Considering Learning Styles in Learning Management Systems: Investigating the Behavior of Students in an Online Course*

Sabine Graf
Vienna University of Technology
Women's Postgraduate College for Internet Technologies, Vienna, Austria
graf@wit.tuwien.ac.at

Kinshuk
Athabasca University
School of Computing and Information Systems
Athabasca, Canada
kinshuk@ieee.org

Abstract

Many researchers agree that considering learning styles increases the learning progress and makes learning easier for students. Learning management systems (LMS) are very successful in e-education but do not incorporate learning styles. As a requirement for taking learning styles into consideration in LMS, the behavior of students in online courses needs to be investigated. In this paper, we analyze the behavior of 43 students based on their learning styles and predefined patterns of behavior. Firstly, we concentrated on whether students with different learning style preferences act differently in the course. This information can be used to create courses that include features for each learning style. Secondly, we investigated correlations between the learning style preferences and the behavior of students during the course. These correlations can be use to develop an approach for identifying learning styles in LMS based on students' behavior.

1. Introduction

Learners have different ways of learning. When the learning style of a student does not match with the teaching style in an educational environment, learners may have problems in learning [4, 6]. In web-based learning systems, more and more attention is paid on incorporating learning styles and providing courses that fit to the students' individual learning style. Some examples of such adaptive systems are CS383 [2], IDEAL [13], and INSPIRE [12].

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 [1]. On the other hand, learning management systems (LMS) such as Moodle [11] or WebCT [14] provide a lot of simple features to administer and create courses. As such, they have become very successful in e-education, but they provide very little or, in most cases, no adaptivity [8].

As a requirement for incorporating learning styles in LMS, analysis about the behavior of learners with respect to their learning styles has to be done. In this paper, we investigate the behavior of learners in an online course within Moodle. Our investigations are based on the learning style model by Felder and Silverman [4], which is described in more detail in Section 2. Based on this model, we identified several patterns of behavior (Section 3), which on the one hand seem to be relevant with respect to the learning style model and on the other hand are commonly used features in LMS. This concept makes our approach applicable for other LMS as well.

The performed study (Section 4) aims at two issues: Firstly, we investigate whether learners with different learning style preferences act differently in the online course. The results (Section 5) show the different preferences and needs of students with different learning styles. Since LMS 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.

Secondly, we investigate the correlation between the learning style preferences and the behavior of the students in the course. From this correlation, it is not only possible to draw conclusions from learning style preferences to the behavior but also to obtain indications from the behavior of students about their learning style preferences. These results provide information which can be used to investigate the

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identification of learning styles in LMS based on the actual behavior of students during an online course.

While already some recent work exists dealing with identifying learning styles based on the behavior of students [3, 7], these approaches are developed for specific systems. When developing an approach for LMS in general, we have to consider that neither the LMS itself nor the structure of most courses is developed in consideration of learning styles. While the above cited works identified relevant patterns of behavior from literature, in this paper we describe a data driven approach to identify relevant patterns with respect to the learning styles.

2. Felder-Silverman learning style model

While several learning style theories exist in the literature, e.g. the learning style models by Kolb [10] and Honey and Mumford [9], Felder-Silverman learning style model (FSLSM) [4] seems to be most appropriate for the use in computer-based educational systems [2]. Most other learning style models classify learners in few groups, whereas FSLSM describe the learning style of a learner in more detail, distinguishing between preferences on four dimensions.

The first dimension distinguishes between an active and a reflective way of processing information. Active learners learn best by working actively with the learning material, e.g. working in groups, discussing the material, or applying it. In contrast, reflective learners prefer to think about and reflect on the material.

The second dimension covers sensing versus intuitive learning. Learners with preference for a sensing learning style like to learn facts and concrete learning material. They tend to be more patient with details and more careful about their work. Furthermore, sensing learners tend to be more practical than intuitive learners and like to relate the learned material to the real world. Intuitive learners prefer to learn abstract learning material, such as theories and their underlying meanings. They like to discover possibilities and relationships, and tend to be more innovative than sensing learners. 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 differentiates learners who remember best what they have seen, e.g. pictures, diagrams and flow-charts, and learners who get more out of textual representation, regardless of the fact whether they are written or spoken.

In the fourth dimension, the learners are characterized according to their understanding. Sequential learners learn in small incremental steps and therefore have a linear learning progress. They tend to follow logical stepwise paths in finding solutions. In contrast, global learners use a holistic thinking process and learn in large leaps. They tend to absorb learning material almost randomly without seeing connections but after learning enough material they suddenly get the whole picture. Then they are able to solve complex problems and put things together in novel ways but find it difficult to explain how they did it. Since the whole picture is important for global learners, they tend to be more interested in overviews and a broad knowledge whereas sequential learners are more interested in details.

