Profiling Student Behavior in a Blended Course
Closing the Gap between Blended Teaching and Blended Learning

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Abstract: Blended learning is often associated with student-oriented learning in which students have varying degrees of control over their learning process. However, the current notion of blended learning is often a teacher-oriented approach in which the teacher identifies the used learning technologies and thereby offers students a blended teaching course instead of a blended learning course (George-Walker & Keeffe, 2010). A more student-oriented approach is needed within educational design of blended learning courses since previous research shows that students show a large variation in the way they use the different digital learning resources to support their learning. There is little insight into why students show distinct patterns in their use of these learning resources and what the consequences of these (un)conscious differences are in relation to student performance. The current study explores different usage patterns of learning resources by students in a blended course. It tries to establish causes for these differences by using dispositional data and determines the effect of different usage patterns on student performance.

1 INTRODUCTION

When discussing learning technologies, there seems to be consensus about its positive impact on education. Phrases as 'new potential', 'rapid and dramatic change' and 'fast expansion' are frequently used when describing new learning technologies. This is no different for blended learning as the abovementioned phrases are used to characterize current developments within the blended learning domain (Henderson et al., 2015).

The definition of blended learning is not clearly defined and can relate to combinations of instructional methods (e.g. discussions, (web) lectures, simulations, serious games or small workgroups), different pedagogical approaches (e.g. cognitivism, connectivism), various educational transfer methods (online and offline) or it can relate to various technologies used (e.g. e-learning, podcasts or short video lectures (Bliuc et al., 2007; Porter et al., 2016).

The common distinction lies in the two different methods used within the learning environment: face-to-face (offline) versus online learning activities.

Blended learning is often associated with student-oriented learning, in which students have varying degrees of control over their own learning process. Blended learning could contribute to the autonomy of the students in which they have more control over their learning path and this autonomy should encourage students to take responsibility for their own learning process (Lust et al., 2013). This approach towards blended learning is in line with a constructivist pedagogical model and is believed to assist in a flexible learning environment where student autonomy and reflexivity is strengthened (Orton-Johnson, 2009). However, in most cases the design of blended learning is mostly aimed at putting technology into the learning environment without taking into account how that technology contributes to the learning outcomes (Verkroost et al., 2008) or encourages student autonomy and reflexivity. The current notion of blended learning is often a teacher-oriented approach in which the teacher determines the learning technologies without considering how these learning technologies

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contribute to flexible learning, student autonomy and course performance. This so called ‘blended teaching’ approach (George-Walker and Keeffe, 2010) lacks a focus on students. To improve the educational design of blended learning, a focus on students is needed so students can choose the ‘right’ learning technologies to be suit their own learning path. What the teacher determines as the ‘right’ technology does not necessary match with the perspective of the learner and will not automatically lead to more student-oriented learning (Oliver and Trigwell, 2005) or encourages student autonomy and reflexivity.

When blended learning design focuses on students and their choices to use the ‘right’ learning technologies, there is a large variety in the choices students display when using the different learning resources to support their learning. Students either heavily rely on a single preferred supporting technology (Inglis et al., 2011) do not use the technology at all (Lust et al., 2011) or apply it in such a way to substitute for the face-to-face activities (Bos et al., 2015), thereby de facto creating their own online course. One blended teaching course can thereby lead to different blended learning courses. There is little insight into why students do or do not use certain learning technologies and what the consequences of these (un)conscious choices are in relation to student performance, although research suggests that goal-orientation (Lust et al., 2013), approaches to learning (Ellis et al., 2008) may be an important predictor of frequency and engagement of use.

Several studies conducted a cluster analysis based on the use of these different learning resources to identify different usage patterns. For example Lust et al., (2013) found four different clusters that reflect differences in the use of the digital learning resources: the no-users, the intensive-active users, selective users and intensive superficial users. Similarly another study (Kovanović et al., 2015) found, also based on cluster analysis, several different user profiles based on the use of digital learning resources and suggest that these differences might be related to differences in students’ metacognition and motivation.

