online users</th><th>Personal user profile</th><th>User-friendliness</th><th>Support</th><th>Documentation</th><th>Assistance in the system</th><th>Adaptability</th><th>Personalisation</th><th>Extensibility</th><th>Adaptivity</th><th>Standards</th><th>System requirements</th><th>Security</th><th>Scalability</th><th>User management</th><th>Authorisation management</th><th>Setup of the system</th><th>Administration of courses</th><th>Assessment of tests</th><th>Organisation of course objects</th></tr>
<tr><td>Maximum values</td><td>*</td><td>*</td><td>|</td><td>+</td><td>+</td><td>+</td><td>*</td><td>*</td><td>*</td><td>#</td><td>+</td><td>*</td><td>*</td><td>+</td><td>+</td><td>#</td><td>#</td><td>#</td><td>+</td><td>+</td><td>*</td><td>#</td><td>*</td><td>*</td><td>#</td><td>+</td><td>*</td><td>+</td><td>#</td><td>*</td><td>|</td><td>+</td><td>#</td><td>#</td></tr>
<tr><td>ATutor</td><td>|</td><td>#</td><td>|</td><td>|</td><td>0</td><td>0</td><td>*</td><td>|</td><td>*</td><td>0</td><td>+</td><td>*</td><td>*</td><td>+</td><td>|</td><td>|</td><td>+</td><td>|</td><td>+</td><td>+</td><td>|</td><td>#</td><td>#</td><td>|</td><td>+</td><td>+</td><td>0</td><td>0</td><td>0</td><td>|</td><td>|</td><td>|</td><td>|</td><td>#</td></tr>
<tr><td>Dokeos</td><td>+</td><td>*</td><td>0</td><td>|</td><td>+</td><td>0</td><td>*</td><td>*</td><td>*</td><td>0</td><td>+</td><td>*</td><td>+</td><td>|</td><td>0</td><td>|</td><td>+</td><td>#</td><td>+</td><td>+</td><td>|</td><td>0</td><td>*</td><td>+</td><td>+</td><td>+</td><td>0</td><td>0</td><td>#</td><td>0</td><td>|</td><td>|</td><td>|</td><td>#</td></tr>
<tr><td>dotLRN</td><td>#</td><td>0</td><td>|</td><td>+</td><td>0</td><td>0</td><td>0</td><td>|</td><td>0</td><td>0</td><td>+</td><td>|</td><td>0</td><td>0</td><td>+</td><td>|</td><td>|</td><td>|</td><td>+</td><td>0</td><td>+</td><td>+</td><td>*</td><td>0</td><td>+</td><td>+</td><td>*</td><td>+</td><td>|</td><td>#</td><td>0</td><td>+</td><td>0</td><td>+</td></tr>
<tr><td>ILIAS</td><td>+</td><td>*</td><td>|</td><td>0</td><td>0</td><td>0</td><td>*</td><td>*</td><td>|</td><td>0</td><td>+</td><td>*</td><td>|</td><td>|</td><td>+</td><td>+</td><td>|</td><td>|</td><td>+</td><td>0</td><td>+</td><td>#</td><td>*</td><td>0</td><td>#</td><td>+</td><td>*</td><td>0</td><td>#</td><td>*</td><td>|</td><td>+</td><td>+</td><td>+</td></tr>
<tr><td>LON-CAPA</td><td>+</td><td>*</td><td>|</td><td>|</td><td>0</td><td>0</td><td>*</td><td>+</td><td>|</td><td>|</td><td>|</td><td>*</td><td>|</td><td>|</td><td>0</td><td>+</td><td>0</td><td>#</td><td>0</td><td>+</td><td>+</td><td>#</td><td>#</td><td>|</td><td>0</td><td>+</td><td>+</td><td>0</td><td>+</td><td>+</td><td>0</td><td>|</td><td>#</td><td>#</td></tr>
<tr><td>Moodle</td><td>*</td><td>*</td><td>0</td><td>+</td><td>0</td><td>+</td><td>*</td><td>*</td><td>*</td><td>#</td><td>+</td><td>*</td><td>*</td><td>|</td><td>+</td><td>+</td><td>#</td><td>#</td><td>+</td><td>+</td><td>#</td><td>+</td><td>*</td><td>|</td><td>#</td><td>+</td><td>+</td><td>+</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td><td>|</td></tr>
<tr><td>OpenUSS</td><td>#</td><td>*</td><td>0</td><td>+</td><td>0</td><td>|</td><td>*</td><td>0</td><td>|</td><td>0</td><td>+</td><td>#</td><td>0</td><td>0</td><td>+</td><td>+</td><td>+</td><td>+</td><td>|</td><td>+</td><td>#</td><td>#</td><td>#</td><td>0</td><td>0</td><td>+</td><td>|</td><td>+</td><td>0</td><td>0</td><td>0</td><td>0</td><td>|</td><td>#</td></tr>
<tr><td>Sakai</td><td>#</td><td>*</td><td>0</td><td>|</td><td>0</td><td>0</td><td>*</td><td>0</td><td>*</td><td>#</td><td>|</td><td>*</td><td>*</td><td>0</td><td>|</td><td>|</td><td>#</td><td>|</td><td>|</td><td>0</td><td>0</td><td>0</td><td>*</td><td>0</td><td>0</td><td>+</td><td>+</td><td>+</td><td>0</td><td>+</td><td>|</td><td>+</td><td>0</td><td>0</td></tr>
<tr><td>Spaghettilearning</td><td>|</td><td>*</td><td>|</td><td>|</td><td>0</td><td>0</td><td>*</td><td>+</td><td>0</td><td>0</td><td>|</td><td>*</td><td>*</td><td>+</td><td>+</td><td>|</td><td>+</td><td>+</td><td>|</td><td>+</td><td>+</td><td>#</td><td>+</td><td>0</td><td>0</td><td>+</td><td>+</td><td>0</td><td>|</td><td>0</td><td>|</td><td>|</td><td>|</td><td>0</td></tr>
</table>

To get the overall evaluation result, the symbols of each category need to be summarised. Figure 4.1 shows the results of the systems in a descending order. Similar to the adaptation category, it is not possible to assign an exact rank for each system. However, it can be seen that Moodle clearly achieved the best evaluation values. Moodle outperforms all other systems in a pairwise comparison due to the low number of unavailable or very poor features and the high number of very good features. Also the second and third rank can be identified clearly. ILIAS surpasses all systems except Moodle and therefore, is ranked as the second best system. Dokeos yields only worse evaluation values than Moodle and ILIAS and is therefore ranked at the third position. ATutor is ranked at the fourth position, together with LON-CAPA, Spaghettilearning, and OpenUSS. Sakai and dotLRN are ranked last because these systems obtained either a worse or an equal estimation in each pairwise comparison. Taking a closer look at the evaluation results of Sakai, it can be seen that there are lots of features estimated as very good but also a large number of features which are not available or very poorly implemented. The reason for this is that Sakai is a new LMS and in the evaluated version only the basic features are implemented. However, the quality of so far implemented features is very good.

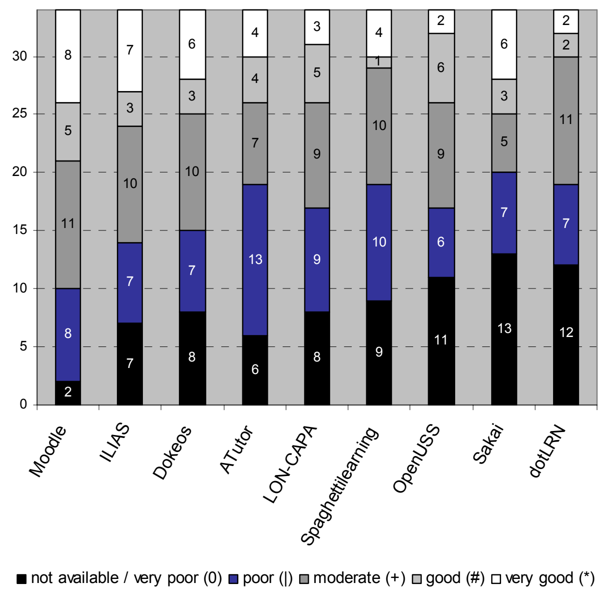

Figure 4.1: Overall evaluation results

Summarising the results of the evaluation, Moodle achieve the best ratings and can be seen as the best system with respect to overall functionality and usage as well as adaptation aspects. Therefore, Moodle was selected as prototype for further investigations and developments, aiming at extending Moodle in a way that it is able to incorporate learning styles. Investigations are based, on one hand, on detecting learning styles from the behaviour of learners in the system and, on the other hand, on enabling the system to generate adaptive courses based on the learners' learning styles.

Although this evaluation was conducted in 2005 and many new versions of the investigated LMSs were released in the meantime, Moodle can still be seen as one of the leading LMSs. Currently, more than 35000 Moodle sites from 196 countries are registered and universities such as the Open University (UK), Athabasca University (Canada), and Vienna University of Technology (Austria) switched to Moodle as their official LMS in the last few years.

4.3 Benefits of the Felder-Silverman Learning Style Model (FSLSM) for the Use in Learning Management Systems

While the previous section focused on selecting a learning management system this section deals with the selected learning style model. As mentioned in Chapter 2, many different learning style models exist in literature. The research about incorporating learning styles in LMSs in this thesis is based on the Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988). In this section, argumentation is provided on the benefits of FSLSM over other learning style models in the context of improving technology enhanced learning by incorporating learning styles in online learning and providing adaptivity based on learning styles.

FSLSM combines several major learning style models. Each of the four dimensions of FSLSM (active/reflective, sensing/intuitive, visual/verbal, and sequential/global) is quite strongly influenced by other learning style models such as the learning style model by Kolb (1984), Pask (1976b) as well as the Myers-Briggs Type Indicator (Briggs Myers, 1962). Although the dimensions themselves are not new, the way in which they are combined and describe the learning styles of students can be seen as new. As mentioned in Section 2.1.10, a student's learning style is described by his/her preference on each of the four dimensions, measured on values between +11 to -11, in steps of +/-2. This enables a quite detailed description of the students' learning styles. In contrast, most other learning style models use few types to describe students' preferred learning styles.

Having a more detailed description of the students' learning styles allows providing more accurate adaptivity. If only the preferred type is known, this information does not include how strong the student belongs to this type. If the student's preference is weak and quite close to another type, his/her needs might be different than for a student who has a strong preference for the same type. By using a scale between +11 and -11 for each dimension, the strength of the learning style preference is measured and can be incorporated when providing adaptivity. Therefore, also a weak learning style preference can be represented and handled. The differentiation between strong and weak preferences is especially important when dealing with more than one dimension. In this case, the dimensions can have overlapping or even contrary implications for providing adaptivity. Therefore, differentiation is essential in order to be able to focus on providing courses that support the strong learning style preferences.

As described in Chapter 2, the stability of learning styles is a controversial issue. While some learning style models consider learning styles as stable over time, subject, and environment, others claim that they can change quite frequently. FSLSM considers learning styles as "flexibly stable", arguing that previous learning experiences and other environmental factors form the learning styles of students (Felder and Spurlin, 2005). Accordingly, learning styles tend to be more or less stable but can change over time, for example, if students train their weak preferences. Due to the more or less stable character of learning styles according to FSLSM, an adaptive system can adjust to the students' learning styles and provide them with adaptive content that supports them in learning. On the other hand, due to the possibility to change students' learning styles, adaptivity can also be used in order to achieve a long term goal of learning, namely to enhance and train students' weak abilities in order to enable them to learn also from material that does not match their preferred learning styles. This thesis focuses on the first issue, namely on providing students with adaptive courses that fit to their learning styles and prove the effectiveness of such an approach in terms of showing that students benefit from courses that match their learning styles. The results of these investigations can be seen as a requirement for the second issue since they show that different courses have different effects on learning for students.

Furthermore, FSLSM is different from other learning style models in terms of considering learning styles as tendencies, meaning that students have a tendency for a specific learning style but might act in some situations differently. By incorporating the concept of tendencies, the description of learning styles considers also exceptions and extraordinary situations. However, the concept of tendencies implies on the other hand that the student modelling approach has to consider that, for example, a student with an active learning style also acts sometimes in a reflective way. Furthermore, with respect to adaptivity, it shows that, when recommending students an adaptive course, at the same time students need to be provided with the opportunity to access all available resources in a course rather than restricting students to the recommended material.

Besides, FSLSM is often used in technology enhance learning and also in adaptive systems. As can be seen from the description of adaptive systems considering learning styles in Section 3.2, FSLSM is the most often used learning style model, where some systems incorporate the whole model and some systems include only some dimensions of FSLSM. Furthermore, some researchers even argue that FSLSM is the most appropriate learning style model for technology enhanced learning (Carver, Howard, and Lane, 1999; Kuljis and Liu, 2005).

4.4 Investigating the Behaviour of Learners in Learning Management Systems with Respect to their Learning Styles

Before investigating how learning styles can be incorporated in LMSs, a study was conducted dealing with analysing the behaviour of students in an online course with respect to their learning styles. Felder-Silverman learning style model as well as many other learning style models points out that different students have different needs and preferences for learning. However, most learning style models, including FSLSM, are proposed for traditional learning rather than for online learning. In this section, investigations about the behaviour of students in an online course within Moodle are described.

The performed study aims at two issues: Firstly, investigations were performed on whether students with different learning style preferences act differently in the online course. The results show the different preferences and needs of students with different learning styles. Since LMSs currently provide the same course for each student, these results can act as the catalyst to make teachers and course developers aware of the needs of their students in order to incorporate these needs into the course development process by providing features for each learning style. Furthermore, the results can be used as recommendation for providing adaptivity based on learning styles in LMSs.

Secondly, investigations were performed with respect to correlations between the learning style preferences and the behaviour of the students in the course. From these correlations, it is not only possible to draw conclusions from learning style preferences to the behaviour but also to obtain indications from the behaviour of students about their learning style preferences. These results can be seen as a basis for further investigations towards identifying learning styles in LMSs based on the actual behaviour of students during an online course.

A general aim of the study is to make the results applicable for other LMSs as well. Therefore, patterns of behaviour were derived, which on one hand seem to be relevant with respect to the learning style model and on the other hand, are based on commonly used features in LMSs. The investigated patterns are described in detail in the next subsection. Subsequently, the design of the study, the results, and the benefits obtained from the results of the study are discussed.

4.4.1 Investigated Patterns of Behaviour

The aim of this study is to analyse the behaviour of students in an online course with respect to their learning styles. FSLSM is based on traditional learning rather than online learning and therefore describes the preferences of students in traditional learning environments. To apply FSLSM in online environments, some sort of mapping between the behaviour in traditional environments and in online environments is necessary. Therefore, patterns in online environments were chosen which are related to the traditional behaviour and were tested for significance with respect to learning styles.

Additionally, the findings of this study should be applicable for LMSs in general rather than only for Moodle. Since different LMSs provide teachers and course developers with the opportunity to integrate different features in an online course, only those features which are implemented in most LMSs and which are also commonly used by teachers and course developers were used in these investigations.

The incorporated features include content objects, outlines, examples, self-assessment tests, exercises, and discussion forums. Furthermore, general navigation preferences of students in the course as well as the sequence in which they visited specific features were investigated. Regarding the sequence, additionally the students' navigation behaviour with respect to marked assignments was considered. In the following paragraphs, a brief description of the features as well as the related patterns to each feature is provided.

Content objects are used to present the content of the course. These content objects can have different formats, depending on the LMS. For example, content can be presented as html-files or pdf-files. Patterns related to the content objects include the number of visits (*content_visit*) as well as the time learners spent on content objects (*content_stay*). Additionally, the time learners spent on content objects including graphics were tracked.

Furthermore, patterns regarding *outlines* of chapters were considered since outlines are explicitly mentioned in FSLSM. Therefore, the number of visits of outlines (*outline_visit*) and the time learners spent on it (*outline_stay*) were included as patterns.

Another feature dealt with *examples.* Examples aim at illustrating the theoretical content in a more concrete way. Again, the number of visits (*example_visit*) and the time learners spent on these objects (*example_stay*) were used as patterns.

Furthermore, *self-assessment* tests were included where students can check their acquired knowledge. Regarding these tests, more detailed information was considered such as the number of questions a learner answered (*selfass_visit*), whether a learner performed all available tests at least once (*selfass_visit_different*), the results a learner achieved (*selfass_performance*), how often a learner revised his/her answers before submitting (*quiz_revisions*), how long a learner spent on the tests (*selfass_stay*), and how long a learner checked his/her results (*selfass_stay_results*). Furthermore, the questions contained in a test can be about facts or concepts, refer to an overview or to details, can be based on graphics rather than on text, or deal with interpreting or developing solutions. The results learners achieved on each kind of questions acted as pattern as well (e.g., *ques_facts*, *ques_concepts*, *ques_details*, and so on).

Another element included *exercises* which serve as practice area where students can try things out or answer questions about interpreting predefined solutions or developing new solutions. The number of visits (*exercise_visit*) and the time students spent on exercises (*exercise_stay*) was considered as pattern. Information about the number of revisions (*quiz_revisions*) as well as students' performance on interpreting (*ques_interpret*) and developing solutions (*ques_develop*) was gathered and combined with the data from self-assessment tests.

For communication issues, *discussion forum* was considered. As patterns, the number of visits to the forum (*forum_visit*), how long learners stayed at the forum (*forum_stay*), and how many messages they posted (*forum_post*) were incorporated.

Additionally, the *navigation* between learning objects as well as the number of logins in the course was incorporated. Information about how often learning objects were skipped in the course sequence by using the navigation menu (*navigation_skip*), how often learners jumped back to the previous learning object (*navigation_back*), as well as how often (*navigation_overview_visit*) and how long they stayed at the course overview page (*navigation_overview_stay*) were considered as patterns.

Furthermore, patterns regarding the *sequence*, in which learners visited specific types of learning objects, were incorporated. The study considered which type of learning object was visited first (e.g., *sequence_content_first*, *sequence_outline_first*, and so on) and last (e.g., *sequence_content_last*, *sequence_outline_last*, and so on) in a course chapter, distinguishing between content objects, outlines, self-assessment tests, exercises, examples, and marked assignments. Marked assignments were considered only in the context of students' navigation behaviour and can be implemented, for example, as questions which have to be answered online or just as a description about what the assignment is about and a possibility for students to upload their answers. Moreover, the order in which content objects, self-assessment tests, exercises, and examples were visited, was used as pattern by comparing, for instance, in how many course chapters a student was visiting a content object before he/she was performing a self-assessment test (*sequence_content/selfass*). This was done for all combinations of the four features, resulting in six patterns (e.g., *sequence_content/exercise*, *sequence_exercise/example*, and so on).

4.4.2 Design of the Study

In this section, information about the design of the study is provided. Although Moodle provides already quite comprehensive tracking mechanisms, some extensions were necessary in order to track all information that we aimed at investigating in the study. These performed extensions in Moodle are described in the next subsection. Subsequently, the investigated course, which deals about Web Engineering, and its structure are described. For investigating the behaviour of students during the course with respect to their learning styles, the ILS questionnaire (Felder and Soloman, 1997) was used. This questionnaire is introduced in more detail in the subsequent subsection.

4.4.2.1 Extensions in Moodle for Tracking Learners' Behaviour

In order to make the results applicable for most LMSs, only commonly used features of LMSs were incorporated. On the other hand, the investigations about the behaviour regarding these features asked for detailed information. Although Moodle provides much information about learners' behaviour in the courses, the need for some extensions emerged. These extensions focused on two issues. On the one hand, they dealt with getting additional descriptions about the learning material in order to distinguish it and be able to draw conclusions about students' behaviour related to specific types of learning material. On the other hand, extensions dealt with improving tracking mechanisms.

In the following two subsections, the conducted extensions to Moodle are described. These extensions enable Moodle to deliver all required information for this study. The extensions were developed for Moodle version 1.4.4.

Extensions regarding Additional Meta-Data

Moodle provides a great number of different features to include in an online course. For the investigations and with respect to the above introduced patterns, only some of these features are of particular interest, namely the resources, the quiz, the assignments, and the forum. In Moodle, learning material regarding all proposed features can be created by using these four different types of learning objects. But for investigations regarding the learners' behaviour, the learning material has to be distinguished with respect to the proposed features, and for some features, an additional description of the material is necessary. In most cases, this differentiation and additional descriptions are not supported by Moodle. Our extensions address these issues and are discussed in the following paragraphs.

The concept of resources in Moodle can be used for presenting content, an outline of a chapter, and an example. For distinguishing between content and outlines, the authoring tool of Moodle was extended by including the possibility for teachers and course developers to specify information about the created learning material by the use of meta-data. When creating a content object or outline, teachers and course developers are asked to specify whether the learning objects can be considered as content object or outline by simply using a checkbox. Furthermore, teachers and course developers are provided with the opportunity to specify whether the material includes graphics. Regarding examples, additionally the text within the examples has to be displayed exactly in the way it is written. This is especially important for courses about programming languages, such as Web Engineering, where the example might include source code that can be executed within the browser. Since the source code in an example should be displayed as it is instead of executing it and displaying the result of the source code, a new type of learning object was created based on the type resource, consisting of a link to a file, but with the difference that the text in an example is displayed exactly as it is.

In Moodle, quizzes can represent self-assessment tests as well as exercises. The difference between exercises and self-assessment tests is that former is more practically oriented with the aim that learners solve tasks and get feedback about their solutions. In contrast, self-assessment tests focus on theoretical issues and can be used to check whether a learner understands the learning material. While the purpose of these two types of quizzes is different, their structure is quite similar. Therefore, it is again necessary to distinguish between these types by the use of meta-data. Thus, Moodle was extended to provide the possibility for teachers and course developers to specify whether they create a self-assessment test or exercise. Additionally, each question in a quiz can be specified according to whether it is about facts or concepts, refers to an overview or to details, is based on graphics rather than on text, and asks students to interpret an existing solution or develop a new solution to a problem. This detailed specification provides information about which type of question a learner handles easily or with difficulty. Again, the teachers and course developers are asked to describe their created questions by meta-data, using a checkbox for specifying the type of question.

Regarding the discussion forum and the marked assignments, no modifications were necessary.

Due to the proposed extensions, Moodle is able to distinguish between all recommended features and provides additional meta-data to describe them. These extensions are a requirement for tracking the behaviour of learners with respect to the proposed features.

Extensions regarding Tracking Activities

Moodle provides comprehensive tracking functions. For each action a learner performs, for example, visiting a particular learning object, an entry is done in a log table in the database, including several information such as the user-id, the action itself, the learning object, and a timestamp. Based on the tracked data in Moodle, for most of the proposed patterns the required data can be extracted from the database. Consequently, only one extension was necessary. This extension deals with the pattern about revisions when learners answer questions in self-assessment tests or exercises. Moodle only tracks the final answers to questions. In order to get more detailed information about what learners are doing during a test, the tracking function was extended by storing each answer which is given by a learner, even if this answer is revised later. When the question asks for a textual answer rather than for choosing between predefined options, additionally the sequence of keys is tracked with attention to the delete and backspace key. These additional data provide information about how often students are revising their answers before submitting a quiz.

In order to make information extraction regarding time spans easier, another extension was conducted. This extension deals with including an additional field *duration* in the log table. As mentioned before, for each learning object (or page) a learner is visiting, an entry is done in the log table. For each entry, a time stamp is stored. The field *duration* is based on this time stamp and the time stamp of the previous visited learning object and shows how long a learner actually stayed at the respective learning object.

4.4.2.2 Description of the Course

The study is based on data from a laboratory course about Web Engineering which was taught at a university in Austria in summer term 2006. The course was divided into two parts, XML and Java. Only for the XML part, all features which were mentioned in Section 4.4.1 such as content object, examples, exercises and so on, were included in Moodle. Therefore, the investigations deal only with the XML part of the course.

The XML part itself consisted of three chapters that included 182 content objects (including 39 graphics) and 14 examples. Students could solve 8 different exercises which allowed them to parse their entered source code and provided the students with feedback. Self-assessment tests were provided for five topics, and included 123 questions overall.

Each chapter also included one marked assignment which had to be done in groups of two. Few days after the submission, each student had to present the solution individually and had to answer questions about it. At the end of the course, each student had to pass a written exam. Although parts of the assignments were done in groups of two, the course was designed in a way that all students needed to learn everything and they were examined on all topics; hence the course was appropriate for investigation of individual learning.

4.4.2.3 Index of Learning Styles Questionnaire

The Index of Learning Styles (ILS) questionnaire is developed for identifying learning styles based on FSLSM and consists of 44 questions (Felder and Soloman, 1997). As mentioned earlier, according to FSLSM each learner has a personal preference for each of the four dimensions. These preferences are expressed by values between +11 to -11 per dimension, with steps of +/-2. This range comes from the 11 questions that are posed for each dimension. When answering a question, for instance, with an active preference, +1 is added to the value of the active/reflective dimension, whereas an answer for a reflective preference decreases the value by 1. Therefore, each question is answered either with a value of +1 (answer *a*) or -1 (answer *b*). Answer *a* corresponds to the preference for the first pole of each dimension (active, sensing, visual, or sequential) and answer *b* to the second pole of each dimension (reflective, intuitive, verbal, or global).

The ILS questionnaire is an often used and well-investigated instrument to identify learning styles. Felder and Spurlin (2005) provided an overview of studies dealing with analysing the response data of the ILS questionnaire regarding the distribution of preferences for each dimension as well as with verifying the reliability and validity of the instrument. Although few studies (e.g., Van Zwanenberg, Wilkinson, and Anderson, 2000; Viola et al., 2007) exist where open issues arose such as weak reliability and validity as well as dependencies between some learning styles, Felder and Spurlin concluded that the ILS questionnaire is a reliable and valid instrument and suitable for identifying learning styles according to FSLSM.

4.4.3 Results

Two different issues were investigated within this study: Firstly, the given data were analysed in order to draw conclusions about whether students with different learning styles, or more precisely with different preferences for the questions of the ILS questionnaire, act differently in the online course. Secondly, the investigations aimed at finding correlations between the answers to the questions and the behaviour of students during the course.

43 students participated in the study. Since all students had either a visual or a balanced learning style and no student indicated a verbal style, further investigations are focused only on the active/reflective, sensing/intuitive, and sequential/global dimension. For statistical analysis, the SPSS software package, version 12, was used (SPSS, 2007).

4.4.3.1 Behaviour vs. Learning Style Preferences

In order to identify significant differences of behaviour in the online course from different answers to questions of the ILS questionnaire, the students were divided for each question, according to their answer (+1 or -1), into two groups. Then these two groups were tested respectively for significant difference for each pattern of behaviour described in Section 4.4.1.

Two tailed t-test was applied for patterns where data were normal distributed and two tailed Mann-Whitney U test (u-test) for patterns where data were not normal distributed. To check whether data were normal distributed, Kolmogorov-Smirnov test was used.

The results are presented in Table 4.4. Only significant values ($p<0.05$) are shown. The table shows the patterns and respectively the ILS questions which lead to a significant result according to t-test or u-test. The T and U values as well as whether t-test or u-test was conducted, the significance level (p), and the direction of the relationship is presented. Regarding the direction, 1 indicates that a high value concerning the pattern refers to the group answered the ILS question with +1 and vice versa.

Regarding the patterns dealing with visiting specific features first or last in a course chapter, only those patterns were included where data from more that 5 students are available. Therefore, only assignments and examples were considered with respect to the first visited learning object, and content objects, examples, self-assessments, exercises, and assignments were considered regarding the last visited learning object.

In the following discussion, for all significant results the respective question is in semantic relation with the pattern unless mentioned otherwise.

Active/Reflective Dimension

According to the results of the active/reflective dimension, spending more time on examples and dealing more intensively with outlines (visiting and spending time) seems to be significant for reflective learning. These findings are in agreement with FSLSM, since reflective learners are described as learners who think and reflect more deeply about the provided learning material.

When looking at the sequence of visited learning objects, a significant preference was found for learners with a reflective preference, indicating that they preferred to visit examples first and then perform exercises. In contrast, learners with an active preference tend to perform exercises first and looked then at examples. While this preference is only in indirect semantic relation with the respective question, it is in agreement with FSLSM, since active learners prefer to try things out and work actively, as they can do with exercises. By looking at examples, active learners see how others have solved a problem rather than try to solve the problem by themselves. Therefore, they seemed to prefer exercises over examples and focused on exercises first. On the other hand, reflective learners gain more from examples, where they can reflect on an already given solution. Therefore, they looked at examples first and afterwards performed exercises.

Table 4.4: Patterns indicating significant differences in students' behaviour based on their learning style preferences regarding ILS questions

	Pattern	Question	t-test/ u-test	T or U	p	Direction
Active / Reflective	outline_visit	q29	t	-2.24	0.031	-1
	outline_stay	q29	u	65.50	0.002	-1
	example_stay	q33	u	143.50	0.045	-1
	selfass_visit	q5	u	154.00	0.050	1
	selfass_stay_results	q5	u	25	0.007	-1
	ques_facts	q5	t	3.21	0.005	1
	ques_interpret	q9	t	-3.32	0.004	-1
	forum_visit	q25	t	-2.92	0.006	-1
	navigation_overview_stay	q13	t	2.17	0.036	1
	navigation_overview_stay	q25	t	-3.02	0.005	-1
	sequence_selfass_last	q25	u	177.50	0.043	-1
	sequence_selfass_last	q29	u	129.50	0.044	-1
	sequence_assignment_last	q13	u	164.50	0.040	1
	sequence_exercise/example	q21	u	136.50	0.049	1
Sensing / Intuitive	content_visit	q26	t	2.69	0.012	1
	outline_visit	q22	t	2.04	0.048	1
	outline_stay	q34	u	123.00	0.036	-1
	example_visit	q2	u	104.00	0.044	1
	example_stay	q10	u	111.50	0.043	1
	ques_overview	q42	t	-2.61	0.018	-1
	quiz_revisions	q10	t	2.47	0.021	1
	forum_stay	q10	t	2.79	0.008	1
	forum_stay	q22	t	2.63	0.012	1
	forum_post	q22	u	117.00	0.001	1
	navigation_back	q22	u	161.50	0.048	1
	sequence_example_first	q26	u	154.00	0.003	1
	sequence_assignment_first	q10	u	99.50	0.014	1
	sequence_example_last	q10	u	135.00	0.022	1
	sequence_example_last	q38	u	170.00	0.035	1
	sequence_content/selfass	q10	u	104.00	0.011	1
	sequence_exercise/selfass	q42	u	153.00	0.029	-1
Sequential / Global	outline_visit	q12	t	2.99	0.005	1
	outline_stay	q44	u	114.50	0.005	1
	selfass_visit_different	q36	u	101.00	0.028	1
	selfass_stay_results	q20	u	33.00	0.024	1
	ques_concepts	q44	t	-2.11	0.049	-1
	ques_graphics	q32	t	2.86	0.010	1
	quiz_revisions	q28	t	3.04	0.007	1
	forum_post	q20	u	149.00	0.014	1
	navigation_skip	q20	u	176.00	0.038	-1
	navigation_overview_visit	q44	t	-2.71	0.010	-1
	sequence_content_last	q12	u	171.00	0.021	1
	sequence_assignment_last	q24	u	145.50	0.037	-1
	sequence_assignment_last	q32	u	127.00	0.007	-1
	sequence_content/exercise	q28	u	34.00	0.020	1
	sequence_content/example	q4	u	76.50	0.038	-1

Furthermore, results show that learners with a reflective preference performed better on questions about interpreting predefined solutions. This is again in line with the argumentation above. Moreover, they spent more time on looking at the results of their self-assessment tests. Again, this behaviour can be referred to the preference of reflecting.

In addition, results also show that reflective learners visited the forum significantly more often than active learners. This is because the forum in the course was mainly used for asking and clarifying questions regarding the assignments which were then answered by a tutor or a teacher. When the forum would be used for active discussions between students, maybe active learners would visit the forum more often.

Regarding active learning, results show that learners with an active preference performed significantly more self-assessment questions than reflective learners. This is in agreement with FSLSM as well, since active learners are characterised to prefer trying things out. Results also show that active learners performed better on questions dealing with facts. Further investigations about this finding need to be done since FSLSM does not include this behaviour in their description of an active/reflective learning style and the semantic relation between behaviour and ILS question is only weak.

Considering the preferred first and last learning objects of active and reflective learners in a course chapter, results show that learners with a reflective preference seem to perform self-assessment tests more often as last object in a course chapter than active learners. In contrast, learners with an active preference tended more often to submit their assignment and then went to the next course chapter; however, this behaviour is only in weak semantic relation with the corresponding ILS question. Since the results also show that learners with an active preference performed self-assessment tests more often than learners with a reflective preference, the findings indicate that active learners used self-assessment tests as support for doing their assignments. In contrast, reflective learners were using these self-assessment tests also after the submission for preparing themselves for the presentation or the exam.

When looking at the pattern indicating how long students spent on the overview page, for one question, students answering with an active preference spent more time on it and for another question students with a reflective preference did. While in the latter case the question was in semantic relation with visiting the overview page, in the former case the question is only in weak semantic relation with the respective behaviour. However, further investigations are necessary regarding this pattern.

Sensing/Intuitive Dimension

Sensing learners are described by Felder and Silverman as learners who prefer concrete material. This can also be seen by our findings, showing that sensing learners visited more often examples and spent more time there than intuitive learners. Moreover, the results show that sensing learners started a course chapter more often with an example than intuitive learners. Also, their last visited learning object in a course chapter was more often an example than for intuitive learners. This indicates that sensing learners were using examples for their preparation for the presentation of the assignments and the written exam.

Another characteristic of sensing learners according to FSLSM is that they tend to be more patient with details and careful about their work. Looking at the pattern about revising their answers in self-assessment tests and exercises, results of the investigations show that learners with a sensing preference changed their answers significantly more often. However, this pattern was only in weak semantic relation with the corresponding question. Furthermore, results show that sensing learners spent more time in the forum and posted more often than intuitive learners. It can be argued that due to their preference for details, they wanted to clarify the specifications by asking in forums and were also interested in the questions and answers of others. Again, when the forum would be used more for discussion, these results may change. As can be seen from the results, sensing learners also tended to visit content objects and outlines more often and also navigated back more often to the previous page. This behaviour may also results from their patience and accuracy.

Another characteristic of sensing learners is that they tend to be more practical oriented and more interested in the application of the learned material in the real world. According to the results of this study, sensing learners tended to start a course chapter more often with looking at the assignment than intuitive learners did. This behaviour may be due to their interest in applications. On the one hand, the assignments present the tasks which have to be done for the course chapter, but on the other hand, assignments are programming tasks that also show how the learned material can be applied.

Intuitive learners are characterised by Felder and Silverman as learners who like challenges. From the results of this study, this is indicated by the sequence of visited learning objects. Accordingly, intuitive learners had a higher preference than sensing learners for performing self-assessment tests first and afterwards looking at the content objects. However, this behaviour is only in weak semantic relation with the corresponding question. Furthermore, the results show that intuitive learners tried to do exercises first and then performed self-assessment tests. In the setting of this study, exercises can be considered as more challenging since they ask students for programming tasks, whereas self-assessment tests provide students with the opportunity to check their theoretical knowledge about the learning material and are less comprehensive.

