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Coping with mismatched courses: students' behaviour and performance in courses mismatched to their learning styles

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Abstract Although learning styles are considered as an important factor in education, students often have to learn in courses that do not support their learning styles. A challenge for technology facilitated learning is therefore to assist and help students to cope with courses that do not match their learning styles by training and developing their less preferred skills. In this paper, the interactions between students' learning styles, their behaviour, and their performance in an online course that is mismatched regarding their learning styles were analysed. The results show which learners need more help in mastering mismatched courses, help in getting a better understanding about how students with good performance record and poor performance record learn with respect to their learning styles, and provide information about how to identify learners who might have difficulties in learning based on their behaviour.

Keywords Learning styles · Student performance · Mismatched courses · Adaptivity

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The area of learning styles is complex and many questions are still open, including a clear definition of learning styles, a comprehensive model which describes the most important learning style preferences, and the question about the stability of learning styles. Educational researchers and theorists generally agree that students learn in different ways and that the consideration of learning styles can help students in learning easily and more effectively. Based on these arguments, several research works dealing with incorporating learning styles in technology-enhanced learning have been conducted. For instance, investigations have been performed about relating individual learning style characteristics to learning objects characteristics (Karagiannidis and Sampson 2004). Furthermore, investigations are conducted towards improving the detection process of learning styles. This can be done by enhancing learning style questionnaires through diminishing the influence of factors that hinder an accurate estimation (Botsios et al. 2008) and by using an automatic approach for identifying learning styles based on students' behaviour in an online course (García et al. 2007; Graf et al. 2008a). Furthermore, several adaptive systems have been developed, aiming at facilitating learning by providing courses or learning materials that match with the student's learning style. Examples of such systems include AHA! (Stash et al. 2006), INSPIRE (Papanikolaou et al. 2003), KOD (Manouselis and Sampson 2002), LSAS (Bajraktarevic et al. 2003), and TANGOW (Paredes and Rodríguez 2004). These systems focus on a short-term goal, namely on supporting students by providing them with a learning experience that matches with their individual learning styles. However, educational theorists such as Messick (1976) and Felder and Spurlin (2005) pointed out that learners should also learn how to cope with courses and learning material that do not match with their preferred ways of learning. Therefore, students should also be trained by using their not-preferred skills and preferences as not all courses and learning environments will adapt to individual 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 students with important life skills. Therefore, another challenge of adaptive systems is to help students to cope with courses that are not well matched with their learning styles and give them suggestions and assistance in developing appropriate skills.

Several studies have been conducted about the behaviour of students in technology-enhanced learning and their learning styles showing that students with different learning styles behave differently in non-adaptive courses (e.g., Graf and Kinshuk 2008; Liegle and Janicki 2006; Lu et al. 2007). These studies show the potential of providing adaptivity with respect to learning styles. Furthermore, several studies have focused on analysing the effects of matched courses in terms of how effective it is to provide students with courses that fit with their learning styles (e.g., Bajraktarevic et al. 2003; Brown et al. 2006; Graf and Kinshuk 2007).

This study investigates how students cope with courses that are mismatched with their learning styles. Therefore, the students' learning styles, behaviour, and performance in a course were analysed, investigating which learners need more help in mismatched courses, which learning strategies students with particular learning styles use and how successful these strategies are, as well as how to identify learners who might have difficulties in learning.

In the current study, the students' learning styles are described based on the Felder–Silverman learning style model (FSLSM) (Felder and Silverman 1988). According to FSLSM, each learner has a preference on each of the four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global), measured on a scale from +11 to

-11 which makes it possible to describe how strong the learners' preference for a specific learning style (such as active, reflective, sensing, intuitive and so on) is.

In order to deeply explore how students cope with mismatched courses, this study focuses on three research questions. The first question deals with the impact of the strength of learning styles on the students' performance in a course, 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' performance. The third research question investigates how students with different learning styles and different performance levels behave in a mismatched course and whether these strategies of behaviour can give indications about students' performance.

The findings of this study are especially relevant for adaptive systems that focus on helping students to learn in courses that do not match with their preferred ways of learning. The results indicate which students might have problems in learning. Based on this study, recommendations can be provided for learning strategies that can help students to cope with such courses.

In the next section, the research design is presented, describing the FSLSM in more detail and introducing the investigated course and general issues about data. The subsequent three sections deal with the three research questions. The last section concludes the paper by discussing possible research directions.

Research design

Data for this study were extracted from a project about enriching learning management systems with adaptivity regarding learning styles (Graf 2007; 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 mismatched group are used in order to analyse learning in a course that does not support the students' learning styles. In the following sections, the selected learning style model, the investigated course, and general issues on data are described.