One of the advantages of blended learning is that the learning activities take place in an online environment, which easily generates data about these online activities. The methods and tools that aim to collect, analyse and report learner-related educational data, for the purpose of informing evidence-based educational design decisions is referred to as learning analytics (Long and Siemens, 2011). Learning analytics measures variables such as total time online, number of online sessions or hits in the learning management systems (LMS) as a reflection of student effort, student engagement and participation (Zacharis, 2015). Learning data analysis from students in a blended learning setting provides the opportunity to monitor students’ use of different learning technologies throughout the course and might provide insight in the gap between the education design of the course and the different learning paths of students.

To better understand student behaviour in a blended learning setting, learning data analysis needs to be complemented with a set of indicators that goes beyond clicks and durations of use. One solution is to combine data from online learning activities with learning dispositions, values and attitudes, which should be measured through self-report surveys (Shum and Crick, 2012) such as the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al. 1991). Learners’ orientations towards learning—their learning dispositions—influence the nature of how students engage with new learning opportunities. Someone who is able to self-regulate his or her own learning process is more likely to use a deep approach towards learning (Vermunt, 1992) Students who use an external regulation strategy are more likely to use a surface approach towards learning. So, adding learning dispositions to data collected from online learning activities could provide better understanding of students’ regulation strategies and their use of learning technologies, and subsequently explain differences in student performance. Indeed, preliminary research shows that dispositional data adds to the predictive power of learning analytics based on prediction models (Tempelaar et al., 2015).

To close the gap between blended teaching and blended learning a deeper understanding of the causes of individual differences of the use of learning resources is needed so the educational design process can be optimized. Dispositional data could be used to determine if differences in students their metacognition and motivation can explain differences in the use of learning resources and what the consequences of these differences are for student performance.

This research aims to answer the following questions:

Q1: Which differences in the use of learning resources can we distinguish?

Q2: Can these differences be explained by dispositional data?

Q3: Do these differences in the use of learning resources have an impact on student performance?

2 METHODS & MATERIALS

2.1 Participants

The participants were 516 freshmen law students (218 male, 298 female, Mage = 22.1, SD = 4.9) enrolled in a mandatory course on Contract Law. Students repeating the course or taking the course as an elective were removed from the results.

2.2 The Blended Learning Course

The course on Contract Law (CL) was an eight-week course. The course had a regular outline for each week.

On the first day of the week students were offered a regular face-to-face lecture in which theoretical concepts were addressed. These lectures were university style lectures, with the instructor lecturing in front of the class. The lectures were recorded and made available directly after the lecture had taken place and were accessible until the exam had finished. If parts of the lectures were unclear, students could use the recorded lectures to revise these parts or revise the entire lecture if needed.

The course consisted of 7 face-to-face lectures, with a 120-minute duration and a 15-minute break in half time. Lecture attendance was not mandatory. During the week several small workgroups were organized with mandatory attendance. Before these workgroups, students had to complete several assignments in the digital exercise book, which contains additional study materials, supplemented with three short essay questions. The students were expected to have studied the digital exercise book before entering the small workgroups. Responding to the short essay questions was not mandatory, but highly recommended by the instructor. In total there were seven exercises that contained short essay questions.

In the final segment of the week students were offered a case-based lecture in which theoretical concepts were explained with cases and specific situations of Contract Law. These seven case-based lectures were also recorded and made available directly after the lecture had taken place and were accessible until the exam had finished. All the recorded lectures were made available through the learning management system (LMS) Blackboard.

To finalize the week students could take a short formative assessment in which the concepts of the week were assessed. These formative assessments contained multiple-choice questions in which knowledge and comprehension were assessed. Completion of these formative assessments was not mandatory. In total there were seven formative assessments available to students.