Two more significant patterns could be found for intuitive learners. One is dealing with the time students spent on outlines, the other one is about the results achieved for questions about overview. The second one may be explained by the preference of details for sensing learners and that they therefore performed worse than intuitive learners on questions about overview. For both patterns the corresponding question was only in weak semantic relation and further investigations are necessary with regard to FSLSM.

Sequential/Global Dimension

According to FSLSM, a main characteristic of sequential learners is that they learn in a linear way, going through the material step by step. Accordingly, our results show that learners with a sequential preference tended to cover all/more topics of self-assessment tests and that they dealt more often with outlines which indicates that they started at the beginning of each chapter rather than jumping in and starting somewhere in between. Moreover, results show that sequential learners significantly more often visited the content first and afterwards performed exercises, as it was recommended in the course structure. In contrast, global learners tend to prefer a more non-sequential path through the course material. This can be seen when looking at the results of skipping learning objects which show that global learners skipped learning objects more often.

The results also show that learners with a global preference visited more often the course overview page. This is in agreement with FSLSM, since global learners are described to prefer getting an overview of the topic/course. While for global learners the overview is very important, sequential learners are more inclined to the details. According to Felder and Spurlin (2005) as well as some other studies (e.g., Van Zwanenberg, Wilkinson, and Anderson, 2000; Viola et al., 2007), it has been shown that a correlation between the sequential/global dimension and the sensing/intuitive dimension exists. This may be caused due to the overlapping of the preference for details. Accordingly, the results of this study show that learners with a sequential preference posted more often in the forum, made more revisions when answering questions, and looked more detailed at the results of their tests. However, the last pattern was only in weak semantic relation with the corresponding question. In contrast, learners with a global preference performed significantly better on questions about concepts. Moreover, results indicate that global learners had higher preference for submitting the assignments and then going to the next course chapter. On the other hand, for sequential learners a preference for content objects as the last visited material in a course chapter was found, however this preference was only in weak semantic relation with the corresponding question. Overall, these patterns give again another indication that sequential learners tend to be more accurate and careful by preparing themselves for the presentations and the final exam after submitting the assignments.

Sequential learners seem to perform also better on questions about graphics. This might be because they remember better the details of the graphics. The behaviour is only in weak semantic relation with the corresponding question. Further investigations on this issue need to be done with respect to the relation between the pattern and FSLSM.

Another pattern, which is in weak semantic relation with the corresponding question and needs further investigations since it is not explicitly supported by FSLSM, is dealing with the preferred sequence of visiting examples and content. According to the results of this study, sequential learners visited more often examples before content objects which is not in agreement with the recommended order of the course structure but might be explained by the correlation to the sensing learning style, where examples play an important role to facilitate learning for sensing learners.

4.4.3.2 Correlations between Behaviour and Learning Style Preferences

The previous analysis pointed out relations where learners who answered questions of the ILS questionnaire differently also acted differently in the online course. In the next analysis, the correlation between both, answers of ILS questions and the behaviour of the learners in the course based on the specified patterns, was investigated. Thus, the resulting relations additionally allow drawing conclusions from the behaviour of the learners to their preferences of learning styles.

Since the values of the patterns are on a continuous scale and the possible answers to the questions of the ILS questionnaire can only be either +1 or -1, point-biserial correlation was performed. Table 4.5 presents the results of the point-biserial correlation analysis (rpb), including the respective patterns, the ILS questions, the correlation coefficient (rpb), the significance values (p) and the direction of the correlation. Again, only significant results are shown ($p<0.05$). Furthermore, with respect to patterns regarding visiting a specific type of learning object first or last in a chapter, only patterns where more than 5 students had a value greater than zero were included, as done in the previous analysis.

From the results, it can be seen that most of the significant relations found by the t-test and u-test were also found by the point-biserial correlation. Therefore, in the following subsections, only the additional relations as well as relations which were found by t-test or u-test but were not confirmed by correlation analysis are discussed.

Active/Reflective Dimension

Regarding the active/reflective dimension, additionally a relation can be seen between active learners and their preference for performing most or all self-assessment tests, supported only by a weak semantic relation of the corresponding question. However, this result is in agreement with FSLSM. The preference of reflective learners to finish a chapter with a self-assessment test more often than active learners could not be confirmed according to results of the correlation analysis.

Furthermore, a correlation can be seen between learners with an active preference and their interest in graphics. However, this correlation is only supported by an indirect semantic relation between the corresponding question and the pattern. The interest in graphics may be explained by the fact that active learners tend to be less interested in reading and reflecting about text but instead look in more details at graphics. Furthermore, this result is supported by the identified correlation between an active and visual learning style which was found by a study dealing with an in-depth analysis of ILS data (Viola et al., 2007). Nevertheless, further investigations seem to be necessary regarding this relation.

Table 4.5: Results of the point-biserial correlation analysis, correlating behaviour of students with their learning style preferences regarding ILS questions

	Pattern	Question	rpb	p	Direction
Active / Reflective	content_stay_graphics	q21	0.34	0.037	1
	outline_visit	q29	-0.33	0.031	-1
	outline_stay	q21	-0.34	0.026	-1
	outline_stay	q29	-0.43	0.004	-1
	example_visit	q33	-0.31	0.042	-1
	selfass_visit	q5	0.43	0.004	1
	selfass_visit_different	q5	0.35	0.022	1
	selfass_stay_results	q1	-0.49	0.016	-1
	ques_facts	q5	0.59	0.005	1
	ques_interpret	q9	-0.64	0.004	-1
	ques_develop	q5	-0.64	0.036	-1
	forum_visit	q25	-0.41	0.006	-1
	navigation_overview_stay	q13	0.32	0.036	1
	navigation_overview_stay	q25	-0.43	0.004	-1
	sequence_assignment_last	q13	0.33	0.030	1
	sequence_exercise/example	q21	0.34	0.025	1
Sensing / Intuitive	content_visit	q26	0.39	0.009	1
	outline_visit	q22	0.30	0.048	1
	example_stay	q10	0.35	0.023	1
	example_stay	q42	-0.43	0.004	-1
	exercise_visit	q10	0.38	0.011	1
	exercise_stay	q10	0.39	0.010	1
	ques_detail	q10	0.43	0.050	1
	ques_overview	q42	-0.52	0.018	-1
	ques_develop	q34	0.66	0.028	1
	quiz_revisions	q10	0.46	0.021	1
	forum_stay	q10	0.40	0.008	1
	forum_stay	q22	0.38	0.012	1
	forum_post	q22	0.48	0.001	1
	sequence_example_first	q26	0.45	0.002	1
	sequence_assignment_first	q10	0.38	0.013	1
	sequence_exercise_last	q10	0.35	0.021	1
	sequence_example_last	q10	0.37	0.015	1
	sequence_example_last	q38	0.31	0.045	1
	sequence_content/selfass	q10	0.43	0.004	1
	sequence_content/selfass	q22	0.33	0.032	1
	sequence_exercies/selfass	q42	-0.32	0.038	-1
Sequential / Global	outline_visit	q12	0.42	0.005	1
	outline_stay	q44	0.34	0.024	1
	selfass_stay	q12	-0.41	0.038	-1
	selfass_stay	q16	-0.40	0.042	-1
	selfass_stay	q20	-0.39	0.046	-1
	selfass_visit_different	q36	0.34	0.024	1
	selfass_stay_results	q28	0.52	0.010	1
	exercise_stay	q40	0.33	0.032	1
	ques_concepts	q44	-0.45	0.049	-1
	ques_graphics	q32	0.56	0.010	1
	ques_develop	q20	-0.78	0.004	-1
	forum_post	q20	0.35	0.021	1
	forum_post	q32	-0.33	0.031	-1
	navigation_skip	q40	0.33	0.032	1
	navigation_overview_visit	q44	-0.39	0.010	-1
	sequence_exercise_last	q12	0.30	0.047	1
	sequence_exercise_last	q28	0.41	0.007	1
	sequence_content_last	q12	0.34	0.028	1
	sequence_assignment_last	q24	-0.33	0.033	-1
	sequence_assignment_last	q32	-0.38	0.013	-1
	sequence_content/selfass	q28	0.31	0.045	1
	sequence_content/exercise	q28	0.39	0.010	1

While the time spent on examples could not be confirmed as an indication for a reflective preference, the number of visits was found as significant pattern. Regarding the performance on questions dealing with interpretation and development of source code, both seem to positively correlate with a reflective preference according to the results of the correlation analysis.

Sensing/Intuitive Dimension

While for learners with a sensing preference the number of visits of examples seems to be not significant according to the results of the correlation analysis, exercises plays an important role. The number as well as the time spent on exercises is positively and significantly correlated with a sensing learning preference. Furthermore, results show that learners with a sensing preference performed more often exercises as their last learning object in a chapter. This indicates that they used exercises to prepare themselves for the oral presentations and the written exam. The preferences of sensing learners for exercises are in agreement with FSLSM.

Regarding the time spent on examples, a significant positive correlation is found for a sensing as well as for an intuitive learning preference which necessitate further investigations.

An additional relation between a sensing learning preference and a better performance on questions about details and code development was found. Both are in agreement with FSLSM.

The impact of navigating back to the previously visited learning objects could not be confirmed by the results of the correlation analysis. Also the pattern indicating that intuitive learners spent more time on outlines was not found as significant according to the correlation analysis. However, this pattern is not explicitly supported by FSLSM.

Sequential/Global Dimension

Regarding the sequential/global dimension, results show that a correlation was found indicating that learners with a global preference spent more time on self-assessment tests and performed better in questions about developing source code. This is in line with FSLSM since the self-assessment tests are based on the learning material and therefore can be answered more easily when learning the material step by step, which tends to be the preferred way of learning for sequential learners. In contrast, for developing source code, more overview knowledge about the concepts is necessary, which tend to favour global learners.

According to the results of the correlation analysis, another pattern was found, indicating the step-by-step navigation of sequential learners. Results show that sequential learners more often visited content objects before they performed self-assessment tests, as it is recommended by the course structure. While the results of the u-test in Section 4.4.3.1 showed that sequential learners tended to visit examples before content objects, this preference was not confirmed by the results of the correlation analysis. However, since this sequence is not in agreement with the recommended order of learning objects and therefore not explicitly supported by FSLSM, the pattern needs further analysis.

According to the u-test, sequential learners tended to look more often at content objects before they went to the next chapter. Regarding correlation analysis, an additional preference for exercises as last learning object of a chapter was found. However, both patterns indicate that sequential learners tend to be more accurate and prepare themselves for the presentation and the exam. The preference for assignments as last learning object of a chapter for global learners was confirmed by the correlation analysis.

Another correlation was found between the time students spent on exercises and a sequential learning preference, supported only by a weak semantic relation between the corresponding question and the behaviour. This correlation needs further investigations since it is not explicitly supported by FSLSM. Regarding the number of postings, once a positive and once a negative correlation was found. A similar disagreement was found for skipping learning material since u-test and correlation analysis indicate different directions of the relationship. However, the result of the correlation is only supported by a weak semantic relation between the corresponding question and the pattern, whereas the result of the u-test seems to be more stable since the pattern is semantically related to the respective ILS question. However, further investigations are necessary for both of these cases. Furthermore, the relation for revising answers in self-assessment tests and exercises could not be confirmed by the correlation analysis.

4.4.4 Benefits

Table 4.6 summarises the results of this study. These results show that learners with different preferences for learning styles act differently in the online course. They used different features such as examples, exercises, and so on with different frequency, performed differently on specific kinds of questions, navigated differently through the course, and visited particular features in a different sequence. The results can also be interpreted in a way that each feature is needed to support a specific learning style and therefore plays an important role in the course. According to Felder and Silverman (1988), learners might have difficulties in learning if their learning style is not supported by the teaching environment. As a solution, they recommended to provide courses with many different features which support different learning styles rather than providing courses that suit only one learning style.

The results of this study can act as catalyst to make teachers and course developers aware of the different needs of their students and also the different ways of learning from the course material. The results point out the preferences of learners with different learning styles. Furthermore, it can be seen that all investigated features are used differently at least regarding one learning style dimension. This shows the importance of each feature and highlights the requirement for providing different features to support each learning style.

Table 4.6: Summary of the results, showing significant differences and correlations between behaviour of students and their learning style preferences regarding ILS questions

	Active / Reflective		Sensing / Intuitive		Sequential / Global	
Patterns	**t/u-test**	**corr.**	**t/u-test**	**corr.**	**t/u-test**	**corr.**
content_visit			✓	✓		
content_stay_graphics		✓				
outline_visit	✓	✓	✓	✓	✓	✓
outline_stay	✓	✓	✓		✓	✓
example_visit		✓	✓			
example_stay	✓		✓			
selfass_visit	✓	✓				
selfass_stay						✓
selfass_visit_different		✓			✓	✓
selfass_stay_results	✓	✓			✓	✓
exercise_visit				✓		
exercise_stay				✓		✓
ques_facts	✓	✓				
ques_concepts					✓	✓
ques_detail				✓		
ques_overview			✓	✓		
ques_graphics					✓	✓
ques_interpret	✓	✓				
ques_develop		✓		✓		✓
quiz_revisions			✓	✓	✓	
forum_visit	✓	✓				
forum_stay			✓	✓		
forum_post			✓	✓	✓	
navigation_skip					✓	✓
navigation_back			✓			
navigation_overview_visit					✓	✓
navigation_overview_stay						
sequence_example_first			✓	✓		
sequence_assignment_first			✓	✓		
sequence_content_last					✓	✓
sequence_example_last			✓	✓		
sequence_selfass_last	✓					
sequence_exercise_last				✓		✓
sequence_assignment_last	✓	✓			✓	✓
sequence_content/selfass			✓	✓		✓
sequence_content/example					✓	
sequence_content/exercise					✓	✓
sequence_exercies/selfass			✓	✓		
sequence_exercise/example	✓	✓				

At the current stage, learning management systems provide the same course for each learner. Learners then have the possibility to use the provided learning material in different ways and as can be seen from these results, they also do so. Besides providing a high amount of learning material that includes some features for each learning style, courses can also be adapted to the individual learning styles of learners. For providing proper adaptivity, it is important to know the preferences of learners with respect to their learning styles. Since FSLSM is developed for learning in traditional learning environments rather than for learning in technology enhanced learning environments, the behaviour of students in such environments has to be investigated and incorporated in the design of adaptation features. Accordingly, the results of this study can be used as the basis for the generation process of adaptation features, especially for learning management systems, and therefore can also act as the basis for the investigations in Chapter 7.

The second part of this study aims at finding correlations between the behaviour of students in an online course and their learning styles. Such a correlation allows, on one hand, inferences from the learning styles to the behaviour of students, and on the other hand, drawing conclusions from the behaviour of the students to their learning styles. The existence of such correlations can be seen as the basis for investigating and developing an automatic approach for detecting learning styles from the behaviour of students in LMSs, as done in Chapter 5.

CHAPTER 5

Automatic Detection of Learning Styles in Learning Management Systems

In Chapter 3, techniques for student modelling were discussed and adaptive systems as well as their approaches for detecting learning styles were introduced. The majority of adaptive systems focussing on learning styles are using a collaborative student modelling approach by asking students to fill out a questionnaire for detecting their learning styles. However, as described in Section 2.3, these questionnaires encounter several problems, leading to the conclusion that instead of asking students about their preferences and behaviour, their actual behaviour during learning can be used as an effective source for detecting their learning styles.

The aim of this chapter is to motivate and introduce an automatic approach for detecting learning styles in learning management systems (LMSs) using Felder-Silverman learning style model (FSLSM). The next subsection describes the need and motivation for an automatic student modelling approach, points out its benefits over the use of questionnaires and gives an overview of related research works dealing with automatic student modelling of learning styles in adaptive educational hypermedia systems. In Section 5.2, an automatic student modelling approach for learning management systems is proposed, aiming at identifying the learning style preferences on each of the four dimensions of FSLSM. First, general issues are discussed dealing with determining the relevant behaviour of students for identifying learning styles. Subsequently, two approaches for inferring learning styles from the determined behaviour are introduced, a data-driven and a literature-based approach. Furthermore, a study is presented, evaluating the data-driven and the literature-based approach for automatic student modelling. In Section 5.3, the use of a more granular distinction of learning styles, in the form of characteristic learning style preferences within the dimensions of FSLSM, is investigated, evaluated and discussed. Based on the resulting findings, a tool for detecting learning styles in learning management systems with respect to preferences on the dimensions and characteristic preferences within the dimensions of FSLSM is implemented. This tool is presented in Section 5.4.

5.1 Introduction in Automatic Student Modelling with Respect to Learning Styles

While collaborative student modelling requires students to explicitly provide some information about their preferences and needs, an automatic student modelling approach is based on the concept of looking at what students are really doing in a course and inferring their preferences and needs from their behaviour and actions in the course. This approach has potential to overcome some problems of detecting learning style based on using questionnaires.

In an automatic student modelling approach, no additional effort in needed on students' part in order to enable the system to get information about their learning styles. They just have to use the system for learning in order to provide the relevant information about their behaviour. Therefore, several problems arising from learning style questionnaires can be overcome since the information from their behaviour is free of uncertainty gained from asking students about their preferences. Such uncertainty can come from a lack of motivation to fill out the questionnaire properly, the influence of expectations from others, and a lack of self-awareness about the own learning preferences.

Furthermore, questionnaires are static and describe the learning style of a student at a specific point in time. This makes the collaborative student modelling approach fault-prone. For example, if a student has had a quarrel with his/her learning group, then he/she might answer all questions dealing with collaborative learning with a negative preference. However, if the problems are sorted out on the next day or if the student would have to answer the questions one day earlier, he/she might answer the questions completely different. As a consequence, a wrong assumption might be concluded from the questionnaire due to the importance of the exact time and therefore the students' mood when he/she is filling out the learning style questionnaire. In contrast, the automatic student modelling approach can be more fault-tolerant due to information gathering over a longer period of time. If the system notices that a student avoids all collaborative actions for a short period of time, it can even classify this as exception and therefore such a situation would have no impact on the learning style detected by the system.

In the situation discussed above, the student prefers a different learning style for a short period of time, but this does not mean that his/her overall tendency for a learning style has changed. However, if students for example train their weak learning style preferences, then their learning styles can also change. However, due to the possibility of frequently gathering and analysing the students' behaviour and actions, the automatic student modelling approach can detect this change and update the information in the student model accordingly.

Automatic student modelling can be used for two different concerns: for building a student model by detecting learning styles from scratch and, if a student model exists already, for updating, improving, and revising the already existing student model.

For example, the TANGOW system (Paredes and Rodríguez, 2004), introduced in Section 3.2.8, uses a mixed student modelling approach. In this system, learners are asked to fill out the ILS questionnaire when they log in the first time. This information is then used to initialise the student model. To update and control the information in the student model, the behaviour of the learners in the system is monitored. If learners behave contrary to the determined learning style preference stored in the student model, the information in the student model is revised. TANGOW incorporates only the sensing/intuitive and the sequential/global dimension of FSLSM and for each dimension one adaptation feature exists. Furthermore, four patterns, each for one learning style preference, are observed for revisions. This automatic student modelling approach is suitable for the system to provide appropriate adaptivity; however, the approach covers only information about the four patterns and therefore, cannot be seen as an approach for detecting the two learning style dimensions completely.

Recent research deals with a fully automatic student modelling approach which considers several patterns per learning style dimension in order to build a student model from scratch. Cha et al. (2006) investigated the use of Decision Trees (DT) (Dunham, 2002) and Hidden Markov Models (HMM) (Rabiner, 1989) for detecting learning styles according to FSLSM. They observed the behaviour of 70 learners during an online course in an intelligent learning environment based on specific patterns. Furthermore, they asked the students to fill out the ILS questionnaire in order to evaluate both models. Several patterns of behaviour were incorporated for each learning style dimension. However, only data from the ILS questionnaire indicating a strong or moderate preference on a specific learning style dimension (> 3 or < -3 according to ILS values) was included in the experiment. While for the visual/verbal dimension, DT achieved better results by obtaining an error rate of 0%, for the sequential/global dimension, HMM performed better by obtaining an error rate of 14.28%. This can be argued by the fact that HMM are able to consider sequences of learners' actions which might be more relevant for the sequential/global dimension. Results for the sensing/intuitive and the active/reflective dimension were for both techniques the same, with an error rate of 22.22% for the sensing/intuitive dimension and 33.33% for the active/reflective dimension. Therefore, conclusions can be drawn that DT and HMM seems to be suitable for detecting learning styles from the behaviour of students and that for certain dimensions of the FSLSM one approach is more suitable than the other. However, it should be noted here that due to the restriction of using only data with either a moderate or a strong preference according to the ILS questionnaire and excluding data with a balanced preference, the proposed approaches are only applicable for identifying students' learning style preference when students have a moderate or strong preference on one or the other pole of the respective dimension. Further investigations with respect to a more accurate approach that also includes balanced preferences are therefore necessary.

Another approach for automatic student modelling was investigated by García et al. (García et al., 2005, 2007). They observed the behaviour of learners during an online course in the system SAVER and performed two experiments to show the effectiveness of Bayesian networks (Jensen, 1996) for identifying learning styles based on the behaviour of students. The approach considered the active/reflective, sensing/intuitive, and the sequential/global dimension of FSLSM. The visual/verbal dimension was not incorporated since no relevant learning material was presented in the course. Overall, 11 patterns were considered for the three dimensions. For the active/reflective dimension, patterns dealing with chat, mail, and forum were used. For the sequential/global dimension, analysis of the way students access information and their performance in exams was incorporated. The sensing/intuitive dimension included the number of visits to exercises, reading material, and examples, the number and time students took for revising their exam and the time students took for finishing an exam. In order to build a model for calculating the preferences on the learning style dimensions for each learner, Bayesian networks were used. Two experiments were conducted to verify the proposed approach by comparing its results with results from the ILS questionnaire. In the first experiment (García et al., 2005), data from 30 students were used to train the Bayesian network and the resulting model was then tested by the data from 10 students. By comparing the results of the proposed approach and the results of the ILS questionnaire, a 100% agreement for the sequential/global dimension and an 80% agreement for the active/reflective and sensing/intuitive dimension were found, using a 3-items scale distinguishing, for example, between an active, balanced, and reflective learning style preference. In the second experiment (García et al., 2007), data from 50 students were used for training the Bayesian network and data from 27 students were used for testing. For calculating the precision of agreement, the degree of similarity between the results of the proposed approach and the results from the ILS questionnaire was considered. As a result, a precision of 77% for the sensing/intuitive dimension, 63% for the sequential/global and 58% for the active/reflective dimension was found. The low precision for the active/reflective dimension was explained by the little use of communication tools by the learners. According to the interviews with students, two reasons for not using communication tools were found: first because students did not like using such tools and second because the course did not promote using them. Therefore, promoting communication tools might lead to better results for identifying students' learning style preferences with respect to the active/reflective dimension since the difference between students who do not like using these tools and those who like using them when appropriate would be visible in the data. Furthermore, García et al. (2007) found out that 86% of the students did not have previous experience in web-based courses, and according to interviews, this inexperience influenced their navigation style towards a more sequential behaviour.

Overall, García et al. (2007) concluded that the results were promising. The Bayesian network obtain good results for the sensing/intuitive dimension and can detect the active/reflective and sequential/global dimension provided that students have some learning experience in web-based courses and that they are encouraged to communicate with each other via communication tools.

The above described approaches are developed for specific systems and therefore are tailored exactly to these systems by using only those features and patterns which are incorporated in the respective systems. Furthermore, the investigated courses are created in consideration of learning styles by using the required features for detecting learning styles. When aiming at developing a generic approach for automatic student modelling in LMSs, several additional issues have to be considered. First, features and patterns have to be selected in a way that most LMSs are able to gather data with respect to the incorporated patterns. Furthermore, it needs to be noted that most courses in LMSs are not created in consideration of learning styles. Therefore, it is not sufficient that only the system can technically track the required information about patterns but teachers also have to use the respective features in their courses. Hence, only commonly used features were selected for an automatic student modelling approach in LMSs. Moreover, the approach has to consider that nevertheless some data might be not available and therefore the approach has to be able to deal with missing data. Thus, a high number of patterns is beneficial.

In the following section, a generic automatic student modelling approach for detecting learning styles in LMSs is introduced, including an evaluation of two different approaches for inferring learning styles from the behaviour of students.

5.2 An Approach for Automatic Detection of Learning Styles based on the Dimensions of FSLSM

The proposed approach for automatic detection of learning styles, depicted in Figure 5.1, can be divided into two parts: in a first step, the required behaviour of learners which is relevant for the detection process needs to be determined. This is usually done based on the literature about the respective learning style model and includes investigations about the incorporated features and patterns, the thresholds for data classification as well as the relevant patterns for each learning style dimension. The second part deals with considerations about how to prepare and use the gathered data about students' behaviour in order to infer learning styles from these data. For this part, two different approaches can be applied, a data-driven approach and a literature-based approach.

The data-driven approach uses sample data in order to build a model for identifying learning styles from the behaviour of learners. For example, Cha et al. (2006) derived relevant patterns for detecting learning styles from the literature and then used Decision Trees and Hidden Markov Models to learn the parameters of the model from data about the behaviour of students and from reference data including the learning style preferences identified by the ILS questionnaire. García et al. (2007) used the same approach except that Bayesian Networks were applied instead of Decision Trees and Hidden Markov Models.

The data-driven approach aims at building a model that imitates the ILS questionnaire. The advantage of such an approach is that the model can be very accurate due to the use of real data. However, the approach strictly depends on the available data and therefore, a representative set of data is crucial to build a model that can be used on one hand to identify learning styles from data of the same course and on the other hand to identify learning styles from data of any other course.

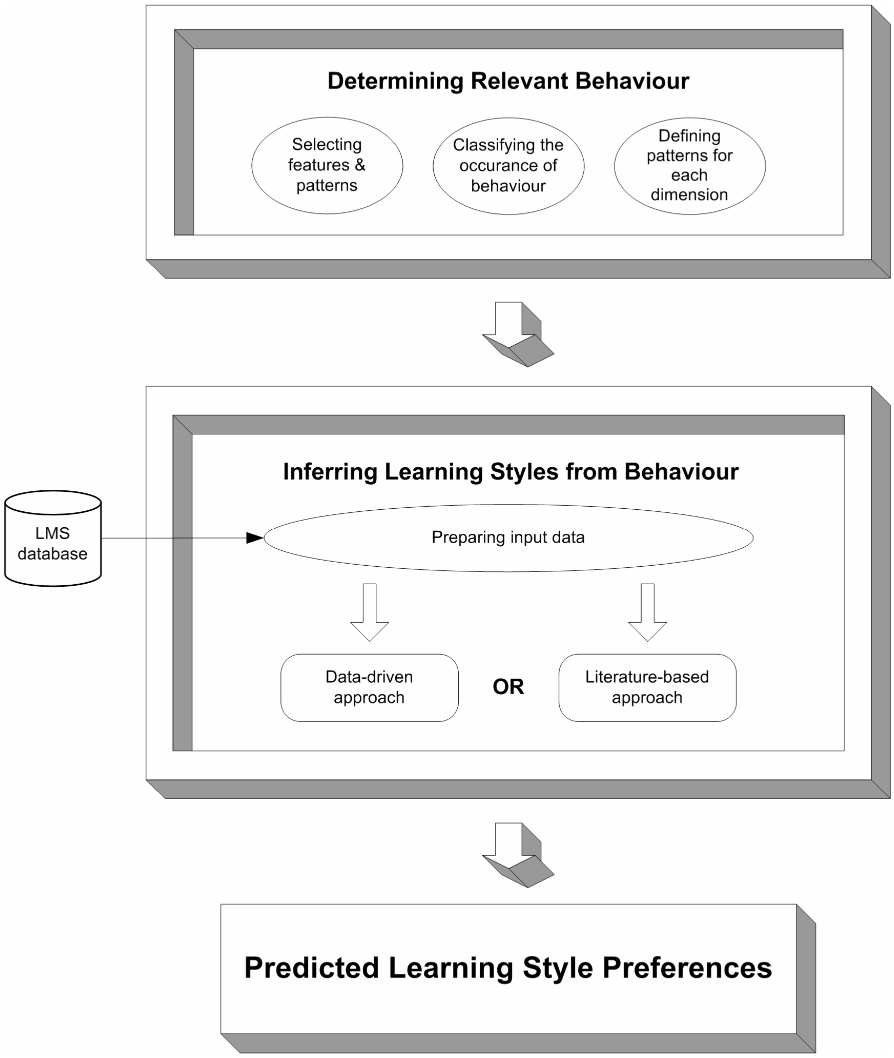

Figure 5.1: Concept for automatic detection of learning styles

The second way of identifying learning styles is to use a fully literature-based approach. According to the literature, learners with a preference for a specific learning style behave in a specific way. With respect to learning management systems, this was confirmed by our study introduced in Section 4.4, where investigations were conducted, looking at whether students with different learning styles behave differently in an online course in a learning management system. The idea of the literature-based approach is to use the behaviour of students in order to get hints about their learning style preferences and then apply a simple rule-based method to calculate learning styles from the number of matching hints. This approach is similar to the method used for calculating learning styles in the ILS questionnaire and has the advantage to be generic and applicable for data gathered from any course due to the fact that FSLSM is developed for learning in general. However, the approach might have problems in estimating the importance of the different hints used for calculating the learning styles.

Figure 5.2 points out the difference between the data-driven approach and the literature-based approach in terms of their relationship to FSLSM. While the data-driven approach is based on the ILS questionnaire and aims at imitating it, the literature-based approach is directly based on the FSLSM, using the information from literature as basis.

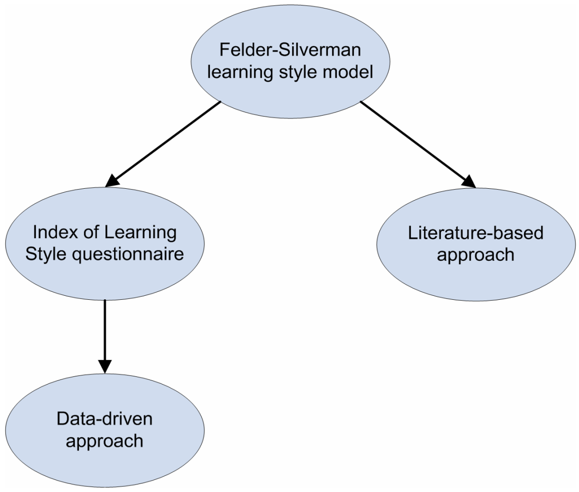

Figure 5.2: Relationship between Felder-Silverman learning style model and the two proposed approaches

The proposed student modelling approach aims at identifying learning styles on a 3-item scale. Therefore, as a result, the proposed approach calculates learning styles, distinguishing between, for example, an active, balanced or reflective learning style.

Subsequently, the proposed automatic student modelling approach is described in more detail. In the next subsection, the incorporated features and patterns, the thresholds for data classification as well as the relevant patterns for each learning style dimension are introduced. Then the method for preparing input data as well as the two approaches for inferring learning styles from the students' behaviour are described. The last subsection presents the evaluation of the automatic student modelling approach, comparing the results of the data-driven approach with the ones from the literature-based approach.

5.2.1 Determining Relevant Behaviour

The aim of the automatic student modelling approaches is to detect learning styles based on the behaviour of students in LMSs. In order to make the approaches applicable for LMSs in general, consideration about which behaviour is relevant for the detection process of learning styles is an important issue. The selection of incorporated features and patterns of behaviour is based on two requirements: first, the patterns need to be relevant for detecting learning styles based on FSLSM and second, the probability that the LMS can gather information about the patterns should be as high as possible. This implies that the selected features need to be included in most LMSs, most LMSs need to be able to track the selected patterns, and the features need to be commonly used by teachers and course developers.

In order to fulfil the first requirement, features and patterns were derived from the literature (Felder and Silverman, 1988). With respect to the second requirement, only features and patterns which are integrated in most LMSs and commonly used by teachers and course developers were selected.

The next subsection describes the incorporated features and patterns. In the second subsection, a description on how to classify the occurrence of behaviour with respect to the incorporated patterns is provided. This classification allows distinguishing between different occurrences of behaviour, such as a high number of visits or a low amount of time spent on a specific type of learning object. Subsequently, the relevant patterns for each learning style dimension are presented.

5.2.1.1 Incorporated Features and Patterns

Similar to this study, the study described in Section 4.4, dealing with investigations on the behaviour of students in LMSs, aimed at contributing results which are significant for LMSs in general. Furthermore, the study described in Section 4.4 pointed out the importance of the investigated features with respect to learning styles. Therefore, the same features were selected, including content objects, outlines, examples, self-assessment tests, exercises, and discussion forums. Furthermore, patterns dealing with the navigational behaviour of students were incorporated.

Regarding the patterns, the mentioned study aimed at investigating a great number of patterns in order to get detailed information about the students' behaviour. In this study, therefore, the number of patterns was restricted to, on one hand, those patterns that are according to the literature and according to the mentioned study relevant for identifying learning styles and, on the other hand, those patterns that are easy to track in order to make the proposed approaches applicable for LMSs in general.

Regarding content, outline, and examples, the number of times and duration students spent on these objects are used as patterns. With respect to the self-assessment tests, the total number of answered questions and the time spent on self-assessment tests are considered as patterns. Moreover, a pattern is included dealing with whether a learners is answering the same question twice wrong. Furthermore, the students' performance on questions dealing with facts or concepts, referring to details or overviews, being about graphics or text, and asking about interpreting a given solution or developing a new one are incorporated as patterns. Additionally, the number of revisions on answers in self-assessment tests is considered as a pattern. Another pattern dealing with self-assessment tests is the time students spent on reviewing their results. Regarding exercises, also the performed number of exercises and the time spent on exercises are used as patterns. Furthermore, the performance on questions about interpreting a given solution and developing a new solution, the number of performed revisions, and the time students reflected on the results of the exercise is combined with the behaviour in self-assessment tests. With respect to the forum, the number of visits, the time students spent in the forum, and the number of postings is included. Regarding navigational behaviour, patterns deal with how often students skipped learning objects via the navigation menu as well as how often they visited and how much time they spent on the course overview page.

As discussed before, the introduced patterns were selected with respect to their commonness in LMSs and based on their relevance for the learning styles dimensions. In the next section, a recommendation for classifying the occurrence of behaviour is introduced and subsequently, relevant patterns for each learning styles dimension and the respective occurrence of behaviour are discussed.

