Considering Cognitive Traits and Learning Styles to Open Web-Based Learning to a Larger Student Community

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Abstract

Learning can take place best when the individual needs of learners such as their prior knowledge, learning styles, and cognitive traits are considered. On the other hand, if the learning environment does not support the learners' needs, learners might have difficulties in learning. This paper shows how cognitive traits and learning styles can be incorporated in web-based learning systems by providing adaptive courses. Such courses fit to the individual characteristics of learners and therefore make learning easier and better accessible for those who have difficulties with the one-size-fits-all courses. The adaptation process includes two steps. Firstly, the individual needs of learners have to be detected and secondly, the courses have to be adapted according to the identified needs. In order to enhance the mechanism of detecting needs of learners, investigations about the relationship between cognitive traits and learning styles are introduced as well. This relationship acts as a good source to get additional information and therefore assists in achieving the aim of providing suitable adaptivity regarding cognitive traits and learning styles in order to help getting more students to learn better.

1. Introduction

While some learners find it easy to learn in a particular course, others find the same course difficult and have severe problems in learning. The reason can be seen in the learners' individual differences such as their different prior knowledge, learning styles, and cognitive abilities [1]. Looking at the prior knowledge, it is obvious that adapting the courses to the prior knowledge of students helps them in learning and makes learning easier for them. For example, when providing a course for advanced learners to beginners, the learners will have problems with the too complex material. On the other hand, if we provide a course for beginners to advanced learners, learners will probably get bored and learning will also not take place in a proper way.

The same is true for other characteristics of learners. In recent years, researchers have focused more and more on investigating the impact of learners' characteristics such as learning styles and cognitive traits in technology enhanced learning. Investigations have been done showing how such characteristics can be incorporated to support learners who have difficulties in learning with the one-size-fits-all courses. These investigations are motivated by educational and psychological theories. For example, the cognitive load theory [2, 3] suggests that learning happens best under conditions that are aligned with human cognitive architecture. Therefore, it is beneficial to incorporate the differences in cognitive architecture in order to avoid cognitive overload and facilitate learning also for students with weak cognitive abilities. Regarding learning styles, Felder, for example, pointed out 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 [4, 5]. On the other hand, incorporating learning styles makes learning easier and leads to better achievement. Bajraktarevic, Hall, and Fullick [6], for example, confirmed this by a study showing that students attending an online course that matches with their preferred learning style (either sequential or global) achieved significantly better results than those who got delivered a course that did not match their learning style.

In contrast to prior knowledge which is directly associated with the topic to learn, cognitive traits and learning styles are domain-independent and can be seen as meta-abilities for learning. Cognitive traits are more or less stable over time [7]. For learning styles researchers still do not agree on whether they can change or not. However, if they can be changed, such changes require training the weak learning preferences in order to enhance them. By incorporating the individual cognitive traits and learning styles of students in technology enhanced learning, we make learning accessible for all learners, independent on their cognitive traits and learning style preferences.

In this paper, we describe how learners with different cognitive traits and preferences on learning styles can be supported and provided with adaptive courses (Section 2). These courses fit to their needs and make learning easier for the learners. However, providing adaptivity requires also knowing the characteristics of learners. In section 3, we show how learning styles and cognitive traits of learners can be detected and introduce an automatic student modelling approach for cognitive traits as well as for learning styles. In order to provide more holistic adaptivity and improve the detection process of learning styles and cognitive traits, we present in Section 4 the investigations on the relationship between learning styles and cognitive traits. Section 5 concludes this paper.

2. Providing adaptive courses

In the following subsections, we introduce concepts to provide adaptive courses based on cognitive traits and learning styles. Adaptation features are introduced which show how learners with specific characteristics can be supported in learning.

2.1. Adaptivity based on cognitive traits

Humans typically have a number of cognitive traits. In this subsection, we focus on cognitive traits which are important for learning. These include working memory capacity, inductive reasoning ability, information processing speed, and associative learning skills. For each of these traits suggestions are introduced on how to support learners with low and high cognitive abilities in adaptive educational systems [8]. These suggestions are based on the Exploration Space Control elements [9] which are elements that can be changed to create different versions of courses to suit different needs. These elements include the number and relevance of paths, the amount, concreteness and structure of content, as well as the number of information resources.

