Correlations between Students' Behaviour in Learning Management Systems and their Learning Style Preferences*

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Abstract: Many researches have been conducted with respect to learning styles in technology enhanced learning, especially in the area of adaptive learning. Most of these researches used assumptions about how students with different learning styles behave in a system based on the respective learning style theory. However, most of these theories are developed for traditional learning rather than online learning. In this study, we investigated the behaviour of students in a learning management system and correlated the students' behaviour with their learning style preferences. The resulting correlations confirm that students with different learning styles behave differently in an online course, which gives another evidence for the potential of adaptive learning based on learning styles. Furthermore, our findings can contribute in the development of adaptive systems, making adaptive features more accurate and automatic student modelling more precise by combining the results of this study with the conclusions from literature.

Keywords: Learning Styles, Behaviour in Learning Management Systems, Student Modelling

Introduction

Several learning style theories and models are proposed in literature and several open issues regarding learning styles exist [6]. However, all learning style models agree that learners have different ways in which they prefer to learn. Furthermore, several researchers and educational theorists agree that considering learning styles in education has high potential to make learning easier for learners.

In recent years, more and more researches have been conducted on incorporating learning styles in technology enhanced learning. Several adaptive systems such as AHA! [18], LSAS [1], and TANGOW [16] were developed and many studies regarding the effectiveness and impact of learning styles in technology enhanced learning were performed [e.g., 1, 3, 10]. Most of these researches were based on the learning style models' description about how students with specific learning styles typically behave in a learning environment. However, most learning style models were developed for traditional learning rather than online learning.

In this study, we investigated the students' behaviour in learning management systems (LMSs) and correlated their behaviour with their learning style preferences. LMSs consider

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a broad range of features and are commonly used in technology enhanced learning. By incorporating only behaviour which is common in technology enhanced learning, our results can be applicable and valuable for LMSs in general. More detailed information about which behaviour in a LMS is characteristic for a specific learning style preference has two main contributions to technology enhanced learning and especially to adaptive learning technologies.

First, this more detailed information can help in student modelling. Currently, learning styles are mostly detected by asking students to fill out a learning style questionnaire. However, recent studies [e.g., 5, 9, 11] are focussing on an automatic student modelling approach, which uses the behaviour of students to infer their learning styles automatically. This approach has several benefits such as being direct and free from the problems of inaccurate self-conceptions of students, being able to consider data from a time span which makes the approach more accurate, and allowing the detection of changes of learning styles. However, typically these approaches are based on behaviour which is described by the respective learning style model, developed for traditional learning. Information about the actual behaviour of students in online learning environments and its correlation to learning style preferences can therefore contribute in making these approaches more accurate.

The second contribution deals with adaptive learning. By verifying a correlation between the students' behaviour and their learning style preferences, we give another evidence for the potential of adaptivity regarding learning styles, showing that students with different learning style preferences behave differently in an online environment and therefore prefer to learn in different ways. Furthermore, the detailed information can help in the development of more accurate adaptivity, fitting the courses to how students' really behave in online learning environments.

In the next section, we introduce the Felder-Silverman learning style model (FSLSM) [7], on which this study is based, as well as characteristics within the dimensions of the FSLSM, which are considered in our study in order to get more detailed information about the students' learning style preferences. Subsequently, the study design is introduced. Section 3 discusses the results of this study and Section 4 concludes the paper.

1. Learning Style Preferences

Most learning style models classify learners in few groups. The Felder-Silverman Learning Style Model [7] was selected for this study since it describes learning styles in very much detail, distinguishing between preferences on four dimensions. By using these dimensions, FSLSM combines major learning style models such as the ones by Kolb [13], Pask [17], and Myers-Briggs [2]. Furthermore, FSLSM is one of the most often used learning style models in technology enhance learning and some researchers even argue that it is the most appropriate model for the use in adaptive educational systems [4, 14].

In the following section, the FSLSM is described in more detail. Subsequently, groups of learning style preferences within the dimensions of the FSLSM are introduced.

1.1 Felder-Silverman Learning Style Model

The FSLSM is based on the idea that each learner has a preference, ranging from +11 to -11, on each of four dimensions. In the following paragraphs, these dimensions are introduced.