5.2.1.2 Classifying the Occurrence of Behaviour

In this section, a classification of occurrence of the learners' behaviour regarding the patterns introduced in the previous section is provided. This classification is necessary in order to make the approach generic and applicable for different courses with different characteristics. A 3-item scale is used which divides the behaviour into three groups: high, moderate and low occurrence. The classification is based on general thresholds rather than on the average behaviour in the respective course. Using general thresholds has the advantage that the results, in the form of identified learning styles, are not depending on the behaviour of other students. In contrast, using the average behaviour for deriving thresholds would result in a predefined distribution of learning styles for each pattern, which might not apply for small and middle-size groups. In order to make our approach also applicable for small and middle-size groups, general thresholds were used. However, as argued, for example, by Alberer et al. (2003) and Roblyer and Wiencke (2003), general thresholds can vary from course to course as well, depending on the structure of the course, the subject, and also on the experiences of the students. In the following paragraphs, recommendations for thresholds based on the literature and on our experience are presented. Table 5.1 summarises the recommended thresholds.

According to Rovai and Barnum (2003), 50 or more forum visits per week and 10 or more postings can be considered as an above average behaviour, while 7 or less forum visits and 1 or less postings per week indicate a below average behaviour. For the time students spend on the forum, no recommendations were given. However, based on the given thresholds for the number of visits, a value of 30 minutes per week can be assumed as above average and a value of 5 minutes per week as below average.

Table 5.1: Recommended thresholds for patterns

Features	Patterns	Description of patterns	Thresholds	
Content	content_visit	percentage of visited content objects (based on the number of available content objects)	75%	100%
	content_stay	percentage of time spent on content objects (based on a predefined expected value)	50%	75%
Outline	outline_visit	percentage of visited outlines (based on the number of available outlines)	75%	150%
	outline_stay	percentage of time spent on outlines (based on a predefined expected value)	50%	75%
Example	example_visit	percentage of visited examples (based on the number of available examples)	25%	75%
	example_stay	percentage of time spent on examples (based on a predefined expected value)	50%	75%
Self-assessment	selfass_visit	percentage of performed self-assessment questions (based on the total amount of available questions)	25%	75%
	selfass_stay	percentage of time spent on self-assessment tests (based on a predefined expected value)	50%	75%
	selfass_twice_wrong	percentage of times a learner answers the same question twice wrong (based on the number of times a learner answered a question twice)	25%	50%
Exercise	exercise_visit	percentage of performed exercises (based on the number of available exercises)	25%	75%
	exercise_stay	percentage of time spent on exercises (based on a predefined expected value)	50%	75%
Self-assessment and exercise	ques_detail	percentage of correctly answered questions about details	50%	75%
	ques_overview	percentage of correctly answered questions about overview knowledge	50%	75%
	ques_facts	percentage of correctly answered questions about facts	50%	75%
	ques_concepts	percentage of correctly answered questions about concepts	50%	75%
	ques_graphics	percentage of correctly answered questions about graphics	50%	75%
	ques_text	percentage of correctly answered questions about text	50%	75%
	ques_interpret	percentage of correctly answered questions about interpreting solutions	50%	75%
	ques_develop	percentage of correctly answered questions about developing new solutions	50%	75%
	quiz_revisions	percentage of times a student revised his/her answer before the submission (based on number of answered questions)	20%	50%
	quiz_stay_results	average time spent on the result page of a self-assessment test or exercise	30 sec.	60 sec.
Forum	forum_visit	number of visits in a forum (per week)	7	50
	forum_stay	time spent in the forum (per week)	5 min.	30 min.
	forum_post	number of postings in the forum (per week)	1	10
Navigation	navigation_skip	percentage of times a learning object is skipped via the navigation menu (based on the number of visited learning objects	1%	2%
	navigation_overview_visit	percentage of times a learner visited the course overview page (based on the number of visited learning objects)	10%	20%
	navigation_overview_stay	percentage of time spent on the course overview page (based on a predefined expected value)	50%	75%

Based on the assumptions of García et al. (2007), the thresholds for visiting examples as well as performing exercises and self-assessment questions can be set to 25% and 75% of the number of available examples, exercises, or self-assessment questions. For visiting content objects, assuming that these objects are required to read in order to understand the topic, a value of 75% and 100% of the available content objects is recommended. The time spent on self-assessment tests, exercises, examples, and content objects can be assumed as 50% and 75% in relation to the expected learning time of students with high interest in the respective type of learning object, following the recommendation of García et al. (2007) in the context of exams. For the time spent on the results of an exercise or self-assessment test, a threshold of 30 seconds and 60 seconds is assumed. Thresholds for the performance of specific question types can be assumed as 50% and 75% of correctly answered questions. However, these thresholds should be based on the respective grading system and should be modified if another grading system fits better. The thresholds for changed answers of an exercise or self-assessment questions are considered as 20% and 50% of all answered questions, as suggested by García et al. (2007). The thresholds regarding how often students answered a self-assessment question twice wrong were assumed as 25% and 50% of times a student is asked the same question twice.

To the best of our knowledge, thresholds for the patterns regarding outline and course overview page as well as the navigation behaviour are not addressed in the literature. Thresholds for visiting outlines are therefore recommended as a value of 75% and 150% of available outlines. The thresholds for the visits of the course overview page are proposed with 10% and 20% of the total number of visited learning objects. The time spent on outline and course overview is again set to 50% and 75% of the predefined time learners with high interest in overviews are expected to spend on these types of objects. Regarding skipping learning objects, we looked at how often students skipped learning objects in relation of the total number of visited learning objects. Thresholds of 1% and 2% of times students used the navigation menu to skip learning objects is assumed.

With respect to thresholds dealing with time students spent on specific types of learning objects, additionally the use of critical values for each type of learning object is suggested. Such critical values represent the maximum time a learner is expected to spend on the respective type of learning object. These critical values aim at avoiding the inclusion of high time spans which occur when students are doing something else than learning and just keep running the online course. If values are recorded that exceed these critical values for the respective type of learning object, they should be replaced by average values.

5.2.1.3 Relevant Patterns for Learning Style Dimensions

In this section, the relevant patterns for each learning style dimension are described and information about whether a high or low occurrence of the respective behaviour is relevant is provided. Both, the relevant patterns and the information regarding occurrence, are based on the literature regarding the FSLSM (Felder and Silverman, 1988).

Table 5.2 summarises the patterns for each learning style dimension. The "+" and "-" indicate a high and low occurrence from the viewpoint of an active, sensing, visual, and sequential learning style. According to FSLSM, the extremes of each dimension are opposed. Therefore, when a high occurrence of a specific behaviour gives indication for one extreme, a low occurrence of the same behaviour gives indication for the other extreme, and vice versa. Thus, the relevant occurrences are simply opposite for a reflective, intuitive, verbal, and global learning style.

As can be seen from Table 5.2, each learning style dimension consists of a relatively high number of patterns, compared to the number of patterns of related works, such as the model introduced by García et al. (2007) as well as one of our previous research work (Graf and Kinshuk, 2006a). A high number of patterns gives more detailed information and is especially important for developing an approach which is capable to identify learning styles in learning management systems in general rather than in one specific system, due to the possibility that information regarding some patterns might not be available.

In the following subsections, the relevant patterns for each learning style dimension are discussed in more detail.

Table 5.2: Relevant patterns for each learning style dimension of FSLSM. (The "+" and "-" indicate a high and low occurrence of the respective pattern from the viewpoint of the active, sensing, visual and sequential dimension)

Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
content_visit (-)	content_visit (-)	content_visit (-)	outline_visit (-)
content_stay (-)	content_stay (-)	ques_graphics (+)	outline_stay (-)
outline_stay (-)	example_visit (+)	ques_text (-)	ques_detail (+)
example_stay (-)	example_stay (+)	forum_visit (-)	ques_overview (-)
selfass_visit (+)	selfass_visit (+)	forum_stay (-)	ques_interpret (-)
selfass_stay (-)	selfass_stay (+)	forum_post (-)	ques_develop (-)
selfass_twice_wrong (+)	exercise_visit (+)		navigation_skip (-)
exercise_visit (+)	ques_detail (+)		navigation_overview_visit (-)
exercise_stay (+)	ques_facts (+)		navigation_overview_stay (-)
quiz_stay_results (-)	ques_concepts (-)		
forum_visit (-)	ques_develop (-)		
forum_post (+)	quiz_revisions (+)		
	quiz_stay_results (+)		

Active/Reflective Dimension

Active learners are characterised as learners who prefer to process information actively by doing something with the learned material, for example discussing it, explaining it, or testing it. On the other hand, reflective learners prefer to think about the material and work alone. Regarding discussing and explaining, communication tools like discussion forum can give indications about the students' preference for active or reflective learning. While active learners are expected to post more often in order to ask, discuss, and explain something, reflective learners are supposed to prefer to participate passively by carefully and frequently reading the postings but only rarely posting by themselves. Therefore, the number of visits and postings can be used as patterns for identifying an active or reflective learning style. Due to the preference of testing and trying things out, active learners are expected to perform more self-assessment tests and more exercises as well as spend overall more time on exercises. On the other hand, active learners are supposed to spend only little time on examples since they prefer more to do something by themselves rather than looking at how someone else has solved a problem. Since reflective learners like to think about the material and reflect about it, they are expected to visit and spend more time on reading material like content objects as well as stay longer at outlines. They also tend to take longer on self-assessment tests as well as on the result pages of self-assessments and exercises since they reflect more on the results. As a consequence, reflective learners are also expected to answer the same question in a self-assessment test less often twice wrong.

Sensing/Intuitive Dimension

Since sensing learners favour concrete material like facts and data, whereas intuitive learners prefer to learn abstract material such as theories and their underlying meaning, analysing the performance on questions about facts as well as on theories and concepts provides an indication about the preferred learning style. Furthermore, in order to learn from concrete material, sensing learners tend to prefer examples. Therefore, the visits and time spent on examples serve as other patterns. On the other hand, intuitive learners are supposed to learn from content objects and use examples only as supplementary material. Therefore, the number and time spent on content objects tend to be higher and the number and time spent on examples tend to be lower. Furthermore, sensing learners like to solve problems based on a standard procedure, which can be again indicated by a high interest in examples in order to see and learn existing approaches and a high number of conducted self-assessment tests and exercises in order to check the acquired knowledge. On the other hand, intuitive learners tend to be more creative and like challenges. Therefore, they are expected to be better in answering questions about developing new solutions, which requires the understanding of underlying theories and concepts. Another characteristic of sensing learners is that they are more patient with details and work carefully but slowly. With respect to the preference for working slowly, the time taken for a self-assessment test is considered as pattern. Because these students tend to check their answers carefully before submitting, another pattern is the number of revisions performed before handing in a test or exercise. Another pattern is the time students spent on reviewing their results, where sensing learners again are expected to spend more time. Furthermore, their preference for being careful with details can be indicated by their performance on questions about details.

Visual/Verbal Dimension

Since verbal learners prefer to learn from words, they tend to like communication with others and discussions. Therefore, they are expected to commonly use the discussion forum. Thus, a high number of visits and postings as well as a high amount of time spent in a discussion forum can indicate a verbal learning style. While verbal learners like to learn from words, visual learners learn best from what they see. Therefore, the performance on questions about graphics as well as on text can act as other patterns. Furthermore, verbal learners are expected to visit reading material such as content objects more often.

Sequential/Global Dimension

Sequential learners are more comfortable with details, whereas global learners tend to be good in seeing the "big picture" and connections to other fields. Therefore, the performance of questions dealing with overviews of concepts or connections between concepts and questions about details serve as patterns for this dimension. Because global learners are interested in getting the "big picture" and an overview, outlines of the course and the chapters are especially important for them. A high number of visits and more time spent on such chapter outlines as well as on the course overview page indicate a global learning style. The course overview page can additionally help global students to relate topics with each other. Furthermore, the global learners' interest in relating and connecting topics to each other helps them to interpret predefined solutions and develop new solutions. Therefore, global learners are expected to perform better on respective questions. The navigation of learners in a course acts also as a pattern denoting a sequential or global learning style. While sequential learners tend to go through the course step by step in a linear way, global learners tend to learn in large leaps, sometimes skipping learning objects and jumping to more complex material. Therefore, the number of skipped learning objects via the navigation menu can act as a pattern. Furthermore, learners can skip learning objects by going back to the course overview page. Therefore, again the number of visits of the course overview page is relevant for identifying a sequential or global learning style.

5.2.2 From Behaviour to Learning Style Preferences

The previous section gave information about which patterns can be used for identifying learning styles, how the data from these patterns can be classified in order to distinguish between a high, moderate, and low occurrence of the respective behaviour, and which patterns give indications for which learning style dimension. Based on this information, this section describes how to calculate learning styles, starting from the raw data about the behaviour of students in the learning management system's database.

The first step for concluding from the students' behaviour to their learning styles is to calculate ordered data with respect to each pattern and prepare them in a way that they can be used as input data for the two proposed approaches for inferring learning styles. This process is described in the next subsection. Subsequently, the two approaches for inferring learning styles, a data-driven approach using Bayesian networks and a literature-based approach using a simple rule-based method for inferring learning styles, are presented.

5.2.2.1 Method for Building Input Data

In the first step, data representing the relevant behaviour of students, introduced in Section 5.2.1.1, needs to be extracted from the learning management system's database. Then, for each pattern, the data are mapped onto a 4-item scale. More formally, let O be the matrix of ordered data, including in rows all students and in columns all patterns, values between 0 and 3 are assigned in order to classify the behaviour of each student for each pattern. Values between 1 and 3 indicate the occurrence of a certain behaviour based on the introduced patterns, where 1 represents a low occurrence, 2 a moderate occurrence, and 3 a high occurrence. The mapping of values between 1 and 3 is based on the thresholds introduced in Section 5.2.1.2. A value of 0 indicates that no information about the respective pattern is available (e.g., no questions about details were performed and therefore no information about the student's performance is available).

It should be pointed out here that no available data in the learning management system's database does not necessarily implies a value of 0 but depends on the respective pattern. If the pattern, for example, counts the number of visits of a specific type of learning object, then no data in the database mean that the student did not visit the respective type of learning object, implying a number of visits of 0, therefore a low occurrence, and hence a value of 1 in the matrix O. In contrast, if the pattern, for example, represents the performance on a specific type of question, no available data about the marks of students implies that no conclusion can be drawn whether the student performs poor, moderate, or good in such questions and therefore, a value of 0 is assigned in the matrix O.

Subsequently, for each learning style dimension, a matrix P_{dim} is built, including in rows all students and in columns all relevant patterns for the respective learning style dimension *dim*, as proposed in Section 5.2.1.3. P_{dim} includes the ordered data from matrix O for all relevant patterns of the respective learning style dimension. The four matrices, each for one learning style dimension, are used as input data for calculating learning styles.

5.2.2.2 A Data-Driven Approach for Inferring Learning Styles using Bayesian Networks

The approach for inferring learning styles, introduced in this section, is based on the idea to use data about the behaviour of students from a sample course as well as reference data about their learning styles for building and training a model which allows then to calculate learning styles from the behaviour of students. The studies by García et al. (2005; 2007) demonstrated that Bayesian networks (Jensen, 1996) technique is an appropriate approach and has potential to infer learning styles from the behaviour of students. Based on their results, they concluded that two requirements seem to be important for inferring learning styles from the behaviour of students: first, students should be promoted to use communication tools such as discussion forum and second, students should have some experience with online courses since inexperienced students might behave differently and therefore the results are influenced in a negative way, especially for the sequential/global dimension. In our study, both requirements are considered.

This section deals with applying Bayesian networks in order to infer learning styles from the behaviour of students in LMSs. In the following subsection, a brief introduction of Bayesian networks is given. A more detailed introduction of Bayesian networks is, for example, provided by Jensen (1996) and Bekele (2005). The subsequent subsection deals with how Bayesian networks were applied for this study.

Introduction on Bayesian Networks

Bayesian networks belong to the group of directed graph models and represent causal relations in a domain. They consist of nodes, which represent random variables, and directed arcs between these nodes, which represent causal impacts between the nodes. The nodes and arcs form a direct acyclic graph. If an arc exists from node A to node B, then A is called the parent node and B is called the child node. The arc between node A and B shows that the parent node A directly influences the child node B. In Figure 5.3, an example of a Bayesian network is demonstrated for inferring learning styles for the active/reflective dimension. The patterns used for calculating the active/reflective learning style preference act as parent nodes and the preference for an active/reflective learning style is the child node, influenced by all parent nodes. The Bayesian network in Figure 5.3 consists only of converging connections, however, Bayesian networks can also include diverging, serial or a mix of these types of connections.

Each node in a Bayesian network is associated with a conditional probability table (CPT), which quantifies the effect of the parent nodes on the respective node. Formally, a CPT can be described by the notation $P(B \mid parent(B))$. Such a table specifies the probability of each possible state of the node given each possible combination of states of its parents. If a node does not have any parent, then the table consists of prior probabilities.

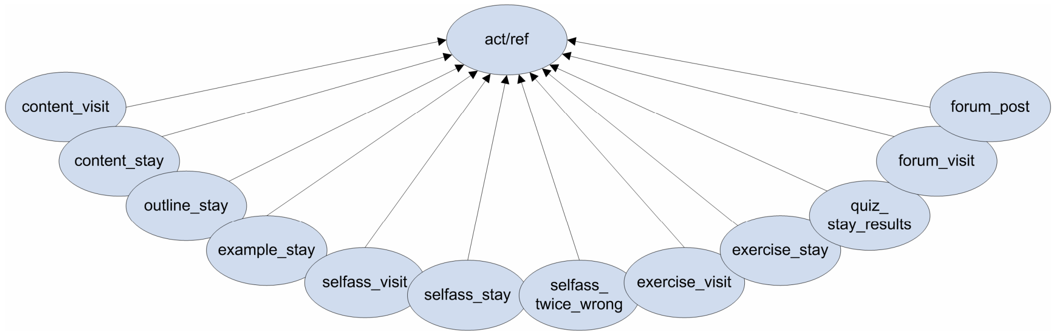

Figure 5.3: Bayesian network for the active/reflective dimension

Learning in Bayesian networks can on one hand deal with the structure of the Bayesian network (structure learning) and on the other hand with the conditional probability distribution (parameter learning), which refers to the process of calculating the values of the CPT. Given the structure and parameters of a Bayesian network, it can be used for drawing inferences by applying a Bayesian network inference algorithms. Several of such algorithms exist, which can be classified in exact and approximate algorithms. Examples for approximate algorithms include probabilistic logic sampling (Henrion, 1988), likelihood sampling (Fung and Chang, 1990; Shachter and Mark, 1990), and backward sampling (Fung and del Favero, 1994), and examples for exact algorithms are introduced by Pearl (1986) and Lauritzen and Spiegelhalter (1988).

Applying Bayesian Networks for Calculating Learning Styles

For this study, the structure of the Bayesian network was derived from literature, based on the description in Section 5.2.1.3, indicating which patterns are relevant for each learning style dimension. Based on these relevant patterns, a Bayesian network, such as the one in Figure 5.3, was manually constructed for each learning style dimension.

In order to calculate the conditional probability distribution, parameter learning was applied in the Bayesian network. As input data for parameter learning, the matrix D_{dim} was built, which extends the matrix P_{dim} by additionally including one column representing scaled data about the learning style preference of the respective dimension for each student. These scaled data were drawn from the ILS values, which indicate the strength of the learning style preferences by values between +11 and -11 in steps of 2, and acted as reference values for learning the parameters. Since this student modelling approach aims at identifying learning styles on a 3-item scale, distinguishing between for example, an active, balanced, and reflective learning style, the ILS values were scaled to values between 1 and 3. The value 1 indicates an ILS value greater than or equal to 5 and therefore – depending on the investigated learning style dimension – a preference for an active, sensing, visual, or sequential learning style. The value 2 indicates an ILS value between +3 and -3 and therefore a balanced learning style and the value 3 indicates an

ILS value smaller than or equal to -5 and therefore a reflective, intuitive, verbal, or global learning style.

For parameter learning as well as evaluating the Bayesian network, D_{dim} was split into training and test data, where training data were used for learning the parameters and test data were used for evaluating the Bayesian network. Training data consists of 90% of the sample and the remaining 10% were used as test data. Dividing the data is essential since the aim of training the network in terms of learning the parameters is to build a network that can classify these data as good as possible with respect to the reference values. By using different data for training and testing, the network is tested to be valid for any other independent and identically distributed dataset. In contrast, when using the same dataset for training and testing, the evaluation proves only that the parameter learning algorithm was successful by building a network that classifies the training data as good as possible.

Given the structure of the Bayesian network and the training data, the parameters of the network were learned in terms of calculating the values of the CPT by applying the expectation maximization (EM) algorithm, a commonly used algorithm for parameter learning which is also suitable for datasets with missing data (Dempster, Laird, and Rubin, 1977; Pollino et al., 2005). For drawing inferences, the clique tree algorithm proposed by Lauritzen and Spiegelhalter (1988) and later clarified by Jensen, Lauritzen and Olesen (1990) is the most commonly used algorithm for Bayesian Network inferences (e.g., Bekele, 2005) and was also used in this study. After applying the clique tree algorithm, the network is ready for inferring learning styles based on the behaviour of learners.

For constructing the Bayesian network and learning the parameter, the GeNIe modelling environment (2007) version 2.0, developed by the Decision Systems Laboratory of the University of Pittsburgh, was used. For inferring learning styles and testing the Bayesian network the tool Netica (2007) version 3.25, developed by the Norsys Software Corp., was used.

5.2.2.3 A Literature-Based Approach for Inferring Learning Styles using a Simple Rule-Based Method

While the previously introduced approach used data in order to build a model for inferring learning styles, this section introduces a literature-based approach, where the model for inferring learning styles is fully derived from literature. This approach is based on the idea that each relevant pattern for the respective learning style dimension, as introduced in Section 5.2.1.3, gives a hint about student's learning style. Based on this information as well as on the information about whether a high or low occurrence of the respective behaviour is supporting a particular learning style, the number of matching hints can be calculated, given the students' behaviour.

More formally, based on the four matrices P_{dim}, including the ordered data of each relevant pattern and each student for the respective learning styles dimension *dim*, a matrix H_{ls} was calculated for each of the eight learning styles ls (active, reflective, sensing, intuitive, visual, verbal, sequential, and global). H_{ls} represents how well the behaviour of a student matches with the respective learning style ls for each relevant pattern and therefore, similar to P_{dim}, has in rows all students and in columns all relevant patterns for the respective learning style dimension. H_{ls} consists of values between 0 and 3. The value of 3 indicates that the student's behaviour gives a strong indication for the respective learning style (e.g., a high number of visits of exercises or a low number of visits of content objects are strong indications for an active learning style). The value of 2 indicates that the student's behaviour is average and therefore does not provide a specific hint. The value of 1 indicates that the student's behaviour is in disagreement with the respective learning style (e.g., a low number of visits of exercises or a high number of visits of content objects for an active learning style). A value of 0 indicates that no information about the student's behaviour is available. In contrast to matrix P_{dim}, this matrix includes information about whether a specific learning style is supported by the student's behaviour with respect to its occurrence rather than indicating the occurrence of student's behaviour itself, as done in matrix P_{dim}.

By summing up the values in H_{ls} and dividing them by the number m of patterns that include available information (assuming that $m > 0$), a measure for the respective learning style is calculated. This measure consists of values between 1 and 3, where 3 represents a strong preference for the respective learning style and 1 represents a strong negative preference for the respective learning style. If no pattern includes available information ($m = 0$), no conclusion can be drawn with respect to the respective learning style.

The employed measure is lower bounded by 1 and upper bounded by 3. In order to make this measure more interpretable, it is normalized to lie between 0 and 1, where 1 indicates a strong preference for the respective learning style and 0 represents a strong negative preference. Since the learning style dimensions in the FSLSM are supposed to have opposite poles, a strong negative preference can also be interpreted as a preference for the opposite pole of the respective learning style dimension. Therefore, measures were calculated only for the active, sensing, visual, and sequential learning style and interpreted accordingly.

It should be noted here that in this approach all indications for a specific learning style are considered to be equally relevant for calculating the respective learning style preference. Looking more in detail at this issue, the relevance of a pattern can depend on different aspects, such as preferences on other learning style dimensions. Therefore, the relevance of a pattern can vary for different learners. Considering, for instance, a learner with a sensing and reflective learning style, the preference for spending much time on examples has high relevance for identifying his/her sensing and reflective preference since this pattern is relevant for both learning styles. On the other hand, looking at a sensing and active learner, the active preference argues for a low amount of time and the sensing preference argues for a high amount of time spent on examples. Therefore, a high amount of time spent on examples can be seen as an important indication for a sensing learner who also has a reflective preference. In contrast, for a sensing learner who also has an active preference, this indication is only of low relevance for identifying his/her preferences on these two dimensions. Equal influences exist for many patterns and also other learning style dimensions. Therefore, considering all patterns equally seems to be a suitable compromise.

5.2.3 Evaluation

The two previous sections presented the theoretical background and approaches for identifying learning styles from the behaviour of students. This section deals with the evaluation of the proposed concept for automatic student modelling, using either a data-driven approach of inferring learning styles or a literature-based approach.

In order to evaluate the proposed concept for automatic student modelling, the behaviour of students was tracked in an online course about object oriented modelling in the learning management system Moodle (version 1.6.3) and the students were asked to fill out the ILS questionnaire in order to provide their learning styles. 127 students participated in this study. In order to track all necessary data from the students' behaviour in the online course, some extensions were implemented in Moodle. These extensions are presented in the next subsection. Subsequently, the online course and its structure are introduced. Due to the characteristics of the course, some adjustments, described in the next subsection, were done with respect to the thresholds for classifying data regarding the occurrence of behaviour. Subsequently, the method of the evaluation as well as the results for automatic student modelling using a data-driven and a literature-based approach are described and discussed.

5.2.3.1 Extensions in Moodle

There are two requirements that an LMS has to fulfil in order to provide data about specific patterns of behaviour. First, if the pattern is based on a certain feature (e.g., example or forum), this feature needs to be supported by the LMS. Since patterns are chosen in awareness of commonly used features, most LMSs should be able to provide learning material according to the proposed features. However, the LMS does not only need to be able to present the required types of learning objects but also needs to be able to distinguish between them. Furthermore, the LMS needs to provide teachers and course developers with the option to specify all necessary information, for example, whether a question is about details or overview knowledge.

Second, the LMS needs to be able to track the required behaviour and store this information in the database. For instance, the number of postings and the time each student spent on an example needs to be stored. Again, most LMSs include the option to track certain behaviour of the learners but what exactly is tracked by the system may differ.

The implemented extensions are similar to the extensions described in Section 4.4.2.1, but were adjusted for Moodle version 1.6.3. In order to fulfil the first requirement, the authoring tool was extended by providing the opportunity for teachers and course developers to provide meta-data for distinguishing between a content object, an outline, and an example, using a checkbox for specifying whether the new object is a content object or an outline and using an additional type of learning object based on the *resource* type of Moodle in order to create an example. Regarding quizzes, again the authoring tool was extended in order to provide teachers and course developers with the opportunity to distinguish between self-assessment tests and exercises. Furthermore, they were given the possibility to specify the kind of questions in more detail, distinguishing according to whether the question is about facts or concepts, refers to an overview or to details, is based on graphics rather than on text, and asks students to interpret an existing solution or develop a new solution to a problem.

Regarding the second requirement, only one extension was necessary, dealing with providing more detailed information about how often students are revising their answers before they submit a self-assessment test or an exercise. Furthermore, a second extension was developed in order to ease the extraction of data regarding time spans. Thus, the additional field *duration* was included into the log table of the database, stating how long a student spent on each visited learning object. Both extensions were described in more detail in Section 4.4.2.1.

5.2.3.2 Investigated Course

In order to get data about the behaviour of students, this study is based on a course about object oriented modelling (OOM), which was taught to undergraduate students in the second semester of Information Systems and Computer Science at a university in Austria. The course was blocked in the second half of the winter term 2006/2007, running for 7 weeks. It consists of a lecture and a practical part, where students had to submit 5 assignments. The whole course was managed via Moodle. The aim of using an LMS was to provide students with additional learning material and learning opportunities in order to facilitate learning.

The online course consisted of 7 chapters. Five chapters dealt with the main concepts of object oriented modelling, where each concept was introduced in one chapter. Furthermore, an introduction chapter and a chapter about the practical use of object oriented modelling were provided. Overall, the course included 424 content objects. Moreover, each chapter included one or two files providing all content objects as print-version. For all chapters, an outline, a conclusion, and a self-assessment test were available. Overall, the seven self-assessment tests included 114 questions. For each of the 5 main chapters, additionally 5 examples and 5 exercises exist. The exercise included overall 181 questions. Both, self-assessment tests and exercises, were based on the same concept, namely by asking students questions and providing the correct answer of the question as feedback. However, they were different in their pedagogical aims. Self-assessment tests included theoretical questions where students could check if they understood the theoretical aspects of the learning material. On the other hand, exercises included practical questions where students had to interpret predefined solutions or develop new solutions to a given problem and therefore could check if they were also able to apply the theoretical knowledge. The chapters dealing with the introduction and practical use did not include examples and exercises. Furthermore, a forum was provided for the course. To examine the knowledge of the students, 5 marked assignments were included within the 7 chapters, where each assignment dealt with one or two chapters. The assignments had to be done in groups of two. Few days after the submission, each student had to present the solution individually and had to answer questions about it. At the end of the course, each student had to pass a written exam. Although parts of the assignments were done in groups of two, the course was designed in a way that all students needed to learn everything and they were examined on all topics; hence the course was appropriate for investigation of individual learning.

5.2.3.3 Adjustment of Thresholds for Classifying the Occurrence of Behaviour due to the Course Characteristics

In Section 5.2.1.2, general thresholds for the used patterns were introduced. As mentioned, these thresholds can change with respect to the characteristics of particular courses. In this section, the conducted adjustments of the thresholds with respect to the OOM course are described. These adjustments are based on the characteristics of the course as well as on consideration of the actual usage of the investigated features in the course.

In the OOM course, communication via the discussion forum was mainly intended and used for asking questions which were then answered by the tutor or teacher. Only in few cases, questions were answered by the students or discussion between students took place. Accordingly, the upper thresholds for forums were lowered, using a value of 14 visits a week (twice a day) for the number of visits and 10 minutes per week for the time students spent in the forum. The values for the lower thresholds were kept, as introduced, at a value of 7 visits a week and 5 minutes per week. Furthermore, the number of postings was lowered as well, using 2 postings per course as lower threshold and 4 postings per course as upper threshold.

When looking at the number of visits of specific types of learning objects, consideration was given on how often students are expected to visit the specific type of learning objects. Regarding exercises, even students with a high interest in exercises were expected to perform them only once since each exercise included many questions and was quite comprehensive. For self-assessment questions, students who are highly interested in checking their knowledge by using self-assessment tests are expected to conduct each question in average more than once since the questions are short and each self-assessment test consists of 5 randomly chosen questions. Similarly, students who are highly interested in examples are expected to visit each example more than once. Therefore, the thresholds for visiting exercises were assumed, as recommended in Section 5.2.1.2, by using values of 25% and 75%. For performing self-assessment questions and visiting examples, the thresholds were raised to 50% and 100%.

Furthermore, the thresholds for the number of visits on content objects were decreased to 10% and 20% since students were also presented with the learning material in the lecture, which they can visit optionally, and had the possibility to download the learning material for print. Therefore, the content objects were mainly used for looking up information when students were conducting, for example, some exercises or were reflecting about the topic. This characteristic helps to identify preference with respect to content objects more easily since the course is designed in a way that all students need to read/hear the content in order to understand the topic. By looking at their preference for visiting content objects, it can be seen whether students prefer to look up something in the content objects or look at examples, if they prefer to check their knowledge by going through the content objects or performing self-assessment tests, and so on.

Regarding the time students spent on particular types of learning objects, thresholds of 50% and 75% of the expected learning time of students with high interest in the respective type of learning object are assumed, as proposed in Section 5.2.1.2. The expected time for examples was set to 15 minutes per chapter. For exercises, a value of 30 minutes per chapter was expected. The expected time for self-assessment tests was set to 3 minutes and for content objects, an expected time of 15 minutes per chapter was assumed. Due to the primary use of content objects for looking up information, the time students spend on the outline is assumed as quite low by a value of 3 minutes during the course. For the expected time students spent on the course overview page, 10 minutes per chapter was assumed.

In order to minimise the error of recording too high time spans in case that students start doing something else and just keep running the online course, values of time spans that exceeds a critical value were replaced by average values. Critical values were set to 20 minutes for visiting examples and performing exercises, 10 minutes for visiting forums, content objects, and self-assessment tests as well as reviewing results of self-assessment tests, and 3 minutes for visiting outlines and overviews. Each of these critical values is, with respect to the respective type of leaning object, quite high in order to ensure that only those entries were replaced where students obviously did something else than learning. The average values which were used for replacement were based on the gathered data from the course. Values were set to 3 minutes for exercises, 2 minutes for self-assessment tests, 30 seconds for forums, examples, and content objects, 15 seconds for the course overview page and reviewing results of self-assessment tests, and 10 seconds for the outlines.

Furthermore, the thresholds for revising answers were changed. In the OOM course, all exercises and self-assessment tests were voluntary and results were not used in any form for marking. Therefore, the motivation for students to carefully check their answers can be supposed to be quite low. Moreover, exercises and self-assessment tests provided learners with the correct answers after they submitted the test, which again decrease the motivation to check answers before submitting, especially for the self-assessment tests which was frequently used and consisted mainly of theoretical questions. Due to these reasons, the thresholds for revising answers of an exercise or self-assessment test were set to 2.5% and 5% of all performed exercises and self-assessment tests.

Table 5.3 summarises all used thresholds and points out the adjustments of thresholds.

Table 5.3: Thresholds for the object oriented modelling course. (* For the number of revisions, the adjusted thresholds are based on the number of performed self-assessment tests and exercises rather than on the answered questions)

Features	Patterns	Thresholds	
Content	content_visit	10% (75%)	20% (100%)
	content_stay	50%	75%
Outline	outline_visit	75%	150%
	outline_stay	50%	75%
Example	example_visit	50% (25%)	100% (75%)
	example_stay	50%	75%
Self-assessment	selfass_visit	50% (25%)	100% (75%)
	selfass_stay	50%	75%
	selfass_twice_wrong	25%	50%
Exercise	exercise_visit	25%	75%
	exercise_stay	50%	75%
Self-assessment and exercise	ques_detail	50%	75%
	ques_overview	50%	75%
	ques_facts	50%	75%
	ques_concepts	50%	75%
	ques_graphics	50%	75%
	ques_text	50%	75%
	ques_interpret	50%	75%
	ques_develop	50%	75%
	quiz_revisions	2.5% (20%)*	5% (50%)*
	quiz_stay_results	30 sec.	60 sec.
Forum	forum_visit	7	14 (50)
	forum_stay	5 min.	10 (30) min.
	forum_post	1/7 (1)	2/7 (10)
Navigation	navigation_skip	1%	2%
	navigation_overview_visit	10%	20%
	navigation_overview_stay	50%	75%

5.2.3.4 Method of Evaluation

This section describes how the proposed concept for automatic student modelling was evaluated, comparing the data-driven and literature-based approach in order to find out how effective the proposed concept is by using either one or the other approach for inferring learning styles. The evaluation is based on the data gathered from the OOM course. These data were used as input data in both approaches for inferring learning styles. For verifying the predicted learning styles of both approaches, students were asked to fill out the ILS questionnaire when they registered in the OOM course. The questionnaire was translated to German in order to make it easier for students to fill it out.