Working memory allows us to keep active a limited amount of information (roughly 7+-2 items) for a brief period of time [10]. Matching courses to the working memory capacity of individual learners aims at considering their abilities and therefore avoiding cognitive overload. For learners with low working memory capacity this can be achieved by decreasing the number and increasing the relevance of paths in a course. Furthermore, less but more concrete content should be presented and the number of available media resources should increase. In contrast, for learners with high working memory capacity, less relevant paths can be presented with the amount of content as well as its abstractness being increased.

Inductive reasoning skills relate to the ability to construct concepts from examples. For learners with low inductive reasoning skills, many opportunities for observation should be provided. Therefore, learning systems can support these learners by providing a high amount of well-structured and concrete information with many paths. For learners with high inductive reasoning skills, the amount of information and paths should decrease to reduce the complexity of the hyperspace and hence enable the learners to grasp the concepts quicker. Moreover, information can be presented in a more abstract way.

Information processing speed determines how fast the learners acquire the information correctly. For learners with low information processing speed, only the important points should be presented. Therefore, the number of paths and information should decrease and the relevance of paths should increase. Additionally, the structure of the information should increase in order to speed up the learning process. In contrast, for learners with high information processing speed the information space can be enlarged by providing a high amount of information and paths.

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

Additionally, the relevance of the paths should decrease to enlarge the information space.

2.2. Adaptivity based on learning styles

Several different learning style models exist in the literature such as the model by Kolb [11], Honey and Mumford [12], and Felder and Silverman [4]. Looking at adaptive educational systems which incorporate learning styles, Felder-Silverman learning style model (FSLSM) is one of the most often used model in recent times and some researchers even argue that FSLSM is the most appropriate model for the use in adaptive web-based educational systems [13, 14].

FSLSM describes the learning style of learners in much detail, distinguishing between preferences on four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global). Each learner has a preference for each of these four dimensions. Therefore, we suggest adaptation feature for each dimension. These features show how courses can be adapted to the individual learning styles of learners.

Since active learners prefer to learn by trying things out and doing something actively, the number of learning objects that supports such kind of learning should increase. This includes objects such as interactive animations, exercises, and self-assessment tests. On the other hand, active learners tend to be less interested in examples, since with examples they can see how others have done something rather than doing it themselves. Therefore, less examples are recommended for active learners. Moreover, active learners tend to prefer learning by talking, explaining, and discussing the material with others and also like to work in groups. Therefore, communication features such as forum and chat, tasks that incorporate such features, as well as group work are beneficial. In contrast, reflective learners prefer to learn by reflecting on the leaning material and thinking things through. Therefore, the number of learning objects asking for active behaviour should decrease. Furthermore, it is recommended to first present the learning material, so that learners can reflect on it and afterwards present examples or ask them to do some tasks based on the learned material.

Sensing learners prefer to learn concrete material such as data and facts. They also prefer to learn from examples. Therefore, the number of examples should increase for sensing learners and examples should be presented before the abstract learning material. Since sensing learners favour sensory perception, the number of multimedia objects such as audio files and interactive animations should increase. Since sensing learners also like practical problem solving, the number of exercises should increase. Moreover, it is known that sensing learners prefer to solve such problems by already learned approaches. Therefore, we recommend providing tasks such as exercises or self-assessment tests only after the learning material. On the other hand, intuitive learners like challenges and therefore such tasks can be presented before the learning material. Since intuitive learners prefer to learn abstract material and do not like repetitions, the number of examples and exercises should decrease. However, in contrast to sensing learners, examples should be presented after the abstract content.

Visual learners remember best what they have seen, whereas verbal learners get more out of words, regardless of whether they are spoken or written. Therefore, it is recommended to provide visual learners with visual material such as graphics, diagrams, images as well as animations, whereas courses for verbal learners should emphasize on text-based material. Additionally, the use of communication features is suggested for supporting verbal learners.

