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Identifying and Incorporating Affective States and Learning Styles in Web-based Learning Management Systems

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Abstract. Learning styles and affective states influence students' learning. The purpose of this study is to develop a conceptual framework for identifying and integrating learning styles and affective states of a learner into web-based learning management systems and therefore provide learners with adaptive courses and additional individualized pedagogical guidance that is tailored to their learning styles and affective states. The study was carried out in three phases, the first of which was the investigation and determination of learning styles and affective states which are important for learning. Phase two consisted of the development of an approach for the identification of learning styles and affective states as well as the development of a mechanism to calculate them from the students' learning interactions within web-based learning management systems. The third phase was to develop a learning strategy that is more personalized and adaptive in nature and tailored to learners' needs and current situation through considering learners' learning styles and affective states, aiming to lead to better learning outcomes and progress.

Keywords: Student Modeling, Learning Management Systems, Affective States, Learning Styles.

1 Introduction

Due to rapid technological advancements over the past half century, technology has become an integral part of learning environments. This has greatly changed the practice of learning. In recent years increased awareness towards the latent benefits of adaptivity in e-learning has been reported. This is due to the realization that traditional learning systems are not able to fulfill the requirements of individualized learning (i.e., learning system tailored to the specific requirements and preferences of each individual) [1]. Adaptive systems aim to support and enhance a student's learning process [2]. In their provision of adaptivity, adaptive systems usually consider the user's knowledge, background, interest, goals, and/or preferences. Adapting to a student's affective states, such as emotions and motivation [3], or his/her learning styles is rarely considered. The Thalmann [4] study reported that within 30 existing adaptive hypermedia systems, learning styles present 13 percent and affective states 3 percent of the adaptation criteria. Shute and Zapata-Rivera [5], and Carberry and de Rosis [6] indicated that capturing useful and accurate learner information on which to base adaptive decisions is a great challenge and research work in this domain is focused at present. Similarly Sangineto et al. [7] declared that to provide personalize web-based courses based on students' learning requirements and methodological preference is an interesting open research area with large application perspective.

Learning management systems (LMSs), such as Moodle and Blackboard, are very successful in e-education but they do not accommodate full fledged adaptivity [8] and, in particular, do not accommodate current adaptivity approaches, such as adaptivity based on learning styles and affective states. Currently, the features the LMSs provide focus on supporting teachers in creating, administering, and managing online courses [9]. The LMSs provide a platform that follows the "one size fits all" approach where the structure and the didactic material of presented courses are usually static. The LMSs currently do not have a mechanism to consider and identify the learner's personal needs and characteristics. On the other hand, modern pedagogical theories and research/models emphasize to personalize the course material, in order to enhance the students' learning (e.g. [10], [11]). Thus, there is a need to turn the attention to identify students' learning style and affective states that influence learning, and combining them in order to provide personalized courses for learners that consider their learning styles and affective states, leading to the achievement of a milestone of delivering personalized e-learning courses in learning management systems and therefore broaden the provision of adaptivity and personalization in commonly used learning systems.

In this paper, we propose an automatic student modeling approach for identifying learning styles and affective states in web-based LMSs. In order to demonstrate the effectiveness of this identification process, we propose an architecture for using the gathered information about students' characteristics for providing adaptivity in LMSs.

2 Basic Concepts and Background

2.1 Learning Styles

Learning styles specify a learner's preferred ways of learning. A learner with a specific learning style can face difficulties while learning when his/her learning style is not supported by the teaching environment [12]. For example, Claxton and Murrell [13] describe that when the instruction presented matches the student's learning style, the student learns more. Based on literature, conclusion can be drawn that the consideration of learning styles in a learning environment influences a student's learning. In the present era, learning styles are being investigated in order to incorporate them into adaptive online learning environments [8]. According to Jonassen and Grabowski [14], adaptive online learning environments are ideal for generating learning style based instructional material in large classes as they do not have the same limitations as human instructors who are unable to focus on individual students due to the lack of required resources and time.

