INTERACTIONS BETWEEN STUDENTS' LEARNING STYLES, ACHIEVEMENT AND BEHAVIOUR IN MISMATCHED COURSES *

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ABSTRACT

Learning styles are considered as an important factor in education, however, often students have to learn from material or in courses which do not support their learning styles. A challenge in the area of adaptivity is not only to provide learners with courses that fit the students' learning styles but can also veer towards supporting students to learn in courses that does not match their learning styles. In this paper, we analyse the interactions between students' learning styles, their achievement, and their general behaviour in a course that is mismatched regarding their learning styles. The impact of the strength of learning style preferences on achievement, correlations between particular learning styles and achievement, as well as students' behaviour with respect to their achievement and their learning styles are analysed and discussed. As a result, we found that students with strong learning style preferences have more difficulties in learning in mismatched courses. Furthermore, the results show that reflective learners can cope better with mismatched courses than active learners. Moreover, we found that learners with different learning styles and achievement have different behaviour in the course as well as identified correlations between the behaviour and the achievement considering the students' learning styles. The results of this study help, on one hand, to get a better understanding of the interactions between students' learning styles, achievement, and behaviour in a mismatched course and, on the other hand, provide information about how to identify learners who might face difficulties in learning in a mismatched course.

KEYWORDS

Learning styles, achievement, behaviour in mismatched courses, adaptivity

1. INTRODUCTION

More and more research is done regarding considering learning styles in technology enhanced learning and several adaptive systems, such as AHA! (Stash et al., 2006), LSAS (Bajraktarevic et al., 2003), and TANGOW (Paredes and Rodríguez, 2004), were developed. With respect to learning styles, we can distinguish between two ways of providing adaptivity. First, students can be provided with courses and learning material that fit their individual learning styles. This way of providing adaptivity aims at a short-term goal, namely to support students as good as possible at the time they want to learn. The second way of providing adaptivity with respect to learning styles aims at long-term goals. Messick (1976) and Felder and Spurlin (2005), for example, suggested that learners should also train their not-preferred skills and

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preferences. Messick argued that when learners acquire more educational experience, they are required to adapt to a variety of instructional methods and styles. The ability to adapt to different instructional styles will prepare them with important life skills. Another challenge in the area of adaptivity is therefore to help students to cope with courses that are not matched to their learning styles and give them suggestions and assistance in developing such skills.

Most research works related to adaptivity focus on the short-term goal, providing courses that match with students' learning styles and analysing its effects (e.g., Bajraktarevic et al., 2003, Brown et al., 2006). In this study, we aim at investigating the relationships between students' achievement, their learning styles, and their behaviour in a course that is mismatched to their learning styles in order to find out which learners need more help in mastering mismatched courses, get a better understanding about how students with good achievement and poor achievement learn with respect to their learning styles, and provide information about how to identify learners who might have difficulties in learning.

We focused on three research questions. The first question deals with the impact of the strength of learning styles on the students' achievement, investigating whether students with strong learning style preferences (for any learning style) have more problems if their learning style is not supported by the learning environment. The second question is based on the first one and deals with investigations about which learning styles are correlated with students' achievement. The third research question deals with investigating how students with different learning styles and different achievement behave in a mismatched course and whether these strategies of behaviour can give indications about students' achievement.

In the next section, we present the experiment design, introducing the applied learning style model, the investigated course, and general issues about data analysis. Section 3, 4, and 5 deal with the three research questions, where each section describes the method of data analysis as well as presents and discusses the results. Section 6 concludes the paper and presents future work.

2. EXPERIMENT DESIGN

Data for this study are extracted from a project about enriching learning management systems with adaptivity regarding learning styles (Graf and Kinshuk, 2007). In this project, learners were divided into three groups, where they were presented either with courses that matched their learning styles, did not match their learning styles, or included all learning objects independent of the students' learning styles. In the current study, only data from the second group are included in order to analyse learning in a course that is mismatched to the students' learning styles. In the following subsections, the selected learning style model, the investigated course, and general issues on data analysis are described.

