Learning Styles and Behavioral Differences in Web-based Learning Settings

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Abstract

Analyzing the behavior of learners in an educational system is the first step towards an implicit method for learning style diagnosis. To this end we performed an experimental study (reported in this paper) involving 75 students, whose interaction with WELSA educational system was monitored and analyzed. The investigation emphasized statistically significant relations between learning preferences and 30 of the behavioral patterns exhibited by the students. Discussions and interpretations of the obtained results are also provided in the paper.

1. Introduction

Learning style is one of the individual differences that play an important role in learning. A widely accepted definition given by Keefe [5] states that learning style represents "the composite of characteristic cognitive, affective, and psychological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment." According to the proponents of learning style models, students with different learning styles have different needs and also different behaviors during the learning process. It should be noted however that most of the learning style theories that have been proposed in the educational psychology literature are conceived for traditional face-to-face educational settings, not for computer mediated instruction. So how can these theories be mapped to technology enhanced learning settings? How is each individual's studying behavior reflected in the patterns of interaction with a web-based learning system? In this paper we try to address these questions by investigating the interaction of the students with a web-based educational system (called WELSA), trying to identify correlations between students' behavioral patterns and their learning styles.

A similar study has been reported by [4], leading to some promising results. However, that study was performed in a learning management system (Moodle [6]) and was based on the Felder-Silverman learning style model [2]. Our study is performed with our own educational hypermedia system (WELSA) and is based on a unified learning style model (ULSM).

ULSM is an integrative set of characteristics extracted from the main learning styles proposed in the literature. The model was created based on a systematic examination of the constructs that appear in the main learning style models and their intensional definitions; it integrates characteristics related to: perception modality, way of processing and organizing information as well as motivational and social aspects. A detailed description of the model as well as the rationale behind it can be found in [8]. In this paper we will use a subset of ULSM, including 12 learning preferences grouped on 6 dimensions: *Visual preference / Verbal preference; Abstract concepts and generalizations / Concrete, practical examples; Serial / Holistic; Active experimentation / Reflective observation; Careful with details / Not careful with details; Individual work / Team work*.

The study is carried out in the framework of a dedicated educational hypermedia system called WELSA (**W**eb-based **E**ducational system with **L**earning **S**tyle **A**daptation). Among many other functionalities, the platform offers a course player component which is of interest in the context of this paper; this module is enhanced with a learner tracking functionality, continuously monitoring the students' interaction with the system. It should be noted that the results obtained in our study can be generalized for any educational system in which the students may exhibit the same patterns of behavior (based on a common set of functionalities of the system).

The rest of the paper is structured as follows: the learner tracking and the behavioral patterns are introduced in section 2. The experimental study is presented in section 3, and its results are discussed and interpreted in section 4. Finally, section 5 concludes the paper, outlining future research directions.

2. Behavioral patterns

Analyzing and interpreting user log files is a valuable source of information about the characteristics of the user (interests, preferences, goals etc). In the context of e-learning, tracking the interaction of the learner with the educational system has been used as an implicit and dynamic method for identifying the knowledge level, motivation and goals of the learners. More recently, these tracking data have started to be used for identifying also the learning style of the students, as in [1, 3, 4, 12].

According to [12], student's behavior in a technology-enhanced learning environment refers to a student's observable response to a particular stimulus in a given domain. Since the communication channel between a student and a web-based learning system usually includes only a keyboard and a mouse, the information that can be obtained is limited; however, it can be enhanced by an appropriately designed interface, which allows collection of all the available information about the student (i.e. each and every keystroke and mouse move). Of course, the communication channel could be extended with such devices as an eye tracker or a video camera or even more sophisticated devices that could monitor student's physical state (brain activity, heart rate, stress level). However, for the context of this paper we will focus solely on the largely available educational systems, which only require a keyboard and a mouse. Learner observable behavior in such an educational hypermedia system includes navigational, temporal and performance indicators, such as: number of hits and time spent on different types of educational resources, navigation pattern, total learner attempts on exercises, results obtained on assessment tests etc.