Currently two approaches are used for identifying learning styles, namely the use of questionnaires and the use data from students' behavior and actions in an online course. Adaptive systems, such as CS383 [15], and ILASH [16] uses a questionnaire to gather information on a student's learning style. According to Shute and Zapata-Rivera [5], there are at least two problems associated with questionnaire (verbal instrument) based information. First, students may provide inaccurate data either purposefully due to privacy concerns, a desire to present themselves in a more prominent way or by accident, i.e., due to a lack of awareness of their own characteristics. The second problem is that completing the questionnaire during the online learning process can be time consuming, which may frustrate students and lead them to provide invalid data in order to arrive at the contents more quickly. To capture the students' learning styles, other systems, such as Arthur [17] and DeLeS [9] adopted an approach based on the actions and behavior of the students during their use of the system for learning. In these approaches, no additional effort on the part of students is required in order to obtain information about their learning styles. The system infers their learning style from their actions. The information captured in this way is free from uncertainty.

2.2 Affective States

In a traditional learning environment, it is very challenging for a teacher to address each student's individual needs due to the large number of students in a classroom. In traditional learning situations, an experienced teacher monitors and draws conclusions from students' learning behavior, which demonstrates, for example, students' affective states. Learning systems that consider a student's affective state boost the amount that can be learned and also augment a student's learning experience [18]. Within the continuum of affective states, we find the traditional affective states, such as anger, fear, joy, surprise, and disgust identified by Ekaman and Friesen [19] as well as other affective states, for instance confidence, confusion, and effort. However, Craig et al [20] reported that traditional affective states do not play a significant role in learning. Several parameters can be used to describe students' affective states, e.g., motivation, interest, and proclivity. Qu, Wang, and Johnson [21] highlight confidence, confusion, and effort among the possible factors influencing a student's motivation. Similarly, the motivational model presented by De Vicente and Pain [22] consists of variables related to trait (control, challenge, fantasy, and independence) and state (confidence, sensory interest, cognitive interest, effort, and satisfaction).
In the following subsections four approaches to identifying affective states are presented.

2.2.1 Verbal Approach

The verbal instrument can be classified as a questionnaire or self report instrument. The difference between questionnaire and self report instrument is, that a questionnaire is usually distributed to the students for submission, so that students can provide explicit information about themselves, i.e., about their affective states, before interaction with the learning environment takes place or after finishing the interaction with the learning environment. With a self-report instrument, on the other hand, students provide explicit information about themselves, i.e., their affective states, during the interaction with a learning environment. The use of a self report instrument is not recommended for either adults or children for the purpose of reporting their affective states. This is due to the fact that self report instruments reflect not only information about ones internal state at a particular moment, but are also influenced by how such a report is perceived [23]. De Vicente and Pain [24] reported that relying exclusively on the use of self reports is not suitable as sometimes students do not update the self report facilities.

2.2.2 Nonverbal Approach

A nonverbal or psycho-physiological instrument measures physical states, such as heart rate, blood pressure, skin conductance, finger temperature, and respiration, to detect affective states via sensors, for instance, strain gauges applied to mouse buttons, special wearable devices, etc [25]. Physiological (nonverbal) instruments are usually applied in controlled environments. Picard et al. [23] highlighted that conducting such controlled experiments dealing with affective states presents a challenge. These kinds of instruments could be limited to a certain type of application due to the possible negative reaction of a user to the use of body sensors [26].

These kinds of instruments suffer due to limitations with regard to predictive power [27]. Such instruments are thus not often used in real-life computer instruction systems. However Picard [28], for example, used this kind of instrument for a piano-teaching computer system capable of detecting a student's expressive timing.

2.2.3 Intrusive Approach

An intrusive instrument measures physical appearances by means of observational cues, such as head nods, eye gaze, gesture, posture, and linguistic expression among others. Picard and Daily [29] highlighted that intrusive instruments influence a student's normal affective state and may thus lead to misinformation. This misinformation develops from a student's feeling that his/her activities are being monitored. Through the program ITSPOKE (Intelligent Tutoring SPOKEn dialogue system), Litman and Silliman [30] investigated the detection of affective states that arose during interactive spoken conversation in natural language. ITSPOKE is a speech-enabled version of text-based dialogue tutoring systems, such as Why2-Atlas [31]. Using Why2-Atlas, a student in response to qualitative physics problem being presented types a natural language answer, whereas using ITSPOKE, a student first types a natural language answer to a qualitative physics problem, ITSPOKE then engages the student in a spoken dialogue to correct misconceptions and provide feedback, and to elicit more complete explanations.