2.1 Felder-Silverman learning style model

An important reason for selecting Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988) for this study was that 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 (1984), Pask (1976), and Myers-Briggs (Briggs Myers, 1962). Furthermore, FSLSM is one of the most often used learning style model in technology enhance learning and some researchers even argue that it is the most appropriate model for the use in adaptive learning systems (Carver et al., 1999, Kuljis and Liu, 2005).

According to FSLSM, each learner has a preference for each of its four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global). *Active* learners learn by trying things out and working with others, whereas *reflective* learners learn by thinking things through and working alone. *Sensing* learners like to learn from concrete material like examples, tend to be more practical, and are careful with details, whereas *intuitive* learners prefer to learn abstract material, like challenges, and are more innovative than sensing learners. *Visual* learners remember best what they have seen, whereas *verbal* learners get more out of words, regardless whether they are spoken or written. *Sequential* learners learn in linear steps, prefer to follow linear stepwise paths, and be guided through the learning process, whereas *global* learners learn in large leaps and prefer more freedom in their learning process.

2.2 Investigated course

The experiment is based on data from an object oriented modelling course which was taught at a university in Austria. The course consists of a lecture and a practical part, where students had to submit 5 assignments. At the end of the course, students had to pass a final exam. The course was managed via an adaptive version of the learning management system Moodle (Graf and Kinshuk, 2007, Moodle, 2008).

The course included six types of learning objects: *content objects* for presenting the learning material, *outlines* of the presented topics, *conclusions* for summarising the most important aspects, *examples* for better illustration and providing students with more concrete material, *self-assessment tests* for letting students check their acquired knowledge, and *exercises* where students could apply the learned knowledge through experimenting and practising.

Adaptivity was provided with respect to three dimensions of the FSLSM, namely the active/reflective, sensing/intuitive, and sequential/global dimension. At the beginning of the course, the learning styles of students were identified by asking them to fill out the Index of Learning Styles (ILS) questionnaire (Felder and Soloman, 1997), an instrument of 44 questions for identifying learning styles based on the FSLSM. The adaptive courses differed regarding the number of presented learning objects of a particular type and the order in which types of learning objects were presented. For example, a matched course for sensing learners includes a high number of examples, while a mismatched course includes only few examples. However, the presented course acted as a recommendation and students had the possibility to access all learning objects via a link at the overview page of the course and were free to visit learning objects in any order.

2.3 General issue on data analysis

As mentioned above, for this study, we included only data from learners who were presented with a mismatched course. Furthermore, three other requirements were applied for including data in our study. Data of students who spent less than 5 minutes on the ILS questionnaire were discarded because the detected learning styles were considered as not reliable enough. Moreover, we included only data from students who submitted at least 3 assignments and performed the final exam which both was a requirement for a positive mark. From the 125 students in the mismatched groups, data from 72 students were included in this study.

For all analyses, the scores on the final exam, ranging from 0 to 250, was used as measure for students' achievement. Furthermore, we excluded outliers in all analyses.

3. THE IMPACT OF THE STRENGTH OF LEARNING STYLES ON STUDENTS' ACHIEVEMENT IN MISMATCHED COURSES

The first research question deals with whether the strength of learning styles has an effect on the students' achievement in mismatched courses. In other words, we investigate whether students with a strong preference for a particular learning style have more difficulties in learning if their learning style is not supported in the learning environment.

Based on the ILS questionnaire, preferences for learning styles are measured by values between +11 and -11, with steps of +/- 2, for each learning style dimension. Considering values greater than +5 or smaller than -5 as a strong preference for the specific learning style, learners were divided into two groups. The first group consists of learners who have a strong learning style preference for at least one of the three investigated learning style dimensions ($N = 39$). The second group consists of learners, who have no strong preference for any of the three learning style dimensions ($N = 33$). After testing whether data are normal distributed, t-test was applied, using a significance level of 0.05, in order to identify whether the learners from these two groups have significant differences in their achievement.