Felder–Silverman learning style model

Many learning style models exist including the models by Kolb (1984), Honey and Mumford (1982), Entwistle (1981), Pask (1976), and Felder and Silverman (1988). Each of these models describes different aspects of how learners prefer to learn in different granularity. The Felder–Silverman learning style model (FSLSM) was selected for this study for several reasons. Felder and Silverman describe learning styles in considerable detail, distinguishing four dimensions. By using these four dimensions, FSLSM combines major learning style models such as the ones by Kolb (1984), Pask (1976), and Myers-Briggs (Briggs Myers 1962). While most learning style models classify learners into a few types, FSLSM is based on the idea that each learner has a preference on each of the four dimensions, measured as values between $+11$ and -11. By using scales rather than types, the strengths of learning style preferences can be described, enabling the model to distinguish between strong and weak preferences for a particular learning style. In addition, FSLSM is different from other learning style models in terms of considering learning styles as tendencies, meaning that students have a core tendency for a specific learning style but can also act differently in particular situations. By incorporating the concept of tendencies, the description of learning styles also considers exceptions and extraordinary situations. Besides, FSLSM is one of the most often used learning style models in technology-enhanced learning and some researchers even argue that it is the most appropriate model for use in adaptive learning systems (Carver et al. 1999; Kuljis and Liu 2005).

The four dimensions of FSLSM are: active/reflective, sensing/intuitive, visual/verbal, and sequential/global. *Active* learners learn by trying things out and prefer to work together 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 such as theories and concepts, like challenges, and tend to be more innovative than sensing learners. *Visual* learners remember best what they have seen, whereas *verbal* learners get more out of words, regardless of 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.

For identifying learning styles according to the FSLSM, Felder and Soloman (1997) developed the Index of Learning Styles (ILS) questionnaire, which includes 44 questions. Felder and Spurlin (2005) summarised studies which report the application of the ILS questionnaire as well as studies which investigated its reliability and validity. As a result, Felder and Spurlin concluded that the ILS questionnaire may be considered as reliable, valid, and suitable.

Course

The study is based on data from an object-oriented modelling course which was taught at a university in Austria. The course consisted of an optional lecture and a compulsory practical part, in which students were required to submit 5 assignments. The assignments had to be done in groups of two. A few days after the submission, each student had to present the solution individually and had to answer questions about it. At the end of the course, each student had to successfully complete a written exam. 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.

An adaptive version of the learning management system Moodle (Graf 2007; Graf and Kinshuk 2007; Moodle 2008) was used for administrating the course and providing students with learning objects and activities. The usage of these learning objects and activities in Moodle was not compulsory for students. The students' grades were calculated only from their scores on the assignments and the final exam.

The online 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. Furthermore, students were encouraged to use the *discussion forum* to communicate with each other as well as with the tutors and the teacher.

Adaptivity based on learning styles was provided with respect to three dimensions of the FSLSM, namely the active/reflective, sensing/intuitive, and sequential/global dimension.

The visual/verbal dimension was excluded since this dimension asks for different presentation modes, for example, including text, audio files, video files, and so on. These learning objects are time-consuming in their development and therefore their inclusion is in disagreement with the overall goal to provide teachers with adaptive functionality in a learning management system without much additional effort.

At the beginning of the course, the learning styles of students were identified by asking them to fill out the ILS questionnaire. Based on the students' learning styles, Moodle automatically generated adaptive courses by using an add-on for providing adaptivity regarding learning styles (Graf 2007; Graf and Kinshuk 2007). These courses differed regarding the number of presented learning objects of a particular type and the order in which the six types of learning objects were presented. For example, an adaptive course for sensing learners included a high number of examples, whereas a mismatched course included only few examples. However, the presented courses 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.

Data

Only data from learners who were presented with a mismatched course were included in the analysis. Furthermore, three other requirements were applied for including data in this study. Data of students who spent less than 5 min on the ILS questionnaire were discarded because the detected learning styles were considered less than reliable. Therefore, data from 38 students were excluded from the study. This relatively high number can be explained by the lack of students' motivation to fill out the learning style questionnaire. Moreover, only data from students who submitted at least 3 assignments were included, which was a requirement for passing the course. This requirement was not fulfilled by 14 students, whereby 5 students were already excluded due to the first requirement. Furthermore, only data from students who attended the final exam were included; 25 students did not write the final exam, including all students who did not submit enough assignments in order to pass the course and 11 students who did not fulfil the first requirement. In addition, data from one student were excluded since he registered twice. Overall, from the 125 students in the mismatched groups, data from 72 students were included in this study.