D'Mello et al. [32] highlighted the importance of a participant's role and grounding criterion in conversation. The grounding criterion is the belief that speech participants understand each other to a criteria defined for the current purposes. If a lack of understanding of the conversation exists between participants, affective states cannot be properly detected.

2.2.4 Non-intrusive Approach

The non-intrusive instrument measures the behavioral and cognitive patterns during interaction between students and the system. The affective state is identified through interaction with the system, such as in MOODS, a prototype of an intelligent tutoring system (ITS) for learning Japanese numbers with an added motivation of a self-report facility [22]. In order to infer students' affective states, some rules were formulated. Their validated results suggest that it is feasible to infer an affective state diagnosis based on the information provided by the computer interaction.

3 A Concept for Identifying Learning Styles and Affective States

In this study, we consider four learning style dimensions (FSLSM) identified by Felder and Silverman [12] and also four affective states: confidence, effort, independence, and confusion identified from a set of affective states by Qu, Wang, and Johnson [21] as well as De Vicente and Pain [22]. These learning style dimensions and affective states were selected because they are significant for students' learning processes and prevalent in student learning interactions in learning management systems.

Presented in the following subsections are patterns of behavior suitable to each learning style dimension and each selected affective state along with the concept/approach for calculating learning styles and affective states from these patterns.

Features commonly used in LMSs were selected as the basis for behavior patterns, in order to make our approach a generally applicable one for LMSs. These features include: content objects, outlines, exercises, self assessment tests, examples illustrating concepts, discussion forum for assignment related queries, discussion /peer rating forum related to the content objects, and assignments. In addition, also considered is the students' navigational behavior within the course. Data obtained from all of these features provides relevant information for identifying students' learning styles and affective states.
The next sections describe characteristics of each learning style dimension and each affective state with respect to relevant models from literature and present the relevant patterns for identifying each learning style and affective state using the models from literature as basis.

3.1 Patterns of Behavior for Identifying Learning Styles

This section presents patterns of behavior to identify the students' learning styles.

3.1.1 Active/Reflective Dimension

According to FSLSM [12], active learners are categorized as learners who prefer to process information actively by doing something with the learned material, such as discussing it, applying it, and explaining it to others. We can therefore assume that the following behavior provides us with information related to a student's active dimension. Participation in discussions through the discussion/peer rating forum related to the content objects gives us an indication about a student's behavior in terms of discussing. Trying a great number of self assessment tests and exercises gives us an indication of a student's behavior in terms of applying. Replying to queries related to assignments posted in the general forum as well as commenting on new posts forwarded by other students related to the content objects in the discussion/peer rating forum gives us an indication with regard to a student's behavior in terms of explaining.

According to FSLSM, reflective learners prefer to think about the material before they act and prefer to work alone. We can therefore assume that the following behavior provides us with information related to the student's reflective dimension. Returning to and spending more time with learning material, such as content objects, as well as spending more time looking at outlines gives us an indication about a student's behavior in terms of thinking. Moreover, spending more time on self assessment tests and exercises in order to produce good results also gives us an indication about a student's behavior in terms of thinking. Passive participation in the form of reading the "discussion/peer rating forum" and "assignment forum" postings rather than actively posting gives us an indication about a student's behavior in terms of working on their own.

3.1.2 Sensing/Intuitive Dimension

According to FSLSM, sensing learners gravitate towards concrete material, such as facts and data. They like to solve problems through well-established procedures. Furthermore, they are more patient with details and work carefully but slowly, and often do well using repetition as a learning tool. We can therefore assume that the following behavior provides us with information related to a student's sensing dimension. The number of visits and time spent on examples gives us an indication about the student behavior in terms of learning from concrete material. Sensing learners tend to prefer examples in order to learn from concrete material. The more visits and more time spent on examples gives us an indication that a student wants to see and learn from existing approaches. Moreover, a great number of attempts at self-assessment tests and exercises provide an indication about a student's behavior in terms of checking the acquired knowledge. The time taken to submit the self-assessment tests and exercises gives us an indication about the pace at which a student works. Repeating the self assessment test and getting a satisfactory score in the final attempt provides an indication related to using the self assessment test as a learning tool.