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 by applying the material and trying things out. Furthermore, they tend to be more interested in

working in groups and discussing the material with others. In contrast, reflective learners prefer to think about and reflect on the material. Regarding communication, they prefer to work alone or maybe in a small group together with a good friend.

The second dimension covers *sensing* versus *intuitive* learning. Learners who prefer a sensing learning style like to learn facts and concrete learning material. They like to solve problems with standard approaches and also tend to be more careful and patient with details. Furthermore, they tend to be more practical than intuitive learners and like to relate the learned material to the real world. In contrast, intuitive learners prefer to learn abstract learning material, such as concepts and theories. They like to discover possibilities and relationships and tend to be more innovative and creative than sensing learners.

The third, *visual*/*verbal* dimension differentiates learners who remember best what they have seen, for example, pictures, diagrams and flow-charts, and learners who get more out of textual representations, regardless of whether they are written or spoken.

The fourth dimension deals with *sequential* and *global* learning. Sequential learners learn in small incremental steps and therefore have a linear learning progress. In contrast, global learners use a holistic thinking process and learn in large leaps. They tend to absorb learning material almost randomly without seeing connections but after they have learned enough material they suddenly get the whole picture. Then they are able to solve complex problems, find connections between different areas, and put things together in novel ways. Because the whole picture is important for global learners, they tend to be interested in overviews and a broad knowledge whereas sequential learners are more interested in details.

The Index of Learning Styles (ILS) questionnaire [8], consisting of 44 questions, is an instrument for identifying learning styles based on the FSLSM. The preferences for each dimension are calculated from the 11 questions per 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.

1.2 Semantic Groups within the Dimensions of the Felder-Silverman Learning Style Model

As can be seen from the description in the previous section, each learning style dimension seems to include different characteristics. In an empirical study [12], the groups of preferences within each dimension of FSLSM were analysed based on data from the ILS questionnaire and their relevance for each dimension was investigated. Table 1 shows the proposed groups and the related answers of ILS questions for each group. A question may appear twice in the table, if the two possible answers to the question point to two groups.

Table 1. Semantic groups associated with the ILS answers

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

The semantic groups within the dimensions provide relevant information in order to consider learning styles more accurately, both for student modelling and providing adaptivity. For example, if a learner has a preference for trying things out and tends to be more impersonal oriented, he/she would have a balanced learning style on the active/reflective dimension. However, a learner has also a balanced learning style if he/she

prefers to think about the material and tends to be more social oriented. Although both learners have different preferences and behaviour in an online course, both are considered equally according to the result of ILS. Considering the proposed semantic groups leads therefore to more accurate information about learners' preferences and to a more accurate model of the students' learning style preferences.

2. Design of the Study

This study is based on data from 127 students who did a course about object oriented modelling at a university in Austria. The course consisted of a lecture and a practical part, where students had to submit 5 assignments and successfully complete a final exam. The course was managed via the LMS Moodle [15]. The aim of using a LMS was to provide students with additional learning material and learning opportunities in order to facilitate learning. The students' interactions with Moodle were tracked in order to get information about their learning behaviour. Furthermore, we asked the students to fill out the ILS questionnaire to get information about their learning style preferences.

In the following subsection, the investigated patterns of behaviour are described in more detail. Subsequently, the method of data analysis is presented.

2.1 Investigated Patterns of Behaviour

The investigated course was based on commonly used features in learning systems. The considered patterns for this study were derived from these features in order to make our results applicable and valuable for LMSs and in turn for technology enhanced learning in general. In the following paragraphs, the features and patterns are described in more detail.

The incorporated features include *content objects* which present 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 used the time learners spent on content objects including graphics and content objects including only text.

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, we considered the number of different examples a learner visited.

Additionally, *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 answered the same question twice wrong, how often a learner revised his/her answers before submission, how long a learner spent on the tests, and how long a learner checked his/her results. Furthermore, the questions contained in a test could be about facts or concepts, referred to an overview or to details, dealt with interpreting or developing solutions, or could 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, the time students spent on exercises, and the performance of students is considered as pattern. Information about the number of revisions, the time they

reflect about the results as well as students' performance on interpreting and developing solutions is gathered and combined with the data from self-assessment tests.

Regarding 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. We considered how often learning objects were skipped in the course sequence, how often learners jump back to the previous learning objects, as well as how often and how long they stayed at the course overview page.