2.3 Measurement Instruments

The data collected from all the online activities (recorded lectures, short essay questions, formative assessments) was supplemented with the collection of learning disposition data and attendance to the face-to-face lectures: the regular lectures and the case-based lectures.

2.3.1 Attendance to the Face-to-Face Lectures

During the entire time frame of the lectures, student attendance was registered on an individual level by scanning student cards upon entry of the lecture hall. The scanning continued until 15 minutes after the lecture had started. The presence of the students was registered for all fourteen lectures of the course, seven regular lectures and seven case-based lectures. Attendance to the regular lectures and the case-based lectures was separately registered in the database.

2.3.2 Use of the Recorded Lectures

The viewing of the recordings was monitored on an individual level and could be traced back to date, time, amount and part of the lecture viewed. For each lecture a separate recording was made, which made it possible to track the viewing trends for that specific recorded lecture.

2.3.3 Short Essay Questions

Since the digital exercise book was offered to students through the LMS, answers given to the short essay questions were also stored in the LMS. These answers were not scored, students were provided with model answers at the end of the week. The LMS registered if a student had answered the questions for that specific week.

2.3.4 Formative Assessments

For each formative assessment a log file within the LMS was created to determine if a student completed the formative assessment. For each separate assessment a log file was created. The participation for the multiple choice and short essay questions was stored separately.

2.3.5 Motivated Strategies for Learning Questionnaire

The Motivated Strategies for Learning Questionnaire (MSLQ) is a self-report instrument for students that assess both student motivations and their metacognitive ability to regulate learning (Pintrich et al., 1991). The MSLQ contains 81 questions of which 31 items determine a student's motivational orientation towards a course and 50 items to assess metacognition. The motivational orientation can be divided into six subscales: intrinsic goal orientation, extrinsic goal orientation, task value, self-efficacy, control beliefs and test anxiety. Metacognition can be scored on nine subscales: rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time and study environment, effort regulation, peer learning and help seeking. For a complete description of the MSLQ and each of its subscales we refer to the manual of the MSQL (Pintrich et al., 1991). For the purpose of this research we used four motivation scales (intrinsic goal orientation, extrinsic goal orientation, task value and self-efficacy) and three metacognition scales (critical thinking, metacognitive self-regulation and peer learning) since these different subscales can be, directly or indirectly, influenced by their educational design within a blended learning course.

The MSLQ was offered to students during the first week of the course. In the second week a reminder was sent out participants.

2.3.6 Final Grade

At the end of the course students took a summative assessment, which consisted of 25 multiple-choice questions and four short essay questions. Final grades were scored on a scale from 1 to 10 with 10 the highest and 5.5 as a pass mark.

2.4 Data Analysis

To establish differences in the use of learning resources a two-step cluster analysis with attendance data, use of the recorded lectures, essay questions and formative assessments was conducted. A two-step cluster analysis determines the natural and meaningful clusters that appear within an educational blended setting. The two-step method is preferred over other forms of cluster analysis when both continuous and categorical variables are used (Chiu et al., 2001) and when the amount of clusters is not pre-determined.

Next a MANOVA between the different clusters was conducted to determine significant differences in student motivations and their metacognition between those clusters (MSLQ). The MANOVA was used to determine if dispositional data could explain the existence of different clusters and subsequently the differences in the use of learning resources.

The last step in the data analysis was to conduct an ANOVA with cluster membership as a factor and with the final assessment as the dependent variable, to determine if differences in the use of the learning resources lead to significant differences in student performance.

3 RESULTS

To determine the natural occurring patterns based on the use of learning recourses a cluster analysis was conducted. As can be seen in Table 1 the auto-clustering algorithm indicated that four clusters was the best model, because it minimized the Bayesian Information Criterion (BIC) value and the change in them between adjacent numbers of clusters.

Table 1: BIC changes in de auto-clustering procedure.

Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change[a]	Ratio of BIC Changes[b]
1	2217.94		
2	1908.87	-309.06	1.33
3	1694.06	-214.82	1.54
4	1581.20	-112.86	2.27
5	1573.28	-7.92	1.11
6	1573.55	.28	1.04

a. The changes are from the previous number of clusters in the table.
b. The ratios of changes are relative to the change for the two-cluster solution.

Table 2 provides insight into the four different clusters and their use of the learning recourses. For each cluster the means of the use are presented as well as the means for the entire population.

Students in cluster 1 hardly attend any of the regular and case-based lectures; they hardly use the short essay questions or the formative assessment but show an average use of recordings of the lectures. They seem to have a slight preference to watch the recordings of the face-to-face lectures over the case-based lectures. Students in cluster 2

Table 2: Means of the learning data of the clusters.

		Lectures		Case-based Lectures		Short Essay		Formative Assessments		Recorded Lectures (minutes)		Recorded Lectures: Case Based (minutes)	
Cluster	N	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
1	103	.28	.63	.12	.35	.53	.99	.49	.87	612	528	384	417
2	143	1.52	1.79	.17	.43	4.58	2.00	3.23	2.03	245	234	209	215
3	186	.39	.86	.21	.57	5.80	1.36	4.83	1.91	1013	421	740	493
4	84	4.80	1.87	2.43	1.83	5.68	2.07	4.93	1.93	301	363	371	326
Total	516	1.40	2.06	.54	1.19	4.39	2.57	3.53	2.45	604	516	462	447

attend some regular lectures, but they hardly attend any of the case-based lectures. They show an average activity on the use of the short essay questions and formative assessments. Students in cluster 3 hardly attend any of either type of face-to-face lectures, but they compensate their lack of attendance by watching the online recordings of both types of lectures. They show an above average activity on the assessments with a slight preference for essay over multiple-choice questions. Students in cluster 4 attend a well above average amount of the face-to-face lectures. They also show an above average activity on the assessments, but with a slight preference for multiple-choice questions over short essay questions. They show a modest use of the recorded lectures.

To determine if the occurrence of these different clusters could be explained by dispositional data, we determined if there were significant differences between the scores on the subscales of the MSLQ between the four clusters. In total 103 students filled out the MSLQ, which is 20% of the population. First the reliability of the subscales of the MSLQ was calculated. These results can be found in Table 3

The reliability of the subscales intrinsic goal orientation, extrinsic goal orientation and metacognitive self-regulation seems to be insufficient. Therefore these subscales were eliminated for further analysis. The low reliability of the subscales is party caused by the limited items that are used to measure these subscales (n=4) and by the lower participation rate.

To determine which subscales of the MSLQ differ significantly between the four clusters a MANOVA was performed. Since the four clusters differ in size, a GT2 Hochberg was chosen to calculate the post-hoc analysis. The results show that only the scales of self-efficacy and peer learning differ among the four different clusters.

Cluster 1 students have a high self-efficacy (M=5.03, SD=1.09) while cluster 4 shows a low self-efficacy (M=4.35, SD=.72). Cluster 4 students also show a strong preference for peer learning (M=3.52, SD=1.28), as do students in cluster 2 (M=3.55, SD=1.34). On the other hand cluster 3 students tend to dislike learning with peers (M=2.49, SD=1.16). The occurrence of the four different clusters can, to some extent, be explained by the dispositional data. To be more specific, the learning dispositions that show a significant difference between the four clusters are the tendency to (dis)like learning with peers and the sense of competence on the subject matter.

Table 3: Reliability of the subscales of the MSLQ (n=103).

	Reliability (Cronbach's Alpha)
Subscale	
Motivation	
Intrinsic goal orientation	.45
Extrinsic goal orientation	.51
Task value	.76
Self-efficacy	.90
Learning strategies	
Critical thinking	.76
Metacognitive self-regulation	.65
Peer learning	.72

To establish if the different patterns in the use of learning resources and subsequently cluster membership lead to differences in student performance, an ANOVA was performed with cluster membership as the factor variable and the final grade as the dependent variable. A GT2 Hochberg performed the post-hoc analysis since the clusters differ in size. The results of the ANOVA can be found in table 4.