According to FSLSM, intuitive learners prefer challenges and are bored by details. Another characteristic of intuitive learners is that they like innovation and dislike repetition. Furthermore, intuitive learners tend to work faster than sensing learners. We can therefore assume that the following behavior provides us with information related to a student's intuitive dimension. Solving an assignment in just a few attempts and also doing so quickly give us an indication about a student's behavior when faced with challenges. A great number of visits to content objects, longer time spent; and low number of visits to examples, shorter time spent, give us an indication about students' behavior of using examples only as supplementary material and are being bored by niceties. Not repeating the self assessment test, after getting a satisfactory or moderate score in the first attempt gives us an indication about a student's behavior with regard to disliking repetition.

3.1.3 Visual/Verbal Dimension

According to FSLSM, visual learners remember best what they can see, such as flowcharts, graphics, and images. We can therefore assume that the following behavior provides us with information related to the student's visual dimension. Performance on questions with visual metaphors or elements can give us an indication about a student's behavior in terms of visual cues.

According to FSLSM, verbal learners prefer to learn from words, regardless of whether they are written or oral. Verbal learners tend to like discussion and communication with others. We can therefore assume that the following behavior provides us with information related to the student's verbal dimension. Frequent visits to and spending time at content objects by the student gives us an indication about a student's verbal dimension. Posting a great number of posts as well as a great number of comments on posts in discussion/peer rating forums related to the content objects gives us an indication about a student's behavior in terms of discussing and communicating.

3.1.4 Sequential/Global Dimension

According to FSLSM, sequential learners are comfortable with details and follow logical stepwise paths when solving problems. We can therefore assume that the following behavior provides us with information related to a student's sequential dimension. The navigation of students through the course in a linear way gives us an indication about a student's sequential behavior.

According to FSLSM, global learners like to get an overview of the contents rather than going into too much detail of the contents being presented. Using this way of learning, they grasp the big picture and build their own cognitive map with respect to the presented contents. We can therefore assume that the following behavior provides us with information related to the student's global dimension: A great number of visits and more time spent on chapter outlines as well as on the course overview page provide an indication about a student's behavior with regard to obtaining the big picture with respect to the course contents.

3.1.5 Summary

The mentioned patterns related to the active /reflective, sensing/intuitive, visual/verbal, and sequential/global dimensions are presented in Table 1. The "-" and "+" indicate a low and high occurrence of the respective pattern from the active, sensing, visual and sequential dimension point of view.

Table 1. Patterns of Behavior for the Detection of Learning Styles

Active /Reflective	Sensing/Intuitive	Visual/verbal	Sequential/global
content_visit(-)	content_visit(-)	quest_graphics(+)	outline_visit(-)
content_stay(-)	content_stay(-)	quest_text(-)	outline_stay(-)
outline_stay(-)	example_visit(+)	content_visit(-)	course_ovview_ visit(-)
forum_content_post (+)	example_stay(+)	content_stay(-)	course_ovview_ stay(-)
forum_content_post_ reply(+)	selasses_visit(+)	forum_content_ post(-)	navigation_skip(-)
forum_assignment_ post_repl(+)	selfassess_stay(+)	forum_content_post_ repl(-)	
selfassess_visit (+)	exercise_visit(+)		
selfassess_stay(-)	exercise_stay(+)		
exercise_visit(+)	selfassess_revision(+)		
exercise_stay(+)	assignment_revision(+)		
	assignment_stay(+)		

3.2 Patterns of Behavior for Identifying Affective States

This section presents patterns of behavior to identify the students' confidence, effort, independence and confusion.

3.2.1 Confidence

Sander and Sanders [33] highlighted that confidence levels differ among students in the same situation and that they also have different levels of confidence in different situations. In this context, a new mediating term was proposed known as academic confidence. Besterfield-Sacre et al. [34] highlighted that academic confidence influences a student's motivation, performance, and retention in their future academic studies. Sander and Sanders [33] conducted a study to measure students' academic confidence. This study yielded six factors in academic confidence. These factors include studying, understanding, verbalizing, clarifying, attendance, and grades.