Furthermore, we considered the learners' *scores* on the final exam as well as the average scores on the compulsory assignments. In addition, we incorporated general patterns about the behaviour of learners in the system, such as the overall time they spent in the course, the number of logins, and the overall number of visited learning objects.

2.2 Method of Data Analysis

Data from students who spent less than 5 minutes on the ILS questionnaire were discarded because the detected learning styles were considered as not reliable enough. Also, we included only data from students who submitted at least 3 assignments and performed the final exam, which was both a requirement for a positive mark. Therefore, data of 75 students were finally used for analyses. For investigating the correlations between students' learning style preferences and their behaviour based on the aforementioned patterns, rank correlation analysis, applying Kendall's τ, was used since the values of the learning style preferences are expressed on an ordinal scale.

3. Results and Discussion

Table 2 shows the results of the correlation analysis of the learning style preferences regarding the semantic groups introduced in Section 1.2 and the patterns of behaviour introduced in Section 2.1. Bold values represent significant correlations, using a significance level of 0.05. In the following paragraphs, we point out and discuss the results in agreement with FSLSM (highlighted using gray background) in more detail. The respective patterns seem to be especially important for student modelling and adaptivity in technology enhanced learning since they are, on the one hand, in agreement with FSLSM and, on the other hand, confirmed by our data-driven study. Results which are significant but not in agreement with FSLSM needs further investigations.

Regarding *social* and *impersonal orientation*, we found that students, who have a high preference for social orientation tend to visit the forum less often and spent less time there. The opposite applies for impersonal orientation. Although this result seems to be in contrast with expectations at first glance, it can be explained due to the forum was mainly used for asking questions to teachers/tutors rather than having active discussion. This might lead to the behaviour that social oriented students prefer other channels of communication like face-to-face. Another correlation was found regarding the preference of spending time on content objects, indicating that learners who tend to be social oriented do not prefer to spend much time on these objects and vice versa for impersonal oriented learners.

Regarding the preference for solving problems by standard procedures and *existing ways*, the results show that a negative correlation with respect to the performance of exercises exists. On the other hand, we found that learners who are more interested in challenges and in solving problems in *new ways* performed better in exercises. Both results

Table 2. Results of correlation analysis (significant results are highlighted in bold font; if they are in agreement with FSLSM gray background is used for highlighting)