Since sequential learners prefer to learn by linear steps with a linear increase of complexity, we recommend presenting first the learning material, then some examples, and afterwards some exercises and tests. Furthermore, sequential learners prefer to have a predefined learning path. This can be supported by hiding links within the learning material and highlighting the back and next buttons. For global learners, it is very important to get the big picture of the topic and they tend to be poor in using partial knowledge. Getting an overview of the topic can be supported by providing outlines and a high number of examples, presented after the learning material. Furthermore, exercises and tests should be presented at the end of a chapter, where the learners have already a better overview about the topic. In contrast, sequential learners can be supported by doing exercises and tests more frequently. Since global learners are interested in related topics and also prefer to go through the material in a non-sequential way by jumping to more complex material, links should be displayed and global learners should have the possibility to access all learning objects. This can be supported, for example, by a navigation menu.

3. Detecting cognitive traits and learning styles

The previous section showed how adaptivity based on cognitive traits and learning styles can be provided. However, a requirement for providing adaptivity is to know the learners' characteristics. This section discusses how cognitive traits and learning styles can be identified and introduces an approach for automatic detection of cognitive traits and learning styles.

3.1. Cognitive Trait Model

Cognitive Trait Model (CTM) [15, 16] is a student model that profiles learners according to their cognitive traits. Four cognitive traits, working memory capacity, inductive reasoning ability, information processing speed, and associative learning skills are included in CTM so far.

The proposition of CTM changes the traditional idea of the student model that is thought of as just a database sitting on the server which is full of numbers for only a particular task. The CTM offers the role of 'learning companion', which can be consulted by and interacted with different learning environments about a particular learner. The CTM can still be valid after a long period of time due to the more or less persistent nature of cognitive traits of human beings [7]. Furthermore, cognitive traits can be seen as domain and context independent [17]. When a student encounters a new learning environment, the learning environment can directly use the CTM of the particular student from a Universal Resource Locator (URL) in the Internet or portable storage media of the student. The learning environment does not need to reconstruct a model of that student. The CTM can also be saved to portable electronic media, such as a flash drive, and accessed every time the student starts up a learning session. In this sense, the CTM is like a learning companion who even though does not know what is to be learned, knows how the learning content can be best presented to the student. The CTM also stands as a cognitive facilitator between the student and the learning environment.

In a typical structure of CTM, the learner interface provides a presentation of the learning environment to interact with the learner. An Interface Listener Component exists that can monitor events created by learner's interactions with a learning environment. Learner interactions are interpreted as a series of learner actions performed on knowledge objects. Actions are then passed on to the Action History Components and are stored in the Action History.

The performance-based model typically exists independently in the adaptive educational systems. It represents the learner's domain competence and models the problem-solving process that the learner undertakes. Certain learner behaviours, called Manifestation of Traits (MOTs), can be used to infer about the cognitive capacity. Information of the performance-based model, such as passing or failing a unit, can be useful for detecting MOTs of some cognitive traits, and therefore data in the performance-based model is used as a source by the MOT Detector Component.

Various MOTs are defined for each cognitive trait. Each MOT is a piece of an interaction pattern that manifests a learner's characteristics (e.g. low inductive reasoning ability). The MOT Detector Component contains knowledge about a number of MOTs and detects those MOTs within a series of actions that are requested from the Action History Component. The Individualised Temperament Network Component (for a detailed description, see [18]) is responsible for calculating the cognitive traits of the learners which are then saved in the Cognitive Trait Model.

3.2. Detecting Learning Styles

Similar to the CTM, the basic concept for detecting learning styles automatically is based on information gathered from the learners' interactions when they are learning/working with the system. Based on the FSLSM, a tool has been developed that aims at automatically identifying learning styles from the behaviour of students in learning management systems (LMS) [19].

FSLSM describes how learners with specific preferences act in traditional learning situations. In order to define significant patterns for detecting learning styles in LMS, we mapped the traditional learning behaviour to behaviour in LMS. Furthermore, only commonly used features such as content objects, example, exercises, tests, forums, and chats were considered in order to keep the approach open for different LMS.

Several patterns were defined for each dimension. For example, patterns that indicate an active learning preference include the number of postings as well as the number of visits in a forum and in a chat. Another example for an indication of an active learning style is the number and time students spent on exercises since we know that active learners like to try things out and work actively with the learned material.