In our approach, we consider five factors of the six mentioned by Sander and Sanders for identifying academic confidence. The exempted factor is grades, which is the only factor that does not co-relate with the student's learning behavior. We can assume that the information related to the student's academic confidence can be obtained by observing the following student behavior: Number of visits to content objects, examples, and outlines gives us an indication about a student's behavior in terms of *studying*. Number of visits to exercises and self assessment tests and consequently successfully solving a high number of questions gives us an indication about a student's behavior with regard to *understanding*. Forwarding a great number of posts as well as commenting on a great number of posts in discussion/peer rating forums related to the content objects gives us an indication about a student's behavior with regard to *verbalizing*. The number of visits to assignment related queries in the forum and also visits to posts related to the content objects via the discussion/peer rating forum give us an indication of a student's behavior with regard to *clarifying*. Counting a student's overall posts in a discussion/peer rating forum related to the content objects, comments/peer rating of posts and replies to queries posted on the assignment-related queries forum give us an indication about a student's behavior with regard to *attendance.*

3.2.2 Effort

The Attribution Theory [35] highlights that effort is an unstable factor, although a student has a great deal of control over it. For example, a student can control his/her effort by trying harder or a student who fails repeatedly in a difficult course could succeed by taking an easier one. Weiner, Heckhausen, and Mayer [36] remarked that student attribution of failure to unstable factors, such as effort or luck, facilitates performance and preserves expectations of future success. For example, if students attribute failure to their low ability, they will expect failure in the future because there is no way they can alter their ability but if students attribute failure to their low effort, they can try harder in the future and experience greater success. A Motivation Theory conception provided by Pintrich and DeGroot [37] enumerates the factors for an individual's willingness to display an interest in learning or exerting effort, such as personal interest and the importance of a task, as well as a student's disposition toward doing the necessary work to complete the task.

Wise and Kong [38] argued that rapid guesses in low-stake situations (absence of personal consequences associated with student test performance), represents low-effort behavior by unmotivated students. Qu, Wang, and Johnson [21] derived the effort exerted by a student in a learning environment from the amount of time the student spent on performing tasks. De Vicente [39] elicited seven rules related to effort from the expert responses about students' interactions in a learning environment. To validate those rules, an empirical study was conducted, which found five rules related to effort to be valid. Validated rules include, for example, if the number of correct answers is high relative to the number of questions within the exercise, the student's effort is to be considered high.

Following the motivational theory concept [37], the Qu, Wang, and Johnson model [21], and De Vicente's [39] validated rules related to effort, we can therefore assume that the following behavior provides us with information related to a student's effort in a learning environment.

A great number of attempts at self assessment tests and exercises give us an indication about a student's behavior in terms of exerting high effort. A great number of visits to the discussion/peer rating forum and consequently, a great number of replies on the discussion/peer rating forum predicts a great deal of effort from the student in such activities. Submission of assignments well before the deadline as well as revision and resubmission of assignments before the deadline in response to negative feedback on the first submission gives us an indication of a student's behavior with regard to exerting high effort.

3.2.3 Independence

Independence (autonomy) is an attribute of a student, in which he/she exhibits agency (intentional behavior) in a learning environment. Academic discourse abounds with synonyms for "*independent learning,*" such as "independent study, student initiated learning, lifelong learning, and autonomous learning" [40]. Jeffries et al. [41] indicated that independent learning involves students' taking greater responsibility for what they learn, how they learn, and when they learn. Singh and Embi [42] mentioned the importance of five factors for looking into a student's abilities to work autonomously during Web-based learning, i.e., planning, organizing, monitoring, evaluating, and computer abilities. Planning and organizing deals with the ability of a student to formulate materials and techniques, learning aims, and a schedule for accomplishing learning tasks; monitoring deals with the ability of a student to check, verify, and correct themselves during learning tasks; evaluating deals with the ability of a student to judge, evaluate, and make decisions on performance in achieving the learning tasks; computer abilities deals with a student's possession of basic computer application skills, to self-access course materials and related links to accomplish their learning tasks.