3. Investigated patterns of behavior

FSLSM is based on traditional learning rather than online learning. To apply FSLSM in online environments, some sort of mapping between the behavior in traditional environments and in online environments is necessary. Therefore, we chose patterns in online environments that are related to the traditional behavior and tested them to be significant with respect to learning styles.

Regarding LMS, different LMS provide different features to include in courses. To make our approach applicable for LMS in general, the patterns focus on commonly used features which on the one hand may support different learning styles and on the other hand are available in most LMS.

The incorporated features include content objects presenting the content of the course. Regarding content objects, we considered the number of visits as well as the time learners spent on content objects. Additionally, we tracked the time learners spent on content objects including graphics.

We also included patterns regarding outlines of chapters since they are explicitly mentioned in FSLSM. Therefore, we again looked at the number of visits of outlines and the time learners spent on it.

Another feature is examples which illustrate the theoretical content in a more concrete way. Again, the number of visits and the time learners spent on these objects are used as patterns.

Furthermore, self-assessment tests are included, where students can check their acquired knowledge. Regarding these tests, we considered more detailed information such as the number of questions a learner answered, whether a learner performed all available test at least once, the results a learner achieved, how often a learner revised his/her answers before submitting, how long a learner spent on the tests, and how long a learner checked his/her results. Furthermore, the questions contained in a test can be about facts or concepts, refer to an overview or to details, deal with interpreting or developing solutions, or can be based on graphics rather than on text. The results learners achieved on each kind of questions act as pattern as well.

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. The number of visits and the time student spent on exercises is considered as pattern. Information about the number of revisions as well as students' performance on interpreting and developing solutions is gathered and combined with the data from self-assessment tests.

For communication issues, discussion forum is considered. As patterns, we incorporated the number of visits to the forum, how long learners stayed at the forum, and how many messages they posted.

Additionally, we incorporate the navigation between learning objects as well as the number of logins in the course. We considered how often learning objects were skipped in the course sequence, how often learners jump back to the previous learning object, as well as how often and how long they stayed at the course overview page.

4. Design of the study

In this section, information about the design of the study is provided. Therefore, the course itself and its structure as well as the questionnaire for identifying learning styles according to FSLSM are described.

4. 1 Description of the course

The study is based on the data from a laboratory course about Web Engineering which was taught at Vienna University of Technology, 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 the previous section such as content object, examples, exercises and so on, were included in Moodle [11]. Therefore, our investigations deal with the XML part of the course only.

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

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.

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4.2 Instrument for identifying learning styles

In order to investigate the behavior of students during the course with respect to their learning styles, these learning styles needed to be identified. Therefore, we used the Index of Learning Styles (ILS), a 44-item questionnaire developed by Felder and Soloman [5]. The ILS identifies learning styles according to FSLSM and is online available.

As mentioned earlier, each learner has a personal preference for each of the four dimensions of FSLSM. These preferences are expressed with values between +11 to -11 per dimension. 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. The higher the value, the stronger is the preference.

The ILS is an often used and well investigated instrument to identify the learning style. An overview of studies dealing with analysing the response data of ILS as well as with verifying the reliability and validity of the instrument is provided by Felder and Spurlin [6].

5. Results

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

43 students participated in our study. Since all students have either a visual or a balanced learning style, no student indicated a verbal style, further investigations are focused only on the active-reflective, sensing-intuitive, and sequential-global dimension.

5.1 Behavior vs. learning style preferences

In order to identify significant differences of behavior in the online course from different answers to questions of the ILS, we divided the students for each question, according to their answer (+1 or -1), into two groups. Then we tested these two groups respectively for significant difference for each pattern of behavior described in Section 3.

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

The results are presented in Table 1. Only significant values ($p < 0.05$) are shown. The first values in parentheses indicated the value of t-test or u-test, p shows the significance level and d describes the direction of the relationship (1 indicates that a high value concerning the pattern refers to the group answered with 1 and vice versa). Also results of correlations (lines with rpb values) are included in table 1 and will be discussed in Section 5.2.

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

According to the results of the active-reflective dimension, it can be seen that 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. Furthermore, it can be seen that they perform better at questions about interpreting predefined solutions (in terms of source code) and that they spend more time on looking at the results of their self-assessment tests. In addition, results also show that an increased number of visits of forum act as a hint for reflective learning. 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 is used for active discussions between students, maybe active learners would visit the forum more often. Regarding active learning, it can be seen that learners with active preference perform significantly more self-assessment questions than reflective learners. This is in agreement with FSLSM as well, since active learners are characterized to prefer trying things out. It seems also to be significant that active learners perform better on questions dealing with facts. Further investigations about this finding need to be done since FSLSM does not include this behavior in their description of an active/reflective learning style. When looking at the pattern indicating how long students spent on the overview page, it can be seen that for one question, students answering with active preference spent more time on it and for another question students with reflective preference did. Hence, it seems that a certain preference for active or reflective learning style does not provide significant information about this pattern.