The learner tracking functionality incorporated in WELSA ensures that all student actions are monitored and recorded by the system. Examples of such actions include: *login, logout, home, jumpToCourse, jumpToChapter, jumpToPage, nextButton, prevButton, outline, accessLO*, each with its associated time stamp. Furthermore, for each visited learning object (LO) we have access to all the information regarding its instructional role, media type, relations to other LOs etc, by consulting the associated educational metadata [9]. The main behavioral indicators refer to the relative frequency of these learner actions, the amount of time spent on a specific action type and the order of performing these actions, all of which can be obtained from the system log, either directly or after some preprocessing.

More specifically, based on the available data in a usual web-based learning environment and the indications from the literature regarding relevant behavioral indicators, we decided to use the following set of patterns (where the prefix "n" stands for "number", "t" stands for "time" and "h" stands for "hits"):

- *t_total* - total time spent on the course
- *action_total* - total number of actions performed while logged in
- *t_instructionalType* and *t_mediaType* - the time spent on each type of LO, where *instructionalType* = *'Definition', 'Example', 'Exercise'* etc and *mediaType* = *'Text', 'Sound', 'Image', 'Video'* etc. In this respect, *t_abstract* and *t_concrete* are also computed, as the time spent on LOs with a rather abstract versus concrete content.
- *h_instructionalType, h_mediaType* – the number of hits (visits) on each category of LOs
- *n_LO, n_distinctLO, n_skippedLO_temp, n_skippedLO_perm* - total number of hits on LOs, total number of distinct LOs accessed, number of LOs skipped temporarily or on a permanent basis respectively
- the order of accessing the LOs is also relevant, being captured in the form of instructional role sequences: *sequence_fundamental_before_illustration, sequence_illustration_before_fundamental, sequence_abstract_first, sequence_concrete_first, sequence_interactivity_before_fundamental, sequence_interactivity_before_illustration, sequence_fundamental_before_interactivity, sequence_illustration_before_interactivity*
- *n_navigationAction* - number of navigation actions of a specific type (e.g. *n_jump, n_jumpCourse, n_nextButton, n_prevButton, n_Outline*)
- *t_chat, n_msg_chat, n_chat_login* – total time spent in chat, number of messages in chat and number of logins into the chat respectively; *t_forum*, *n_forum_login, n_forum_msg, n_forum_reads* – total time spent in forum, number of logins into the forum, number of messages posted in the forum and number of messages read in the forum respectively
- *grade_tests* – grades obtained on evaluation tests.

We are also interested in the performance of students in some particular types of assessment tests, which are reflected in the following indicators: *grade_mediaType, grade_abstract, grade_concrete, grade_details, grade_overview, grade_connections, grade_directApplication, grade_generalizations, grade_synthesis, grade_analysis.* The total time spent on taking a test (*t_test*), the number of revisions performed on each test (*n_revisions_test)*, the number of test retakes *(n_testRetakes)*, the number of mistakes made when taking a test *(n_mistakes_tests)*, as well as the number of hints used in solving a test *(n_hints)* can also offer indications of the student's learning style.

• *n_individualAssignment, n_groupAssignment* - choice of individual assignments versus collaborative assignments.

We can also compute *relative values* for the above patterns, such as the percentage of time spent on each category of LOs (e.g. *t_instructionalType / t_total_LO * 100*), the relative frequencies of LO visits (e.g. *h_mediaType / n_LO*), the number of *Next* button clicks over the total number of navigation actions, the grade obtained on test items requiring synthesis competencies versus the average grade obtained in the course etc. In what follows we will use these relative values rather than the absolute ones since they are more meaningful (e.g. knowing the amount of time a student spent on images is only relevant in the context of her/his total study time). Please note that for reasons of simplicity we will use the above pattern names to denote also the relative values.

3. Experimental study

3.1. Settings

In order to experimentally investigate the behavior of students with different learning styles in an educational hypermedia system, we performed a study involving 75 undergraduate students in the field of Computer Science. As test platform we used WELSA educational system and a course module in the area of Artificial Intelligence. The course module deals with search strategies and solving problems by search and is based on the fourth chapter of Poole, Mackworth and Goebel's AI textbook [7]. The course consists of 4 sections and 9 subsections, including a total of 46 learning objects. The course also includes access to two communication tools, one synchronous (*chat*) and one asynchronous (*forum*) and offers two navigation choices – either by means of the *Next* and *Previous* buttons, or by means of the *Outline*. This course was conceived so as to provide a beneficial educational experience for the students but at the same time to help gather useful information from the learners' studying behavior, as we have shown in [9].