In our approach we consider four factors of the five mentioned by Singh and Embi for identifying autonomous abilities. The exempted factor is computer abilities, as we assume that students have similar abilities to access the course materials and related links to accomplish their learning tasks using the leaning management system. According to Singh and Embi [42], we can therefore assume that the following behavior provides us with information related to a student's abilities to work autonomously: Visiting content objects, outlines, examples, and posting and visiting posts related to content objects on the discussion/peer rating forum give us an indication of a student's behavior in terms of planning; peer rating of posts in a discussion/peer rating forum related to the content objects, submission of assignments, even in several attempts, give us an indication of a student's behavior in terms of monitoring; the number of attempts of self assessment as well as the number of attempts at exercises give us an indication of a student's behavior in terms of evaluating.

3.2.4 Confusion

Recent research highlights confusion as an important affective state for scientific investigation [43]. Confusion is a state of uncertainty about how to act or what to do next [44]. Craig et al. [20] conducted a study related to the role of affective states in learning with Auto Tutor, coding confusion as a state when students seem perplexed and unsure of how to continue or are struggling to understand the material. Rozin and Cohen [45] indicated that confusion and cognitive disequilibrium often go hand-in-hand, and in states of uncertainty and perturbation there is need for clarification or more information. Qu, Wang, and Johnson [21] indicated that a student is most likely to get stuck or frustrated in a highly confused state. Baker et al. [46], mentioned that a confused student is likely to game the system.

According to Qu, Wang, and Johnson [21] and Baker et al. [46], we can therefore assume that students in a state of confusion can be divided into two types 1) stuck and 2) gamer.

Stuck students are assumed to be those who solve a low number of exercises and self assessment tests. Moreover, they are assumed to be the ones who leave a great number of questions un-attempted in exercises and self assessment tests, and answer the same question twice or more often wrong in the self assessment test. Stuck students are also assumed to be those who visit a great number of examples and spend more time on each example. In terms of submission of assignments, stuck students are assumed to be the ones who post repeated and quick inquiry messages over the forum related to assignment. Stuck students are assumed to be the ones who have a high number of assignment submission attempts for each assignment. They are assumed to be the ones who stay longer on content objects. They tend to visit a great number of postings related to the content objects but in contrast, they are assumed to be the ones who forward a low number of peer ratings related to the posted content objects on the discussion/ peer rating forum. Gamer students are assumed to be those who misuse the available system. They are assumed to be involved in gaming activities while attempting the self assessment tests, such as inputting answers quickly and repeatedly, until the system provides the feedback, i.e., correct answer. These patterns of stuck and gamer students provide us with information related to a student's level of confusion.

3.2.5 Summary

The mentioned patterns related to confidence, effort, independence, and confusion are presented in Table 2. In this table, the high occurrence of the respective pattern is assumed to demonstrate high confidence, effort, independence, and confusion.

3.3 From Behavior to Learning Styles and Affective States

The patterns described in section "Patterns of Behavior for Identifying Learning Styles" are incorporated for each learning style dimension and the patterns described in section "Patterns of Behavior for Identifying Affective States" are incorporated for each affective state. The high or low occurrence of these patterns indicates a specific learning style preference and a specific affective state level. Based on this available information, data about students' behavior can be used to calculate hints for specific learning style preferences and also specific affective state levels.

The approach for calculating hints for specific learning style preferences and also specific affective state levels is based on the approach proposed by Graf, Kinshuk, and Liu [47] for calculation of learning styles from patterns of behavior. Accordingly, hints are denoted by four values, i.e., 0–3 where 3, if used for learning style preference, indicates that the student’s behavior gives a strong indication toward the

Table 2. Patterns of Behavior for the Detection of Affective States

Confidence	Effort	Independence	Confusion
i. Studying	selfassess_visit	**i. Planning & organizing**	selfassess_visit
content_visit	selfassess_stay	content_visit	exercise_visit
outline_visit	exercise_visit	outline_visit	example_visit
example_visit	exercise_stay	example_visit	example_stay
ii. Understanding	forum_content_visit	forum_content_visit	forum_assignment_post
exercise_visit	forum_content_post_repl	forum_content_post	assignment_revision
selfassess_visit	assignment_revision	**ii. Monitoring**	content_stay
iii. Verbalising		forum_content_post_repl	forum_content_visit
forum_content_post		assignment_revision	forum_content_post_repl
forum_content_post_reply		**iii. Evaluating**	
iv. Clarifying		selfassess_visit	
forum_assignment_visit		selfassess_stay	
forum_content_visit		selfassess_revision	
v. Attendance		exercise_visit	
forum_content_post		exercise_stay	
forum_content_post_repl			
forum_assignment_post_repl			