	trying something out	social oriented	think about material	impersonal oriented	existing ways	concrete material	careful with details	new ways	abstract material	not carefule with details	pictures	spoken words	written words	difficulty with visual style	detail oriented	sequential progress	from parts to the whole	overall picture	non-sequential progress	relations/connections
content_visit	-0.02	-0.14	0.04	0.14	0.07	-0.02	0.1	-0.04	0.03	-0.15	-0.02	-0.03	0	0.07	-0.03	0.08	-0.11	0.09	-0.05	-0.07
content_stay	0	**-0.18**	0.03	**0.17**	0.11	-0.06	0.12	-0.08	0.08	-0.13	-0.02	-0.03	0.03	0.06	-0.01	0.08	-0.09	0.06	-0.04	-0.09
content_stay_text	0.02	-0.08	-0.03	0.09	0.15	-0.03	0.1	-0.14	0.08	-0.06	-0.01	0	0.06	-0.03	0.02	0.06	0.07	-0.06	0	-0.08
content_stay_graphics	0.08	0.01	-0.09	0	0.04	-0.03	0.13	-0.01	-0.09	-0.02	0.06	-0.06	0.06	-0.22	0.07	-0.01	-0.12	0.05	0.06	-0.06
outline_visit	-0.12	-0.03	0.05	0.08	0.11	-0.01	0.09	-0.08	0.01	-0.08	0.04	-0.04	-0.03	-0.15	0	0.01	-0.05	0.04	-0.03	0.02
outline_stay	-0.09	-0.03	0.02	0.08	0.11	-0.04	0.04	-0.07	0.04	0	0.03	-0.02	-0.03	**-0.19**	0.05	0.04	0.01	-0.02	-0.05	-0.02
example_visit	-0.02	-0.1	0	0.15	0.05	0.1	0.01	-0.08	-0.04	-0.05	0.07	0.09	**-0.2**	-0.08	0.01	0.05	-0.01	0	-0.08	0.01
example_visit_diff	-0.05	-0.1	0.04	0.13	0.08	0.14	0.05	-0.11	-0.07	-0.08	0.11	0.06	**-0.21**	-0.05	-0.03	0.06	-0.09	0.07	-0.08	-0.02
example_stay	0	-0.1	-0.01	0.13	0.07	0.13	-0.03	-0.11	-0.04	0.02	0.09	0.08	**-0.23**	-0.01	0.01	0.05	0.03	-0.02	-0.14	0.04
selfass_visit	0.01	-0.06	0.07	-0.01	0.17	0.14	**0.31**	**-0.19**	-0.1	**-0.27**	0.04	-0.03	0.03	-0.13	0.12	**0.22**	-0.04	-0.04	**-0.27**	-0.11
selfass_visit_different	0.05	-0.08	0.02	0.03	0.12	0.07	**0.24**	-0.16	-0.03	-0.19	0.05	-0.07	0	-0.07	0.13	**0.19**	0.03	-0.1	**-0.23**	-0.11
selfass_stay	0.04	0.07	-0.09	-0.02	-0.03	-0.12	-0.12	0.01	0.14	0.19	0.1	-0.17	-0.1	0.18	0.09	0.02	0.12	-0.12	-0.02	-0.04
selfass_performance	-0.05	-0.11	0.1	0.07	-0.04	-0.06	**0.27**	0.02	0.06	**-0.27**	-0.05	0.12	0	-0.07	0.15	0.14	-0.11	-0.02	**-0.23**	-0.03
selfass_twice_wrong	-0.01	0.16	-0.1	-0.08	-0.02	-0.19	-0.05	0.06	0.12	0.08	0.01	-0.12	0.06	-0.01	-0.12	-0.03	0	0.07	0.03	0.04
quiz_revisions	0.15	-0.07	-0.11	0.08	-0.08	-0.11	0.02	0.04	0.16	-0.04	-0.04	0	0.07	0.02	-0.09	0.05	**-0.22**	0.17	0.01	-0.11
quiz_stay_results	-0.05	-0.03	0.03	0.04	0.03	-0.14	-0.04	-0.02	0.16	0.04	-0.12	0.04	0.07	0.17	0.05	0.13	0	-0.04	-0.04	-0.14
ques_detail	-0.04	-0.06	0.12	0.01	0	-0.04	**0.3**	-0.01	0.04	**-0.28**	0.03	0.04	-0.06	-0.06	0.17	0.1	-0.14	-0.01	-0.19	0
ques_overview	-0.05	-0.16	0.1	0.12	-0.14	-0.16	0.17	0.13	0.14	-0.18	-0.15	**0.22**	0.07	-0.06	0.08	0.18	-0.15	0.04	**-0.26**	-0.04
ques_factual	-0.05	-0.13	0.11	0.08	0.03	-0.02	**0.24**	-0.05	0.04	-0.18	-0.03	0.12	-0.01	-0.05	0.16	0.15	-0.13	-0.01	**-0.23**	-0.04