In the first group, the mean score of the final exam is 174.26 and in the second group it is 190.97. The result of the t-test shows a significant difference between the two groups ($t = 2.521$, $p < 0.05$), indicating that learners with a strong preference for at least one of the three learning style dimensions have significantly lower scores on the final exam than learners with no strong preference for any learning style dimension. This result is in agreement with Felder and Silverman's argumentation (Felder and Silverman, 1988, Felder and

Soloman, 1997) and shows the importance of adaptivity regarding learning styles, especially for learners with strong learning style preferences.

4. CORRELATIONS BETWEEN LEARNING STYLES AND ACHIEVEMENT IN MISMATCHED COURSES

The second research question aims at investigating the correlations between students' learning styles (active, reflective, sensing, intuitive, sequential, and global) and their achievement in the course. This research question deals with whether learners with specific learning style preferences have more difficulties in learning or learn easier in mismatched courses than learners with other learning style preferences.

In this analysis, rank correlation analysis was used, calculating Kendall's tau and Spearman's rho. Table 1 shows the results of the correlation analyses. As can be seen from the results, the active/reflective dimension is weakly but significantly correlated with the learners' achievement, indicating that reflective learners tend to have better achievement in mismatched courses, while active learners tend to have more difficulties in learning in mismatched courses. From this result, we can conclude that adaptivity is especially important for active learners. For the sensing/intuitive and sequential/global learning style dimensions, no significant correlations were found, which means that specific preferences regarding these learning style dimensions do not influence the achievement of learners.

Table 1. Results of correlation analyses between learning styles and achievement

		active/reflective	sensing/intuitive	sequential/global
Kendall	tau	**-0.187**	-0.063	-0.006
	p	**0.028**	0.456	0.941
Spearman	rho	**-0.266**	-0.095	-0.015
	p	**0.024**	0.425	0.900

5. STUDENTS' BEHAVIOUR IN MISMATCHED COURSES IN RELATION TO THEIR LEARNING STYLES AND ACHIEVEMENT

The third research question deals with the general behaviour of students in mismatched courses, considering their learning styles and their achievement in the course as well as which strategies concerning the behaviour in the course are successful and not successful for learners with specific learning styles. The information about non-successful strategies can be used to identify when students have difficulties to learn and the information about successful strategies can be used for recommending students how to cope with mismatched courses.

5.1 Method

For investigating the general behaviour of students in the mismatched course, we looked at four variables: the time students spent in the course, the number of logins, the number of visited learning objects, and the number of requests for additional learning objects. For the time, we set thresholds in order to avoid the inclusion of learning breaks. We considered a maximum time span of 20 minutes for examples and exercises and for all other learning objects a maximum time span of 10 minutes. Furthermore, we included only the time spent on learning objects rather than considering also administrational activities. Regarding the number of requests for additional learning objects, we used the percentage of requests in relation to the number of visited learning objects.

In order to answer the proposed research question, three analyses were performed. For the first analysis, we divided learners according to their scores on their final exam in two groups, using the average score of all learners in the mismatched course as threshold. Then, for each of the three learning style dimensions, two subgroups were built based on the learning style preferences (e.g., active and reflective), using a threshold of 0. After testing the data regarding normal distribution, for each variable, t-test was performed in order to analyse whether a difference between the learning style preferences on each dimension exists. Taking the active/reflective learning style dimension, high scores, and the variable regarding time as example, this analysis gives information about whether active learners who achieved high scores spent significantly more (or less) time in the course than reflective learners who achieved high scores.