Since the final exam was designed and used for examining students' gained knowledge in the course, the scores on the exam were considered as a reliable measure for students' performance. In this written exam, students had 45 min to answer questions about the content of the course. The scores ranged from 0 to 250 and were used as performance measure for all analyses in this study.

For all analyses, the occurrence of outliers with respect to performance and/or behaviour in the course was checked and outliers were excluded.

The impact of the strength of learning styles on students' performance in mismatched courses

The first research question dealt with whether the strength of learning styles has an effect on the students' performance in mismatched courses. In other words, this analysis

Table 1 The impact of strength of learning style preferences on performance in the course

	N	Mean	Standard deviation	Differences in scores between groups (*t*-test)	
				t	*p*
Group 1 (strong learning style preferences)	39	174.26	29.62	2.52	0.014
Group 2 (others)	33	190.97	26.02		

investigated whether students with a strong preference for a particular learning style had more difficulties in learning if their learning style was 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. By 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 consisted of learners who had a strong learning style preference for at least one of the three investigated learning style dimensions. In this study, 39 students belonged to this group. The second group consisted of learners, who had no strong preference for any of the three learning style dimensions, which was true for 33 students in this study. After testing whether data were normally distributed, *t*-test was applied, using a significance level of 0.05, in order to identify whether the learners from these two groups had significant differences in their performance in the course.

The results of the *t*-test can be seen in Table 1. The mean score of the final exam from all students is 181.92 (SD = 29.07). In the first group, the mean score of the final exam is 174.26 (SD = 29.62) and in the second group, the mean score is 190.97 (SD = 26.02). The results of the *t*-test show a significant difference between the two groups, $t(70) = 2.52$, $p < .05$, indicating that learners with a strong preference for at least one of the three learning style dimensions had significantly lower scores on the final exam than learners with no strong preference for any learning style dimension. This result is in agreement with the argumentation of Felder and his colleagues (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.

Correlations between learning styles and performance in mismatched courses

The second research question involved the correlations between students' learning styles (active, reflective, sensing, intuitive, sequential, and global) and their performance in the course. The goal was to show which learning styles have an impact on students' performance. Therefore, this research question dealt with whether learners with specific learning style preferences find it more difficult or easier to learn 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 2 shows the results of the correlation analyses. Significant results are indicated by an asterisk and written in bold font, using a significance level of 0.05. As can be seen from the results, the active/reflective dimension is weakly but significantly correlated with the learners' performance, indicating that reflective learners tend to achieve

Table 2 Correlation analyses between learning styles and performance

		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

higher scores in mismatched courses, while active learners tend to have more difficulties in learning in mismatched courses. This result seems to be plausible since, if reflective learners are provided with a course which emphasises only on active learning, they still have the possibility to reflect and think about the contents by themselves. However, if active learners are provided only with learning material that emphasises reflective learning, they usually do not have possibilities to do some activities or experiments with the contents by themselves and therefore need to learn entirely according to their less preferred learning style. Therefore, a conclusion can be drawn that adaptivity is especially important for active learners. For the sensing/intuitive and sequential/global learning style dimensions, no significant correlations were found. This means that specific preferences regarding these learning style dimensions do not influence the performance of learners in mismatched courses.

Students' behaviour in mismatched courses in relation to their learning styles and performance

The third research question dealt with the general behaviour of students in mismatched courses, considering their learning styles and their performance in the course. The goal was to find out 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 in learning and the information about successful strategies can be used for recommending students how to cope with mismatched courses.

Method

For investigating the general behaviour of students in the mismatched course, four variables were considered: 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 time, thresholds were set in order to avoid the inclusion of learning breaks. A maximum time span of 20 min was considered for examples and exercises and for all other learning objects a maximum time span of 10 min was used. Furthermore, only the time spent on learning objects was included and not the time spent on administrative activities. Regarding the number of requests for additional learning objects, the percentage of requests in relation to the number of visited learning objects was used.

In order to answer the proposed research question, three analyses were performed. The first analysis investigated the differences in behaviour patterns between learners with the same performance level, distinguishing between high and low scores, but different learning style preferences on each dimension of the FSLSM. Therefore, learners were divided 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 exists between the learning style preferences on each dimension. Taking the active/reflective learning style dimension, high scores, and the variable regarding time as an 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. The results of this analysis show whether learners with different learning styles and similar performance behave differently in the course. Therefore, the results make it possible to draw conclusions about the students' behaviour based on their learning styles and performance in the course.