ques_conceptual	-0.05	-0.12	0.11	0.07	-0.07	-0.09	**0.26**	0.05	0.07	**-0.28**	-0.04	0.11	0	-0.09	0.13	0.13	-0.12	0	**-0.21**	-0.03
ques_graphics	-0.03	-0.02	0.15	-0.06	0.08	0.08	**0.29**	-0.2	0.08	-0.21	0.12	-0.06	-0.1	-0.04	0.08	**0.33**	-0.07	0.01	**-0.36**	-0.23
ques_text	-0.04	-0.12	0.1	0.07	-0.04	-0.06	**0.27**	0.02	0.06	**-0.27**	-0.05	0.13	0	-0.07	0.16	0.15	-0.12	-0.02	**-0.23**	-0.04
ques_codeint	0.17	-0.17	-0.09	0.14	0.06	0.01	**0.27**	-0.15	0.07	**-0.26**	0.04	0.03	-0.07	-0.1	0.17	0.14	-0.16	-0.01	-0.08	-0.14
ques_codedev	0.13	**-0.3**	-0.07	0.24	-0.13	-0.26	0	0.09	**0.27**	0.12	0.21	-0.16	-0.18	-0.02	0.02	-0.09	-0.1	0.06	0.01	0.13
exercise_visit	0.07	-0.11	-0.01	0.08	0.11	0.15	**0.27**	-0.15	-0.13	**-0.28**	0.1	-0.05	-0.09	**-0.21**	0.12	0.14	-0.05	-0.03	-0.19	-0.05
exercise_stay	0.03	-0.1	-0.01	0.1	0.04	0.07	**0.21**	-0.07	-0.06	**-0.24**	0.06	0.01	-0.05	**-0.22**	0.08	0.12	-0.03	-0.03	-0.15	-0.06
exercise_performance	0.16	-0.22	-0.19	**0.3**	**-0.33**	**-0.4**	-0.12	**0.26**	**0.39**	0.08	0.15	-0.1	-0.18	0.07	-0.03	-0.11	0.08	-0.01	0.02	0.12
forum_visit	0.01	**-0.18**	0.02	**0.18**	0.05	0.14	**0.18**	-0.08	-0.09	-0.16	-0.01	0.07	-0.06	0.05	-0.1	**0.21**	0.08	0	**-0.19**	-0.17
forum_stay	-0.02	**-0.2**	0.03	**0.2**	0.02	0.03	0.12	-0.06	0.04	-0.12	-0.02	0.08	-0.08	0.15	-0.08	**0.2**	0.08	0	**-0.19**	-0.14
forum_post	0.1	-0.02	-0.07	0	0.03	0.08	0.12	-0.04	-0.13	-0.11	-0.04	0.06	-0.05	**0.23**	0.07	0.17	0.14	-0.11	**-0.28**	-0.06
navigation_skip	0.07	**-0.27**	-0.05	**0.27**	0.13	-0.04	0.06	-0.08	0.06	-0.08	-0.12	0.11	0.07	0.07	0.02	0.13	-0.17	0.08	**-0.21**	-0.04
navigation_back	-0.09	-0.1	0.04	0.14	0.01	-0.04	0.03	0.04	0.06	-0.19	-0.08	0.1	0.02	0	**-0.21**	0.09	-0.09	**0.17**	-0.11	-0.06
navigation_overview_visit	-0.13	-0.04	0.05	0.08	0.01	-0.09	-0.16	0.09	0.03	0.13	-0.07	0.03	0.02	0.08	**-0.23**	-0.09	0.06	0.1	0.01	0.11
navigation_overview_stay	-0.06	-0.12	0.07	0.13	0.12	0.05	**0.2**	-0.14	0	-0.16	0.05	-0.03	-0.05	-0.08	-0.02	**0.24**	0.05	-0.03	**-0.3**	-0.11
score_exam	0.04	-0.11	0	0.09	-0.03	-0.03	0.14	0.02	0.03	**-0.2**	-0.06	0.13	-0.05	-0.04	0.03	0.16	-0.15	0.06	-0.1	-0.15
score_assignment_avg	0.02	-0.12	-0.03	0.16	-0.06	-0.12	-0.07	0.08	0.14	0	-0.06	0.09	0.02	0.06	-0.09	0.01	**-0.18**	0.15	0.08	-0.09
course_time	0.03	-0.13	0.01	0.13	0.12	0.1	**0.26**	**-0.16**	-0.05	**-0.24**	0.04	-0.03	-0.02	-0.1	0.1	**0.27**	0.02	-0.06	**-0.29**	-0.15
course_login	0.04	-0.11	-0.01	0.1	0.07	0.13	**0.19**	-0.13	-0.06	-0.15	0.04	0.02	-0.09	-0.02	0.06	**0.19**	0.17	-0.14	**-0.26**	-0.08
course_visitedLO	0.02	-0.16	0.04	0.13	0.13	0.13	**0.29**	-0.16	-0.1	**-0.27**	0.01	0.04	-0.02	-0.13	0.05	**0.26**	-0.02	-0.01	**-0.27**	-0.15