The experiment lasted for 4 hours: 2 hours were reserved for course studying and 2 hours for discussions and filling-in some questionnaires. For the first part of the experiment, the students accessed WELSA and all of their interactions with the system were recorded. Afterwards, the students were asked to self-assess their ULSM learning preferences, using a dedicated questionnaire.

3.2. Results

The next step in our study was to analyze the recorded data of the students. After a preliminary analysis of the system logs we discarded data from 4 students, who did not actually follow the course (2 of them were logged out from the system because of prolonged inactivity and did not log in again and 2 of them spent all the time on chat). As described in the previous section, WELSA records 18 distinct types of student actions (such as *login, logout, home, jump, nextButton, prevButton, outline, accessLO* etc), each with its associated time stamp. For our experiment, a total of 9467 student actions were recorded by the system, with a minimum of 76 and a maximum of 212 actions per student. Of course, these raw data need to be pre-processed in order to yield some useful information. The first step is to compute the duration of each action, eliminating the erroneous values (for example, an LO access time of less than 3 seconds was considered as random or a step on the way to another LO and therefore not taken into account). Relative durations and frequencies of actions were then computed starting from these values. The whole process is automatically performed by the WELSA Analysis tool; the output of the tool is the set of relevant patterns, as identified in the previous section.

Next we applied statistical analysis tests to identify significant differences in the patterns of behavior exhibited by students with different ULSM preferences. To this end, we divided the students in two groups, with regard to each of the opposite ULSM preferences and we applied two-tailed t-test or two-tailed u-test on the two groups, depending on the distribution normality (which was checked with the Kolmogorov-Smirnov test). The tests were applied using SPSS software package [11]. The results are presented in Table 1, including only the values for which we obtained statistical significance ($p<0.05$). t, u and p values are included, as well as the group for which higher values of the patterns were recorded (H).

4. Discussions and interpretation of results

According to the results obtained for the Visual / Verbal dimension, a higher amount of time spent on image and video resources, as well as a higher number of accesses to those resources is significant for a Visual preference. Similarly, a high volume of time spent on text resources is significant for a Verbal preference. These findings are in agreement with the intensional definition of the Visual / Verbal dimension. Furthermore, Visual students were found to spend more time on examples than Verbal students. This could be explained by the fact that a large part of the examples included in the course were in graphical format (either images or videos).

Table 1. Behavioral patterns for which statistically significant differences were found between the two student groups

Visual / Verbal
t_Image (u = 193.00, p = 0.014, Visual → H)
t_Image + t_Video (u=174.00, p=0.006, Visual → H)
h_Image (u=206.00, p=0.023, Visual → H)
h_Image + h_Video (u=220.00, p=0.040, Visual→ H)
t_Text (u = 198.00, p = 0.017, Verbal → H)
t_Example (u = 213.00, p = 0.031, Visual → H)
Abstract / Concrete
t_Fundamental (u=123.00, p=0.019, Abstract → H)
t_Definition (u=130.00, p=0.027, Abstract → H)
t_Example (u=70.00, p=0.001, Concrete → H)
h_Definition (u=139.00, p=0.040, Abstract → H)
h_Example (u=124.00, p=0.020, Concrete → H)
t_Image (u=94.00, p=0.004, Concrete → H)
grade_abstract (u=142.00, p=0.045, Abstract → H)
grade_concrete (u=143.00, p=0.047, Concrete → H)
Serial / Holistic
n_nextButton (t=2.87, p=0.005, Serial → H)
n_outline (t=-4.02, p=0.000, Holistic → H)
n_jump (t=-3.04, p=0.003, Holistic → H)
t_AdditionalInfo (t=-2.46, p=0.016, Holistic → H)
n_returns_LO (t=-3.08, p=0.003, Holistic → H)
t_Exercise (t=2.31, p=0.024, Serial → H)
Active experimentation / Reflective observation
t_time (u=173.00, p=0.013, Reflective → H)
t_Interactivity (t=2.24, p=0.028, Active → H)
h_Interactivity (u=199.00, p=0.037, Active → H)
Careful with details / Not careful with details
t_Details (t=2.21, p=0.030, Careful → H)
h_Details (u=262.00, p=0.048, Careful → H)
t_Fundamental (t=2.93, p=0,005, Careful → H)
n_outline (t=-2.61, p=0.019, Not careful → H)
grade_details (u=181.00, p=0.002, Careful → H)
Individual work / Team work
n_chat_msg (t=-2.18, p=0.034, Team → H)
t_chat (t=-2.08, p=0.043, Team → H)