The second analysis investigated the difference in behaviour patterns between learners with the same learning style but different performance levels (high or low scores). Therefore, learners were first separated 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 (active, reflective, sensing, intuitive, sequential, and global) 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 exists with respect to students' performance levels. 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. The results of this analysis show whether learners with the same learning style but different performance levels behave differently in the course and use different learning strategies. Similar to the first analysis, the results make it possible to draw conclusions about the students' behaviour based on their learning styles and performance.

The third analysis investigated the correlations between the performance and the behaviour patterns of students with the same learning styles. Therefore, learners were again separated 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' performance 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. The results of this analysis make it possible to draw conclusions about the students' behaviour based on their learning styles and performance. Additionally, these results make it possible to infer the performance of students with particular learning styles from their behaviour.

Results

Table 3 shows the mean and standard deviation for each variable with respect to the six learning styles and the two performance levels. Since some results were found where the significance values were slightly higher than the applied significance level of 0.05, these results are explicitly described as tendencies. These tendencies would be worth to be analysed with a larger number of students in a further study. In the following sections, the results for each learning style dimension are discussed.

Table 3 Mean values and standard deviation values of behaviour in a mismatched course with respect to learning styles and performance levels

Learning style	Performance level	*N*	Time (h)		Number of logins		Number of visited learning activities		Number of requests for additional LO (%)	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD
Active	High score	18	7.07	4.39	32.20	7.76	619.06	359.37	8.16	5.84
	Low score	20	4.60	2.71	33.58	14.49	417.68	237.42	8.84	6.68
Reflective	High score	23	5.73	3.00	30.63	7.93	571.35	303.82	7.55	4.70
	Low score	11	2.86	1.72	30.55	12.74	329.09	159.08	9.14	6.51
Sensing	High score	29	6.55	4.29	30.04	9.50	593.93	346.32	8.12	5.52
	Low score	18	5.07	4.18	34.18	15.80	401.24	246.21	8.40	6.35
Intuitive	High score	12	6.58	3.04	32.40	5.08	588.33	284.54	5.58	2.57
	Low score	13	3.88	1.48	30.23	10.62	364.23	133.49	9.69	6.91
Sequential	High score	21	7.56	4.24	34.82	8.97	648.76	319.18	8.47	5.79
	Low score	15	3.47	2.15	36.21	15.22	382.29	237.43	6.10	5.82
Global	High score	20	5.51	3.36	29.22	7.24	447.28	201.68	7.14	4.48
	Low score	16	4.77	3.04	26.07	8.67	387.75	198.48	11.61	6.12

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, $t(26) = -1.83$, $p = .079$.

For active learners, another tendency can be seen, indicating that learners with high scores tend to spend more time in the course, $t(28.306) = -2.03$, $p = .052$, and visit more learning objects, $t(35) = -2.02$, $p = .051$, than learners with low scores. With respect to correlations between students' performance 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, $r = .28$, $p = .089$, and the visited learning objects, $r = .32$, $p = .061$, confirming the abovementioned results.

When comparing the behaviour of reflective learners with high scores and reflective learners with low scores, the time, $t(30) = -2.80$, $p < .01$, and the number of learning objects, $t(31.582) = -3.05$, $p < .01$, 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 (Felder and Silverman 1988), 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' performance and the variables, these findings were confirmed. A positive correlation was found, indicating that reflective learners significantly benefited from spending more time in the course, $r = .44$, $p < .05$, and visiting more learning objects, $r = .38$, $p < .05$. 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.

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, $t(33.296) = -1.94$, $p = .061$.

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, $t(44) = -1.98$, $p = .054$, can be seen, indicating that sensing learners with high scores visited more learning objects than sensing learners with low scores. Looking at correlations, significant results for the time, $r = .29$, $p < .05$, and the number of visited learning objects, $r = .34$, $p < .05$, were found, indicating that sensing learners with high scores tend to spend a large amount of time in the course and visit many learning objects, while sensing learners with low scores tend to spend only little time in the course and visit fewer learning objects. These results can be explained by the characteristics of sensing learners according to FSLSM, saying that sensing learners tend to be more careful and therefore benefit from taking more time for learning and visiting more 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' performance and can show when learners might face difficulties in learning.

For intuitive learners, a significant difference was identified between learners with low scores and learners with high scores with respect to the time, $t(15.938) = -2.77$, $p < .05$, and number of learning objects, $t(23) = -2.55$, $p < .05$. Furthermore, a tendency for the number of requests for additional learning objects, $t(16.019) = 1.97$, $p = .066$, was found, indicating that intuitive learners with high scores tend to ask for less additional learning objects than intuitive learners with low scores. Based on this result, 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 results were found.