Sensing learners are described by Felder and Silverman as learners who prefer concrete material. This can be also seen by our findings, showing that sensing learners visit more often examples and spend more time there than intuitive learners. 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 tests or exercises, it can be seen that sensing learners significantly more often change their answers. It can also be seen that sensing learners spend more time in forum and post more often than intuitive learners. So, it can be argued that due to their preference for details, they want to clarify the specifications by asking in forums and are also interested in the questions and answers of others. Again, when the forum is used more for discussion, these results may change. As can be seen from the results, sensing learners also tend to visit learning material and outlines more often and also navigate back more often to the previous page. This behavior may also result from their patience and accuracy. For intuitive learners, only two significant patterns could be found. 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 achieve worse than intuitive learners on questions about overview. However, further investigations are necessary for both relations with regard to FSLSM.

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 sequential learners tend to cover all/more topics of self-assessment tests and that they deal more often with outlines which indicated that they start at the beginning of each chapter rather than jumping in and starting somewhere in between. This can also be seen when looking at the results of skipping learning objects showing that learners with a global learning style preference skip learning objects more often. From our results, it can also be seen that learners with global preference are more often visiting 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 [6], it has been proven that the sequential-global dimension correlates slightly with the sensing-intuitive dimension. This may be caused due to the overlapping of the preference for details. Accordingly, our results show that sequential learners more often post in forum, look more details of

Table1. Results of analyses for significant relation between patterns and ILS questions

active/reflective	sensing/intuitive	sequential/global
content_stay_graphics	**content_visit**	**outline_visit**
q21 (rpb=0.34, p=0.04, d=1)	q26 (t=2.69, p=0.01, d=1)	q12 (t=2.99, p=0.00, d=1)
outline_visit	q26 (rpb=0.39, p=0.01, d=1)	q12 (rpb=0.42, p=0.00, d=1)
q29 (t=-2.24, p=0.03, d=-1)	**outline_visit**	**outline_stay**
q29 (rpb=-0.33, p=0.03, d=-1)	q22 (t=2.04, p=0.05, d=1)	q44 (u=114.50, p=0.00, d=1)
outline_stay	q22 (rpb=0.30, p=0.05, d=1)	q44 (rpb=0.34, p=0.02, d=1)
q29 (u=65.50, p=0.00, d=-1)	**outline_stay**	**selfass_stay**
q29 (rpb=-0.43, p=0.00, d=-1)	q34 (u=123.00, p=0.04, d=-1)	q12 (rpb=-0.41, p=0.04, d=-1)
q21 (rpb=-0.34, p=0.03, d=-1)	**example_visit**	q16 (rpb=-0.40, p=0.04, d=-1)
example_visit	q2 (u=104.00, p=0.04, d=1)	q20 (rpb=-0.39, p=0.05, d=-1)
q33 (rpb=-0.31, p=0.04, d=-1)	**example_stay**	**selfass_visit_different**
example_stay	q10 (u=111.50, p=0.04, d=1)	q36 (u=101.00, p=0.03, d=1)
q33 (u=143.50, p=0.04, d=-1)	q10 (rpb=0.35, p=0.02, d=1)	q36 (rpb=0.34, p=0.02, d=1)
selfass_visit_different	q42 (rpb=-0.43, p=0.00, d=-1)	**selfass_stay_results**
q5 (rpb=0.35, p=0.02, d=1)	**ques_detail**	q20 (u=33.00, p=0.02, d=1)
selfass_stay_results	q10 (rpb=0.43, p=0.05, d=1)	q28 (rpb=0.52, p=0.01, d=1)
q1 (rpb=-0.49, p=0.02, d=-1)	**ques_overview**	**ques_concepts**
ques_visit	q42 (t=-2.61, p=0.02, d=-1)	q44 (t=-2.11, p=0.05, d=-1)
q5 (u=154.00, p=0.05, d=1)	q42 (rpb=-0.52, p=0.02, d=-1)	q44 (rpb=-0.45, p=0.05, d=-1)
q5 (rpb=0.43, p=0.00, d=1)	**ques_develop**	**ques_graphics**
ques_facts	q34 (rpb=0.66, p=0.03, d=1)	q32 (t=2.86, p=0.01, d=1)
q5 (t=3.21, p=0.00, d=1)	**ques_revisions**	q32 (rpb=0.56, p=0.01, d=1)
q5 (rpb=0.59, p=0.00, d=1)	q10 (t=2.47, p=0.02, d=1)	**ques_develop**
ques_interpret	q10 (rpb=0.46, p=0.02, d=1)	q20 (rpb=-0.78, p=0.00, d=-1)
q9 (t=-3.32, p=0.00, d=-1)	**exercise_visit**	**ques_revisions**
q9 (rpb=-0.64, p=0.00, d=-1)	q10 (rpb=0.38, p=0.01, d=1)	q28 (t=3.04, p=0.01, d=1)
ques_develop	**exercise_stay**	**exercise_stay**
q5 (rpb=-0.64, p=0.04, d=-1)	q10 (rpb=0.39, p=0.01, d=1)	q40 (rpb=0.33, p=0.03, d=1)
forum_visit	**forum_stay**	**forum_post**
q25 (t=-2.92, p=0.01, d=-1)	q10 (t=2.79, p=0.01, d=1)	q20 (u=149.00, p=0.01, d=1)
q25 (rpb=-0.41, p=0.01, d=-1)	q10 (rpb=0.40, p=0.01, d=1)	q20 (rpb=0.35, p=0.02, d=1)
navigation_overview_stay	q22 (t=2.63, p=0.01, d=1)	q32 (rpb=-0.33, p=0.03, d=-1)
q13 (t=2.17, p=0.04, d=1)	q22 (rpb=0.38, p=0.01, d=1)	**navigation_skip**
q13 (rpb=0.32, p=0.04, d=1)	**forum_post**	q20 (u=176.00, p=0.04, d=-1)
q25 (t=-3.02, p=0.00, d=-1)	q22 (u=117.00, p=0.00, d=1)	q40 (rpb=0.33, p=0.03, d=1)
q25 (rpb=-0.43, p=0.00, d=-1)	q22 (rpb=0.48, p=0.00, d=1)	**navigation_overview_visit**
	navigation_back	q44 (t=-2.71, p=0.01, d=-1)
	q22 (u=161.50, p=0.05, d=1)	q44 (rpb=-0.39, p=0.01, d=-1)