Second, we separated learners first according to their learning styles, using again a threshold of 0 in order to distinguish, for example, between learners with an active and reflective learning style preference. Then subgroups were built for each of the six learning styles by dividing students into two groups based on their scores, using again the mean score of all learners in the mismatched course as threshold. After testing data for normal distribution, t-test was performed for each variable in order to analyse whether a difference with respect to students' achievement exists. For instance, this analysis gives information about whether active learners who achieved high scores spent significantly more (or less) time in the course than active learners who achieved low scores.

In the third analysis, we separated learners again according to their learning styles. For each of the six groups, correlation analysis was performed, using Pearson's r, in order to find correlations between students' achievement and the four variables. For instance, this analysis gives information about whether active learners with high scores tend to spend a high (or low) amount of time in the course, whereas active learners who achieved low scores tend to spend a low (or high) amount of time in the course.

5.2 Results

Table 2 shows the mean for each variable with respect to the six learning styles and the two achievement groups. Since we found few results where the significance values were slightly higher than the applied significance level of 0.05, we explicitly describe these results as tendencies. These tendencies would be worth to be analysed with a larger number of students in a further study. In the following subsections, the results for each learning style dimension are discussed.

Table 2. Mean values of behaviour in a mismatched course with respect to learning styles and achievement

Learning style	Achievement	N	Time (in hours)	Number of logins	Number of visited learning activities	Number of requests for additoinal LO (in %)
active	high score	18	7.07	32.20	619.06	8.16
	low score	20	4.60	33.58	417.68	8.84
reflective	high score	23	5.73	30.63	571.35	7.55
	low score	11	2.86	30.55	329.09	9.14
sensing	high score	29	6.55	30.04	593.93	8.12
	low score	18	5.07	34.18	401.24	8.40
intuitive	high score	12	6.58	32.40	588.33	5.58
	low score	13	3.88	30.23	364.23	9.69
sequential	high score	21	7.56	34.82	648.76	8.47
	low score	15	3.47	36.21	382.29	6.10
global	high score	20	5.51	29.22	447.28	7.14
	low score	16	4.77	26.07	387.75	11.61

5.2.1 Active / reflective learning style dimension

When comparing active learners and reflective learners with respect to their behaviour in the course, both for learners with low and high scores, no significant differences were found. However, a tendency was identified with respect to the time, indicating that active learners with low scores spent more time in the course than reflective learners with low scores ($t = -1.827$, $p = 0.079$).

For active learners, another tendency can be seen, indicating that learners with high scores tend to spend more time in the course ($t = -2.031$, $p = 0.052$) and visit more learning objects ($t = -2.022$, $p = 0.051$) than learners with low scores. With respect to correlations between students' achievement and the investigated variables, no significant correlations were found, however, a tendency hints at a positive correlation for the time students spent in the course ($r = 0.280$, $p = 0.089$) and the visited learning objects ($r = 0.315$, $p = 0.061$).

When comparing the behaviour of reflective learners with high scores and reflective learners with low scores, the time ($t = -2.804$, $p < 0.01$) and the number of learning objects ($t = -3.045$, $p < 0.01$) is identified to be highly significant, indicating that reflective learners with high scores spent more time in the course and visited more learning objects than reflective learners with low scores. These results are in line with the description of the FSLSM, stating that reflective learners prefer to learn by thinking things through, for which a higher amount of time and visited learning objects seems to be a requirement. Looking at correlations between the learners' achievement and the variables, these findings are confirmed. We found a positive correlation, indicating that reflective learners significantly benefit from spending more time in the course ($r = 0.441$, $p < 0.05$) and visiting more learning objects ($r = 0.378$, $p < 0.05$). Moreover, the correlation can be interpreted in a way that for identifying learning difficulties in mismatched courses, for reflective learners the time spent in the course as well as the number of visited learning objects is a good indicator.

5.2.2 Sensing / intuitive learning style dimension

Comparing the behaviour in the course between sensing and intuitive learners, both with low and high scores, no significant difference was found. However, a tendency can be seen, indicating that sensing learners with high scores ask more often for additional learning objects than intuitive learners with high scores ($t = -1.941$, $p = 0.061$).