Data needs to meet three requirements in order to be used as input data in this study. First, the time students take to submit the ILS questionnaire was recorded. Data of students who spent less than 5 minutes on the ILS questionnaire were discarded because the detected learning styles were considered as not reliable enough. Second, only data from students who submitted at least 3 assignments were included, which was a requirement for a positive mark. This requirement was chosen in order to exclude students who dropped out since the data from those students do not show representative behaviour. Third, only data from students who performed the final exam were included, which was also a requirement for a positive mark. This requirement is important since it ensures that for all students the preparation for the final exam is included in the data. Overall, data from 75 students were finally used for this study.

In the following two subsections, description is provided on how to evaluate the concept of automatic student modelling using either the data-driven or the literature-based approach.

Method of Evaluation Using the Data-Driven Approach

The basic idea of a data-driven approach is to use data in order to train a model. As mentioned in Section 5.2.2.2, data were therefore split into training data and test data. Both data included information about the behaviour of students and about their learning styles as identified by the ILS questionnaires. Training data were then used to train the Bayesian network (as described in Section 5.2.2.2) and test data were used for testing the effectiveness of the resulting Bayesian network for identifying learning styles based on the behaviour of students.

In the testing process, the Bayesian network was used to infer learning styles from the information about the behaviour of students included in the test data. The predicted learning styles were then compared with the information about the learning styles in the test data. Since the approach was designed in order to identify learning styles by distinguishing between 3 values, for instance, an active, balanced, and reflective learning style, both the learning styles based on the ILS values as well as the predicted learning styles are on a 3-item scale.

In order to measure the precision of the results of the Bayesian network, including not only whether a specific learning style was identified correctly but also how close the predicted learning style is to the learning style based on the ILS values, the following measure proposed by García et al. (2007) was used:

$$\text{Precision} = \frac{\sum_{i=1}^{n} Sim(LS_{predicted}, LS_{ILS})}{n} \cdot 100, \tag{5.1}$$

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

In order to achieve reliable results, 5 runs were conducted for each Bayesian network, where each Bayesian network was build for identifying one learning style dimension of FSLSM. Each run includes parameter learning, drawing inferences, testing the network, and calculating the precision measure. For each run, different training and test data were used. Therefore, training and test data were split based on a 10-fold technique. Accordingly, the dataset was partitioned into 10 sub-samples. For each run, one sub-sample is used as test data and the remaining 9 sub-samples are used for training the network, where each of the sub-samples are used at most once for testing. The average precision value of the 5 runs was used as a result for the respective Bayesian network.

Method of Evaluation Using the Literature-Based Approach

While in a data-driven approach, the model for calculating learning styles is based on and trained with sample data, the model from the literature-based approach is built without sample data. Therefore, the whole set of data can be used for verifying the literature-based approach. In order to make both approaches comparable, the same measure was applied. Thus, the ILS values were mapped again on a 3-item scale with the same thresholds as described in Section 5.2.2.2. For scaling the results of the literature-based approach, ranging from 0 to 1, values of 0.25 and 0.75 were used as thresholds. These thresholds are based on experiments, showing that using the first and last quarter for indicating learning style preferences for one or the other extreme of the respective dimension and using the second and third quarter for indicating a balanced learning style, achieves better results than dividing the range into 3 parts. This can be explained due to the characteristics of the literature-based approach, where it seems to be more appropriate to identify preferences for the extremes only if a strong indication exists. Based on the scaled ILS values (LS_{ILS}) and the scaled results of the literature-based approach ($LS_{predicted}$), the formula 5.1 was applied and the result was used as measure for the literature-based approach.

5.2.3.5 Results

Table 5.4 shows the results achieved by using the data-driven approach for inferring learning styles. The table presents the results of each run and each learning style dimension as well as the average results for each learning style dimension. As can be seen from this table, the average results show only moderate precision, ranging from values between 62.5% and 68.75%. Furthermore, for the sensing/intuitive and the sequential/global dimension, the results of each run differ quite strongly among each other.

Table 5.4: Results achieved by using the data-driven approach

	act/ref (in %)	sen/int (in %)	vis/ver (in %)	seq/glo (in %)
Run 1	68.75	43.75	68.75	50.00
Run 2	68.75	56.25	81.25	81.25
Run 3	62.50	68.75	75.00	68.75
Run 4	50.00	68.75	56.25	50.00
Run 5	62.50	87.50	62.50	81.25
Average	62.50	65.00	68.75	66.25

Table 5.5 presents a comparison of the average results achieved by using the data-driven approach and results achieved by using the literature-based approach. The comparison shows clearly that for each dimension, the literature-based approach yields better results than the data-driven approach. The results achieved by using the literature-based approach range from 73.33% to 79.33% and can be seen as good results, indicating high precision. Further discussion about the results is provided in the next section.

Table 5.5: Results achieved by using the data-driven approach and the literature-based approach

	act/ref (in %)	sen/int (in %)	vis/ver (in %)	seq/glo (in %)
Data-driven approach	62.50	65.00	68.75	66.25
Literature-based approach	79.33	77.33	76.67	73.33

5.2.3.6 Discussion

Although the study proposed by García et al. (2007) demonstrated promising results by using Bayesian networks for identifying learning styles from the behaviour of students, according to our results, the use of Bayesian networks yields only to moderate results. For the sensing/intuitive dimension, the study by García et al. achieved a result of 77%, which is higher than the average result achieved by our study (65%). However, García et al. conducted only one run and the results of all 5 runs in our study range from 56.25% to

87.5%. For the active/reflective dimension, García et al. concluded that the students' involvement in communication tool is essential for achieving reasonable results for this dimension. The discussion forum in our course aimed at providing students with the possibility to ask questions to the teachers and tutors and was also used for this purpose by the students. Furthermore, the patterns of the active/reflective dimension in our study do not only rely on the communication tools, as done in the study proposed by García et al., but incorporate also the preferences dealing with trying something out and reflecting about the learning material, which are parts of the active/reflective dimension as well. The average result of our study regarding the active/reflective dimension is slightly higher than the result obtained by the study of García et al. (58%), but still moderate by a value of 62.5%. Furthermore, García et al. proposed that the students' inexperience in online learning can have negative effect on the identification process of learning styles, especially for the sequential/global dimension. The investigated course was taught for students in the second semester, blocked in the second half of the semester. At the respective university, Moodle is widely used for courses. Therefore, students are expected to have already gained some experience with online courses during their studies. However, the average result of the sequential/global dimension in our study (66.25%) is only slightly higher than the result of the study proposed by García et al. (63%). For the visual/verbal dimension, no results were obtained by the study of García et al.

In summary, the results achieved by using the data-driven approach show that the approach has potential to identify learning style preferences but the precision is only moderate, ranging from values between 62.5% and 68.75%. A possible reason for the moderate precision of the results is the relatively small number of training data. In this study, data from 67 students were used for training the Bayesian network. However, when looking at the number of patterns, even for the visual/verbal dimension, which has the lowest number of patterns, namely only 6 patterns, 729 ($=3^6$) possible different states exist since each pattern can have 3 states, excluding the possibility of missing values in these considerations. For the sensing/intuitive dimension, where 13 patterns are proposed, 1594323 ($=3^{13}$) different states exist. Using input data from only 67 students might therefore lead to moderate precision when drawing conclusions about such a high number of states.

Looking at the results achieved by using the literature-based approach, values are higher than those achieved by using the data-driven approach for all dimensions. The resulting values, ranging from 73.33% to 79.33%, can be considered as good results and show that the proposed concept for automatic student modelling using the literature-based approach can be seen as a suitable instrument for inferring learning styles based on the students' behaviour in online courses.

5.3 Considerations of Characteristic Preferences within the Learning Style Dimensions of FSLSM

FSLSM as well as most other learning style models incorporated in educational systems are developed for learning in general rather than only for online learning. Therefore, not all aspect of the learning style model might be incorporated in every course. For courses in adaptive systems, this is often the case due to the restriction of most adaptive systems to specific functions of web-based education, supporting only particular features such as the presentation of content or the use of quizzes (Brusilovsky, 2004). Although LMSs include a great variety of features which might support all aspects of the learning style model, still some aspects of the learning style model might get lost, for example, simply because the teacher did not include the respective feature. This might be irrelevant, when a system aims only at detecting specific aspects of learning styles from the behaviour of students and then providing adaptivity according to these specific aspects, such as for example in TANGOW (Paredes and Rodríguez, 2004). However, when aiming at building an accurate and holistic student model, it is important to consider which aspects of the learning style model can be detected and which can not due to unavailability of information.

In the next subsection, a study is introduced which aims at investigating the learning styles introduced by Felder and Silverman (1988) in more detail in order to identify the characteristic preferences of each learning style dimension as well as their relevance for the dimension. This information can help in developing a more accurate approach for automatic student modelling. The subsequent subsection introduces an automatic student modelling approach for detecting the identified characteristic preferences within learning style dimensions.

5.3.1 Investigations on Characteristic Preferences within the Learning Style Dimensions of FSLSM

In this section, a study is introduced dealing with analysing data based on FSLSM to provide a more detailed description of its learning styles. This study aims at identifying characteristic preferences of each of the four dimensions of FSLSM in order to be able to make a more gradual distinction within the learning style dimensions. Furthermore, the degree of how representative each characteristic preference is for each learning style dimension is analysed.

Such detailed information is beneficial in many ways. In general, a more detailed description of learning styles has potential to improve student modelling and as such leads to a more accurate model of the student. This again helps to provide more suitable adaptivity while allowing more detailed research about learning styles.

With respect to automatic student modelling, such detailed information about learning styles is needed to check whether all characteristic behaviour described in the learning style model can be mapped as well as identified from the behaviour in the system. Being aware of the characteristics and their relevance for the respective learning style dimensions leads to a better estimation of the results of the approach and hence, to a more meaningful application of the identified information.

In order to investigate the learning styles of students, a study with 207 students was performed. 122 students from a university in New Zealand and 85 from a university in Austria took part in the study. The mixed group of students, from bachelor to PhD level, was recruited from particular courses such as Web Engineering and Information Management, and was mostly studying Information Systems. To detect the learning styles of the students, they completed the ILS questionnaire (Felder and Soloman, 1997). In the following subsection, a general analysis on the data from the ILS questionnaire is presented. Subsequently, a grouping of questions based on their semantic meaning is proposed. Then, linear discriminant analysis was used in order to detect the most representative characteristics of each learning style dimension as represented in the gathered data. Furthermore, analysis was conducted on how representative these characteristics are for the specific learning style dimensions. For cross-validation, empirical frequencies analysis as well as correlation analysis was used.

Table 5.6: Distribution of preferences (distinguishing between strong/moderate and balanced preferences)

	str./mod. active	balanced	str./mod. reflective	str./mod. sensing	balanced	str./mod. intuitive	str./mod. visual	balanced	str./mod. verbal	str./mod. sequential	balanced	str./mod. global
Frequency	49	127	31	61	110	36	133	68	6	33	141	33
Percentage	24%	61%	15%	29%	53%	17%	64%	33%	3%	16%	68%	16%

5.3.1.1 Frequencies of Occurrence of Learning Styles

According to the distribution of preferences for each dimension, 57% of the students participating in the study were found to have an active preference, 58% a sensing preference, 87% a visual preference, and 56% a global preference. Table 5.6 shows a more detailed description, classifying the preferences of learners in strong/moderated (ILS values from +5 to +11 or -5 to -11) and balanced (ILS values from +3 to -3). Looking at the overview of similar studies given by Felder and Spurlin (2005), our results are mainly in agreement with the results of these studies. Some small differences can be seen in the sensing/intuitive dimension, where slightly more intuitive learners have attended our study, as well as in the sequential/global dimension where more global learners have participated.

5.3.1.2 Grouping of Questions

Looking at FSLSM, it can be seen that each learning style is described by different characteristics. Based on the description of FSLSM (Felder & Silverman, 1988), the questions in the ILS questionnaire were manually grouped according to the similarity of semantics. These semantic groups represent characteristic preferences identified for each learning style. Table 5.7 presents the semantic groups as well as the questions belonging to these groups. A question may appear twice in the table, if the answer to the question points to two different groups.

Table 5.7: Semantic groups associated with the ILS questions

Style	Semantic Groups	ILS Questions (Answer a)	Style	Semantic Groups	ILS Questions (Answer b)
Active	trying something out	1, 17, 25, 29	Reflective	think about material	1, 5, 17, 25, 29
	social oriented	5, 9, 13, 21, 33, 37, 41		impersonal oriented	9, 13, 21, 33, 41, 37
Sensing	existing ways	2, 30, 34	Intuitive	new ways	2, 14, 22, 26, 30, 34
	concrete material	6, 10, 14, 18, 26, 38		abstract material	6, 10, 18, 38
	careful with details	22, 42		not carefule with details	42
Visual	pictures	3, 7, 11, 15, 19, 23, 27, 31, 35, 39, 43	Verbal	spoken words	3, 7, 15, 19, 27, 35
				written words	3, 7, 11, 23, 31, 39
				difficulty with visual style	43
Sequential	detail oriented	4, 28, 40	Global	overall picture	4, 8, 12, 16, 28, 40
	sequential progress	20, 24, 32, 36, 44		non-sequential progress	24, 32
	from parts to the whole	8, 12, 16		relations/connections	20, 36, 44

5.3.1.3 Analyses of Characteristic Preferences within the Learning Style Dimensions of FSLSM

According to the classification provided in Table 5.7, some analyses were performed in order to detect how relevant the identified groups are for each learning style dimension. The analyses were performed based on the data from the ILS questionnaire.

In order to find the most representative semantic groups of each dimension, Fisher linear discriminant analysis (e.g., Duda, Hart, & Stork, 2000), a well known multivariate method for linear optimal separating dimensionality reduction, was conducted. Then the model given by linear discriminant analysis was compared with some empirical results regarding both frequencies and correlation analysis in order to cross-validate it. The statistical analyses were performed in Matlab, version 7 R14 (Matlab, 2007).

Investigating the Relevance of Semantic Groups within Learning Style Dimensions

In order to apply consistently statistical methods, data were transformed in frequencies, i.e. on absolute scale, as follows. Let Q be the 207x44 matrix containing in rows individuals and in column the answer to each ILS question. For each question q_i, two numerical variables, namely the two answers to each questions, $a_1 = 1$ if $q_i = 1$ (otherwise 0) and $a_2 = 1$ if $q_i = -1$ (otherwise 0) were obtained.

Let A be the 207 x 88 matrix containing in rows individuals and in columns the a_i, i=1, …, 88. The matrix A has rank at most 44 by construction, since two columns are constrained to sum up to 1 in rows. Fisher linear discriminant analysis (LDA) was then performed on the whole matrix A of learners' answers to the ILS questionnaire.

This method, a well known multivariate method for dimensionality reduction, is able to find the optimal linear direction of separation. This direction is given by a vector of coefficients w, usually one-dimensional, that maximise the inter-class separation. Within this vector, the highest absolute values of coefficients indicate the most important variables for discrimination. In this study, LDA was used to find the most important ILS questions for discriminating between each learning style dimension according to the answers given by the learners. A more formal description of the conducted LDA is given by Graf et al. (2007).

Due to the rank deficiency and to the redundancy of the matrix A, the outcome of LDA showed a vector w in which the coefficients associated with each answer were equal in absolute values, but opposite in signs according to the association with each style inside each of the four ILS dimensions.

In order to detect the importance of each semantic group within the learning style dimensions, the coefficients of w associated with each answer were investigated using a synthetic index of the importance of each group of questions according to each learning style dimension, calculated as the average of the absolute values of the coefficients related to each answer in Table 5.7. Table 5.8 summarises the results.

Since a high value indicates a strong impact of the semantic group for the respective learning style, it can be seen that for an active learning style the preference for trying something out has more impact than the preference for social orientation (e.g., for discussing and explaining learning material to each other or working in groups). On the other hand, for a reflective learning style, the social behaviour is more relevant than the preference to think/reflect about learning material. That means that for supporting students with a reflective learning style, it is important to give them the opportunity to work individually.

Regarding the sensing/intuitive dimension it can be seen that the preference for concrete learning material seems to be most important for learners with a sensing learning style. The preference for abstract material is most relevant for intuitive learners. While for sensing learners, the carefulness with details seems to be less representative, the tendency for being not patient and not careful with details is characteristic for intuitive learners.

Table 5.8: Relevance of groups on the learning style dimensions (values > 0.5 are highlighted)

Styles	Semantic Groups	Act/ Ref	Sen/Int	Vis/Ver	Seq/Glo
Active	try something out	**0.639**	0.113	**0.536**	0.211
	social oriented	0.452	0.146	0.190	0.180
Reflective	think about material	**0.597**	0.122	0.486	0.217
	impersonal oriented	**0.698**	0.143	0.175	0.170
Sensing	existing ways	0.237	**0.568**	0.301	0.174
	concrete materials	0.178	**0.777**	0.380	0.245
	careful with details	0.147	0.409	0.329	0.456
Intuitive	new ways	0.193	**0.678**	0.309	0.237
	abstract material	0.225	**0.715**	0.453	0.173
	not careful with details	0.008	**0.699**	0.026	0.151
Visual	pictures	0.238	0.227	**0.944**	0.167
Verbal	spoken words	0.202	0.189	**0.648**	0.171
	written words	0.171	0.199	**1.086**	0.258
	difficulty with visual style	0.297	0.388	**0.789**	0.078
Sequential	detail oriented	0.224	0.218	0.290	**0.800**
	sequential progress	0.100	0.237	0.432	**0.686**
	from parts to the whole	0.123	0.154	0.113	**0.839**
Global	overall picture	0.174	0.186	0.202	**0.819**
	non-sequential progress	0.140	0.175	**0.520**	**0.715**
	relations/connections	0.074	0.278	0.375	**0.869**

For the visual learning style, only one semantic group exists, which is also highly representative. For the verbal learning style, the most representative group is the preference for written words. But also spoken words and the difficulty with visual style seem to play a relevant role. It is interesting to note that the results of the visual/verbal dimension show additionally an impact regarding the groups of trying something out and a non-sequential learning progress. Since these relations are not described in FSLSM, further investigations are necessary.

Regarding the sequential/global dimension, all six semantic groups of the dimension show high relevance for the respective learning styles. Most important is the preference for relations and connections to other areas for global learners, while for sequential learners the ability to infer from parts to the whole solution is most relevant. The groups for a sequential or non-sequential way of learning achieved for both learning styles the lowest value, but are still representative.

Cross Validation by Empirical Frequencies and Correlation Analysis

In order to cross-validate the results, both Pearson's correlations and empirical frequencies were used. Regarding empirical frequencies, comparison was made on how often students with a particular learning style answer a question with a specific preference. Considering the active/reflective dimension as an example, a question is representative if students with an active learning style answer this question clearly more often with an active preference than student with a reflective learning style. To prove that questions for the active/reflective dimension are representative, the percentage of active learners, answering a question with an active preference, is compared with the percentage of reflective learners, answering the question with an active preference. The difference of these percentage values acts as a measure indicating how representative a question is for the active/reflective dimension. Accordingly, measures for all other dimensions were calculated. 7 questions of the active/reflective dimension, 10 of the sensing/intuitive dimension, 9 of the visual/verbal dimension, and 5 of the sequential/global dimension achieved a difference of 30% or more. All these questions except one belonged to the respective dimension. The one exception indicated a sequential/global learning style but seems to be representative for the sensing/intuitive dimension as well as for the sequential/global dimension. This can be explained by the existing correlation between the sensing/intuitive and sequential/global dimension (reported in Felder & Spurlin, 2005 as well as identified by the performed correlation analysis). Overall, this analysis shows that almost all of the questions are highly representative for their dimensions.

In order to identify the most representative questions for each dimension, the questions were ranked according to the above introduced measure. The five most representative questions for each dimension are shown in Table 5.9.

Regarding the active/reflective dimension, it can be seen that the first, third and fifth ranked questions deal with social oriented behaviour asking whether students are considered as outgoing, gotten to know many other students in a class, and like to work in groups. In contrast, the second and fourth ranked questions are about whether students tend to try things out or think the learned material through. These two characteristics were identified in the previous section as well. As a result of both analyses, it can be seen that social behaviour as well as the preference for trying things out or thinking things through are important for the active/reflective dimension. Since discriminant analysis is more accurate for distinguishing relevant aspects, the outcomes provided by it underline better the difference of the impact of all four semantic groups for active learners and reflective learners.

Regarding the sensing/intuitive dimension, it can be seen clearly that the first four questions are dealing with the preference for concrete material like facts and data or abstract material such as concepts and theories. Therefore, this characteristic seems to be the most representative one for this dimension. This is also confirmed by the results of the discriminant analysis. The fifth question is about whether a student considers himself/herself as realistic or innovative and belongs to the group of existing ways/new ways, which can be seen as the second important characteristic according to discriminant analysis.

Regarding the visual/verbal dimension, it is interesting to see that the first two questions from the verbal point of view are about written text, question three and five consider written and spoken words and only the fourth question is about spoken words only. While questions dealing with the preference for written words seem to be more relevant than questions about the preference for spoken words, the results nevertheless indicate that for verbal learners, both written and spoken language are important. For visual learners, only one semantic group exists, namely to learn best from what students see, which can be obviously seen from the resulting questions. Overall, the results are in agreement with the results from the discriminant analysis.

Table 5.9: The five most representative questions for each dimension of the ILS according to frequencies analysis

	Rank	Question No.	Question
Active / Reflective	1	37	I am more likely to be considered (a) outgoing. (b) reserved.
	2	1	I understand something better after I (a) try it out. (b) think it through.
	3	13	In classes I have taken (a) I have usually gotten to know many of the students. (b) I have rarely gotten to know many of the students.
	4	25	I would rather first (a) try things out. (b) think about how I'm going to do it.
	5	21	I prefer to study (a) in a study group. (b) alone.
Sensing / Intuitive	1	6	If I were a teacher, I would rather teach a course (a) that deals with facts and real life situations. (b) that deals with ideas and theories.
	2	38	I prefer courses that emphasize (a) concrete material (facts, data). (b) abstract material (concepts, theories).
	3	18	I prefer the idea of (a) certainty. (b) theory.
	4	10	I find it easier (a) to learn facts. (b) to learn concepts.
	5	2	I would rather be considered (a) realistic. (b) innovative.
Visual / Verbal	1	31	When someone is showing me data, I prefer (a) charts or graphs. (b) text summarizing the results.
	2	11	In a book with lots of pictures and charts, I am likely to (a) look over the pictures and charts carefully. (b) focus on the written text.
	3	7	I prefer to get new information in (a) pictures, diagrams, graphs, or maps. (b) written directions or verbal information.
	4	19	I remember best (a) what I see. (b) what I hear.
	5	3	When I think about what I did yesterday, I am most likely to get (a) a picture. (b) words.
Sequential / Global	1	36	When I am learning a new subject, I prefer to (a) stay focused on that subject, learning as much about it as I can. (b) try to make connections between that subject and related subjects.
	2	20	It is more important to me that an instructor (a) lay out the material in clear sequential steps. (b) give me an overall picture and relate the material to other subjects.
	3	8	Once I understand (a) all the parts, I understand the whole thing. (b) the whole thing, I see how the parts fit.
	4	44	When solving problems in a group, I would be more likely to (a) think of the steps in the solution process. (b) think of possible consequences or applications of the solution in a wide range of areas.
	5	4	I tend to (a) understand details of a subject but may be fuzzy about its overall structure. (b) understand the overall structure but may be fuzzy about details.

In the sequential/global dimension, the first, second, and fourth questions deal with whether students prefer a sequential way of learning (from the viewpoint of a sequential style) or whether relationships and connections to other areas are more important for them (from the viewpoint of a global style). The other questions are about the other two semantic groups respectively for a sequential and global learning style. As expected according to the results from discriminant analysis, all relevant groups are covered by the 5 most relevant questions. While for the global learning style the order of relevance is in agreement in both analyses, for the sequential style the preference for a sequential learning progress seems to be less relevant according the discriminant analysis.

Looking at correlations inside frequencies of the answers according to each of the eight learning styles (active, reflective, sensing, intuitive, visual, verbal, sequential, and global), interesting features emerged. Correlations were calculated over the total number of positive answers to each of the 88 answers allowed by the ILS questionnaire (2 possible answers for each question), transforming then data from a binary scale to an equivalent numeral one, for coherence and consistency with the applications of Pearson's correlation coefficients and related p values.

Many high (greater than 0.7) values were found and related p values were very small ($p < 0.05$), indicating a significance. In particular, a great number of high absolute values of correlation coefficients involve questions belonging to all groups associated with the active/reflective dimension and cross dimension correlations between these groups; questions belonging to all groups associated with the sequential/global dimension and cross correlation questions between these groups, and questions belonging to the groups associated with the visual/verbal dimension (pictures/spoken and written words).

Looking at the results, it seems that some correlations between dimensions of learning styles are likely. This hypothesis needs a deeper and dedicated investigation both of the analyses presented by literature (Felder & Spurlin, 2005) and the statistical analyses performed on this dataset in order to be tested and explained.

In conclusion, results of the empirical frequencies as well as correlation analysis confirm the results from the LDA. However, LDA seems to be able to give a more accurate indication about the importance of each semantic group.

5.3.2 An Approach for Automatic Detection of Learning Styles based on the Preferences within the Dimensions of FSLSM

The previous section presented investigations about semantic groups, representing characteristic preferences within the learning style dimensions of FSLSM. The relevance of each group for each dimension was shown. In this section, an approach for automatic detection of learning styles preferences with respect to the proposed semantic groups is introduced. This approach is similar to the approach for automatic detection of preferences based on learning style dimensions, described in Section 5.2. Regarding determining the relevant behaviour, the relevant patterns for each semantic group are presented in the next subsection. However, the investigated features and patterns as well as the classification of occurrence of behaviour are the same as proposed in Section 5.2.1.1 and Section 5.2.1.2. For calculating learning styles, the literature-based approach was applied. The evaluation of the approach for detecting preferences on semantic groups is based on the same modifications in Moodle, the same course and adjustments of thresholds for classifying the occurrence of behaviour than the approach for detecting preferences on learning style dimensions. Therefore, only the method of evaluation, the results and discussion for automatic detection of preferences on semantic groups is described in the subsequent subsections.

5.3.2.1 Determining Relevant Behaviour

Since the proposed features and patterns as well as the classification of occurrence of behaviour is assumed to be the same as for automatic student modelling for learning style dimensions (described in Section 5.2.1.1 and 5.2.1.2), this section discusses only the relevant patterns for each semantic group of each learning style dimension and related behaviour of learners with a preference for a specific semantic group is pointed out. The relevant patterns as well as the related behaviour are based on the literature about FSLSM (Felder and Silverman, 1988). In contrast to the learning style dimensions, which are bi-polar as proposed by Felder and Silverman, semantic groups, for example, the group indicating a preference for concrete material and the group indicating a preference for abstract material does not necessarily represent completely opposite preferences. This comes from the fact that the semantic groups are based on a different set of ILS answers. Furthermore, this assumption allows considering the preference of learners in more detail, for example, distinguishing between a learner who has a strong preference for concrete material but also can cope with abstract material, indicating a balanced preference for the group about abstract material. In the next subsections, the patterns for each semantic group are discussed.

Semantic Groups within the Active/Reflective Learning Style Dimension

According to the proposed classification in Section 5.3.1.2, the active/reflective dimension consists of four groups, dealing with trying things out and thinking about the material as well as social oriented and impersonal oriented behaviour. The relevant patterns for each group are described in the following paragraphs and are summarised in Table 5.10.

Learners with a preference for the semantic group of *trying things out* like to experiment with the material. They like learning by trial and error and they prefer to work actively with the learning material. Therefore, a higher interest in exercises, where they can experiment and learn in an active way, can be expected and patterns such as the number of visits and the time spent on exercises were considered as indication for a preference for trying things out. Furthermore, a high preference for performing self-assessment tests is assumed, which can be measured from the number of performed tests. However, learners who have a preference for trying things out tend to see self-assessment tests as an active way of learning with only little reflection. Such a lack of reflection can be seen when looking at how often learners answer the same question twice wrong. Moreover, learners who prefer to try things out tend to spend less time on reflecting and reviewing the results of self-assessment tests and exercises. Furthermore, they tend to have a lower preference for examples, since examples show how something can be done rather than letting students do it actively by themselves. Therefore, the time students spent on examples can act as a pattern for identifying their preference towards trying things out. Moreover, their preference for reading content, in terms of visits and time spent on content objects, as well as spending time on an outline can be seen as other patterns, where a low number or time of visits indicate a preference for trying things out.

Table 5.10: Relevant patterns for groups within the active/reflective learning style dimension

Active Learning Style		**Reflective Learning Style**	
trying something out	social oriented	think about material	impersonal oriented
content_visit (-)	forum_visit (-)	content_visit (+)	forum_visit (+)
content_stay (-)	forum_post (+)	content_stay (+)	forum_post (-)
outline_stay (-)		outline_stay (+)	
example_stay (-)		selfass_visit (-)	
selfass_visit (+)		selfass_stay (+)	
selfass_twice_wrong (+)		selfass_twice_wrong (-)	
exercise_visit (+)		exercise_visit (-)	
exercise_stay (+)		exercise_stay (-)	
quiz_stay_results (-)		quiz_stay_results (+)	

Learners who have a preference for the semantic group of *thinking about the material* focus more on a reflective way of learning. They like to read the learning content and reflect about it. Therefore, a high number of visits on content objects and a high amount of time spent on content objects and outlines can act as an indication for a preference for thinking about the material. Furthermore, they are expected not to prefer to learn from features which ask them to participate actively, such as exercises. Therefore, a low number of performed exercises and a low amount of time spent on exercises can give indications about a preference for thinking about the material. Furthermore, the students' behaviour on self-assessment tests can give some indications. Due to the more active character of self-assessment tests, students who have a preference for thinking about the material tend to perform them less often. However, when they perform a test, they are expected to spend more time on answering the questions. Furthermore, due to their preference for reflecting, students are supposed to answer questions twice wrong less often, which can therefore be used as a pattern. Moreover, they are expected to spend more time on checking and reflecting on the results of self-assessment tests and exercises, in terms of checking the right answers and reflecting about the wrong ones.

In order to get information about students' tendency regarding social orientation, only few possibilities exist in commonly used LMSs. With respect to the incorporated features, only discussion forums can give indications. Students who have a preference for the semantic group referring to the preference of being *social oriented* like to communicate with others, discuss learning material and explain it to others. Therefore, the number of postings in a discussion forum can give indications about the preference of learners regarding the social orientation group. Learners who are *impersonal oriented* and have a preference for this semantic group are expected to have a preference for working alone but also for reflective learning. With respect to forums, impersonal oriented learners are therefore expected to focus more on participating in a passive way. Their preference for reflective learning leads to an interest in reading what others have written, which results in a high number of visits of forum entries.

Semantic Groups based on the Sensing/Intuitive Learning Style Dimension

The sensing/intuitive learning style dimension can be divided into 6 semantic groups. The relevant patterns are described in the following paragraphs and are summarised in Table 5.11.

Table 5.11: Relevant patterns for groups within the sensing/intuitive learning style dimension

Sensing Learning Style			Intuitive Learning Style		
existing ways	concrete material	careful with details	new ways	abstract material	not carefule with details
example_visit (+)	content_visit (-)	selfass_stay (+)	example_visit (-)	content_visit (+)	ques_detail (-)
example_stay (+)	content_stay (-)	ques_detail (+)	example_stay (-)	content_stay (+)	selfass_stay (-)
selfass_visit (+)	example_visit (+)	quiz_revisions (+)	selfass_visit (-)	example_visit (-)	quiz_revisons (-)
exercise_visit (+)	example_stay (+)	quiz_stay_results(+)	ques_develop (+)	example_stay (-)	quiz_stay_results(-)
ques_develop (-)	ques_facts (+)			ques_concepts (+)	
				ques_develop (+)	

Learners with a preference for the semantic group for *existing ways* like to solve problems with standard procedures, which they have learned and practised before. They are expected to prefer to test their acquired knowledge by the use of self-assessment tests as well as by performing exercises. Therefore, the number of performed self-assessment tests and exercises act as a pattern for this preference. Furthermore, students who like to solve problems based on standard procedures tend to have problems in coming up with new ways of solving problems and therefore are expected to achieve poorer results on questions about generating new solutions, which is therefore used as a pattern. Since examples show existing ways of solving specific problems and students can learn standard procedures for solving problems from such examples, a high number of visits and time spent on examples act as indications for a preference of this semantic group.

Learners who prefer challenges and solving problems in new ways tend to have a preference for the semantic group of *new ways*. They tend to be more creative and innovative and get easily bored by solving the same kind of problems always with the same standard procedure. A low number of performed self-assessment tests can therefore act as an indication for this preference. Furthermore, a low number of visit and low amount of time spent on examples, where existing solutions are presented, is considered as another hint for a preference for this semantic group. Moreover, students who like challenges and solving problems in new ways are expected to perform better in questions about solving and developing new solutions, which is also used a pattern for this group.

Learners who have a preference for the semantic group regarding *concrete material* like to learn from examples, which show the material in a more concrete way. Therefore, they visit examples more often and spent more time on these objects. On the other hand, content objects present the material in a more abstract way and therefore, a low interest in content, in terms of a low number of visits and a low amount of time spent on such objects, can act as an indication for a preference for concrete material. Furthermore, learners with a preference for this group tend to like to learn concrete information like data and facts. Therefore, they are expected to achieve better results on questions dealing with facts and concrete information, which acts as a pattern as well.

Learners who like to learn abstract material such as concepts, theories and their underlying meaning have a preference for the semantic group regarding *abstract material*. They are expected to prefer learning from the content material and use examples only as supplementary information. Therefore, a high number of visits on content objects and a high amount of time spent on such objects as well as a low number of visits on examples and a low amount of time spent on examples can act as indication for a preference for abstract material. Furthermore, learners who like to learn concepts and theories are supposed to perform better in questions about concepts and theories as well as in questions about generating new solutions where they need the knowledge about the concepts and theories.

The preference for the semantic group regarding being *careful with details* can be seen especially from the behaviour and performance in self-assessment tests and exercises. Learners who are careful with details tend to check their answers more carefully and therefore are expected to spend more time on self-assessment tests. Furthermore, they are expected to make more revisions on their answers in self-assessment tests and exercises and tend to check their results on self-assessment tests and exercises more carefully. Moreover, learners with a preference on this semantic group are supposed to be good in remembering details and therefore, their results on questions about details can act as another pattern.

The same patterns were used when identifying whether a student has a preference for the semantic group referring to be *not careful with details*. Again, the time students spent on self-assessment tests, how often they revised their answers of self-assessment tests and exercises, how long they stayed at the result pages of self-assessment tests and exercises, and how good they performed on questions about details were considered as patterns.