Sequential/global learning style dimension

Comparing sequential and global learners, it can be seen that sequential learners with high scores visited significantly more learning objects than global learners with high scores, $t(34.233) = -2.39$, $p < .05$. This is in line with the characterisation of their learning styles according to FSLSM since sequential learners typically learn by going through learning objects in a sequential order without skipping them. Furthermore, a tendency was found showing that sequential learners with high scores also spent more time in a course than global learners with a high score, $t(39) = -1.71$, $p = .095$. On the other hand, global learners with low scores asked significantly more often for additional learning objects, $t(29) = 2.56$, $p < .05$, 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 a negative effect on their learning outcome. Regarding the number of logins, significant results for learners with high scores, $t(33) = -2.04$, $p < .05$, and learners with low scores, $t(20.630) = -2.17$, $p < .05$, were found, indicating that, in both cases, sequential learners logged in more often than global learners.

For sequential learners, results show that learners with high scores spent significantly more time in the course, $t(31.110) = -3.71$, $p < .01$, and visited more learning objects,

$t(33) = -2.67$, $p < .05$, than learners with low scores. The correlation analysis confirmed the results regarding the time, $r = .40$, $p < .05$, and number of learning objects, $r = .41$, $p < .05$, and furthermore make it possible to draw 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, $r = .34$, $p < .05$, 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 preferences. 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, $t(34) = 2.53$, $p < .05$, for additional learning objects than learners with high scores. This is in line with the results discussed above, showing again that global learners with a successful learning performance do not search too much for additional learning objects. Regarding correlations, no significant results were found for global learners.

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 performance levels chose different strategies for behaving in a mismatched course. Comparing the preferences on each learning style dimension with respect to students' performance levels, significant results could be found only for the sequential/global dimension. 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, results show 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 who achieved high scores and which strategies are used by learners who achieved low scores, considering different learning styles. While the results only allow inferring the behaviour in the course from a specific learning style and performance level, correlation analysis allows additionally predicting the performance from the behaviour in the course. In other words, it shows which strategies can lead to good performance for each learning style and how to identify behaviour which leads to poor performance 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 performance for all learners independent of their learning styles. However, for reflective, sensing, and sequential learners these two variables seem to be a particularly 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 performance. As discussed before, sequential learners typically prefer to be guided in the learning process and go through the learning material step by step. However, each learner has preferences on each of the four dimensions of the FSLSM. Therefore, if the learning material is mismatched to their learning styles, learners with a sequential preference can benefit from looking at additional learning objects, which might fit their other learning styles, rather than strictly relying on the predefined structure and learning objects of the mismatched course. For example, let's consider a learner with a strong sequential and sensing learning style in a mismatched course that includes only abstract material without any examples. This learner can benefit from requesting additional learning objects like examples which would fit better his/her sensing learning style preference. Thus, the variable about additional requests can not only be an indicator for poor performance 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.

Conclusions and future work

In this paper, a study was presented investigating the interactions between students' learning styles, behaviour, and performance in a course which does not match their learning styles according to the Felder–Silverman learning style model (FSLSM). First, the impact of the strength of learning style preferences on the students' performance in the course was analysed. 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 mild learning style preferences. This finding shows that learners with strong learning style preferences can especially benefit from adaptivity, either aiming at providing them with courses that match with their learning styles or providing them with suggestions on how to learn from mismatched courses. Subsequently, investigations were conducted regarding which learning style preferences have an impact on the students' performance. Results show that reflective learners can cope better with the mismatched course, whereas active learners seem to have more difficulties. Again, the findings give 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. Furthermore, a detailed analysis was conducted about students' behaviour in a mismatched course and the relation to their learning styles and performance. Results show that students with different learning styles and performance levels behave differently in the course. The findings help in getting a deeper understanding about the relationship between students' learning styles, performance, and behaviour in mismatched courses. Furthermore, correlations were found between the students' behaviour in the course and their performance in the course for some learning styles. These correlations allow inferring students' performance from their behaviour, considering their respective learning styles, and therefore, allow identifying when students seem to have difficulties in learning and providing them with suggestions on how to overcome them.

In the context of technology-enhanced learning and development of educational systems, our findings can be used on the one hand for identifying which students are more endangered to have difficulties in learning and when students seem to have difficulties in learning based on their behaviour in the course. On the other hand, our findings provide information about facilitating these students with adaptive support and suggestions on how to overcome these difficulties by recommending learning strategies which were successful for learners with the same learning style. Furthermore, the system can provide additional information for teachers, alerting them once it infers students having difficulties in learning.

Future work will deal with further investigations, considering more detailed variables about students' behaviour in the course as well as the interactions between different learning style preferences. Additionally, 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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