the results of their tests, and make more revisions when answering questions. In contrast, global learners performed significantly better on questions about concepts than sequential learners. Sequential learners seem to also perform better on questions about graphics. This might be because they remember better the details of the graphics. However, further investigations on this issue needs to be done.

5.2 Correlations between behavior and learning style preferences

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

Since the values of the patterns are on a continuous scale and the possible answers to the questions of ILS can only be either +1 or -1, point-biserial correlation was performed using SPSS. Table 1 includes also the results of the point-biserial correlation (rpb values indicates the correlation coefficient).

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

Regarding the active-reflective dimension, additionally a relation can be seen between active learners and their interest in graphics as well as their preference for performing most or all self-assessment tests. While latter is in agreement with FSLSM, 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 more details in graphics. Nevertheless, further investigations seem to be necessary since this behavior is not explicitly described according to FSLSM. 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 be correlated with a reflective preference according to the results of the correlation.

While for learners with sensing preference the numbers of visits of examples seems to be not significant according to the calculated correlation, exercises plays an important role. The number as well as the time spent on exercises correlates significantly with a sensing learning preference. These findings regarding exercises are in agreement with FSLSM. Regarding the time spent on examples, a significant correlation is found for a sensing as well as for an intuitive learning preference which again necessitate further investigations. An additional relation between sensing learning preference and a better performance in questions about details and code development was found. Both are in agreement with FSLSM. The impact of navigating to previous learning objects could not be confirmed by the results of the correlation.

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 when developing source code. This is in line with FLSMS 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, instead for developing source code where more overview knowledge about the concepts is necessary. Another correlation was found between the time students spent on exercises and a sequential preference. This relation needs further investigations with respect to 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. Therefore, further investigations are necessary for both of these cases. Furthermore, the relation for revising answers in tests or exercises could not be confirmed.

6. Conclusion and future work

In this paper, the behavior of students in an online course is analyzed based on their learning styles and predefined patterns of behavior. Several patterns were found where students with different learning style preferences showed significantly different behavior in the online course. These results seem to be important in order to provide courses that include features which fit to different learning styles. Furthermore, the patterns of behavior and the learning style preferences were analyzed with regard to correlations. Again, several significant correlations were found. These results additionally allow drawing conclusions from the behavior of students to their learning styles.

Future work will deal with the gathered information about correlations of learning styles and behavior. This information can be used to investigate an approach for identifying learning styles based on the behavior of learners in LMS.

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