respective learning style and similarly, if 3 is used for affective state level, it gives a strong indication toward the respective affective state. The value 2 used for either learning style preference or affective state level indicates that the student’s behavior is average and therefore does not provide a specific hint. Similarly, value 1 used for either learning style preference or affective state level indicates that the student’s behavior is in disagreement with the respective learning style or affective state, and value 0 indicates that no information about the student’s behavior is available. In order to categorize the student’s behavior for each pattern into four values, thresholds from the literature (e.g. [47], [48], [49]) are used as a basis, with the additional consideration of the characteristics of the respective course.

By adding up all hints and dividing them by the number of patterns providing available information, a measure for each respective learning style and respective affective state is individually calculated and the equivalent mathematical notation is shown in formula 1, where *x* denote a hint value for each pattern providing available information. The x can have a value in the range of 0 to 3, n denote the number of patterns providing available information, and i denote a respective pattern number.

$$\frac{\sum_{i=0}^{n} x_i}{n} \text{ where } 0 \le x_i \le 3 \qquad (1)$$

This measure is then normalized on a range from 0 to 1 for both learning style and affective state. The value 1 represents a strong positive level and the value 0 represents a strong negative level for the particular learning style and affective state. In case no information is available for all patterns of a learning style dimension or affective state, no conclusion can be drawn.

4 The Architecture of an Affective States and Learning Style Module

The “Affective States and Learning Style” module (ALSM) aims to recognize the students’ learning styles (LS) and affective states (AS) during students’ interactions in a web-based learning management system environment and thereafter to provide students with a suitable learning strategy. The suitable learning strategy is adaptive in nature and realized through an adaptive course generator (ACG) and an adaptive affective tactic generator (AATG). ALSM considers different types of learning objects which are typically available in LMSs. These learning objects are composed into individual courses and have the potential to support students with different learning styles. Additionally ALSM considers some new types of learning objects in the LMSs such as Relationships, Scaffolds and Questions for additional pedagogical guidance of students. These learning objects in combination with some of the available learning objects in LMSs have the potential to support students when their affective states are identified to be below average. Figure 1 shows the architecture of ALSM

The module is being attached to a learning management system providing the system with the essential “learning style and affective state” information in order to determine the learning strategy presented to the learner. The main purpose of ALSM is to create an appropriate learning environment for students, taking into account particular affective states in combination with learning styles and offering personalized learning that considers both of these students’ characteristics.

The ALSM has two main components: The Affective States and Learning Styles Identification Component, and the Affective Learning Style Pedagogy Component.

4.1 The Affective States and Learning Styles Identification

This component consists of its two sub components i.e. the Learning Style (LS) and the Affective State (AS) component.

4.1.1 The Learning Style Component

This component (Figure 1) is responsible for the recognition of the students' learning styles. The learning style component further consists of its four sub components. The four sub components represent the active/reflective, sensing/intuitive, visual/verbal and sequential/global learning styles dimension. These four learning style sub components are responsible for identifying, storing and frequently updating information about the four learning style dimensions pointed out by Felder and Silverman [12].

4.1.2 The Affective State Component

This component (Figure 1) is responsible for the recognition of the students' particular affective states. The affective states component further consists of its four sub components. The four sub components represent students' confidence, effort, independence and confusion. Those four affective states sub component are responsible for identifying, storing, and frequently updating information about the particular affective states. Those particular affective states have been identified from a set of affective states to be relevant and important for learning [21], [22].