The tool consists of two components. The data extraction component is responsible for extracting the relevant data according to the defined patterns of behaviour from the LMS database and passes this data to the calculation component. The calculation component is responsible for calculating learning styles from the gathered data by using an approach similar to the method of the ILS questionnaire [5] - a 44-item questionnaire for identifying learning styles based on FSLSM. The result of each dimension is converted to a 3-item scale, indicating e.g. an active, balanced, or reflective learning style.

4. Relationship between cognitive traits and learning styles

So far, we looked at learning styles and cognitive traits separately. By considering both, cognitive traits and learning styles, a more holistic adaptivity can be provided. We investigated the relationship between cognitive traits and learning styles in order to get additional information about the learners. The additional information can be used in systems that consider only either learning styles or cognitive traits to extend the student model. This leads to more holistic adaptivity by including both learning styles and cognitive traits. Furthermore, the additional information from the relationship can be used to improve the detection of learning styles and/or cognitive traits. This strengthens the existing student models and leads to a better support for holistic adaptivity.

In a comprehensive literature review [20] the relationship between each dimension of the FSLSM and working memory capacity (WMC), a cognitive trait included in the CTM, was investigated. By looking at studies that deal with the interaction of learning styles, cognitive styles, and cognitive traits, direct and indirect relationships between the dimensions of FSLSM and WMC were concluded. As a result from the literature review, it can be summarized that learners with high WMC tend to prefer a reflective, intuitive, and sequential learning style. On the other hand, learners with a low WMC tend to have a more active, sensing, and global learning style. For the visual/verbal dimension, only a one-directional relationship was identified rather than a bi-directional correlation as for the other dimensions. Therefore, learners with low WMC tend to prefer a visual learning style but learners with high WMC might have visual or verbal preferences. On the other hand, learners with verbal learning style tend to have a high WMC but learners with a visual learning style might have high or low WMC.

In order to confirm the results from the literature review, we conducted an experiment with 297 students. Each student was asked to fill out the ILS questionnaire [5]. ILS is a 44-item online questionnaire for identifying learning styles based on FSLSM. Furthermore, participants were asked to perform the Web-OSPAN task [21], which is an online tool for detecting the working memory capacity. After data cleansing, data from 225 participants were finally used for analyses.

As a result of the study, we found evidence for a significant relationship between the active/reflective dimension, indicating that learners with a strong preference for either active or reflective learning tend to have low WMC, whereas learners with a balanced learning style tend to have high WMC. Regarding an active learning preference, our results are in agreement with the conclusions from the literature review, since both associate low WMC with an active learning preference. However, regarding a reflective preference, conclusions from literature argued for high WMC. According to our results, active and reflective preferences are associated with low WMC, whereas a balanced learning style is related to high WMC.

For the sensing/intuitive dimension, we found a relationship between a sensing and balanced learning styles. This relationship indicates that learners with a sensing learning style tend to have low WMC and the more balanced the learning style becomes, the higher is the tendency to have high WMC. This is in agreement with the conclusions from literature. Furthermore, according to literature this increase of tendency for high WMC continues, the more intuitive the learning style preference becomes. For this second part of the relationship, we found no evidence in the data.

The results of the visual/verbal dimension were in agreement with the results from literature. Therefore, learners with low WMC tend to have a visual learning style but learners with visual learning style might have high or low WMC. On the other hand, learners with a verbal learning style tend to have high WMC but learners with high WMC tend to have a verbal or visual learning style.

According to literature, evidence exists for a relationship between a sequential learning style preference and high WMC as well as a global learning style preference and low WMC. Based on the data of the study, we did not find any evidence that yield to this conclusion. Therefore, our findings are in disagreement with literature for the sequential/global dimension and further analyses are necessary.

5. Conclusions

This paper discussed how cognitive traits and learning styles can be incorporated in technology enhanced learning. It is known that learners with a strong preference for a certain learning style have difficulties in learning if this learning style is not considered by the teaching environment. Also it is known that if the learning material overwhelms the cognitive abilities of students, this leads to negative effects in learning. By providing courses that match to the individual characteristics of students, the access to education is opened and facilitated for all those who otherwise may have difficulties in learning. This opens learning for a larger student community and facilitates more students to learn better.

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7. References

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