Semantic Groups based on the Visual/Verbal Learning Style Dimension

This section describes the relevant patterns of semantic groups in the visual/verbal dimension. Table 5.12 summarises the proposed patterns for each group.

Table 5.12: Relevant patterns for groups within the visual/verbal learning style dimension

Visual Learning Style	Verbal Learning Style		
pictures	spoken words	written words	difficulty with visual style
content_visit (-) ques_graphics (+) forum_post (-)	-	content_visit (+) ques_text (+) forum_visit (+) forum_stay (+) forum_post (+)	ques_graphics (-)

The semantic group regarding *pictures* refers to the preference of learners to learn from pictures, such as graphics, images, flow charts, and so on, rather than from words. A pattern that can give indications about the preference of a student for learning from pictures deals with the students' performance on questions about content that was presented in graphics. Furthermore, learners who prefer to learn from pictures are expected not to prefer to learn from content objects which are mainly in written words. Moreover, they are supposed to use the forum only little for discussing learning material, in terms of posting a message in the forum.

For the semantic group referring to the preference for *spoken words*, no suitable patterns exist based on the incorporated features in this study. Possible patterns to identify the preference for spoken words in online environments include, for example, the use of audio files, video files, and voice-based discussions in the course. However, since this study focuses on proposing a concept that can be used in different LMSs and does not ask too much from teachers and course developers, features that use spoken words were excluded.

Learners who have a preference for the semantic group regarding *written words* like to learn from written words. Therefore, they are expected to prefer to learn from content objects which include mainly text and are also supposed to look up information more often from content objects. Thus, a high number of visits of content objects can give indications for a preference for written words. Furthermore, the performance of students on questions about content presented in a written form was considered. Moreover, learners who like to learn from written words are supposed to use the forum as an additional source of information and for learning. Therefore, a high number of visits, a high amount of time spent in the forum and a high number of postings were used as indications for a preference for written words.

A preference for the semantic group regarding *difficulties with visual material* can be identified by looking at the performance of students on questions about content that was presented in graphics.

Semantic Groups based on the Sequential/Global Learning Style Dimension

The next paragraphs describe the relevant patterns for semantic groups on the sequential/global dimension. Table 5.13 summarises the proposed patterns for each group.

Table 5.13: Relevant patterns for groups in the sequential/global learning style dimension

Sequential Learning Style			Global Learning Style		
Detail oriented	sequential progress	from parts to the whole	overall picture	non-sequential progress	relations/connections
outline_visit (-) outline_stay (-) ques_detail (+) navigation_ overview_visit (-) navigation_ overview_stay (-)	navigation_skip (-) navigation_ overview_visit (-)	outline_visit (-) outline_stay (-) navigation_ overview_visit (-) navigation_ overview_stay (-)	outline_visit (+) outline_stay (+) ques_overview(+) navigation_ overview_visit (+) navigation_ overview_stay (+)	navigation_skip(+) navigation_ overview_visit (+)	ques_overview (+) ques_intpret (+) ques_develop (+) navigation_ overview_visit (+) navigation_ overview_stay (+)

Learners who can be considered as more detail oriented rather than focussing on the overall picture of the topic have a preference for the semantic group regarding *detail oriented*. Learners who have a preference for the semantic group regarding detail oriented are expected to be good in answering questions dealing with details. However, they are supposed to spend only little time with getting an overview of the course, which can be seen from a low interest in outlines (visits and time spent on outlines) and the course overview page (visits and time spent on overview page).

For some learners, getting the overall picture of the course is very important. These learners have a preference for the semantic group of the *overall picture*. This preference can be seen from a high interest in outlines, expressed by a high number of visits and a high amount of time spent on outlines, and the course overview page, also expressed by a high number of visits and a high amount of time spent on it. Furthermore, students who are interested in the overall picture are expected to perform better in questions dealing with overview knowledge.

Learners who have a preference for the semantic group regarding a *sequential progress* tend to prefer navigating in a sequential way by going through the course step by step. Furthermore, they prefer a linear increase of complexity while learning. An indication for this preference can be gathered from the preference of skipping learning objects. Skipping learning objects can be usually done in two ways, either by using the navigation menu and selecting the preferred next learning object rather than using the next button, or by going back to the course overview page and selecting a learning object from there. Therefore, a low number of using the navigation menu as well as a low number of visits of the course overview page gives indication for a preference for this group.

On the other hand, a preference for a *non-sequential progress* can be identified by a high number of visits of the course overview page and a high number of accessing the navigation menu for skipping learning objects.

Another preference for learning includes focussing first on understanding all parts of the course in order to get the whole picture. This preference is represented by the semantic group about *from parts to the whole*. An indication for this preference is provided by the tendency to focus not on getting an overview but rather focussing on the learning material itself. Therefore, a low interest in outlines (visits and time spent) and in the course overview pages (visits and time spent) can act as indications.

For some learners connections and relations between topics are an important issue when learning. The semantic group of *connections and relations* represents this preference. An indication for this preference can be seen from a higher interest in the course overview page (visits and time spent), where learners can see the different topics and can access them. On the other hand, learners who focus on the connection and relations between topics are expected to be good in answering questions dealing with overview knowledge as well as questions dealing with interpreting existing solutions and developing new solutions, where in both cases the knowledge about different topics and the ability to relate them to each other is essential.

5.3.2.2 From Behaviour to Learning Style Preferences

The study about automatic student modelling with respect to preferences on learning style dimensions demonstrated that the literature-based approach for inferring learning style preferences from the behaviour of students achieved clearly better results than the data-driven approach. Therefore, for this study, the literature-based approach, described in detail in Section 5.2.2.3, was applied for calculating the preferences on the semantic groups from the behaviour of learners. For preparing the input data derived from the data from the learning management system's database, the same method, described in Section 5.2.2.1, was used as for the study dealing with detecting preference on dimension.

5.3.2.3 Evaluation

The evaluation of this study is based on the evaluation of the study dealing with the approach for automatic student modelling of preference on learning style dimensions. The same extensions for Moodle were applied, the same course was used for gathering data about the behaviour of students as well as about their learning styles, derived from their answers on the ILS questionnaire, and the same adjustments of thresholds for classifying the occurrence of behaviour were conducted. The method of evaluation is based on the one proposed for the literature-based approach in the Section 5.2.3.4. However, in this study additionally other measures were introduced in order to get more accurate results. These measures are described in the next subsection. Subsequently, the results are presented and discussed.

Method of Evaluation

The method of evaluation for detecting preferences on semantic groups is, similar to the one for detecting preferences on learning style dimensions, based on the behaviour of students in an online course as well as on information about their learning styles, gathered from the ILS questionnaire. The predicted learning style preferences are calculated by the literature-based approach using as basis the relevant patterns for the respective semantic groups introduced in Section 5.3.2.1. Results range from 0 to 1, as explained in Section 5.2.2.3. Regarding ILS questions, a value of 0 was assigned for each answer for an active, sensing, visual, or sequential learning style preference and a value of 1 was assigned for each answer for a reflective, intuitive, verbal, or global learning style preference. The values of all relevant questions for the respective semantic group (as proposed in Section 5.3.1.2) were then summed up and normalised on a range from 0 to 1.

In this study, three measures are used for investigating the effectiveness of the proposed approach of automatic student modelling. The first measure is the same as the one used in the previous study, considering the precision of results, when using a 3-item scale for ILS values and predicted values. In the previous study, this measure was used in order to compare the results of the data-driven approach, which are only available on a 3-item scale, with the results from the literature-based approach, which are originally not scaled. However, using scales leads to a certain inaccuracy since all results within one sector are treated equally. Considering, for example, a range of 0 to 1, a 3-item scale with thresholds at 0.33 and 0.66, and a reference value of 0.32, then a predicted value of 0 would indicate an agreement with the reference value since both are in the same sector. However, a predicted value of 0.34 would be in disagreement with the reference value since they are in different sectors, although the absolute difference between both values is only 0.02.

The second measure aims at incorporating the absolute difference between the reference value and the predicted value and can therefore be seen as more accurate for measuring results achieved by using the literature-based approach. The absolute difference between the predicted learning style preference and the learning style preference according to the ILS questions is therefore used as measure. The measure is calculated by subtracting both values for each student, summing up the resulting values, and dividing the sum by the number of students.

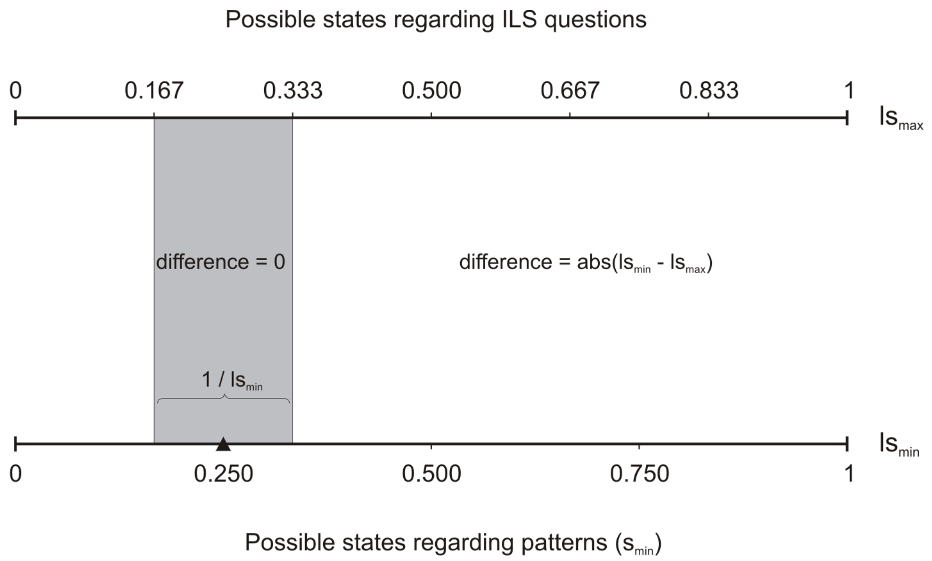

Figure 5.4: Illustration of the third measure

When looking at the semantic groups, it can be seen that for most groups the number of possible state with respect to patterns and the number of possible states with respect to ILS questions differs. Taking as example the group of impersonal orientation, there are 2 patterns and 6 questions relevant. Since each pattern can have 3 different values, distinguishing between whether a hint regarding this pattern is low (1), moderate (2) or high (3) in agreement with the preference of the respective semantic group, 5 different results, ranging from 2 to 6, arise when summing up the values of the two patterns. Figure 5.4 shows the 5 possible results on the normalised range. Regarding the ILS questions, 7 possible results, ranging from 0 to 6, arise when summing up the values (0 or 1) from the 6 relevant questions. Figure 5.4 again shows the 7 possible results on the normalised range. As is depicted in the figure, different numbers of states for questions and patterns cause some inaccuracy when calculating the absolute differences between both results. For example, let the learning style value according to the ILS questions be 0.33. In this case, it is not possible to predict a value with an absolute difference of 0. The closest predicted value is 0.25. On the other hand, for a predicted value of 0.25, the ILS values of 0.33 and 0.17 are both equally close and would be the best match. The third measure aims at reducing the error from the different number of states from patterns and questions. Let s_{min} be the number of states in the range with the lower number of states, either for patterns or for questions, ls_{min} be the result in terms of the learning style preference on the range with the lower number of states, and ls_{max} be the result on the range with the higher number of states. In order to reduce the error from the different number of states, an area with the width $1/s_{min}$ is built around ls_{min} (marked by the gray area in Figure 5.4). If $ls_{min} - 1/(2s_{min}) \leq ls_{max} \leq ls_{min} + 1/(2s_{min})$, then an absolute difference of 0 is assumed since ls_{min} is the best match for ls_{max}. In all other cases, the absolute difference is calculated by $abs(ls_{min} - ls_{max})$. The absolute difference is calculated for each student, values are summed up, and divided by the number of students. This average absolute difference is used as the third measure. Figure 5.4 illustrates this measure for the impersonal oriented group, assuming a predicted value of 0.25.

Results

Table 5.14 presents the results with respect to the proposed measures. For the first measure, values equal or greater than 70 can be considered as good result, indicating a high precision for predicting learning styles. For the second and third measure, values equal or smaller than 0.25 were considered as good results.

Table 5.14: Results. (Values indicating a high precision for predicting learning style preferences are marked in bold font)

Dimensions	Semantic groups	Measure 1	Measure 2	Measure 3
Act/Ref	trying something out	65.33	**0.247**	**0.233**
	social oriented	**70.00**	**0.220**	**0.201**
	think about material	**70.00**	**0.250**	**0.242**
	impersonal oriented	**71.33**	**0.226**	**0.218**
Sen/Int	existing ways	55.33	0.342	0.318
	concrete material	**70.67**	**0.240**	**0.230**
	careful with details	**73.48**	0.309	**0.227**
	new ways	66.00	0.289	0.282
	abstract material	60.67	0.288	0.274
	not careful with details	52.27	0.472	0.305
Vis/Ver	pictures	**77.33**	**0.234**	**0.228**
	spoken words	-	-	-
	written words	**78.00**	**0.237**	**0.227**
	difficulty with visual style	53.95	0.461	0.263
Seq/Glo	detail oriented	66.00	0.411	0.399
	sequential progress	66.67	0.296	0.275
	from parts to the whole	63.33	0.333	0.309
	overall picture	66.67	0.302	0.293
	non-sequential progress	68.67	0.420	0.303
	relations/connections	56.00	0.367	0.344

Discussion

As can be seen from Table 5.14, the semantic groups of the active/reflective dimension yield good results with respect to all measures. Therefore, conclusion can be drawn that the proposed approach is suitable for identifying the preferences for these groups. For the group referring to trying things out, the first measure achieved only a moderate result. However, this moderate result seems to come from the inaccuracy of scaling values since the second and third measure yield good results.

Regarding the sensing/intuitive dimension, the semantic groups referring to concrete material and a preference for being careful with details yield good results and therefore the proposed approach seems to be appropriate to detect preferences with respect to these two groups. Interesting is the high difference between the second and third measure for the group referring to the preference of being careful with details, where the different number of states with regard to the patterns and questions seems to have a high impact. The moderate result for the group referring to the preference of being not careful with details comes from the inaccuracy due to the existence of only one relevant question. For the groups referring to a preference for existing ways, new ways, and abstract material, only moderate results were found, which indicates that the proposed approach is only able to detect these preferences with a moderated precision. This moderate precision might be caused from the incorporated features and patterns, which seem to provide not enough information to detect these preferences with high precision. Further investigations are necessary with respect to identify features and patterns which provide highly relevant information about these preferences.

For the semantic groups of the visual/verbal dimension, overall good results were achieved. The semantic group referring to the preference for pictures as well as the one regarding the preference for written words showed high precision, so that the proposed approach can be considered as suitable for detecting preferences for these semantic groups. The semantic group for spoken language was not incorporated in the approach since no patterns were available. For the semantic group dealing with difficulties with the visual style only moderate results were achieved. This was expected since only one pattern is considered as relevant for this group and the information about the learning style preference from the ILS questionnaire is also based on one question only.

Regarding semantic groups within the sequential/global dimension, results were generally only moderate or poor. These less accurate results can be explained by the overlapping of patterns within semantic groups, where the patterns mostly point to a general sequential/global preference, while ILS questions point to different semantic groups. According to the features and patterns investigated in the course, it was difficult to find patterns which belong only to one specific semantic group. Further investigations are necessary, dealing with the extension of the proposed course structure in order to find information that gives exact information for the respective semantic groups rather than general information about the learning style dimension.

In conclusion, the proposed approach for automatic student modelling achieved accurate results for all semantic groups of the active/reflective dimension and for some groups of the visual/verbal and sensing/intuitive dimension. For the sequential/global dimension, further investigations towards more representative patterns, which provide information about the specific semantic groups rather than the overall dimension, are necessary.

5.4 DeLeS – A Tool for Detecting Learning Styles in Learning Management Systems

DeLeS stands for "Detecting Learning Styles" and is a tool that extracts information about the students' behaviour from learning management systems and uses this information for calculating learning styles. DeLeS is a standalone tool and can be used for any learning management system. It aims at detecting learning styles from a certain amount of data from the database of the LMS. As a result, the tool provides a list consisting of the learning style preferences of all students with respect to learning style dimensions and semantic groups. These identified learning style preferences, on the one hand, provide teachers with more information about their learners, and on the other hand, the identified learning style preferences can act as a basis for providing adaptivity with respect to learning styles.

The tool is based on the considerations and findings of the previous two sections (Section 5.2 and 5.3). It uses the literature-based approach for inferring learning styles, since this approach yields better results than the data-driven approach. The architecture of the tool can be seen in Figure 5.5. The tool consists of two components, the *data extraction component* and the *calculation component*.

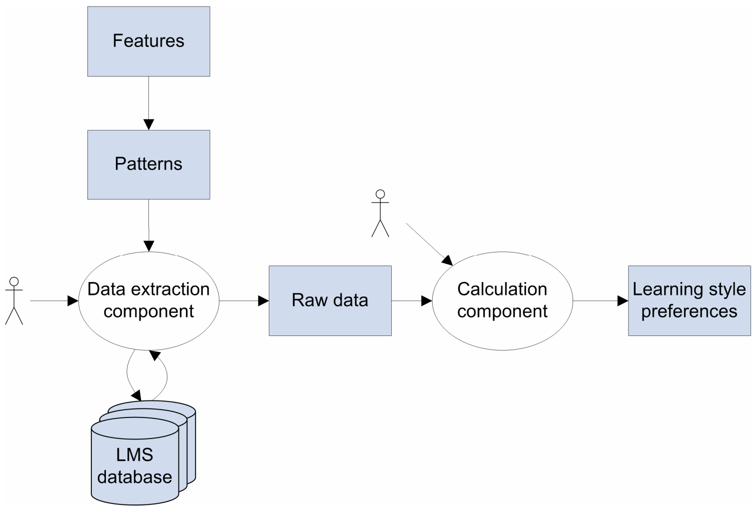

Figure 5.5: Tool architecture

The data extraction component is responsible for extracting the relevant data from the LMS database in order to calculate learning style preferences with respect to dimensions and semantic groups. Therefore, it requires information about which features and patterns of behaviour need to be extracted, as described in Section 5.2.1.1. Because the tool is generated for LMSs in general rather than for only one specific system, heterogeneity of database schemata needs to be considered. As a result, the data extraction component delivers raw data which represent the behaviour of the learners regarding the determined patterns. These raw data are then passed to the calculation component, which is responsible for transforming the data (described in Section 5.2.2.1) and applying the literature-based approach (described in 5.2.2.3) in order to infer learning style from these data.

Both components allow user interaction. In the data extraction component teachers are required and supported to provide the necessary information about the location of the data for each pattern. For this task, teachers are required to be familiar with the LMS database in order to specify where particular data can be found. The user interaction in the calculation component is optional and deals with modifying thresholds for classifying the occurrence of behaviour. Since these thresholds might change due to particular characteristics of a course, teachers have the possibility to modify the predefined thresholds. Furthermore, the tool provides teachers with basic functions such as saving and opening their configurations for a specific course.

In the following subsections, the two components as well as the options for user interaction are described.

5.4.1 Data Extraction Component

Heterogeneity of databases is a well know issue in the research area of schema integration, interoperability, and also data extraction. According to Sheth (1998), information heterogeneity can be classified into three types: *Syntactical* heterogeneity involves different data formats and representations, *structural* heterogeneity deals with different data models and schemata, and *semantic* heterogeneity incorporates different interpretations.

Concerning syntactical heterogeneity, the extracted data are restricted to information about the time students spent on specific types of learning objects, the students' performance on specific types of questions, and the number of specific events, for example, the number of times a student visits a forum. Since most LMSs store the required data by using the same data format and representations, syntactical heterogeneity can be assumed. The main considerations for the proposed tool deal with structural heterogeneity in terms of incorporating different database schemata. Furthermore, semantic heterogeneity is considered by asking the teachers to define the location of specific data in the database as well as allowing them to set thresholds and parameters which can be used, for example, in order to eliminate problems with different measures.

The process of data extraction is illustrated in Figure 5.6. To extract data from different database schemata, first a global schema needs to be built. This can be done by a bottom-up approach, using the LMS database schemata as a basis, or by a top-down approach, where the required information acts as a basis. Because LMS databases can include much more information than is needed for detecting learning styles and database schemata from different LMSs have quite different structures, the top-down approach was applied. As can be seen in Figure 5.6, each table of the global schema includes data representing one pattern.

Since automatically finding the required information for the global schema in each LMS database is not possible, teachers need to be supported as much as possible in specifying where the required information is located. Therefore, the information needed for the global schema should be easy to extract from the LMS database. In most LMS databases the required information is stored in an event-based way. For example, for each visit of a specific learning object or each posting in a forum, an entry is added. Therefore, the raw data needed for calculating the learning style preferences are cumulated, presenting, for example, how often each learner has visited a specific type of learning object in relation to the total number of available learning objects of the same type or the total time students spent on a specific type of learning object. For keeping data extraction from the LMS database to the global tables as simple as possible, the top-down approach was adapted in a way that global tables store data in a non-cumulated, event-based way rather than in the cumulated form required for raw data (see Figure 5.6).

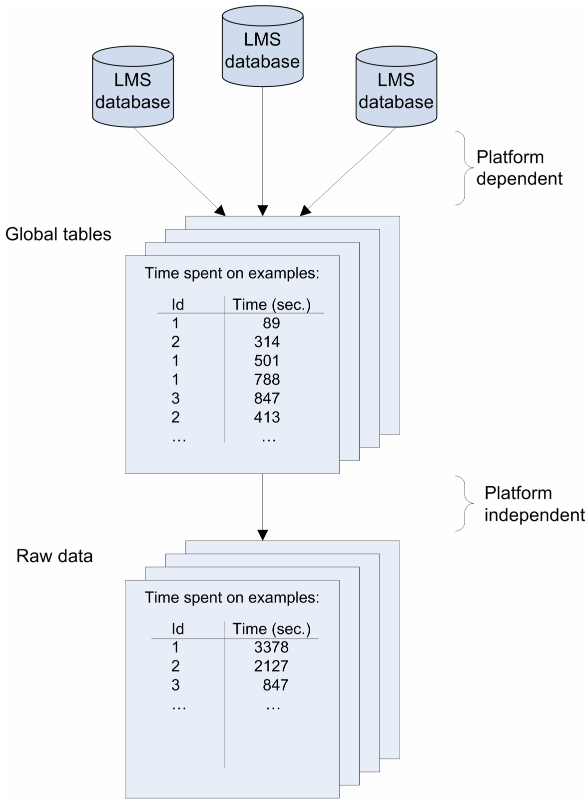

Figure 5.6: Process of data extraction

For supporting the teacher in specifying the location of the required information for the global schema, an editor is provided, described in detail in Section 5.4.3. Once a teacher has used the editor for specifying the location of the required information, data for the global tables can be extracted and the raw data can be calculated by the tool automatically.

5.4.2 Calculation Component

For calculating learning styles, the raw data act as input for the calculation component. In this component, there are two main steps. First, ordered data are calculated from the raw data based on thresholds for classifying the occurrence of behaviour. The tool includes predefined thresholds, as described in Section 5.2.1.2. However, thresholds can also be modified by the teacher according to the characteristics of the respective course, which was described for example in Section 5.2.3.3, when adjusting the thresholds to the object oriented modelling course. The calculation of ordered data, represented by the matrix O, as well as the calculation of the relevant ordered data for each learning style dimension (*dim*) and each semantic group (*group*), represented by the matrices P_{dim} and P_{group}, is done as described in Section 5.2.2.1. The latter calculation is based on the description of relevant patterns for learning style dimensions in Section 5.2.1.3 and for semantic groups in Section 5.3.2.1. Second, the data of P_{dim} and P_{group} are used as input data for the literature-based approach. By applying the literature-based approach, preferences for learning style dimensions and semantic groups are calculated. These preferences are then exported as a text file, containing the calculated preferences for each student.

5.4.3 User Interaction for Specifying Required Information

In this section, a brief description of the features of DeLeS with respect to user interaction aspects is presented. The aim for user interaction in DeLeS is to provide the system with required information in order to calculate learning style preferences. This information includes which patterns are supported by the LMS, where the respective data of each supported pattern can be found, and information about parameters of the course such as the number of specific types of learning objects. Additionally, teachers can adjust the thresholds for each supported pattern.

When starting DeLeS, a configuration file is created, stored in xml format and based on a standard set of information, which includes the predefined thresholds as described in Section 5.2.1.2 and considers all patterns as supported. As can be seen in Figure 5.7, the teacher is asked to provide a name for the configuration file, the name of the LMS as well as information for establishing a connection for the LMS database. For opening the same configuration file at a later point of time, the configuration name and the LMS name need to be entered again.

The created xml file is divided in three parts, including the login data, data about parameters as well as data about features and patterns. Data about parameters as well as

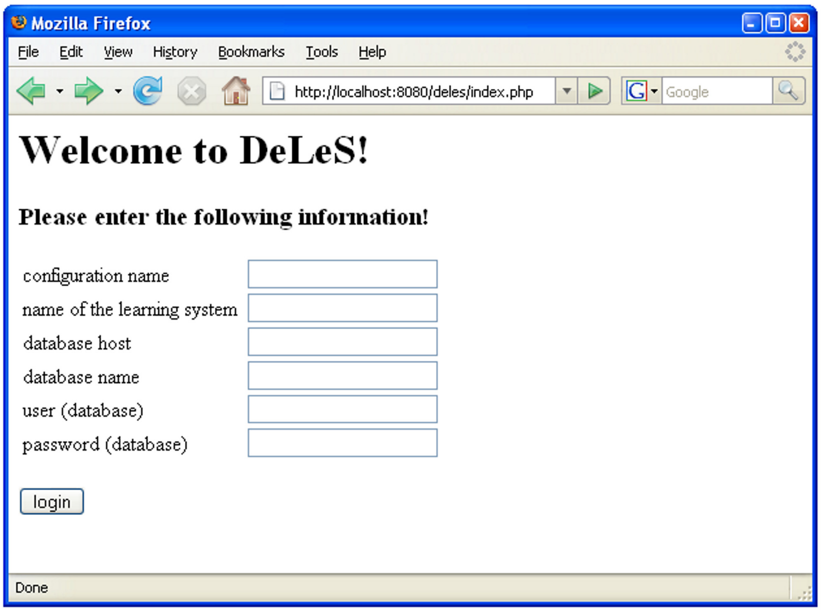

Figure 5.7: Login page of DeLeS

features and patterns can be specified in the main page of DeLeS (illustrated in Figure 5.8). The link "Configure Parameters" leads to a page (shown in Figure 5.9), where the required parameters can be specified. In this page, teachers are asked for the number of self-assessment questions, exercises, examples, content objects, and outlines in the respective course. These values are needed in order to use meaningful thresholds for the number of visits of these types of learning objects, for example, using 25% and 75% of the performed exercises over all available exercises as thresholds. Furthermore, teachers are asked for specifying the expected time an interested learner is supposed to spend on particular types of learning objects, the critical values which indicate from when on a learner is already doing something else than learning with the currently visited learning object, and average values which state how long learners spent on average on particular types of learning objects. The considered types of learning objects include all available types, namely content objects, outlines, examples, self-assessment tests, exercises, forums, the course overview page, and result pages of self-assessment tests and exercises. These values are needed for calculating the thresholds for time spans, where the threshold indicates a percentage of the expected values. The critical and average values are used in order to improve the accuracy when extracting data with respect to time spans from the LMS database. While the parameters regarding the number of available types of learning objects need to be set by the teachers, the parameters regarding time spans are already set to predefined values, which can be changed by the teachers if necessary.

As can be seen in Figure 5.8, the main page shows all features and patterns, including a brief description of each pattern. Each pattern can be deactivated if the LMS or the course does not provide information regarding the respective pattern. This can be done by clicking on the link “deactivate” behind the respective pattern. After doing so, the pattern is written in gray font and the link changes its name to “activate”. A deactivated pattern can be activated by clicking on the link “activate”.

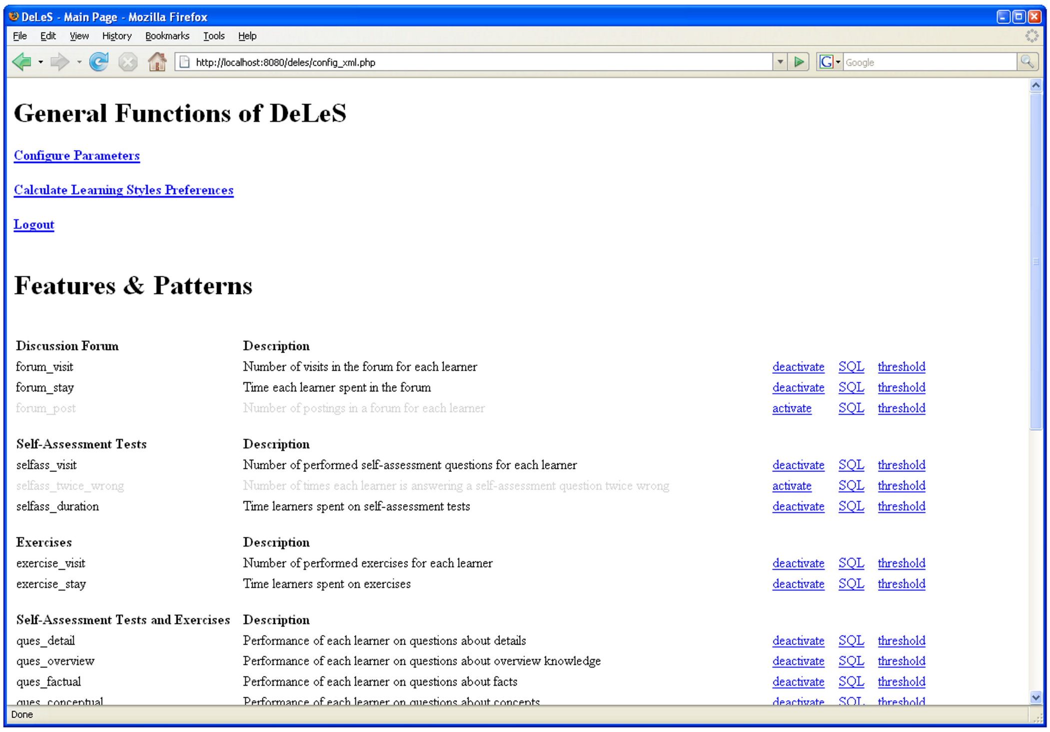

Figure 5.8: Main page of DeLeS

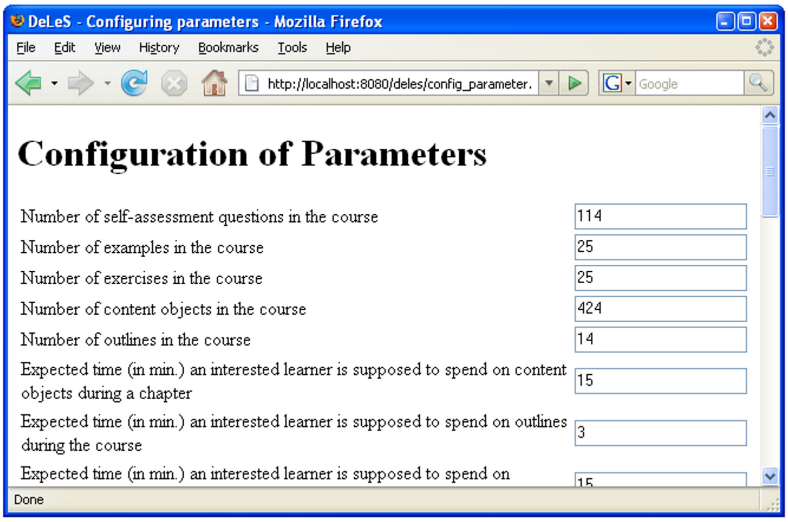

Figure 5.9: Configuration of parameters in DeLeS

If information about a pattern can be provided by the system, the location of the required data in the database has to be specified. This can be done by using the SQL editor, which is reachable via the “SQL” link for each pattern. In the first step, the SQL editor shows the required fields for providing information about the respective pattern and asks the teacher to specify which tables are needed to extract the required data (illustrated in Figure 5.10a). As discussed in Section 5.4.1, data are asked to be provided in an event-based way. Looking, for instance, at the pattern regarding visits of examples, only the user-id of each learner at each time he/she visited an example is required. In order to get this information in the extended version of Moodle (introduced in Section 5.2.3.1), two tables are necessary, the table *mdl_log* and *mdl_resource*. Besides using the editor, teachers can also write the SQL statement directly in the respective text field and save the location of the pattern. Furthermore, if a location was already specified at a previous point of time, the respective SQL statement appears in this text field and additionally the resulting entries, when applying the stored SQL statement in the database, are shown.

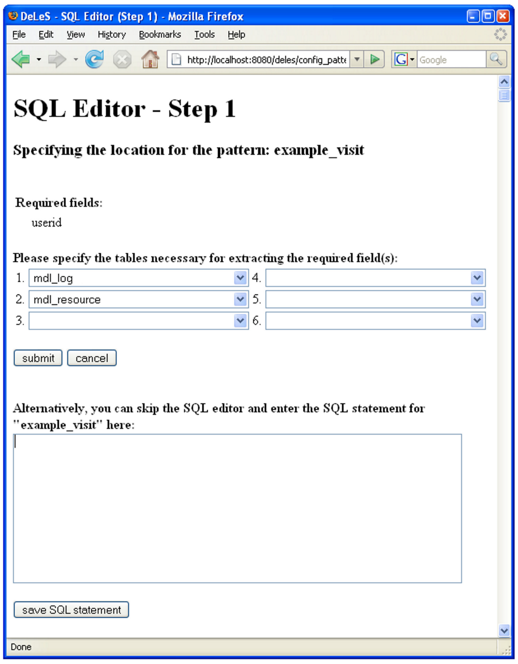

Figure 5.10a: Step 1 in the SQL editor of DeLeS

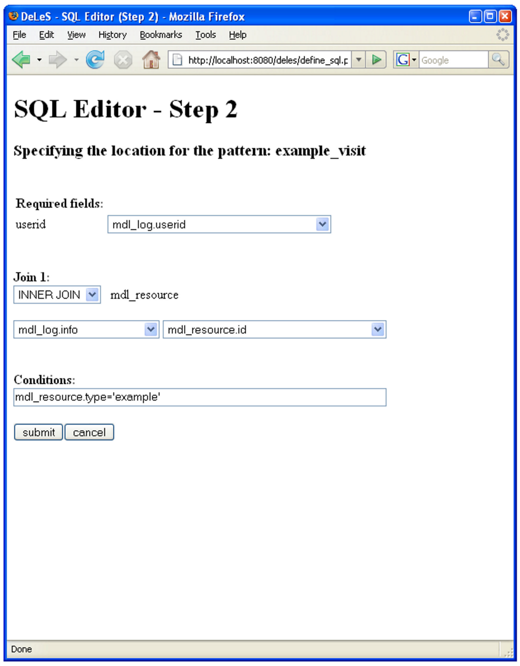

Figure 5.10b: Step 2 in the SQL editor of DeLeS

In the second step of the SQL editor (illustrated in Figure 5.10b), three kinds of information are asked. First, all required fields need to be specified. For the number of visits of examples, the information about the user-id is in the table *mdl_log* and the field *userid*. The second kind of information deals with connections between tables. If more than one table is selected in the previous step, the editor additionally asks for the connection between these tables. The kind of join can be selected, distinguishing between left, right, and inner join. Furthermore, for each connection, two fields, each from one table, need to be specified which include the same semantic information and act as connectors between both tables. For the number of visits of examples, the field *info* of the table *mdl_log* and the field *id* of the table *mdl_resource* are used as connectors. The third part allows the teacher to include conditions, for instance, regarding the number of visits of examples a statement can be specified stating that the field *type* of the table *mdl_resource* needs to be equal to the string 'example'. The used syntax for these conditions is based on SQL syntax. After submitting the required information, the editor builds a SQL statement and shows the statement as well as the result of the SQL statement, when applying it to the database, in the next page. After confirming, the SQL statement is stored in the configuration file.