When comparing the behaviour of sensing learners with high scores and sensing learners with low scores, again no significant difference was found, but a tendency regarding the number of learning objects ($t = -1.982$, $p = 0.054$) can be seen, indicating that sensing learners with high scores visited more learning objects than sensing learners with low scores. Looking at correlations, we found significant results for the time ($r = 0.290$, $p < 0.05$) and the number of visited learning objects ($r = 0.335$, $p < 0.05$), indicating that sensing learners with high scores tend to spend a high amount of time in the course and visit many learning objects, while sensing learners with low scores tend to spend only less time in the course and visit fewer learning objects. Again, another interpretation of this result is that the time and the number of visited learning objects can act as an indicator for the learners' achievement and can show when learners have difficulties in learning. These results can be explained by the characteristics of sensing learners, saying that they tend to be more carefully and therefore take more time for learning and visit more learning objects.

For intuitive learners, a significant difference was identified between learners with low scores and learners with high scores with respect to the time ($t = -2.765$, $p < 0.05$) and number of learning objects ($t = -2.555$, $p < 0.05$). Furthermore, we found a tendency for the number of requests for additional learning objects ($t = 1.974$, $p = 0.066$), indicating that intuitive learners with high scores tend to ask for less additional learning objects than intuitive learners with low scores. Based on these results, intuitive learners seem to be able to learn well even from mismatched material which might be explained by their preference for challenges. Regarding correlation analysis, no significant result was found.

5.2.3 Sequential / global learning style dimension

Comparing sequential and global learners, it can be seen that sequential learners with high scores visited significant more learning objects ($t = -2.389$, $p < 0.05$) than global learners with high scores. This is in line with the characterisation of their learning styles since sequential learners typically learn by going through learning objects in a sequential order without skipping them. Furthermore, we found a tendency that sequential learners with high scores also spent more time in a course than global learners with a high score ($t = -1.711$, $p = 0.095$). On the other hand, global learners with low scores asked significantly more often for additional learning objects ($t = 2.565$, $p < 0.05$) than sequential learners with low scores. Although global learners prefer to have little guidance and more control over their learning path and learning process, it seems that they easily search too much for additional learning objects which has negative effect on their learning outcome. Regarding the number of logins, we found significant results for learners with high scores ($t = -2.039$, $p < 0.05$) and learners with low scores ($t = -2.166$, $p < 0.05$), indicating that, in both cases, sequential learners logged in more often than global learners.

For sequential learners, we found that learners with high scores spent significantly more time in the course ($t = -3.714$, $p < 0.01$) and visited more learning objects ($t = -2.666$, $p < 0.05$) than learners with low scores. The correlation analysis confirms the results regarding the time ($r = 0.399$, $p < 0.05$) and number of learning objects ($r = 0.410$, $p < 0.05$) and furthermore allows the conclusion that sequential learners benefit significantly from a high amount of time and a high number of visited learning objects. Moreover, a positive correlation with respect to the number of requests for additional learning objects ($r = 0.336$, $p < 0.05$) was found, indicating that sequential learners with high scores tend to ask more often for additional learning objects than sequential learners with low scores and that asking for additional learning objects has a positive effect on their learning progress. Although, according to FSLSM, sequential learners prefer to go through the learning material in a sequential way, this result makes sense since each learner has a learning style preference on each of the four learning style dimensions of the FSLSM and searching for additional learning objects might help learning according to another learning style preference. However, the number of additional requests is still similar to the average number of requests in mismatched courses.

For global learners, the comparison between learners with low and high scores shows that learners with low scores asked significantly more often ($t = 2.533$, $p < 0.05$) for additional learning objects than learners with high scores. Regarding correlations, no significant result was found for global learners.