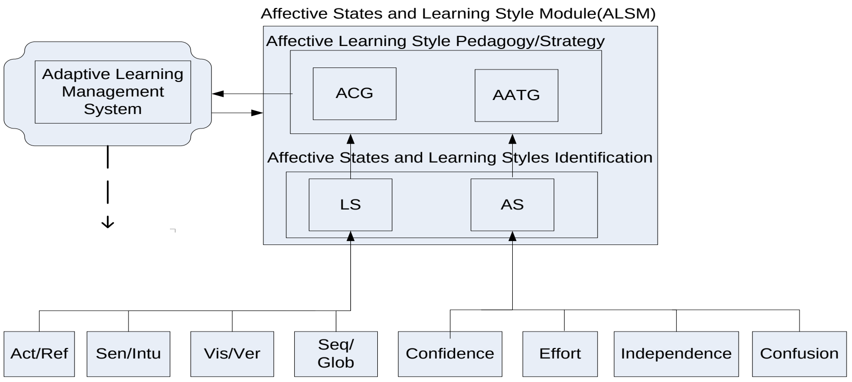

Fig.1. The architecture of ALSM

4.2 The Affective Learning Style Pedagogy Component

The students' learning styles and affective states, after being recognized by the respective components, are used by the affective learning style pedagogy component (Figure 1). The Affective Learning Style Pedagogy Component consists of its two sub components i.e. adaptive course generator (ACG) and adaptive affective tactic generator (AATG). The ACG and AATG are introduced to facilitate students' learning by considering not only their learning styles but their affective states as well.

4.2.1 Adaptive Course Generator

This sub component deals with adaptive sequencing of learning objects according to students' learning styles. This is accomplished by the ACG component using the available learning style information for generating an adaptive course based on the available learning material and activities. The adaptive sequencing is based on recommendations from [9]. The adaptive sequencing changes the sequence of examples, self assessment tests, and exercises and whether they are presented prior to content objects, after the content objects, or at both locations. Another adaptation feature is the number of presented examples, self assessment tests, and exercises.

4.2.2 Adaptive Affective Tactic Generator

This sub component deals with adaptive selection and presentation of additional elements from the AATG repository when a student's affective state is identified to be below average and therefore indicates that the student is experiencing learning difficulties. The AATG component uses the available affective state information in combination with the available learning style information in order to provide students with chunks of information that help them in their current situation. The AATG repository contains elements such as Definitions, Pictures, Applications, Examples, Relationships, Scaffolds, Exercises, and Questions for additional pedagogical guidance of students. The AATG component selects and presents those elements for pedagogical guidance that fit best to students' learning styles according to the learning style dimensions of the Felder-Silverman learning style model [12]. The mapping between learning styles and suitable pedagogical guidance is based on recommendations from [50].

5 Discussion and Conclusion

In this paper, we introduced the affective states and learning style module which helps to bring adaptivity based on learning styles and affective states into web-based learning management systems. This enhanced module relies on an automatic student modeling approach for identifying learning styles and affective states in LMSs. The prescribed approach uses students' behavior while learning to gather hints about their learning styles and affective states. Based on the obtained indications related to behavior, learning styles and affective states are calculated using a simple rule-based mechanism. The gathered information is then used to provide students with appropriate, pedagogical material and guidance.

Graf, Kinshuk, and Liu [47] investigated behavior patterns with respect to students' learning styles when considering learning-style based adaptivity in LMSs. We introduced and investigated additional patterns, such as the ones based on a discussion/peer rating forum related to the content objects and the ones related to assignments. Furthermore, we looked into detecting affective states based on students' behavior in LMSs. The investigated patterns of behavior correspond to students' different learning styles and affective states, in order to provide the students with personalized support.

Related work about affective states identification focuses on the development of specific learning systems such as VFTS [21], MOODS [22] and a web-based system focuses on Hebrew vocabulary [51]. Some efforts have been made to incorporate the affective factor in the self assessment test for LMSs [52], such as mentioning the level of confidence while attempting each question. However, these efforts have been made simply for the purposes of avoiding rapid guessing (gaming) and measuring students' actual knowledge. Our approach includes features commonly used for LMSs. Therefore, this approach is applicable for LMSs in general. Developing an approach that is applicable to LMSs in general is more challenging than developing it only for one specific system. It requires consideration of the different features the different LMSs can support as well as the availability of data regarding the patterns from the LMSs database.

Future work will deal with the attachment of an ALSM to a learning management system, so that a personalized pedagogical material and guidance can be provided as well as validate our approach through a study with students.

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