As mentioned before, for each pattern, thresholds for classifying the occurrence of behaviour are predefined, as described in Section 5.2.1.2. These thresholds can be adjusted in order to fit better the characteristics of the respective course. This can be done by clicking on the link "threshold", which leads to a page that shows the current thresholds and allows changing and saving it in the configuration file.

Once all information are specified, the teacher can click on „Calculate Learning Styles" and the tool starts to extract information from the LMS database and use it to infer learning style preferences. As a result, the learning style preferences of all students with respect to dimensions and semantic groups are stored in a text file.

5.5 Contributions of the Proposed Approaches for Automatic Detection of Learning Styles in Learning Management Systems

This chapter introduced investigations dealing with how learning styles can be automatically detected in LMSs based on information from students' behaviour and actions. A general approach for automatic student modelling in LMSs with respect to learning styles was designed, implemented, and evaluated. For inferring learning styles from the behaviour and actions of students, two different approaches, a data-driven and a literature-based approach, were tested. According to the results of the evaluation, the literature-based approach achieved better results for identifying learning style preferences on each of the four dimensions of Felder-Silverman learning style model. Based on the results of the literature-based approach, the proposed concept for automatic student modelling can be seen as appropriate for detecting learning styles with high precision. Furthermore, investigations were conducted on characteristic preferences within the learning style dimensions. After analysing data from the ILS questionnaire, semantic groups were build which refer to characteristic preferences within a learning style dimension. Based on these semantic groups, an approach for automatic student modelling was developed, using the literature-based approach, which already achieved good results for detecting learning styles based on preferences on learning style dimensions. Looking at preferences within the learning style dimensions in more detail and distinguishing between them makes student modelling more accurate and leads to a more detailed student model. Results of the proposed approach showed that automatic student modelling with respect to learning style preferences on semantic groups yields good results for preferences on all semantic groups of the active/reflective dimension and some semantic groups of the sensing/intuitive and visual/verbal dimension. For preferences on the sequential/global dimension, only moderate results were achieved, necessitating for further investigations in terms of finding patterns which provide more relevant information about the respective learning style preferences on the semantic groups of the sequential/global dimension. The achieved findings were implemented in a tool, which allows teachers to automatically detect students' learning style preferences in an online course in an LMS.

Detecting learning styles automatically from the behaviour and actions of learners in LMSs has two benefits. First, the information about students' learning styles can improve the process of learning and teaching. Making students aware of their preferred way of learning can help them in understanding why some topics are easy and others are more difficult for them. Furthermore, students can see their weak preferences and might start to train them. Besides, the teaching process can be improved by an awareness of the students' learning styles. Teachers can check whether their courses support different learning style preferences or focus only on supporting few learning styles. In the latter case, teachers can improve their courses by providing also some learning activities in order to support students with other learning styles.

The second benefit deals with providing adaptivity in LMSs. Identifying learning styles and storing the information about students' learning styles in the student model is a requirement for providing adaptivity. While the proposed approach is an automatic student modelling approach, it is still static, meaning that information about the students' behaviour is collected and then, at one specific point of time, learning style preferences are calculated. However, such a static approach is the basis for further investigations towards a dynamic student modelling approach, where information about students' behaviour and actions are processed on the fly in order to react and interact with students and provide them immediately with individualised support.

While the first benefit can also be obtained by using a learning style questionnaire, the proposed approach for automatic detection of learning styles has potential to provide more reliable and less error-prone results since it is based on data from a specific time span rather than from data which are recorded at one point of time. Furthermore, students do not have any additional effort such as answering questions and the approach is free of uncertainty gained from asking students about their preferences. With respect to the second benefit, questionnaires can only be used for static student modelling. On the other hand, the proposed approach can act as a basis for developing a dynamic automatic student modelling approach, which analyses learners' behaviour and actions immediately and uses this information to provide adaptivity.

CHAPTER 6

Improving the Detection of Learning Styles by Using Information from Cognitive Traits

The previous chapter introduced an approach for using the students' behaviour and actions within a course in order to identify their learning styles. However, other sources can also contribute to the detection process of learning styles by providing additional information about learning styles. Such additional information can help in improving automatic student modelling towards building a more accurate student model. In this chapter, the potential of cognitive traits for providing additional information for the detection process of learning styles is investigated.

Humans typically have a number of cognitive abilities (or traits). Cognitive abilities can be defined as the abilities to "perform any of the functions involved in cognition" (Colman, 2006), whereby cognition can be defined as "the mental activities involved in acquiring and processing information" (Colman, 2006) or more concretely "the mental process of knowing, including aspects such as awareness, perception, reasoning, and judgment" (Pickett, 2001). Important cognitive abilities for learning include working memory capacity, inductive reasoning ability, information processing speed, associative learning skills, and meta-cognition.

Similar to learning styles, recent research regarding cognitive abilities deals with their consideration in adaptive educational hypermedia systems. For example, suggestions are introduced on how to support learners with low and high cognitive abilities such as working memory capacity, inductive reasoning ability, information processing speed, and associative learning skills in adaptive educational hypermedia systems (Kinshuk and Lin, 2003). Furthermore, research is conducted on identifying the students' cognitive traits by using an automatic student modelling approach. The Cognitive Trait Model (CTM) (Kinshuk and Lin, 2004; Lin and Kinshuk, 2005) is a student model that profiles learners according to their cognitive traits. Four cognitive traits, namely, working memory capacity, inductive reasoning ability, processing speed, and associative learning skills, are included in the CTM so far. The identification of the cognitive traits is based on the behaviour of learners in a learning system. Various patterns, called *Manifestations of Trait* (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 and Kinshuk, 2004) is responsible for calculating the cognitive traits of learners based on the information from the MOTs. The CTM can still be valid after a long period of time due to the more or less persistent nature of cognitive traits of human beings (Deary et al., 2004).

Investigating the relationship between learning styles and cognitive traits has several benefits (described in detail in Section 6.5). Most important for the scope of this thesis is the use of data from cognitive traits in order to improve the detection process of learning styles. However, equally, the data from learning styles can be used to improve the detection process of cognitive traits. Furthermore, information about learning styles and cognitive traits allows for provision of more holistic adaptivity in terms of considering students' learning styles as well as their cognitive traits in adaptive educational hypermedia systems.

To exemplify the relationship between learning styles and cognitive traits, the interaction of the Felder-Silverman learning style model (FSLSM) with working memory capacity is investigated. In the next subsection, an introduction of working memory capacity is given, describing working memory capacity as well as its interaction with learning. Then a comprehensive literature review is presented, introducing studies that provide indications for a relationship between the four dimensions of FSLSM and working memory capacity. Subsequently, two experiments with real data are presented, where learners filled out the Index of Learning Styles (ILS) questionnaire in order to provide information about their learning styles and performed a task in order to provide information about their working memory capacity. Results of the analyses are discussed and compared with the results from the literature review. Moreover, discussion is provided on the benefits of the identified relationship for adaptive educational hypermedia systems.

6.1 Introduction on 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. Richards-Ward (1996) named it the Short-Term Store to emphasise its role of temporal storage of recently perceived information. Baddeley (1986) tried to study and understand the working memory by decomposing it into three components: the *Central Executive* acts as the controlling component, the *Phonological Loop* is the slave component for verbal information processing and storage, and the *Visual-Spatial Sketch-Pad* is the slave component for visual/graphical information processing and storage. Based on Baddeley's assumption that the working memory consists of separate components for concerning verbal and nonverbal materials, the dual-code hypothesis was developed (Clark and 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. 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. Furthermore, the domain experience seems to have an impact on the effectiveness of presenting information in dual-code in terms of a decreasing (and even negative) effect with increasing learner experience (Kalyuga, Chandler, and Sweller, 2000).

While Baddeley (1986) defined working memory in terms of structures, Salthouse et al. (1989), for instance, have defined working memory in terms of processes. They proposed that working memory consists of a storage capacity which is sensitive to the number of items presented, and an operational capacity which is sensitive to the number of operations performed on items. The structure of working memory was not emphasised in this view. The processing/operational efficiency was regarded as the sole determinant of the performance of working memory. 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 and Babcock, 1991).

While different views on the structure of the working memory exist, researchers now agree that it consists of both storage and operational sub-systems (Richards-Ward, 1996). A more detailed discussion on the different views on working memory capacity is provided by Lin (2007).

Like learning styles, working memory influences the learning process. Research on working memory (Anderson, 1983; Byrne, 1996; Case, 1995; Huai, 2000; Kearsley, 2007; Salthouse and Babcock, 1991; Scandura, 1973) has demonstrated 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. 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).

As a consequence, similar to learning styles, adaptivity based on cognitive traits such as working memory capacity can help students in learning. On the other hand, providing content that exceeds the cognitive abilities of a student affects the learning progress in a negative way and leads to poor student performance.

6.2 Literature Review on the Relationship between FSLSM and Working Memory Capacity

In order to use the information about working memory capacity to improve the detection process of learning styles, the relationship between learning styles and working memory capacity was investigated. Therefore, first, a comprehensive literature review was conducted, looking at studies that deal with the interaction of learning styles, cognitive styles, and cognitive traits. From these studies, indirect relationships between the dimensions of FSLSM and working memory capacity were concluded.

In the following subsections, these studies are introduced and discussed. First, background information is provided for building indirect relationships between working memory capacity and learning styles, and subsequently studies providing evidence for a relationship between each learning style dimension and working memory capacity are presented.

6.2.1 Background for Indirect Relationships between Learning Styles and Working Memory Capacity

In our investigations regarding the relationship between learning styles and working memory capacity, cognitive styles were additionally incorporated in order to build indirect relationships. One of the most extensively studied cognitive styles with wide application to educational problems is the field-dependence/field-independence dimension (Witkin et al., 1977 quoting Witkin, Dyk, Faterson, Goodenough, and Karp, 1962/1974; Witkin, Lewis, Hertzman, Machover, Meissner, and Wapner, 1954/1972; Witkin, 1976). The perception of a field-dependent person is strongly dominated by the prevailing field, whereas a field-independent person experiences items more or less separate from the surrounding field. Therefore, a field-independent person is likely to overcome the organisation of a field or restructure it, whereas a field-dependent person tends to adhere to the organisation of the field as given. A main characteristic of field-independent people is that they tend to be more analytical and also more interested in abstract and theoretical issues, whereas field-dependent people tend to be more attentive to the social frames of reference and are therefore considered as more socially oriented. Field-dependent people are described as warm, tactful, considerate, socially outgoing, affectionate by others, as well as know and be known by more people. Field-independent people are more impersonally orientated and are described as cold, individualistic, and unaware of their social stimulus value (Witkin et al., 1977).

Several studies exist in the literature showing that field-dependent people generally have low working memory capacity and field-independent people have high working memory capacity (Al Naeme, 1991; Bahar and Hansell, 2000; El-Banna, 1987; Pascual-Leone, 1970). Furthermore, there are some relations between the field-dependent/field-independent dimension and the dimensions of FSLSM. Thus, this interaction can be used to make indirect relationships between working memory capacity and the dimensions of FSLSM.

The thinking style introduced by Hudson (1966) can also be used for linking FSLSM to working memory capacity. According to Hudson, two styles of thinking exist: convergent and divergent. People using a convergent style of thinking are good in dealing with facts and bringing them together for solving problems that ask for one solution. This is the required type of thinking in conventional intelligence tests (Santrock, 2005). Therefore, convergent learners tend to score better in this kind of test and are defined as high IQ learners by Hudson. In contrast, divergent learners have their strength in creativity. They tend to be good in thinking in novel ways, coming up with unconventional solutions, and creating a great variety of ideas out of a given stimulus. Therefore, they are considered as highly creative learners who score better in open-ended tests where not a single correct answer is asked but learners have to use their creativity in order to find possible solutions.

Bahar and Hansell (2000) investigated the relationship between the convergent and divergent cognitive styles (Hudson, 1966), the field-dependence/field-independence dimension (Witkin et al., 1977), and working memory capacity. Furthermore, they studied the effect of these psychological factors on the performance of word association tests and the grid type of questions. They conducted a study with about 400 students and let students perform tests to measure their psychological factors as well as a word association test and grid questions. For our investigations, only the findings about the interactions between field-dependence and field-independence dimension, convergent and divergent styles, and working memory capacity are of particular interest. According to the students' scores of the personality tests, a significant positive correlation between the field-dependent cognitive style and low working memory capacity, and the field-independent cognitive style and high working memory capacity was identified. This relation is in line with several other studies, as discussed above. Moreover, the results of the study showed a significant positive correlation between students' convergence/divergence test results and the results of the working memory capacity test. According to this, divergent students tend to have high working memory capacity and convergent students tend to have low working memory capacity. No significant relationship was found between the convergent/divergent style and field-dependence/field-independence, but tendencies indicate that divergent learners are more likely to prefer a field-independent cognitive style and convergent learners tend to prefer a field-dependent cognitive style. In summary, the study shows the existence of an overlap between a convergent thinking style, low working memory capacity, and field-dependence. In contrast, an interaction exists between divergent thinking, high working memory capacity, and field-independence.

Another important link between working memory and learning styles can be found through literature on dyslexia. The term dyslexia refers to specific learning difficulty regarding written language (Jeffries and Everatt, 2004). Simmons and Singleton (2000) studied a group of dyslexic university students by comparing their reading comprehension ability with non-dyslexic students, and found that "dyslexic students were specifically impaired in constructing inferences when processing complex text" (p. 178). No difference was found between the dyslexic and non-dyslexic groups when literal questions, which only required information that was explicitly stated in the text, were asked. However, significant differences were found when inferential questions were given, which required the students to integrate more than one piece of information or use their prior knowledge to interpret an ambiguous statement. Dyslexic students did not do very well in inferential questions and the cause was found to be working memory deficiency (Simmons and Singleton, 2000). Calvo's (2001) experiment of the reading-span task also provided evidence that working memory is essential for elaborative inference during reading by taking an important role in the text-integration process. The inferential ability takes the role of bridging the gap between the necessary semantics (Calvo, 2001).

Beacham, Szumko, and Alty (2003) studied the effect of different presentation modes in online courses for dyslexic students. All students performed the ILS questionnaire in order to provide information about their learning styles. As argued by Simmons and Singleton (2000) citing Beech (1997), Hanley (1997), Nicolson and Fawcett (1997) and Palmer (2000), dyslexics have impaired working memory capacity. Although these studies did not clearly answer whether the relationship between low working memory and dyslexia is bi-directional (i.e., low working memory implies dyslexia and dyslexia implies low working memory), nonetheless they gave support to the argument that learners with lower working memory tend to have poorer reading ability.

6.2.2 Sensing/Intuitive Dimension and Working Memory Capacity

According to Hudson (1966), divergent students are very similar to intuitive students. Both tend to be creative and score better in open-ended tests than in tests where only a single answer is asked. In contrast, convergent students have strong similarities with sensing students. Based on these similarities and on the results of Bahar and Hansell's study (2000) regarding the relationship between convergence/divergence and working memory capacity, it can be concluded that sensing learners tend to have low working memory capacity, whereas intuitive learners tend to have high working memory capacity.

Another main feature of the sensing/intuitive dimension is the concrete-ness (as opposed to abstract-ness) of the preferred learning material. According to Witkin et al. (1977) quoting the work of Biggs, Fitzgerald, and Atkinson (1971), Heath (1964), Jay (1950), Pemberton (1952) and Stidham (1967), a characteristic of field-independent learners is that they tend to be more interested in abstract and theoretical issues. Because intuitive learners are also described to have a preference to learn abstract material such as concepts and theories, an overlap can be seen in an intuitive learning style and a field-independent cognitive style. This interaction is also confirmed, for example, by studies of Davis (1991) as well as Ford and Chen (2000), saying that field-dependent learners, like sensing learners, prefer concrete material, whereas field-independent learners, like intuitive learners, prefer to learn abstract material. As a consequence of the interaction between working memory capacity and field-dependence/independence, another pointer is found, arguing that sensing learners are likely to be field-dependent and therefore tend to have low working memory capacity, whereas intuitive learners tend to have a field-independent cognitive style and high working memory capacity.

Furthermore, an association can be found between working memory capacity and concreteness/abstractness in structural learning theory (Scandura, 1973). Structural learning theory postulates that the information learned are rules. In order to identify and learn low-order (fundamental) rules, learners should be presented with representative problem samples of the low-order rules and the corresponding solutions prior to given high-order (advanced) rules. The number of representative problem samples should increase for learners with low working memory capacity so that they can grasp low-order rules first and use them to generate high-order rules (Kinshuk and Lin, 2005). From the line of inference according to the structural learning theory, learners with low working memory capacity and sensing learners can be similarly categorised by having preference for learning with examples. Similarly, learners with high working memory capacity and intuitive learners can be categorised to have a preference for learning with abstract concepts.

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

6.2.3 Active/Reflective Dimension and Working Memory Capacity

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

This relationship is further substantiated by the characteristics of field-dependent and field-independent learners. According to Witkin et al. (1977), field-dependent learners are described as socially oriented and with a preference for interaction and communication with others in groups. In contrast, field-independent learners are characterised as impersonally oriented. This is also confirmed by a study about the effect of a hypermedia environment, conducted with 177 students (Summerville, 1999). Interviews with the participants showed that field-dependent learners prefer more step-by-step instructions with more human direction. This shows again that social interaction is important for field-dependent learners. Field-dependent and field independent learners are classified in the low working memory capacity and high working memory capacity groups respectively in the above discussion. Therefore, this is another indication for a link between low working memory capacity and an active learning style as well as between high working memory capacity and a reflective learning style.

Another study, which is also in line with the proposed relationship, was conducted by Hadwin, Kirby, and Woodhouse (1999). They investigated the relationship between note-taking, review, and students' working memory capacity. The results of this study showed that students with high working memory capacity performed better in class when they primarily listened during lectures and reviewed notes provided by the lecturer. While this result is initially somewhat surprising, it is quite in line with our reasoning. According to Felder and Silverman (1988), reflective learners need time to think and reflect about the learned material and "… do not learn much in situations that provide no opportunity to think about the information being presented (such as most lectures)" (p. 678). Providing notes for learners gives them more time to listen and reflect, which is especially important for reflective learners. Because reflective learners as well as learners with high working memory capacity learn better when they have more time to listen, this study supports the above argued interaction between a reflective learning style and high working memory capacity.

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

From all evidence above, postulation about the relationships can be made between an active learning style and low working memory capacity, and between a reflective learning style and high working memory capacity.

6.2.4 Visual/Verbal Dimension and Working Memory Capacity

As discussed in Section 6.1, several views have suggested that working memory consists of separate components for verbal and nonverbal information (Baddeley, 1986; Paivio, 1986). However, there are also studies that do not emphasize the structural view of working memory: Salthouse et al. (1989) as well as Daneman and Carpenter (1980) viewed working memory as a process; and Atkinson and Shiffrin (1968) defined working memory as the gateway allowing information to be transferred to the long-term memory. In the study from Beacham, Szumko, and Alty (2003) quoted in the discussion below, working memory is viewed as a whole instead of divided components.

Beacham, Szumko, and Alty (2003) found that 97% of the dyslexic learners are visual learners and the remaining 3% also sat just in the mild-verbal range. They further stated that "this was to be expected since dyslexic people do tend to be talented in the areas of creativity and visual thinking" (Beacham, Szumko, and Alty, 2003, p. 23 quoting West 1997; Mortimore, 2003). Beacham, Szumko, and Alty (2003) further quoted McLoughlin's (2001) work, which stated "An inefficient working memory will clearly undermine skill acquisition and learning. Describing dyslexia … [as a working memory deficit] … can help explain both the persisting writing language difficulties …" (p. 16), as a rationale to explain why low working memory would cause problem in reading comprehension. This rationale is in agreement with Simmons and Singleton's (2000) view that the cause of inability to solve inferential problems (and thus dyslexia) is due to insufficient working memory capacity. Comprehension of text would certainly be undermined by insufficient capacity to buffer what was read before. It is fair to argue that learners with severe deficiencies in working memory would have problems in reading, meaning dyslexia, and according to Beacham, Szumko, and Alty (2003) would likely prefer visual learning.

The study by Wey and Waugh (1993) supports this conclusion. Wey and Waugh have investigated the performance of 61 students when working either with text-only based instructions or instructions with text and graphics. In the text-only group, field-independent learners performed better than field-dependent learners. No significant differences were found in the group using text and graphics. In other words, field-dependent learners have difficulties in learning text-only material and benefit more from material that contains text as well as graphics. In reference to the discussion above, showing that field-independent learners tend to have high working memory capacity and field-dependent learners low working memory capacity, the results of Wey and Waugh's study are in line with the studies about dyslexia. Both argue that learners with low working memory capacity (and a field-dependent cognitive style) benefit from visual material and therefore prefer a more visual learning style. However, the identified relationship is only one-directional, since no indication was found that a preference for a visual learning style implies low working memory capacity.

6.2.5 Sequential/Global Dimension and Working Memory Capacity

An empirical study by Huai (2000) investigated the relationship between working and long-term memory capacities and a serial/holistic learning style. The difference between holistic (described in Huai, 2000) and global learning style (described in Felder and Silverman, 1988) is only nominal. The same applies to serial and sequential learning styles. Results of Huai's study show that learners with holistic/global learning style have significantly smaller working memory than learners with serial/sequential learning style (those who are highly capable of following and remembering sequentially fixed information).

According to Witkin et al. (1977) and Felder and Silverman (1988), field-independent learners, like sequential learners, can easily learn material that is separated from its context, whereas field-dependent learners, like global learners, learn best when given a large context in which to embed new learning. Furthermore, field-independent learners are considered as analytical, equal to serial learners, and field-dependent learners are characterised as more global, like holistic learners. This is also confirmed, for instance, by the study by Liu and Reed (1994), investigating the behaviour of 63 students in hypermedia-assisted language learning.

The study by Ford and Chen (2000) also investigated the interaction between field-dependence/independence and holistic/serial biases. Also this study drew conclusions about the behaviour of students in a hypermedia learning environment and investigated the interaction between individual differences, learning behaviour, and learning outcome. Individual differences also include cognitive styles like holistic and serial biases according to Pask (1976b) and field-dependence/independence according to Witkin et al. (1977). The results showed several patterns, for example, the navigation mode and the interest in specific kinds of learning objects that link holistic (global) and field-dependent styles as well as serial (sequential) and field-independent styles. At this point, we also want to mention that some similarities exist between serial and field-dependent learners as well as between holistic and field-independent learners. For example, both serial and field-dependent learners tend to preserve the original order or structure of a course during the learning process. However, according to the scores of the personality tests a significant correlation between holistic and field-dependent cognitive style and serial and field-independent cognitive style was detected in the study. Similar results are also recorded by several other studies (Ford and Chen, 2000, quoting Ash, 1986; Brumby, 1982; Entwistle, 1981; Jonassen and Grabowski, 1993; Riding and Cheema, 1991).

As a consequence, the findings about field-dependence/independence and holistic/serial biases support our reasoning that learners with high working memory capacity (and therefore a tendency to field-independence) are likely to prefer serial and respectively sequential learning style, whereas learners with low working memory capacity (likely to be considered as field-dependent) tend to have holistic and respectively global learning style.

Beacham, Szumko, and Alty (2003) had also recorded higher preference (14% higher) of a global learning style to a sequential learning style among dyslexic learners (low working memory capacity). They quoted another supportive finding from Mortimore (2003) saying that “dyslexic learners are inclined to focus more successfully upon the outline of any topic rather than its details and sequences of information” (Beacham, Szumko, and Alty, 2003, p. 24).

All sources are pointing to the link between high working memory capacity and sequential learners, and low working memory capacity and global learners.

6.2.6 Conclusions from Literature

The results of current investigations from literature show that relationships exist between the four dimensions of Felder-Silverman learning style model and working memory capacity. According to these results, learners with high working memory capacity tend to have reflective, intuitive, and sequential learning style. On the other hand, learners with low working memory capacity tend to have active, sensing, and global learning style.

Table 6.1: Mapping of Felder-Silverman learning style dimensions and working memory capacity

<table>
<tr><th></th><th>High Working Memory Capacity</th><th>Low Working Memory Capacity</th></tr>
<tr><td rowspan="8">Felder-Silverman Learning Style Dimensions</td><td>Reflective</td><td>Active</td></tr>
<tr><td colspan="2">Beacham, Szumko, and Alty (2003)
Hadwin, Kirby, and Woodhouse (1999)
Kolb (1984)
Summerville (1999)
Witkin et al. (1977)</td></tr>
<tr><td>Intuitive</td><td>Sensing</td></tr>
<tr><td colspan="2">Bahar and Hansell (2000)
Davis (1991)
Ford and Chen (2000)
Hudson (1966)
Kinshuk and Lin (2005)
Scandura (1973)
Witkin et al. (1977)</td></tr>
<tr><td>Verbal or Visual</td><td>Visual</td></tr>
<tr><td colspan="2">Beacham, Szumko, and Alty (2003)
Simmons and Singleton (2000)
Wey and Waugh (1993)</td></tr>
<tr><td>Sequential</td><td>Global</td></tr>
<tr><td colspan="2">Beacham, Szumko, and Alty (2003)
Ford and Chen (2000)
Huai (2000)
Liu and Reed (1994)
Mortimore (2003)
Witkin et al. (1977)</td></tr>
</table>

Table 6.2: Mapping of cognitive style and working memory capacity

	High Working Memory Capacity	Low Working Memory Capacity
Cognitive Styles	Field-independent	Field-dependent
	Al-Naeme (1991) Bahar and Hansell (2000) El-Banna (1987) Pascual-Leone (1970)	
	Divergent	Convergent
	Bahar and Hansell (2000)	
	Serial	Holistic
	Huai (2000)	

While these relationships are bi-directional, for the visual/verbal dimension only a one-directional relationship was identified. This relationship indicates that learners with low working memory capacity tend to have visual learning style, however, learners with visual learning style can have either a low or high working memory capacity, or respectively – when looking from the viewpoint of verbal learners – verbal learners tend to have high working memory capacity but learners with high working memory capacity can have a preference of either visual or verbal learning style.

The identified relationships are summarised in Table 6.1, including references to the supporting studies. Table 6.2 presents studies about the relationship between cognitive styles and working memory capacity, which are used as basis for indirect relationships between the learning style dimensions and working memory capacity.

It should be pointed out that all mentioned relationships show tendencies. For example, current investigation indicates that most of the learners with low working memory capacity (but not all) tend to have active learning style.

6.3 Analysing the Relationship between FSLSM and Working Memory Capacity

As can be seen from the literature review, a relationship between learning styles and working memory capacity seems to exist. However, the indications are based on indirect relationships between learning styles, cognitive styles, and working memory capacity. The studies introduced in this section aim at analysing the direct relationship between the four dimensions of FSLSM and working memory capacity in order to verify the identified relationship from literature. Two studies were conducted, an exploratory study with 39 students and the main study with 297 students. For identifying the students' learning styles and working memory capacity, a collaborative student modelling approach was used, asking students to fill out the ILS questionnaire and perform a task for detecting their working memory capacity. In the following two subsections, the two studies and their results are presented.

6.3.1 Exploratory Study

In order to get more information about the identified relationships from the literature, an exploratory study with 39 students was conducted, 19 of them were from a university in New Zealand and 20 were from a university in Austria. In the next subsection, the instruments for identifying students' learning styles and working memory capacity are introduced and subsequently the statistical method and results of the study are presented.

6.3.1.1 Instruments

In this section, the two instruments for identifying learning styles and working memory capacity are presented. For the purpose of this study, all students were asked to conduct both instruments in order to provide information about their learning styles and working memory capacity.

Identification of Learning Styles

For identifying learning styles according to FSLSM, the ILS questionnaire (Felder and Soloman, 1997), described in detail in Section 4.4.2.3, was used. The ILS questionnaire is a commonly used instrument for identifying learning styles with respect to FSLSM. In this study, students were asked to fill out the questionnaire online. Since students from Austria were expected to have good English skills despite German being their native tongue, the questionnaire was provided in English for all participants of the study.

Identification of Working Memory Capacity

Several measures for identifying working memory capacity exist in the literature. In this section, a brief introduction of these measures is given. A more detailed discussion is provided by Lin (2007).

The first measures for working memory capacity were based on the assumption that working memory (called short term memory at this time) consists only of a storage component. These measures were called simple span tasks (Turner and Engle, 1989). In a simple span task, a subject is presented with a series of stimulus items, where items can be either digits (simple digit span task) or words (simple word span task). The maximum number of stimulus items a subject can correctly recall is used as a measure for his/her working memory (Turner and Engle, 1989).

Researchers now agree that working memory capacity is more than just the transient storage capacity, and consists of two sub-systems; one of which is responsible for storage of information and the other for operational processing. Different kinds of complex span tasks, which account for the additional processing aspect, were developed to reflect the two subsystems of working memory. According to de Neys et al. (2002), the operation word span task has become one of the most popular tasks to measure working memory capacity. In this task, subjects are required to perform simple arithmetic operations such as (2 * 3) + 4 = 10. After each operation, a word is presented. The subjects are asked to answer true or false to a group of arithmetic operations and at the end asked to recall the words presented after each operation in the correct order.

De Neys et al. (2002) adapted the operation word span task into a computerised and group administer-able task called GOSPAN. GOSPAN is designed for native Dutch speakers. Therefore, words in the operation word span task were replaced by high frequency Dutch words. In total, 60 operations and 60 words were presented, which were divided into 2-6 operation/word pairs. The presentation of operations and words as well as answering whether an operation is true or false is done on the computer; however, writing down the recalled words is done by using pen and paper, requiring a supervised environment. Empirical data from de Neys et al. (2002) showed that GOSPAN is highly correlated to the operation word span task.

Lin developed a fully web-based version of the operation word span task called Web-OSPAN (Lin, 2007; Web-OSPAN, 2007), which was used in our study. The procedures of GOSPAN were adopted into Web-OSPAN. Students were presented with operations which they had to answer with true or false. After each operation, a word was presented, which the students had to memorise. After 2-6 such operation/word pairs, the students were asked to type in the words in the correct order. Overall, 60 operation/word pairs were presented.

Web-OSPAN differs from GOSPAN in two major issues. Firstly, subjects can perform the whole task on the computer by typing the recalled words rather then using pen and paper. Secondly, the task can be done online without supervision. This further increases the possibility that the task can be administered to a group of users and increase the possible group size. However, it has to be noted that a subject could be tempted to manipulate (cheat) the system in order to obtain a higher score. To avoid this problem 1) respondents are explicitly instructed not to use other means of assistant, and 2) a motivation for not cheating is provided by the offer of a useful learning strategy suitable for the subject's working memory capacity. Other mechanisms are also employed to prevent and detect dishonest manipulations. For example, if a subject takes more than 6 seconds gazing at the operation, a warning message (in red capital letters) is displayed to remind the subject to give a response, and the subject's data from this series are singled out because of the likelihood of using other tools. The value of 6 seconds was used due to a pilot studies done by de Neys et al. (2002), which showed that 6 seconds are sufficient to give a correct answer to the operations.

As proposed by Turner and Engle (1989), the total number of correct arithmetic operations (referred to as *process measure*, ranged from 0-60), the total number of correct recalled words (referred to as *WMC values*, ranged from 0-60), and the maximum set size the subject had the words recalled correctly (referred to as *set size memory span*, ranged from 0-6) are recorded and the total number of correctly recalled words is used as a measure for working memory capacity. Furthermore, the *mean response latency* of the calculations is recorded, as done by GOSPAN (de Neys et al., 2002). Additionally, Web-OSPAN records a *partial correct memory span* (ranged from 0-60), which counts words as correct even if the order of the words is not correct.

Web-OSPAN is available in English and Traditional Chinese and was extended by a German version for this study in order to provide Austrian students with words in their native tongue. In our study, therefore, the English version was used for students from New Zealand and the German version was used for students from Austria. The English words were extracted from Leech, Rayson, and Wilson's (2001) list of word frequencies composed from the British National Corpus. For selecting the German words the COSMAS corpus (2003) provided by the Institute for German language in Mannheim was used. All extracted words have frequencies higher than five per million – a criteria followed by de Neys et al. (2002).

Using Web-OSPAN in the students' native tongue seems to be important since working memory is measures by the students' ability to memorise and recall words. While native speakers can relate a word immediately with its meaning, learners with moderate language skills may have to translate the word first or maybe do not know the meaning of the word at all. This makes it more difficult to remember the words and leads to poor results in this task.

6.3.1.2 Methods of Statistical Data Analysis

The data collected from the ILS questionnaire and the Web-OSPAN task were analysed using the SPSS software package, version 12 (SPSS, 2007) in order to find relationships between the four dimensions of FSLSM and working memory capacity.

Since for the active/reflective, sensing/intuitive, and sequential/global dimension, a bi-directional relationship was identified from literature, correlation analysis was used in order to verify the relationships. Due to the range of the ILS values, including values from +11 to -11 by steps of 2, rank correlation analysis (Kendall's tau and Spearman's rho) was applied.

For the visual/verbal dimension, literature argued for a one-directional relationship to working memory capacity. From the identified relationship, the following conclusions can be drawn: (1) learners with a low working memory capacity tend to prefer a visual learning style (but visual learners can have either high or low working memory capacity) and (2) highly verbal learners tend to have a high working memory capacity (but learners with a high working memory capacity prefer either a visual or a verbal learning style). For both statements, group comparison tests were conducted. First, the distribution of the data was tested by Kolmogorov-Smirnov test and respectively, t-test or Mann-Whitney-U test was applied.

6.3.1.3 Results

In this section, the results of the conducted analyses are presented. Since a significant relationship was found only for two dimensions, these dimensions are presented first.