5.3 Benefits from analysing students' behaviour in mismatched courses

As can be seen from the results described in the previous section, students with different learning styles and different achievement chose different strategies for behaving in a mismatched course. Comparing the preferences on each learning style dimension with respect to students' achievement, only for the sequential/global dimension significant results could be found. Differences for the number of logins, the number of visited learning objects, and the number of requests for additional learning objects were identified, either for learners with high scores, low scores, or both. Furthermore, we found that reflective, intuitive, and sequential learners with high scores spent more time in the course and visited more learning objects, and global learners with high scores asked less often for additional learning objects, each in comparison to learners with same learning styles and low scores.

These results provide a description about which strategies are used by learners with good achievement and which strategies are used by learners with poor achievement, considering different learning styles. While the results only allow inferring the behaviour in the course from a specific learning style and achievement, correlation analysis allows additionally predicting the achievement from the behaviour in the course. In other words, it shows which strategies can lead to good achievement for each learning style and how to identify behaviour which leads to poor achievement with respect to each learning style.

Results of the correlation analysis show a significant and positive correlation for reflective, sensing, and sequential learning styles with respect to the time and the number of visited learning objects. The time and number of visited learning objects is, of course, relevant for all learners and, taking an extreme example, not spending any time in the course and visiting any learning objects will lead to poor achievement for all learners independent of their learning styles. However, for reflective, sensing, and sequential learners these two variables seem to be a particular good indicator for identifying when learners have difficulties and might be frustrated in learning since their behaviour is then not in line with their typical behaviour they prefer for learning. Furthermore, a positive and significant correlation was found for sequential learners with respect to the number of requests for additional learning objects, showing that a low amount of requests can indicate and lead to poor achievement. As discussed before, sequential learners typically prefer to be guided in the learning process and go through the learning material step by step. If the learning material is mismatched to their learning styles, including not only their preference with respect to the sequential/global dimension but also to the other dimensions of FSLSM, they can benefit from not strictly relying on the predefined structure and learning objects of the mismatched course but also look at additional learning objects which might fit their other learning styles. For example, considering a learner with a strong sequential and sensing learning style in a mismatched course that includes only abstract material without any examples, the learner can benefit from requesting additional learning objects like examples which would fit better his/her sensing preference. Thus, the variable about additional requests can not only be an indicator for poor achievement but can also be used as a recommendation for helping learners to learn easier from the learning material by encouraging sequential learners to search for learning material that fits better to their other learning style preferences.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we presented a study about the interactions between students' achievement, learning styles, and behaviour in a course which does not match their learning styles according to the Felder-Silverman learning style model (FSLSM). Results show that learners with strong preferences for a specific learning style have more difficulties in learning, in terms of achieving lower scores, than learners with milder learning style preferences. This finding shows that especially learners with strong learning style preferences can benefit from adaptivity, either aiming at providing them with courses that matched their learning styles or providing them with suggestions how to learn from mismatched courses. Furthermore, results show that reflective learners can cope better with a mismatched course, whereas active learners seem to have more difficulties. Again, the finding gives information about which learners might be more at risk of having problems in learning in mismatched courses and point out that for active learners it is especially important to provide them with some activities that fit their learning styles or give them hints about how to cope with the mismatched material. Moreover, results show that students with different learning styles and achievement behave differently in the course. The findings help in getting a deeper understanding about the relationship between students' learning styles, achievement, and behaviour in mismatched courses. Furthermore, correlations were found between the students' behaviour in the course and their achievement for some learning styles. These correlations allow concluding from the behaviour of learners to their achievement, considering their respective learning styles, and therefore, allow identifying when students seem to have difficulties in learning and providing them with suggestions how to overcome them.

In the context of technology enhanced learning, our findings can be used as basis for either alerting teachers when students seem to have difficulties in learning or for letting the system provide personalised suggestions how to overcome such problems.

Future work will deal, on one hand, with further investigations, considering more detailed variables about students' behaviour in the course as well as the interactions between different learning style preferences. On the other hand, further work will include the application of our findings in technology enhanced learning, building a tool that identifies when students have difficulties in learning.

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