confirm our expectations since exercises aimed at challenging the learners and asked them for coming up with new ways of solving problems. In addition, learners with a preference for solving problems in new ways used the self-assessment test less often and spent overall less time in the course. This behaviour might be explained due to the dislike of repeating things and that self-assessment tests ask students to check their already acquired knowledge.

Learners who prefer *concrete material* were also found to perform poorer in exercises while learners with a preference for *abstract material* yield better results. This is due to the requirement of understanding the abstract content in order to be able to solve exercises correctly. Learners who preferred abstract material were especially good in questions about developing new solutions, which is in line with our expectations, since the knowledge about abstract material like concepts and theories is a requirement for developing new solutions.

According to our results, learners who tend to be *careful with details* prefer to visit the forum more often, are good in answering self-assessment questions, especially the ones about details, facts, concepts, graphics, text, and interpreting predefined solutions. Furthermore, those learners tend to perform self-assessment tests more often and perform more different tests. In addition, a correlation regarding visiting and staying at exercises was found, indicating that learners who are more careful with details prefer to use exercises more often and longer for learning. Furthermore, they stay longer at the course overview page, spent more time in the course, visit more learning objects, and login more often. For the preference of being *not careful with details*, many characteristic patterns deal with self-assessment tests. These learners tend to visit less of those tests and have poor

performance on them, especially in questions about details, concepts, text, and interpreting existing solutions. Furthermore, they tend to visit exercises less times and spent less time on them. We also found that they spent less time in the course and visited less learning objects. Furthermore, a correlation was found for the performance on the final exam, indicating that learners who tend to be less careful with details tend to have lower scores. All these results are plausible and in line with FSLSM and our expectations.

For the preference of *written words*, results showed that learners dislike examples. In a course about object oriented modelling, this might be especially true since most examples are models, which consist mostly of graphics. A negative correlation for the number of visits, the number of visiting different examples, and the time spent on examples was found.

Furthermore, the results show that learners with *difficulties with the visual style* (and therefore a more verbal preference) prefer to post in the forum more often. This is in line with our expectations, since posting in a forum does not require any visual preferences.

With respect to learners who are *detail oriented*, we found that they tend to move back to previous pages less often and visit the course overview page less often. It seems that detail oriented learners look more carefully at the content when they visit it the first time and therefore need to revisit the page less often, neither through moving back nor through the course overview page. A preference for getting the *overall picture* of the learning material is, on the other hand, positively correlated with moving back to the previous page.

Learners, who prefer a *sequential learning progress*, tend to visit forums more often and spent more time there. This might be explained by the characteristic of the forum, which provided help if something was not clear for the students. Furthermore, these learners performed self-assessment tests more often and performed more different tests. These two issues refer to the preference of going sequentially through the learning material. This behaviour can also explain the positive correlation regarding the time they spent in the course, the number of logins, and the number of visited learning objects. For learners, who prefer a *non-sequential learning progress*, we found again the correlation regarding visiting and staying at a forum. Regarding self-assessment tests, data showed more clearly that learners who prefer a non-sequential progress do not like performing these tests. They conducted them less often, conducted less different tests, and performed worst in the tests, especially in questions about overview knowledge, facts, concepts, graphics, and text. In addition, a negative correlation was found regarding the time spent in the course, the number of logins, and the number of visited learning objects, indicating that learners with a non-sequential preference use the course less intensively.

4. Conclusions and Future Work

Many researchers and pedagogues argue that the incorporation of learning styles has high potential to help students in learning and make learning easier for them. Accordingly, several researches have been conducted on incorporating learning styles in adaptive systems. For example, features for providing adaptivity based on learning styles were recommended and used by adaptive systems [e.g., 1, 3, 10] and automatic approaches for identifying learning styles from the behaviour of students were developed [e.g., 5, 9, 11]. However, most of these studies were based on the description of the learning style theory about how students with specific learning styles prefer to behave in learning environments.

In this paper, we investigated how students with specific learning style preferences behave in a LMS from a data-driven point of view, analysing the correlations between their behaviour and their learning style preferences. Our findings show several significant correlations which are in agreement with the patterns proposed in the learning style theory and used by studies about adaptive systems and automatic student modelling approaches.

However, some of our findings are in agreement with the learning style theory but are typically not considered by these studies and some are not explicitly mentioned by the learning style theory but appear in our data. By incorporating our data-driven findings in the development of adaptive features, more accurate adaptivity can be provided. Furthermore, by considering these findings in the selection process of relevant patterns for automatic detection of learning styles, students' learning styles can be identified more precisely. In addition, our findings show that students with different learning style preferences act differently in an online course and give therefore another evidence for the potential of adaptive learning based on learning styles.

Future work will deal with considering our findings for improving automatic detection of learning styles and adaptivity in learning systems. Furthermore, we will further investigate the significant patterns which are not explicitly mentioned by FSLSM.

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