Regarding the Abstract / Concrete dimension, results show that learners with an Abstract preference accessed more frequently and spent significantly more time on definitions and fundamental resources, while learners with a Concrete preference favored examples. Another behavior that was found to be significant for the Concrete preference is the high amount of time spent on images. Again this can be explained by the fact that most of the images included in the course were used for illustrating and exemplifying fundamental concepts. Moreover, Concrete students performed significantly better on evaluation items dealing with practical aspects, while Abstract students obtained higher grades on theoretical items.

As far as the Serial / Holistic dimension is concerned, several navigation actions were found to be significant: the use of the Next button was higher in case of Serial students, while Holistic learners preferred to jump through the pages by means of the outline. Holistic learners also tended to return more often to already visited resources, as well as spend more time on additional information. Serial students on the other hand spent more time on exercises. This can be explained by the fact that exercises were placed at the end of each section, which was convenient for serial learners but less convenient for the holistic learners, who didn't have an overall idea of the course yet.

The behavioral patterns that were found to be significant for the Active experimentation / Reflective observation dimension are the amount of time and the number of accesses to interactive resources (higher in case of students with an Active experimentation preference). The overall amount of study time was also significantly higher in case of learners with Reflective observation preference; this can be explained by the more patient nature of these students, as compared with the impulsive, "jump right in" nature of the Active students.

Students who declared to be more careful with details indeed spent significantly more time on remarks, demonstrations, additional information as well as fundamental resources as compared to the less careful ones. Additionally, they obtained better grades on items requiring a high level of detail. Students who are less careful with details visited the outline more often – this could be explained by their tendency to skip some parts of the course, which purportedly included too many details.

Finally, students who prefer to work in teams spent a longer time in chat, posting also more messages than their more individually-oriented peers.

A few more comments are in order. First, no significant results were found regarding the order of accessing the results. When later questioned about this behavior, the vast majority of the students (88.73%) explained that they chose to access resources in the given order, since they considered they should follow the order suggested by the teacher. The justifications of the chosen order are pretty similar: "because I thought the course was intentionally ordered in this way", "because it seemed normal to follow the order proposed by the person who made the course", "out of convenience", "I didn’t like the fact the course started with definitions and theory – I would have understood better if there were some examples first. But since this was the order proposed by the teacher, I thought I should follow it." The fact that students unthinkingly chose to follow the proposed order because "teachers know better", despite their own preferences, confirms the importance of an appropriate ordering of resources. Even if students have the possibility to choose their preferred order, the less experienced ones will rely on the choice already made for them by the course author. These statements come to confirm the importance of the individualized ordering of resources, something that can be so easily achieved by means of adaptive hypermedia, but is so easily overlooked.

Secondly, it should also be noted that, due to the constraints of the experiment (i.e. only one 2 hours session), the learners had neither the time nor the incentive to use the provided forum. However, significant results regarding forum usage might be obtained in a different context (e.g. a longer experiment, fostering collaboration between students).

5. Conclusions

This analysis showed that students with different ULSM preferences behave differently in an educational hypermedia system, emphasizing also some relations between these preferences and students’ behavioral indicators; statistical significance ($p<0.05$) was obtained for 30 patterns.

Investigating the behavior of students in an educational system is the first step towards automating the process of learning style diagnosing. Based on these findings, we derived some rules for learner modeling and used them to actually diagnose students’ ULSM preferences. The promising modeling results reported in [10] are a further proof of the validity of our approach. Nevertheless, analyzing the traces of the students’ interactions with the system remains a delicate task, often requiring further information about the context and not simply a one-to-one correspondence between behavioral indicators and learning preferences.

As future work, we plan to repeat the experiments with learners of variable age, field of study, background knowledge and technical experience, as well as to apply more complex statistical analysis tests. Also it would be interesting to include more behavioral patterns in the investigation, which could be collected by means of an eye tracker and/or a video camera attached to our system.

6. References

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