Sensing/Intuitive Dimension and Working Memory Capacity

Findings from literature point to a correlation between a sensing/intuitive learning style and working memory capacity, indicating that sensing learners tend to have a low working memory capacity and intuitive learners are more likely to have a high working memory capacity, and vice versa. According to the regression line, this trend is indicated but according to the conducted correlation analysis, there is no significant relationship between students' sensing/intuitive learning preference and their working memory capacity.

Looking at the data and the subjects' characteristics in more detail, differences in the subjects' language skills can be seen. Bearing in mind that Austrian students conducted the Web-OSPAN task in German and the ILS questionnaire in English, all Austrian students had very good German skills – most of them are native speakers – and good English skills. For the New Zealand students, both instruments were presented in English but the English skills varied quite markedly. Only a few students were native speaker and at least half of them had only moderate English skills. As discussed before, especially for the Web-OSPAN task, where students have to remember words, good language skills are crucial and poor skills can lead to poor results on the task.

Therefore, the data from the 20 students from Austrian were analysed separately. The conducted correlation analysis resulted in a significant negative correlation between the sensing/intuitive dimension and the WMC values (tau=-0.420, p=0.015; rho=-0.475, p=0.012) as well as the set size memory span (tau=-0.542, p=0.014; rho=-0.562, p=0.010). Therefore, conclusions can be drawn that for students with good language skills, the expected relationship between a sensing/intuitive learning style and working memory capacity is supported.

Visual/Verbal Dimension and Working Memory Capacity

Since our dataset includes only two students with highly verbal learning style, it is not possible to draw any reliable conclusions from these two students dealing with the statement that highly verbal learners tend to have a high working memory capacity, as identified from literature.

To verify the other statement resulting from the literature review, only the visual part of the dimension was analysed. The hypothesis to be tested was whether learners with a low working memory capacity have a highly visual learning style. Therefore, learners were divided into a low working memory capacity (LWMC) group and a high working memory capacity (HWMC) group. The mean of the LWMC group is 7.75 and the one of the HWMC group is 5.737. A 1-tailed t-test with unequal variance was used. The significance level was set to 5%.

Results show that the mean of the LWMC group is significantly larger than that of the HWMC group (T=1.773, p=0.043). This result further confirms the indications from literature, pointing out that learners with low working memory capacity tend to have a highly visual learning style.

Furthermore, investigations were conducted on data from Austrian students only, excluding students from New Zealand due to their often only moderate English skills. The significant results (T=2.190, p=0.027) show even more clearly that learners with low working memory capacity tend to have a highly visual learning style.

Active/Reflective as well as Sequential/Global Dimension and Working Memory Capacity

According to literature, a bi-directional relationship between the active/reflective and the sequential/global dimension was identified. However, according to the results of this study, no evidence for such a relationship was found. The results of the correlation analysis showed no significant correlations, neither for data from the overall sample size nor for the data from Austrian students only.

6.3.1.4 Conclusions from the Exploratory Study

The exploratory study was conducted in order to find further indications supporting the relationships between the four dimensions of FSLSM and working memory capacity identified from literature. The results obtained are promising. For the visual/verbal dimension as well as for the sensing/intuitive dimension, further support of the identified relationship by literature was gained. For the other two dimensions, no significant correlations were found.

The results of the exploratory study again confirm the existence of relationships between learning styles and working memory capacity, even when using a small sample size. Therefore, results endorse the conduction of a study with a larger sample size. A larger sample size yields to more reliable results by using more representative data. Furthermore, it makes more detailed analyses possible.

An important issue we learnt from this study is to be even more aware of the language skills of students and provide them with a version of Web-OSPAN that shows words in their native tongue.

6.3.2 Main Study

Following up the exploratory study, the main study aimed at analysing the relationship between learning styles and working memory capacity in detail by the use of a larger sample size. Another experiment, similar to the one conducted for the exploratory study, was, therefore, performed. This time, all participants of the study were students from a university in Austria. A total of 297 students participated in terms of performing two instruments, one for identifying learning styles and the other for identifying working memory capacity. The participation of students only from Austria minimises the problem regarding the match between the language used in Web-OSPAN task and the native tongue of the participants, since most students of the respective university are native German speakers or have very good German skills.

6.3.2.1 Instruments

Equally to the exploratory study, students were asked to conduct the German version of the Web-OSPAN task for identifying their working memory capacity. With respect to learning styles, the ILS questionnaire was again used. However, for this study, the answers and questions of the questionnaire were translated to German in order to ease the answering process for students. While in the exploratory study, students were personally asked to fill out the ILS questionnaire and only those who were willing to do so, filled it out, in this study, the ILS questionnaire was included in the registration process for the learning management system used in the object oriented modelling course, a compulsory course for undergraduate students in Information Systems. Although students were contacted and asked to fill out the questionnaire, it seemed to be important to record additionally to the students' answers the time students took until they completed the questionnaire. This allowed for checking whether students filled out the questionnaire properly.

6.3.2.2 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 minutes on the ILS questionnaire were discarded because they did not meet the experiment requirements. Data from 225 students were finally used for analysis.

Since for example, van Zwanenberg, Wilkinson, and Anderson (2000) found low internal consistency reliability of the ILS questions, Cronbach's coefficient alpha was calculated using the SPSS software package, version 12 (SPSS, 2007). Cronbach's coefficient alpha is based on the average of all possible split pair correlations of the questions and is a common metric for this form of reliability. In order to increase the reliability, question 41 (according to the numbers/sequence of questions in the ILS questionnaire) from the active/reflective dimension, question 42 from the sensing/intuitive dimension, question 35, 39, and 43 from the visual/verbal dimension, and question 16 and 24 from the sequential/global dimension were removed. This modification resulted in a reliability of 0.524 for the active/reflective dimension, 0.687 for the sensing/intuitive dimension, 0.691 for the visual/verbal dimension, and 0.595 for the sequential/global dimension. While these alpha values are still low, Tuckman (1999) argued that values greater than 0.5 are acceptable for attitude assessments such as the ILS questionnaire and therefore all ILS dimensions can be assumed as reliable.

Data analysis was done by a general and an in-depth analysis, using SPSS software package, version 12 (SPSS, 2007). 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 and Silverman, 1988; Felder and Spurlin, 2005) and with respect to the performed reduction of questions for increasing reliability. Since maximum 3 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 working memory capacity 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. To detect whether data were normally distributed or not, Kolmogorov-Smirnov test was used. 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 working memory capacity 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 conduced literature review 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_y includes only data from verbal learners. Then, for each sub-dataset, the number of learners in working memory capacity 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 working memory capacity. Afterwards, results for F_{ver} and F_{vis} were compared. The same was done for the two sub-datasets including learners with only high working memory capacity (F_{high}) and only low working memory capacity (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.

6.3.2.3 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.

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 6.3 summarises the results.

Table 6.3: 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

Sensing/Intuitive Dimension and Working Memory Capacity

The results of the correlation analysis of the sensing/intuitive values and all measures of the Web-OSPAN task show a significant 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 working memory capacity 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 working memory capacity and an intuitive learning style with high working memory capacity. The results of the chi-square test (χ^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 working memory capacity.

Table 6.4: 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 rho=-0.055	p=0.451 p=0.425
In-depth (all data)	Chi-square test	**χ^2=8.628**	**p=0.013**
	Correlation (absolute ILS values)	tau=-0.036 rho=-0.051	p=0.465 p=0.449
	Correlations to other relevant measures		
	Set size memory span	**tau=0.113** **rho=0.137**	**p=0.046** **p=0.045**
In-depth (only sen/bal)	Correlation	tau=-0.077 rho=-0.105	p=0.174 p=0.176
	Correlations to other measures		
	set size memory span	**tau=-0.132** **rho=-0.157**	**p=0.041** **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 rho=0.121	p=0.182 p=0.193
	WMC categories: u-test	U=1041.5	p=0.055
	ILS categories: t-test	T=-0.839	p=0.403

Looking at the sub-dataset $S_{sen/bal}$, a significant 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 indicates an indirect relation to working memory capacity. Accordingly, a sensing learning style is associated with a low working memory capacity and a balanced learning style is associated with a high working memory capacity. 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 working memory capacity shows that learners with low working memory capacity tend to have a significantly higher preference for a sensing learning style than learners with high working memory capacity. 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 working memory capacity 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.

From these results (summarised in Table 6.4), conclusions can be drawn that a sensing learning style is associated with low working memory capacity and the more balanced the learning style becomes, the higher working memory capacity 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 7 learners had an ILS values smaller or equal to -8.

Active/Reflective Dimension and Working Memory Capacity

In the general analysis, no significant correlations were found between working memory capacity 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 highly significant 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, 0.003) was found. These correlations show that learners with a balanced learning style tend to have high working memory capacity, whereas learners with either a very active or a very reflective learning style tend to have low working memory capacity. This hypothesis is furthermore supported by the results of the analysis of the sub-dataset $S_{act/bal}$ and $S_{ref/bal}$.

Looking at the sub-dataset $S_{act/bal}$, which includes only data indicating an active or balanced preference, the correlation analysis resulted in a negative significant 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 show that active learners tend to have low working memory capacity and balanced learners tend to have high working memory capacity (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 working memory capacity group and low working memory capacity group over the active/balanced values and indicating that learners with low working memory capacity have a significantly more active learning style than learners with high working memory capacity.

On the other hand, looking at $S_{ref/bal}$, the reflective/balanced part of data, a low significant, 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 indicating that reflective learners have significantly lower working memory capacity than balanced learners.

Table 6.5: 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 rho=0.000	p=0.952 p=0.998
In-depth (all data)	Chi-square test	**χ^2=7.889**	**p=0.019**
	Correlation (absolute ILS values)	**tau=-0.169** **rho=-0.222**	**p=0.001** **p=0.001**
	Correlations to other relevant measures (absolute ILS values)		
	Set size memory span	**tau=-0.140** **rho=-0.161**	**p=0.015** **p=0.015**
	Partial correct memory span	**tau=-0.167** **rho=-0.216**	**p=0.002** **p=0.003**
In-depth (only act/bal)	Correlation	**tau=-0.173** **rho=-0226**	**p=0.002** **p=0.003**
	Correlations to other relevant measures		
	Set size memory span	**tau=-0.162** **rho=-0.191**	**p=0.014** **p=0.013**
	Partial correct memory span	**tau=-0.142** **rho=-0.188**	**p=0.022** **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 **rho=0.163**	p=0.061 **p=0.045**
	WMC categories: u-test	U=2068.5	p=0.130
	ILS categories: t-test	**T=-3.094**	**p=0.002**

From all these evidences (summarised in Table 6.5), conclusion can be drawn that a significant relationship between the active/reflective dimension and working memory capacity exists. This relationship shows that the more balanced the learning style is, the higher working memory capacity 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 working memory capacity the learners tend to have.

Visual/Verbal Dimension and Working Memory Capacity

As expected, both from the review of literature (Section 6.2) and the exploratory study, no significant result for a bi-directional relationship between working memory capacity and the visual/verbal dimension was found, either with general analysis or with in-depth analysis. Since, according to the literature and the exploratory study, a one-directional relationship was detected, 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 working memory capacity, correlation between frequencies and visual/verbal preferences shows a highly significant and strong positive correlation for both, learners with low working memory capacity (tau=0.857, p=0.002) and learners with high working memory capacity (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.

Table 6.6: 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 rho=-0.059	p=0.381 p=0.382
In-depth	Chi-square test	χ^2=1.308	p=0.520
One-directional Relationship	Only for learners with low working memory capacity: Correlation betw. frequencies and vis/ver dimension	**tau=0.857**	**p=0.002**
	Only for learners with high working memory capacity: Correlation betw. frequencies and vis/ver dimension	**tau=0.889**	**p=0.001**
	Only for visual learners: Correlation betw. frequencies and WMC values	tau=0.455	p=0.520
	Only for verbal learners: Correlation betw. frequencies and WMC values	**tau=0.51**	**p=0.033**

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 working memory capacity, whereas few verbal learners have low working memory capacity. 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 (summarised in Table 6.6) confirm the existence of a one-directional relationship, which indicates that learners with a verbal learning style tend to have high working memory capacity, whereas visual learners have either high or low working memory capacity.

Sequential/Global Dimension and Working Memory Capacity

According to literature, indications exist for a relationship between a sequential learning style preference and high working memory capacity as well as a global learning style preference and low working memory capacity. 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 a significant relationship (see Table 6.7).

Table 6.7: Results from statistical analysis of the sequential/global dimension and WMC values

	Statistical Approach	Coefficient	Significance
General	Correlation	tau=0.004 rho=0.001	p=0.935 p=0.993
In-depth	Chi-square test	χ^2=1.344	p=0.511

6.3.2.4 Conclusions from the Main Study

The in-depth analysis of the relationship between learning styles and working memory capacity gained interesting results. For the active/reflective dimension, a non-linear relationship was found, indicating that learners with a strong active or strong reflective learning style tend to have low working memory capacity and the more balanced the learning style is, the higher working memory capacity students tend to have. For the sensing/intuitive dimension, only significant results were found for balanced learning styles towards sensing learning styles, indicating that learners with a sensing learning styles tend to have low working memory capacity and the more balanced the learning style becomes the higher students' working memory capacity tend to be. Regarding the visual/verbal dimension, evidence for a one-directional relationship was found, where learners with a verbal learning style tend to have high working memory capacity but learners with high working memory capacity might have either a visual or a verbal learning style. For the sequential/global learning style dimension, no significant relationship was found.

In the next section, the results from literature as well as the results from both conducted studies are compared and discussed.

6.4 Discussion

Comparing the results from literature review with those from the conducted studies, the results of the exploratory study and that of the main study, are mostly in agreement.

With respect to the visual/verbal dimension, literature review as well as both studies achieved the same result, namely a one-directional relationship between the visual/verbal learning style dimension and working memory capacity. This relationship indicates that learners with low working memory capacity tend to have a visual learning style; however, learners with a visual learning style might have a high or low working memory capacity. Respectively, learners with a verbal learning style tend to have high working memory capacity but learners with high working memory capacity might have a visual or verbal learning style.

Regarding the sensing/intuitive dimension, the literature review showed a linear correlation, indicating that sensing learners tend to have low working memory capacity and intuitive learners tend to have high working memory capacity, and vice versa. The results of the exploratory study confirmed this linear correlation. According to the results of the main study, a sensing learning style is also associated with low working memory capacity and the more balanced the learning style becomes the higher working memory capacity tends to be. This is in agreement with the conclusions from literature and from the exploratory study. However, according to literature and the exploratory study, learners with an intuitive learning style tend to have high working memory capacity. For this second part of the relationship, no evidence was found in the data of the main study. A reason for this might be that only few (7 out of 225) learners with a strong intuitive learning style participated in the main study.

With respect to the active/reflective dimension, a linear correlation was found from literature, arguing that learners with an active learning style tend to have low working memory capacity and learners with a reflective learning style tend to have high working memory capacity. In the exploratory study only a general analysis aiming at finding linear correlations was performed and as a result, no relationship was found for the active/reflective dimension. In the main study, a more detailed analysis was conducted and a non-linear relationship was discovered, indicating that learners with a strong active or strong reflective preference tend to have low working memory capacity and the more balanced the learning style becomes the higher working memory capacity tend to be. The result of the main study is partially in agreement with the conclusions from literature, since both associate low working memory capacity with an active learning preference.

However, regarding a reflective preference, conclusions from literature argued for high working memory capacity, whereas the results of our study found evidence for a tendency of low working memory capacity.

Looking at the sequential/global dimension, neither the exploratory study nor the main study found any evidence for a relationship between the sequential/global learning style dimension and working memory capacity. However, according to literature, indications exist for a linear correlation between a sequential learning style preference and high working memory capacity as well as a global learning style preference and low working memory capacity (and vice versa). Therefore, results from our studies are in disagreement with literature.

Overall, two disagreements from the obtained results can be identified: the first deals with the sequential/global dimension, where a relationship is found by literature but not by our studies and the second one refers to the reflective learning style preference, which is associated once with low working memory capacity and once with high working memory capacity. In both cases, further research is required. However, for the other learning style preferences, a relationship to working memory was identified and confirmed. In the next section, the benefits of these relationships for the use in technology enhanced learning, especially with respect to student modelling issues, are discussed.

6.5 Benefits of a Relationship between FSLSM and Working Memory Capacity

The identified relationships provide additional information about the learners. This additional information can be used to enhance the student modelling process, leading to a more reliable and richer student model, which again allows providing more accurate and holistic adaptivity.

In particular, the relationship between learning styles and working memory capacity can be of benefit for two types of adaptive educational hypermedia systems. The first type of systems are those which are capable of detecting either only cognitive traits or only learning styles. For these systems, the relationship yields additional information about the respective other students' characteristic. Therefore, a system that is able to detect only cognitive traits such as working memory capacity can use the identified relationships to get also some information about the learning styles of each learner. This additional information can be used to get a richer student model and provide more holistic adaptivity by considering not only cognitive traits but also learning styles. Furthermore, the relationship can be of use for systems that are only able to detect learning styles. Then, the identified relationship allows getting some information about the working memory capacity, which again enriches the student model and enables the system to provide more holistic adaptivity.

The second type of systems which can benefit from the relationship between learning styles and cognitive traits are systems that incorporate both, learning styles and cognitive traits. In the previously mentioned 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 interaction between learning styles and cognitive traits can be used to build a more reliable student model. As can be seen from Chapter 5, the automatic detection of learning styles is a complex process. The same is true for detecting cognitive traits, as mentioned in the beginning of this chapter. In both cases, current research is using the behaviour and actions of learners during an online course and inferring their learning styles and cognitive traits from this behaviour and actions. This process needs a lot of interaction between the learners and the system and therefore takes time to provide a reliable conclusion about the learners' learning styles and cognitive traits.

The relationship between learning styles and cognitive traits can improve the automatic detection process by providing more information. This additional information has potential to speed up the detection process of learning styles as well as improve the reliability of the student model. For the automatic student modelling approach for learning styles, introduced in Chapter 5, the additional information from cognitive traits, derived from the identified relationship, can be treated similarly to information about patterns of behaviour relevant for particular learning styles. Hence, the additional information can be included in the calculation process of learning styles. Incorporating more data in the calculation processes leads to a more reliable result and therefore improves student modelling. Furthermore, the same can be done for improving the detection process of cognitive traits by treating, for example, the additional information of learning styles similarly to the information about Manifestations of Traits in the Cognitive Trait Model and therefore includes it into the calculation process of cognitive traits.

In summary, conclusions can be drawn that cognitive traits such as working memory capacity have the potential to contribute in the detection process of learning styles. The existence of relationships between learning styles and working memory capacity is a positive example, encouraging investigations regarding other cognitive traits, which are relevant for learning, such as inductive reasoning ability, information processing speed, associative learning skills, and meta-cognition.

CHAPTER 7
Providing Adaptive Courses in Learning Management Systems based on Learning Styles

Adaptivity in educational systems refers to the ability of systems to automatically adapt to the learners' needs and characteristics. For providing proper adaptivity, identifying the needs and characteristics, in the case of this thesis, particularly the learning styles, is a crucial issue. Chapter 5 dealt with investigations about identifying learning styles, proposing an approach for automatic detection of learning styles using information from the behaviour of students during their learning process. Subsequently, Chapter 6 discussed the potential of incorporating additional information from cognitive traits in order to improve the detection process of learning styles.

This chapter focuses on how courses can be adapted to the learning styles of students and how learning management systems (LMSs) can be extended in order to automatically generate such adaptive courses. In the following subsection, a description is given about how Felder-Silverman learning style model (FSLSM) can be considered in adaptive educational hypermedia systems, pointing out how courses can differ for students with different learning styles. Subsequently, a meta-model for incorporating FSLSM in learning management systems is introduced. The next subsection proposes a concept for generating adaptive courses based on student's learning styles in learning management systems. This concept was implemented and evaluated in Moodle (2007). The developed extensions for Moodle as well as the results of the evaluation are presented in the subsequent subsections.

7.1 Overview of the Consideration of Felder-Silverman Learning Style Model in Technology Enhanced Learning

As discussed in Section 3.2, several systems exist which provide adaptivity based on one or more dimensions of FSLSM. While Section 3.2 provided a general overview of these systems, this section points out how online courses can be adapted in order to fit students' learning styles with respect to FSLSM. In the following subsections, various suggested and already implemented adaptation features are discussed for each dimension of FSLSM.

7.1.1 Active/Reflective Dimension

While active learners prefer to learn by trying things out, do something actively, and learn in groups by discussing and explaining learning material to each other, reflective learners learn by thinking and reflecting on the learning material and prefer to learn alone. Carver, Howard, and Lane (1999) argued that the nature of hypermedia systems inherently supports both active and reflective learning. These systems force students to make choices and visit specific learning material which facilitates active learning. On the other hand, reflective learning is supported since students can reflect and think about the material at any point in their studies. Therefore, no adaptivity regarding the active/reflective dimension is provided in CS383 (Carver, Howard, and Lane, 1999).

The adaptation features of MASPLANG (Peña, 2004; Peña, Marzo, and de la Rosa, 2002) are based on the ones of CS383 but were extended with respect to the functionality of the system. While reflective learners are presented with lesson objectives, case studies, lectures, and conceptual maps, instructional strategies for active learners focus on nucleus of knowledge. With respect to media format, slide shows based on text as well as linear text is recommended for reflective learners, while for active learners only linear text is suggested. Navigation based on arrows (back and forward) and providing printings, general vision maps, and filters is suggested for both, active and reflective learners. Reflective learners are additionally provided with online help. On the other hand, communication and collaboration tools are more emphasised for active learners, recommending them features such as chat, forum, and emails, while for reflective learners only the emails function is highlighted.

Hong and Kinshuk (2004) also pointed out the importance of collaboration and communication features for active learners in their description about how to implement FSLSM in web-based educational systems. Furthermore, they recommended experimentations, brainstorming, and activities such as guessing possible questions and answering them with other students for supporting active learners. For reflective learners, they suggested encouraging them to write short summaries about the already learned material and emphasising activities where learners can watch and listen. Furthermore, they pointed out the need for reflective learners to think about the material and suggested to stop periodically to think about possible applications, questions, and what they have been learned already.

7.1.2 Sensing/Intuitive Dimension

While sensing learners prefer to learn concrete material such as data and facts as well as learning from examples, intuitive learners prefer to learn abstract material such as concepts and theories. An example for a system that incorporates the sensing/intuitive dimension of FSLSM is TANGOW (Paredes and Rodríguez, 2004), which provides adaptivity by modifying the order of tasks. For sensing learners, an example is presented first and then the explanation is given, whereas an intuitive learner is first provided with the explanation and then with an example.

This feature is also suggested by Hong and Kinshuk (2004). Furthermore, they recommended presenting sensing learners more with facts, concrete material, and data. Also, more hands-on activities and practical material as well as applying theory in practice and relating information to the real world was suggested for supporting sensing learners. For intuitive learners, they recommended more abstract content like concepts and theories, letting students discover possibilities, fostering their creativity and innovative talent, and asking them for interpretations that link data and facts.

In CS383 (Carver, Howard, and Lane, 1999), slide shows, hypertext, the response system, the digital library, and media clips such as movies, graphics and audio objects are recommended for sensing learners, whereas for global learners, the learning objectives, slide shows, the response system, and media objects are recommended.

In MASPLANG (Peña, 2004; Peña, Marzo, and de la Rosa, 2002), sensing learners are supported by presenting them with case studies, conceptual maps, multimedia slide shows, graphics, digital movies, audio objects, and linear text. For intuitive learners, lesson objectives, conceptual maps, text and multimedia based slide shows, graphics, digital movies, audio objects, and linear text are presented. All available navigation tools and communication tools are suggested for sensing and intuitive learners.

7.1.3 Visual/Verbal Dimension

Looking at the visual/verbal dimension, most adaptive systems work on the basis of providing visual learners with visual material such as graphics, diagrams, flow charts, images, videos, demonstrations, conceptual maps, colour notes with highlighters, slides with multimedia, and animations, whereas courses for verbal learners are text-based or include audio objects (Carver, Howard, and Lane, 1999; Hong and Kinshuk, 2004; Peña, 2004; Peña, Marzo, and de la Rosa, 2002). Additionally, Carver, Howard, and Lane (1999) pointed out the use of lesson objectives and hypertext for verbal learners and suggested the use of slide shows and the digital library for both, visual and verbal learners. In MASPLANG (Peña, 2004; Peña, Marzo, and de la Rosa, 2002), additionally case studies and a focus on synthesis are recommended for supporting visual learners, lectures are suggested for verbal learners, and the use of conceptual maps is recommended for visual and verbal learners. Hong and Kinshuk (2004) emphasised the use of hypertext for verbal learners as well as additionally suggested letting students write summaries about the learning material, work in groups, and discuss and lecture learning material.

7.1.4 Sequential/Global Dimension

The sequential/global dimension is often used in adaptive systems. A main characteristic of sequential learners is that they prefer to learn in linear steps with a linear increase of complexity. They like guidance and having a predefined learning path through the course. On the other hand, global learners prefer to have more freedom in navigation and like to explore the course by themselves. Accordingly, TANGOW (Paredes and Rodríguez, 2004) incorporates the sequential/global dimension by providing adaptivity based on modifying the order of elements within tasks in a course. For a sequential learning style, a more structured path through the learning material is provided, whereas global learners are presented with a more open course structure.

Bajraktarevic, Hall, and Fullick (2003) proposed a system that provides sequential learners with small chunks of text-only information and also hides all links apart from the next and back buttons for navigation in order to provide a more structured path. In contrast, for global learners pages comprised elements such as a table of contents, a summary, diagrams, an overview of information, and so on. These elements are presented in order to facilitate learners to get the overall picture of the topic, which is especially important for global learners. Additionally and similar to TANGOW, several links within the text are presented in order to provide an open structure.

Similarly, Hong and Kinshuk (2004) suggested implementation rules to present the learning material step by step in a logical order, to constrict links for sequential learners, and to show global learners the big picture of the course and provide all available links for them. Furthermore, they emphasised the use of slides for sequential learners and suggested focussing on the context and relevance of the topic, relating the topic to already learned material, and presenting lesson objectives for global learners. Hypertext as well as video and audio objects were recommended for both, sequential and global learners.

In CS383 (Carver, Howard, and Lane, 1999), slide shows, hypertext, and media objects are recommended with higher priority, whereas for global learners, lesson objectives, hypertext, the response system, the digital library, and media objects are suggested.

In MASPLANG (Peña, 2004; Peña, Marzo, and de la Rosa, 2002), sequential learners are presented with conceptual maps, slide shows including text and multimedia objects, digital movies, audio objects, linear text, navigation using back and forward arrows, printings, online help, and collaborative tools like chat, forum, and email. For global learners, the recommended course focuses on synthesis and provides learners with lesson objectives, graphics, digital movies, general vision maps, filters, and collaborative tools like chat, forum, and email.

7.2 A Meta-Model for Supporting Adaptive Courses in Learning Management Systems

The previous section gave a general overview about how online courses can be adapted to the students' learning styles and showed how learning styles are considered in adaptive systems. This section focuses on incorporating learning styles in LMSs and presents a meta-model for supporting adaptive courses in LMSs with respect to learning styles based on FSLSM. This meta-model aims at recommending a course structure, including several types of learning objects, that allows LMSs to provide adaptive courses.

As discussed in Chapter 4, LMSs are commonly used in technology enhanced learning but provide only little or, in most cases, no adaptivity. The proposed meta-model, depicted in Figure 7.1, considers several types of learning objects which are typically available in LMSs. These types are similar to the types used in previous studies described in Chapter 4 and Chapter 5 and include content objects, collections of multimedia objects and links, examples, exercises, self-assessment tests, chat, and forum. As can be seen, some new types of learning objects are included in the set such as collections of multimedia objects and links as well as chat. These types are more time-consuming in the development of the learning objects themselves (for collections) or the development of tasks including the use of these types (for chat), and were therefore not considered in previous studies. However, since the meta-model aims at proposing a course structure that recommends types of learning objects, based on their potential for supporting students with different learning styles rather than based on their development time, these types were included in the meta-model.

The generation of adaptive courses in LMSs is based on the idea that a plenty of learning objects of different types exist and that these learning objects can be composed into individual courses that fit the students' preferred ways of learning. In the following paragraphs, the proposed meta-model is introduced and for each type of learning object, the potential for supporting students with different learning styles is described. The recommendation for each type of learning objects is based on the learning style theory itself (Felder and Silverman, 1988), the usage in adaptive systems mentioned in the previous section and our study described in Section 4.4, which aimed at investigating the behaviour of students in LMSs.

The meta-model is based on the assumption that each course consists of one or more chapters, which again consists of one or more learning units. Each learning unit includes one or more learning objects which can be from several types.

Each *course* includes an outline at the beginning, presenting all chapters, and a conclusion summarising the highlights of the course. Similarly, each *chapter* has an outline and conclusion. To provide global learners with a better orientation, outlines can additionally be presented after each chapter or after each learning unit. Presenting learners with outlines has potential to help them in getting an overview about the topics, which is especially important for global learners.

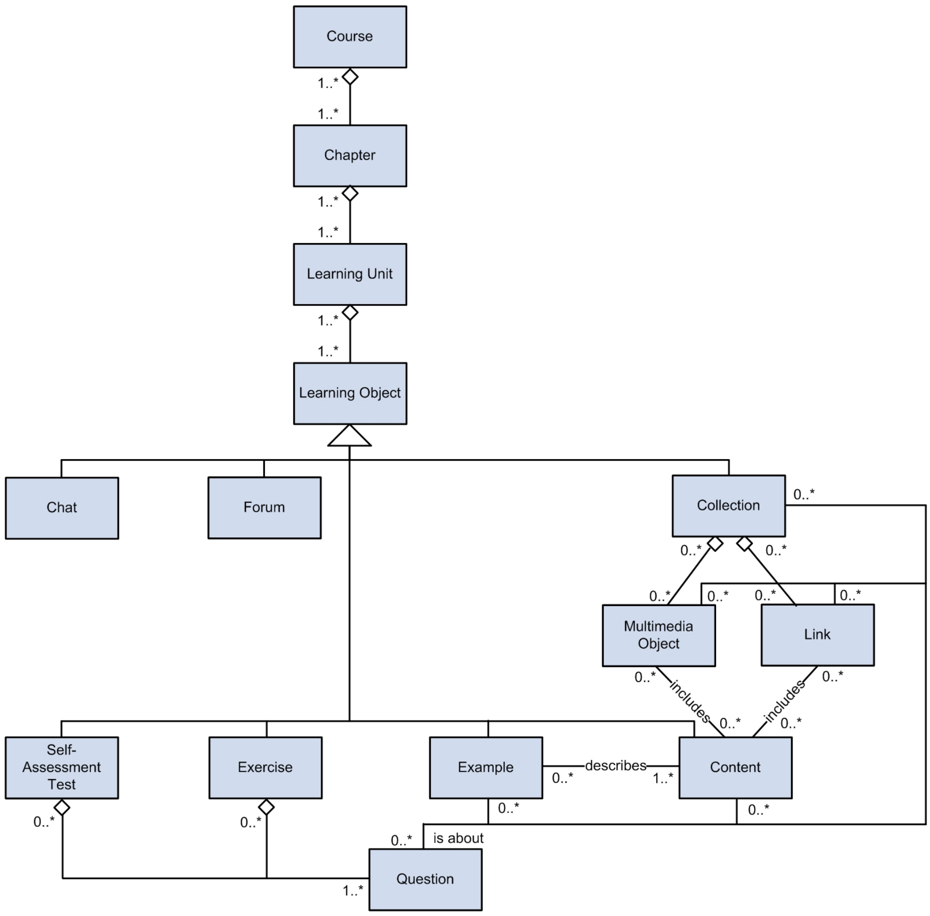

Figure 7.1: A meta-model for supporting adaptive courses in LMSs

Content objects represent the content of the course in small pieces. They can include text as well as all other kinds of multimedia material. Additionally, the content objects can contain *links*, for example, to additional information about the current concept or to related topics. By providing these links, global learners have the possibility to relate the learned material to other topics and to get additional information. For sequential learners, the links can be hidden to make the course more linear. However, a *collection* of links can be presented, for example, at the end of a chapter for sequential learners. Furthermore, *multimedia objects* can be integrated into content objects. For example, audio objects can include short statements from an expert on a specific topic, and interactive animations can help learners to understand by trying out. Therefore, multimedia objects are a good supplement to textual content and can support visual, verbal, active, and sensing learners. However, multimedia objects can also be hidden to avoid cognitive load or to provide a more linear learning path. Also, a collection of multimedia objects can be provided in order to structure the material more clearly. Outlines and conclusions can be seen as special kinds of content objects, supporting especially global learners. In general, slides which are used for traditional education might be applied as content objects after a short revision and a possible enrichment with multimedia material.

The meta-model also contains *examples*, which are used for better illustration. Each example is related to one or more specific content objects. Examples are especially important for sensing learners. Therefore, courses which are adapted to the needs of sensing learners can consist of more examples than courses for intuitive learners, or examples can be presented before showing other types of learning objects.

Furthermore, the meta-model includes *exercises*. To provide learners with opportunities to practice, exercises consist of several questions about interpreting predefined solutions or developing new solutions. Such exercises are especially important for active and sensing learners. Therefore, a course for these learners can include more exercises than a course for reflective and intuitive learners. Furthermore, the position of exercises in the chapter can be adapted. Since intuitive learners like challenges, presenting them with exercises in the beginning of the chapter can motivate them for learning. On the other hand, asking reflective, sensing, and global learners to perform exercises before they have learned material about the topic can frustrate them and should therefore be avoided.

For testing the acquired knowledge, the meta-model contains *self-assessment tests*. The results of the self-assessment tests as well as some feedback are available for the learners after submitting the tests. The questions contained in such a self-assessment test can be about facts or concepts, refer to an overview or to details, be based on graphics or text, or deal with interpreting or developing solutions. Each question is related to certain learning object(s). Thus, learners can be easily guided to explanations if they need hints. Self-assessment tests can be adapted, for example, with regard to the number of questions and their position in the course. For active and intuitive learners, providing self-assessment tests in the beginning can motivate them for learning, on the other hand – similar to exercises – asking reflective, sensing, and global learners to perform self-assessment tests before they have learned material about the topic can frustrate them and should therefore be avoided.

As discussed in the previous section, communication is an important issue, especially for active and verbal learners, providing them with an opportunity to work together, discuss topics, and ask for and give explanations. To enable learners to communicate with each other as well as with teachers in LMSs, *forums* and *chats* are considered in the meta-model. For instance, the course can include content specific forums/chats, where learners can discuss specific topics of the course, and general forums/chats, where learners can talk about more general issues. Additionally, a virtual office hour, where learners can ask questions by chatting with their teachers at a predefined time, can be integrated. An example for supporting active and visual learners is to assign them tasks which ask for using communication tools. Another opportunity is to highlight and recommend students more often to use the communication tools in order to discuss with their class mates.

7.3 A Concept for Providing Adaptive Courses in Learning Management Systems

The previous section introduced a meta-model suggesting several types of learning objects which are typically available in LMSs and have potential to support students with different learning styles. Based on some of these types of learning objects, a concept was developed which aims at enabling LMSs to generate courses that automatically adapt to the learning styles of students.

The proposed concept is independent of the LMS since it is based on types of learning objects which are typically available in LMSs. The concept aims at providing adaptivity on a general basis, adapting courses with respect to the sequence and the number of specific types of learning objects in order to support the individual learning styles of students. This kind of adaptivity allows keeping the system simple and easy to use for teachers and course developers.

The objective of the proposed concept is to combine the advantages of LMSs with those of adaptive systems. Therefore, a main concern is to support students as good as possible by presenting them with courses that fit their individual learning styles. On the other hand, a main concern is to keep the adaptive LMS simple to use for teachers and course developers and ask them for as little as possible additional effort. For this reason, only three of the four dimensions of FSLSM, namely the active/reflective, sensing/intuitive, and sequential/global dimension, were considered in the concept. The visual/verbal dimension was excluded since this dimension asks for different presentation modes, for example, including text, audio files, video files, and so on, which are time-consuming in their development.

In the following subsection, the course elements, including the incorporated types of learning objects as well as the course structure, are introduced. Subsequently, the requirements for teachers and course developers for using an adaptive LMS are pointed out. The last subsection describes the adaptation features, which are based on the selected types of learning objects and show how a course can change in order to support the individual learning styles of students.

7.3.1 Course Elements

The concept for providing adaptive courses is based on the meta-model described in Section 7.2. Specific course elements were selected from the meta-model, considering the requirement to keep the additional effort for teachers and course developers as little as possible.

In general, the assumption is made that a course consists of several chapters, where for each chapter, adaptivity can be provided. Each chapter includes an *outline* of the presented topics as well as a *conclusion* that summarises the most important aspects of the chapter. For presenting the content of the course, *content objects* are considered which are pages that include the relevant learning material. Furthermore, *examples* were incorporated. Examples are used for better illustration and provide students with more concrete material. Moreover, students can check their acquired knowledge by the use of *self-assessment tests*. Another element includes *exercises* which serve as practice area where students can try things out or answer questions about interpreting predefined solutions or developing new solutions.

7.3.2 Requirements for Teachers and Course Developers

Two requirements for teachers and course developers exist in order to use an adaptive LMS based on the proposed concept. Firstly, teachers and course developers are required to provide learning objects of the proposed types (content objects, outlines, conclusions, examples, self-assessment tests, and exercises) in order to fully apply the concept. If some of these types of learning objects are not included in the course, only partial adaptivity can be provided. On the other hand, a course can, of course, include also other types of learning objects. However, they are not considered in the adaptation process and are presented at predefined positions in the chapter.

The second requirement deals with annotating the respective types of learning objects, so that the system is able to distinguish between them. Depending on the respective LMS, this can be done either intuitionally by selecting the particular type of learning object when creating it or, if the selection of types in the LMS does not match with the types proposed in our concept, then teachers and course developers are required to provide additional meta-data in order to clearly distinguish between the proposed types. For example, in Moodle the module "quiz" is suitable for creating self-assessment tests and exercises. Therefore, teachers and course developers have to specify whether the created quiz is a self-assessment tests or exercises by, for example, simply using a check box, which is provided by the authoring tool of the LMS.

7.3.3 Adaptation Features

Adaptation features indicate how a course can change for students with different learning styles. These features are based on the types of learning objects described in Section 7.3.1 and refer to the sequence and the number of presented learning objects.

The adaptation features include the sequence of examples, exercises, and self-assessment tests and determine whether they are presented before the content objects, after the content objects, or at both positions. Another adaptation feature is the number of presented examples and exercises. Moreover, the use of outlines was adapted by either presenting them only once before the content objects or additionally between the topics of the chapter in order to provide students with a better overview. Furthermore, the conclusion can be presented either after the content objects in order to summarise the learned material before applying the knowledge by performing other tasks (e.g., exercises) or they are presented at the end of the chapter in order to give students a final summary of the chapter.

Figure 7.2 presents the general structure of each chapter in the course as well as two examples of adapted courses, showing the same chapter respectively. The content objects are the central elements in each chapter, which have a fix position in the middle of the chapter. Before the content, an outline is presented. Additionally, outlines can be presented between content objects, before a new topic is shown. Before the outline and the content objects, examples, self-assessments, and exercises can be presented and after the content objects, a conclusion, examples, self-assessment tests, and exercises can be provided. Furthermore, the chapter can end with a conclusion.

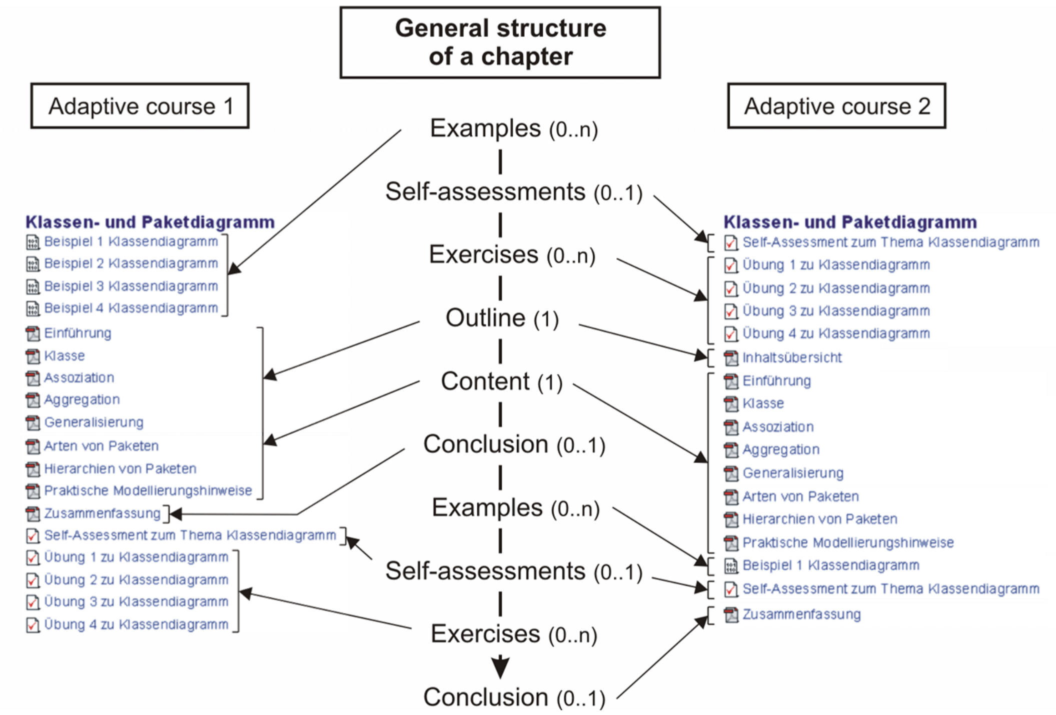

Figure 7.2: General structure of each chapter in an adaptive course

In the following paragraphs, description is provided on how the introduced adaptation features can be used to suit the students' preferences on each incorporated learning style dimension. However, it should be mentioned at this point that the basic idea of the proposed concept is to recommend students a course structure; however, students should always have the possibility to view all available learning objects and visit them at any time they want.

According to FSLSM, active learners prefer to learn by trying things out and doing something actively. Therefore, the number of exercises is increased and self-assessment tests are presented at the beginning and at the end of a chapter. After the self-assessment tests and exercises at the end of the chapter, a final summary is provided in order to conclude the chapter. Moreover, active learners tend to be less interested in examples, since examples show how others have done something rather than let them doing it themselves. Therefore, a small number of examples is presented for active learners. Since outlines do not emphasise active learning, outlines are only presented once before the content objects rather than additionally between the topics. In contrast, reflective learners prefer to learn by reflecting on the leaning material and thinking things through. Therefore, the number of elements asking for active behaviour (such as exercises and self-assessment tests) is decreased. Furthermore, first the learning material in terms of content objects is presented so that learners can reflect on it and afterwards examples are shown or they are asked to do some tasks based on the learned material. Moreover, outlines are additionally provided between the topics and a conclusion is presented straight after all content objects in order to facilitate the learners to reflect about the already learned material.

Sensing learners prefer to learn concrete material such as data and facts as well as like to learn from examples. Therefore, the number of examples is increased and examples are presented before the abstract learning material. Since sensing learners also like practical problem solving, the number of exercises is increased. Moreover, sensing learners prefer to solve such problems by already learned approaches. Therefore, providing tasks such as exercises and self-assessment tests only after the learning material is recommended. On the other hand, intuitive learners like challenges and therefore tasks like self-assessment tests and exercises are recommended to be presented before the learning material. Since intuitive learners prefer to learn abstract material and do not like repetitions, the presentation of outlines between topics is avoided and the number of examples and exercises is decreased. However, in contrast to sensing learners, examples are presented after the abstract content.

Since sequential learners prefer to learn in linear steps with a linear increase of complexity, presenting first the learning material, then some examples, and afterwards a self-assessment test and some exercises is recommended. Since sequential learners are more interested in a predefined learning path than in getting the overview of the course, outlines are presented only before the content objects. In contrast, for global learners it is very important to get the big picture of the course. This is supported by providing outlines additionally between the topics, presenting a conclusion straight after the content, and providing a high number of examples after the learning material. Furthermore, global learners tend to be poor in using partial knowledge. Therefore, the presentation of examples, exercises, and self-assessment tests is avoided at the beginning of a chapter and supported at the end of a chapter where the learners already have a better overview of the learned material.

7.3.4 Calculating Adaptive Courses

The above mentioned descriptions of how to suit courses to specific learning styles (active, reflective, sensing, intuitive, sequential, and global) shows special cases, assuming that a learner has, for example, only a preference for an active learning style. However, according to the FSLSM, learners can have preferences on all learning style dimensions. Therefore, an approach was developed that calculates the suitable state of each adaptation feature for a combination of learning style preferences.

Based on the above descriptions of how to suit courses to specific learning styles, a matrix was built, having in rows all adaptation features and in columns all incorporated learning styles. A value is determined for each adaptation feature and each learning style, indicating whether the specific adaptation feature supports a specific learning style (+1), should be avoided in order to support the learning style (-1), or has no effect for the learning style (0). Based on the actual learning styles of the students (e.g., active, sensing, and global), the respective values are summed up for each adaptation feature, using additionally the strength of the learning style preference as weight, distinguishing between a strong (2), moderate (1), and balanced (0) preference. The results of the adaptation features shows how courses should be composed, indicating whether learning objects of a specific type should be presented at a specific position or respectively how many of these learning objects should be presented.

This approach also allows dealing with combinations of learning style preferences that result in conflictive implications regarding adaptation features. For instance, if a learner has a strong active learning style, a high number of exercises should be presented in order to suit his/her learning style. However, if the learner also has a strong intuitive learning style, a low number of exercises is recommended. The above introduced approach allows considering both preferences and therefore results in presenting a moderate number of exercises for a student with a strong active and intuitive learning style.

7.4 Implementation of the Proposed Concept in Moodle

Based on the performed evaluation of LMSs described in Section 4.2, Moodle was selected to be extended by an add-on that enables Moodle to automatically generate courses that fit the students' preferred learning styles according to the proposed concept in the previous section. Figure 7.3 shows the implemented extensions of the add-on in the architecture of the LMS.

The first extension deals with detecting and storing the learning styles of the students. For detecting learning styles, the Index of Learning Styles (ILS) questionnaire (Felder and Soloman, 1997) was used. The ILS questionnaire was added to the registration form in Moodle, which allows calculating the learning style preferences from the students' answers and storing the preferences in the student model. As suggested by literature (Felder & Spurlin 2005), the preferences were only distinguished between a strong, moderate, and balanced preference (e.g., strong active, moderate active, balanced, moderate reflective, and strong reflective) rather than storing the result of the ILS questionnaire, which are values between +11 to -11 for each dimension.

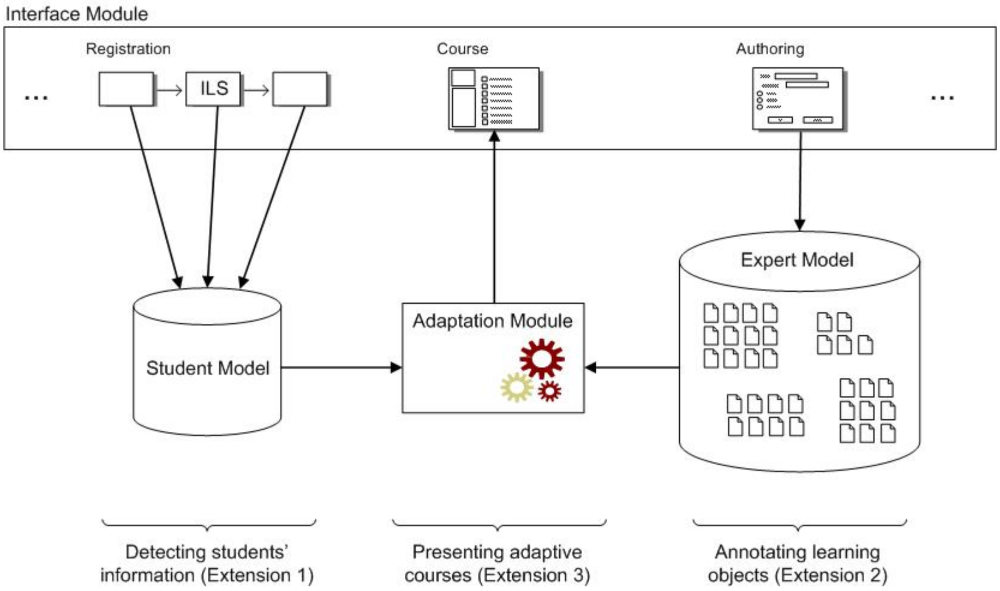

Figure 7.3: Extensions of the LMS architecture for providing adaptive courses

The second extension deals with the authoring tool of Moodle as well as the expert model, which is responsible for storing all available learning objects. As mentioned before, a requirement for generating adaptive courses is to distinguish between the different types of learning objects. In Moodle, the module "quiz" can be used to present exercises and self-assessment tests and the module "resource" can be used to present content objects, outlines, conclusions, and examples. Therefore, some of the extensions described in Section 4.4.2.1 were also used for this add-on. This includes the new module "example" as well as adding check boxes in the authoring interface for quizzes and resources in order to provide teachers and course developers with the opportunity to specify the created learning object according to the required types in the proposed concept. Besides the required types of learning objects, teachers and course developers is also given the opportunity to specify a learning object as non-adaptive, meaning that it will not be included in the adaptation process. Non-adaptive learning objects can be presented at three positions in the chapter, which can be again specified by the teacher or course developer. These positions are before the adaptive material, after the adaptive material, or before the content objects in order to provide teachers with the possibility to add some non-adaptive information regarding the content objects. All meta-data given by the teachers and course developers are stored in the expert model.

The third extension enables the system to automatically provide courses that fit the learning styles of students. Therefore, the adaptation module was developed, which is responsible for generating and presenting students with adaptive courses. This can be done in four steps: first, the information about students' learning styles is accessed through the student model. Second, based on the students' learning style preferences, the values of each adaptation feature are calculated according to the approach introduced in Section 7.3.4. The values of the adaptation features indicate how individual courses should be composed. In the third step, the suitable learning objects are accessed through the expert model and composed to individual courses according to the values of the adaptation features. In the fourth step, the individual courses are presented to the students via the interface of the LMS.

The add-on was developed in PHP for Moodle version 1.6.3. In summary, the add-on enables Moodle to gather data about the students' learning styles by asking them to fill out the ILS questionnaire, provide teachers and course developers with the opportunity to specify the learning objects based on the required types of learning objects, and generate and present adaptive courses that fit the students preferred learning styles.

7.5 Evaluation

In order to evaluate the effectiveness of the proposed concept for providing adaptivity, the adaptive version of Moodle was used for a course at a university in Austria by 437 students. In the following subsections, the study design, the method of statistical data analysis, and the results of the performed analyses are presented. The last subsection deals with discussing the results.

7.5.1 Design of the Study

This study is based on data from the same course than the studies described in Section 5.2.3 and Section 5.3.2.3. The course dealt about object oriented modelling and was taught at a university in Austria, in winter term 2006/2007, running for 7 weeks. The course consists of a lecture and a practical part and was managed via Moodle. As described in Section 5.2.3.2, the aim of using an LMS was to provide students with supplementary learning material and learning opportunities in order to facilitate learning.

The online course consisted of 7 chapters, five main chapters dealing with concepts of object oriented modelling, an introduction chapter, and a chapter about the practical use of object oriented modelling. Due to the focus on the chapters about the concepts, only for these five main chapters adaptivity was provided. For these five chapters, all required types of learning objects were included. For assessing the performance of students, students had to submit 5 assignments and perform a final exam. More details about the course, such as the number of provided learning objects for each type and the marking procedure, are described in Section 5.2.3.2.

When students registered in Moodle, they were asked to fill out the German version of the ILS questionnaire. Afterwards, they were assigned randomly to one of three groups: students belonging to the first group were presented with a course that matched their learning styles (referred to as *matched group*), the second group got a course that mismatched their learning styles (referred to as *mismatched group*), and the third group were provided with a course where all available learning objects were presented in a default sequence independent of the students' learning styles (referred to as *standard group*). Students were not told to which group they were assigned and they belonged to their assigned groups for the whole course. When the students logged in to the course, Moodle automatically presented the course according to the assigned group and the students' learning styles respectively. However, the presented course acted as a recommendation. Independent of the assigned group, students had the possibility to access all learning objects via a link at the overview page of the course. This option was explicitly pointed out when introducing the course in the first lesson.

Providing some students with a course that did not match with their learning styles might lead to disadvantages for them over students from the matched and the standard group. On the other hand, students from the matched group might have advantages over students from the standard and mismatched group. However, it should be pointed out that any course fits some learning style and therefore, in every course some learners have an advantage over others. The only difference between such a course and our course is that in the former, it depends on the teaching style of the teacher who has an advantage and who has a disadvantage. On the other hand, in our course, the assignment of groups was done randomly. Additionally, in our course, students had always the opportunity to access all available learning objects, independent of their assigned groups.

7.5.2 Method for Statistical Data Analysis

Equally to the studies described in previous chapters, data of students who spent less than 5 minutes on the ILS questionnaire were discarded because the detected learning styles were considered as not reliable enough. Furthermore, only data from students who submitted at least 3 assignments were included. Submitting at least 3 assignments was a requirement for a positive mark and therefore helped to exclude students who dropped out. Finally, data of 235 students were used for analyses, whereby 79 students belonged to the matched group, 78 to the mismatched group, and 78 to the standard group.

The aim of the analysis was to show differences over the three groups. Therefore, the students' performance and behaviour in the course was investigated. Regarding the performance, the average score on the assignments (ranged from 0 – 50) was considered. The average score was used rather than the total score, since the requirements for a positive grade was to submit at least 3 assignments and having more than 50% of the scores. Therefore, some students left out the last assignments when they had enough scores for a positive mark. Since the focus of our analysis is on the effect of learning rather than on the final marking, the average mark was considered as more reliable. Additionally, the analysis includes the score on the final exam. Regarding the behaviour in the LMS, the time students spent in the course, the number of logins into the learning environment, and the number of performed learning activities was considered. For the time, thresholds were set in order to avoid the inclusion of learning breaks. A maximum time span of 20 minutes was considered for examples and exercises and for all other learning objects a maximum time span of 10 minutes was used. Furthermore, only the time spent on learning activities rather than considering also administrational activities were included. For the behaviour in the course, the total number and amount of time rather than the average over the performed assignments was used. The reason is that students had to learn all chapters in order to pass the final exam, regardless of whether they had submitted all assignments. Furthermore, the number of times learners left the recommended learning path and asked for not recommended learning objects was investigated. The percentage of times learners visited not recommended learning objects related to the overall number of visited learning objects was considered.

For analysing differences between the three groups, group comparison methods were applied for each variable (e.g., time, number of logins, and so on), using the SPSS software package, version 12 (SPSS, 2007). Outliers were excluded for each group and variable. Two tailed t-test was applied for the variables where data were normal distributed and two tailed Mann-Whitney-U test (u-test) for variables where data were not normal distributed. To check whether data were normal distributed, Kolmogorov-Smirnov test was used.

7.5.3 Results

Table 7.1 gives an overview of the behaviour and performance of students in different groups, showing the mean and standard deviation of all variables and all groups. The results of the performed tests (t-test or u-test) for finding significant differences between the three groups for each investigated variable can be seen in Table 7.2. Significant results are highlighted in bold font. The T and U values as well as whether t-test or u-test was conducted, and the significance levels (p) is presented.

As can be seen from the results, a significant difference was found with respect to the time students spent on learning activities for the matched and mismatched group as well as for the matched and standard group. According to the results, students belonging to the matched group spent significantly less time in the course (on average 3.78 hours) than students from the mismatched group (on average 5.55 hours) and standard group (on average 5.56 hours). The same tendency can be seen for the number of logins. Students

Table 7.1: Mean and standard deviation of the behaviour and performance of the investigated groups

Variable	Matched Group		Mismatched Group		Standard Group	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Time spent on learning activities (in hours)	3.78	2.06	5.55	3.79	5.56	3.94
Number of logins	27.68	8.14	30.64	10.75	31.85	10.24
Number of visited learning activities	432.41	269.10	466.37	265.81	464.77	279.32
Average score on assignments (out of 50)	41.94	4.12	42.10	3.78	42.88	3.16
Score on final exam (out of 250)	175.85	27.67	183.48	30.40	182.33	26.59
Percentage of requests for additional LOs	6.59	4.52	8.30	5.66	6.90	3.70

Table 7.2: Results of the comparison between groups with respect to the investigated variables

Variable	t-test/ u-test	Matched & Mismatched Group		Matched & Standard Group		Mismatched & Standard Group	
		T or U	p	T or U	p	T or U	p
Time spent on learning activities	U	**1927**	**0.014**	**1960**	**0.020**	3014	0.921
Number of logins	T	-1.819	0.071	**-2.659**	**0.009**	-0.684	0.495
Number of visited learning activities	U	2517	0.327	2513	0.466	2684	0.837
Average score on assignments	T	-0.245	0.807	-1.569	0.119	-1.377	0.171
Score on final exam	T	-1.443	0.152	-1.336	0.184	0.228	0.82
Percentage of requests for additional LOs	T	**-2.093**	**0.038**	-0.474	0.636	1.819	0.071

belonging to the matched group logged in significantly less often (on average 27.68 times) than students belonging to the standard group (on average 31.85). Regarding the number of visited learning activities, no significant difference was found. This might be due to the fact that visiting a higher number of learning objects does not necessarily indicate that the students learned more. Other parameters such as low working memory capacity or an active and/or global learning preference might be the reason for students to go back more often to already visited learning objects or to prefer to explore the learning environment by looking around and clicking on different learning objects before starting to actually learn the content. Therefore, this variable needs further analysis in order to find out whether it is in agreement with the other two variables dealing with the students' behaviour. Regarding the performance of students in terms of scores, significant differences between the groups were found neither for the assignments nor for the final exam. Furthermore, the number of times students were requesting additional, not recommended learning objects was investigated. According to the results, it can be seen that students from the mismatched group asked significantly more often for additional learning objects (on average 8.30% of visited learning objects) than students from the matched group (on average 6.59% of visited learning objects).

7.5.4 Discussion

Based on the results, conclusion can be drawn that students from the matched group spent less time in the course but achieved on average the same scores as students from the mismatched and the standard group. This is in agreement with our expectations and confirms that learning from courses that fit the individual learning styles of students make learning easier for students. Furthermore, according to the results, students from the mismatched group used the possibility to access additional, not recommended learning objects more often than students from the matched group. This gives another indication that students belonging to the matched group were more satisfied with the recommended course than students from the mismatched group.

Many studies exist in literature, dealing with the effectiveness of incorporating learning styles in traditional and online education and the impact on performance and/or behaviour. Jonassen and Grabowski (1993) as well as Coffield et al. (2004a) gave a comprehensive overview of studies for several learning styles models. Overall, it can be concluded that the results are quite conflictive. Some studies showed a positive effect and indicated that providing adaptive courses helps students in learning and others did not find such evidence. As Jonassen and Grabowski (1993) summarised, several reasons for such inconsistent results are known, including "small samples size, abbreviated treatments, specialised aptitude constructs or standardised tests, and a lack of conceptual or theoretical linkage between aptitudes and the information-processing requirements of the treatment" (Jonassen and Grabowski, 1993, p. 28).

Only few studies, for instance, the study by Bajraktarevic, Hall, and Fullick (2003) and by Brown et al. (2006) investigated the effect of adaptivity based on FSLSM in online environments with respect to students' performance and/or behaviour. Again, conflictive results were obtained.

Our study is different from these studies in several issues. In our concept different dimensions of the FSLSM are considered rather than using only one of them. This allows providing more accurate adaptivity by incorporating different aspects of learning styles as proposed by the learning style model. Furthermore, our approach only provides a recommendation for students, but they do have the opportunity to leave the recommended learning path and access all available learning objects. Moreover, a high number of students participated in this study, which was explicitly mentioned by Jonassen and Grabowski (1993) as limitation of some API studies. Also, the concept for providing adaptive course is integrated in an LMS rather than in adaptive systems, which are especially developed for this purpose. LMSs might be a more familiar environment for students and teachers and provide teachers with several advantages regarding the organisation and management of courses.

In summary, we demonstrated how LMSs can be enabled to provide adaptivity based on learning styles and showed that the proposed concept for providing adaptivity in LMSs is effective in supporting students. This study provides another evidence, showing that adaptive courses which fit the students' learning styles helps students to learn more effectively and therefore facilitated better learning for them. On the other hand, by enhancing LMSs with adaptivity, teachers can continue holding their courses in LMSs and therefore, taking all advantages of LMSs.

CHAPTER 8
Conclusion

This chapter summarises the work conducted within this thesis. In the next subsection, a summary of the performed research is given and the contributions of this work are highlighted. Subsequently, limitations of the research work are described. The thesis concludes with a discussion on future work.

8.1 Summary and Contributions

The objective of this thesis was to combine the advantages of learning management systems (LMSs) with those of adaptive systems. While LMSs focus on supporting teachers in creating, administrating, and managing online courses, such systems provide only little, or in most cases, no adaptivity for learners. On the other hand, adaptive systems support learners by providing courses that are tailored to their needs and characteristics but are rarely used in practice due to their lack of support for teachers. The aim of this thesis was to extend typical LMSs by the functionality of providing adaptivity based on learning styles referring to the Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988). At the same time, such an adaptive LMS should not lose its simplicity and should continue to be simple and easy to use for teachers.

In order to provide adaptivity based on learning styles in LMSs, the learning styles of learners need to be known first. Therefore, an automatic student modelling approach for detecting learning styles from the behaviour and actions of learners was developed. For each of the four learning style dimensions of the FSLSM, relevant patterns of behaviour were selected, which were based on commonly used features in LMSs. For inferring learning styles from the behaviour and actions of learners, a data-driven approach using Bayesian networks and a literature-based approach using a simple rule-based method were implemented. The evaluation showed that the literature-based approach achieved higher results than the data-driven approach and identified learning styles with high precision. Hence, the proposed concept including the literature-based approach can be seen as a suitable instrument for automatic detection of learning styles. Furthermore, the detection of characteristic preferences within learning style dimensions was investigated. Again, relevant patterns were determined and the literature-based approach was applied. The evaluation showed that all characteristic preferences of the active/reflective dimension and some characteristic preferences of the sensing/intuitive and visual/verbal dimension were identified with high precision. For the sequential/global dimension, most relevant patterns gave indications for more than one characteristic preference within the sequential/global dimension which led to only moderate or even poor results. The concepts for identifying learning styles as well as characteristic preferences within learning style dimensions were implemented in a standalone tool, which aims at automatically extracting the relevant data from an LMS database and calculating learning styles and characteristic preferences within learning style dimensions by using the literature-based approach.

Automatic detection of learning styles has several advantages over the use of questionnaires. First, students do not have any additional effort and just need to use the system for learning. Second, the approach is free of uncertainty that comes into play during asking students about their preferences. Third, the approach has potential to be less error-prone since it uses data from a time span rather than from a specific point in time. The developed tool allows teachers to detect their students' learning styles in an easy way. On the one hand, this information can be used to make students and teachers aware of the students' learning styles, helping students to better understand their learning processes and motivating teachers to extend their teaching strategies or materials if they do not support different learning styles. On the other hand, the information about students' learning styles is a requirement for providing adaptive courses in educational systems.

In order to improve the automatic detection of learning styles, investigations were conducted about using also other sources of information. Within this thesis, the potential of cognitive traits, in particular working memory capacity, was investigated. Therefore, a comprehensive literature review, an exploratory study, and a main study were performed. For three of the four dimensions, a relationship between learning styles and working memory capacity was identified. Further investigations are necessary for the sequential/global dimension as well as the reflective learning style due to conflicting results of the literature review and the two studies.

The identified relationships between learning styles and working memory capacity can be used as additional information in the detection process of learning styles and therefore, have potential to help in improving the accuracy of identified learning styles. Additionally, the relationships can also be used for improving the detection process of working memory capacity, and they can help getting at least some information about either learning styles or working memory capacity if the respective system includes only one of them.

Once learning styles are known, adaptivity can be provided. Within this thesis, a concept for providing adaptive courses in LMSs was developed. This concept was implemented in Moodle, enabling Moodle to automatically generate and present courses that fit students' learning styles. The evaluation showed that students, who were presented with a course that matches their learning styles, spent significantly less time in the course but yield on average the same grades than students who were presented with a mismatched or standard course. On the other hand, students who were presented with a course that did not match their learning styles asked significantly more often for additional learning objects than students who were presented with the matched course.

The proposed concept and implemented add-on to Moodle gives another indication for the effectiveness of providing adaptivity based on learning styles and shows that adaptive courses make learning easier for students. Furthermore, the proposed concept demonstrates how combinations of learning style preferences can be considered which leads to more accurate adaptivity.

By extending LMSs with adaptivity, teachers can continue holding their courses in LMSs and using the advantages of LMSs. On the other hand, students are supported in learning by being provided with courses that fit their individual learning style.

8.2 Limitations

A limitation of this thesis can be seen in the restricted pool of test persons, who participated in our studies. Participants of all studies were students, mostly from the same university in Austria, studying Information Systems or Computer Science. Although universities are one of the major target groups of LMSs, and therefore, university students are most suitable as test persons, it might be interesting to confirm our results with non-university students as test persons or with university students from other majors or other countries.

8.3 Future Work

The findings and prototypes developed in this thesis can be used as the basis for further research and developments regarding providing advanced adaptivity, especially in LMSs. Future work can focus, on one hand, on extending the different parts of research conducted within this thesis and, on the other hand, on combining these parts. In the following paragraphs, possible future directions are discussed in more detail, starting with each part of research and concluding with combining the parts.

Regarding the automatic detection of learning styles, this thesis proposed a concept for static student modelling, which means that data are gathered over a period of time and then used to calculate learning styles. The conducted research can be seen as the basis for the development of a dynamic student modelling approach, in which the information about students' behaviour and actions are processed immediately and the student model is updated frequently. Additionally, data can be analysed in more detail, for example, in order to exclude exceptional behaviour from the detection process or to monitor changes in the learning styles.

Future work will also deal with incorporating the information about the relationships between learning styles and working memory capacity into the detection process of learning styles as well as evaluating the effectiveness of the additional information with real data. Furthermore, other cognitive abilities such as inductive reasoning, information processing speed, associative learning skills, and meta-cognitive skills can be investigated with respect to their potential to provide additional information for improving the automatic detection of learning styles.

In addition, the tool for detecting learning styles can be extended. On one hand, this can be done by incorporating the information about cognitive traits in the calculation process of learning styles as well as providing a user interface for gathering this information. On the other hand, the user interface for teachers can be extended in order to provide teachers additionally with some statistics about the students' behaviour in the online courses.

Future work will also deal with analysing the concept for providing adaptivity in more detail. For example, investigations can be performed on finding out whether there are adaptation features which have more impact than others or whether there are learning styles which can be supported in a better way by the proposed concept than others. Another aim of future research will be to extend the concept for providing adaptivity in terms of making it more generic. Currently, the concept is based on a predefined course structure, including six types of learning objects (content, outlines, conclusions, examples, self-assessment tests, and exercises) as well as predefined adaptation features based on these types of learning objects. Future work will deal with allowing teachers to define which types of learning objects they want to include in the adaptation process as well as defining respective adaptation features. This will allow teachers to use their courses as they are and just adjust the adaptation mechanism to their courses rather then the other way around. Furthermore, teachers will be able to include all desired features of the respective LMS regardless of whether these features are commonly used or not.

Another direction of future work will be to combine the different parts of research by joining the automatic detection of learning styles with the functionality to provide adaptive courses. The dynamic student modelling approach can be used to monitor students' behaviour and performance in order to intervene when students seem to need support. By asking students about whether a course should be adapted and/or giving them some choices based on their learning styles for adapting the course, the system can provide them with the requested activities as well as use the students' choices as valuable feedback. From the behaviour of students in the adapted courses, the system can again get feedback about the performed adaptation. Based on the gathered feedback, the system is able to learn the students' needs and incrementally develop an accurate and reliable student model. This will allow the system to provide students with courses where adaptation is frequently improved in order to fit the students' needs.

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Curriculum Vitae

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Education

2003 – 2007:	**Ph.D. in Information Systems (Dr. rer. soc. oec.)** Institute of Software Technology and Interactive Systems, Vienna University of Technology, Austria Supervisor: Dr. Kinshuk; Co-Supervisor: Dr. Gerti Kappel Thesis: *Adaptivity in Learning Management Systems focussing on Learning Styles*
1998 – 2003:	**M.Sc. in Information Systems (Mag. rer. soc. oec.)** University of Vienna and Vienna University of Technology, Austria Supervisor: Dr. Kurt Heidenberger; Co-Supervisor: Dr. Axel Focke Thesis: *Selection and Implementation of an Ant Colony Optimisation Algorithm for Routing Patients in the Management Game INVENT (in German)*
1993 – 1998:	Secondary School with Technical Focus (HTL) Department of Computer Science & Business Management
1985 – 1993:	Primary School and Elementary School

Job Experience

2003 – 2007:	Graduate researcher and project assistant at Women's Postgraduate College for Internet Technologies, Institute of Software Technology and Interactive Systems, Vienna University of Technology
2001 – 2003:	Tutor at University of Vienna at the Institute of Software Science and the Institute of Computer Science and Business Informatics
2001 – 2003:	Webmaster at the company Syscom (part-time)
1998 – 2000:	Organised and held courses about several software programs for the companies Syscom, Datus and Solo (part-time)
1996 – 2000:	Organised and held computer courses for teenagers and children at the company Seminar Zentrum Mariahilf during school holidays
July 1995:	Gained first work experience at the computer centre of Raiffeisen bank

Publications

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