Results of the ANOVA showed that students in cluster 1 and 2 have significant lower course performance than students in cluster 3 and 4. There is no significant difference in course performance between students in cluster 3 and cluster 4.

Table 4: Average score on the assessment for the different clusters.

Cluster number	N	1	2
1	103	4.04	
2	143	4.44	
3	186		5.16
4	84		5.41

Note: α = 0.05

4 DISCUSSION

The current study explores the different usage patterns by students of (digital) learning resources. It tries to establish the causes for these differences by using dispositional data and determines the effect of these different usage patterns on student performance.

Results indicate that there are four usage patterns of the learning resources as defined by a two-step cluster analysis. These differences in user patterns show similarities with previous determined profiles of technology uses in a blended learning setting: the no-users (cluster 1), superficial users (cluster 2), selective active users (cluster 3) and intensive active users (cluster 4) (Lust et al., 2013; Kovanović et al., 2015). However, our results revealed that cluster 3 students show a clear preference for online learning activities and avoid face-to-face activities and are hence called the selective online users.

When adding dispositional data, gathered by the MSLQ, to the four clusters we see some emerging patterns that could explain the causes for differences in the use of (digital) learning resources. The no-users in cluster 1 are characterized by a high score on the subscale of self-efficacy, which may indicate that they tend to overestimate their performance at the beginning of the course and they are confident they will do well. This overestimation presumably leads them to decide against attending face-to-face lectures or using the online assessment tools to determine if they master the subject matter.

The superficial users, cluster 2, are a more balanced group showing a moderate activity on the use of all learning resources. Although the MSLQ showed no significant difference in the subscales for this group, they have the lowest score of the four clusters on the subscale extrinsic goal orientation. Their desire to do well in this course is less evident compared to the other clusters. This lack of desire reflects in their superficial use of learning resources: they use most learning resources in a modest way, just enough to get by but eventually they fail the course.

The selective online users in cluster 3 tend to dislike peer learning. Their tendency to avoid their peers reflects in their behaviour to compensate their lecture attendance with online recordings. They show a slight preference for open essay questions relative to multiple-choice questions. This usage pattern reflects a mastery approach towards although their lack of lecture attendance would suggest otherwise, as indicated by Wiese and Newton (2013). They suggest that students with a surface learning strategy tend to use learning technologies as a substitute for other learning activities. However, current research shows that students with a mastery approach do substitute face-to-face lectures with online recordings of these lectures.

The intensive active users in cluster 4 visit the face-to-face lectures most frequently and are distinguished by a low level of self-efficacy. A low level of self-efficacy suggests they are insecure about their performance in the course. They primarily visit the face-to-face to find reassurance via the lecturers or their peers. This need for reassurance is reflected in their use of formative digital quizzes, in which they prefer to use the multiple-choice questions above the short essay questions. They have a need to assess and reflect on their progress and performance.

In the current research dispositional data play only a minor role in explaining the differences between usages of the different learning resources. This is in contrast with Tempelaar et al. (2015) who found that learning disposition data serves as a good proxy at the start of the course for predictive modelling. The students in the research of Tempelaar et al., (2015) are more diverse, often with an international background.

Differences in the use of learning recourses do have an impact on student performance. Learning analytics is often used to predict student performance and to model learning behaviour (Verbert et al., 2012) but more important is its purpose to detect undesirable learner behaviour during a course and adapt the blended course design so the probability that these behaviours occur is reduced and redirected. For example, students in cluster 1 tend to overestimates their skills, resulting in an underuse of the learning resources. This cluster would benefit from an educational design that allows students to gain insight into their own overestimation.

One of the claimed advantages of blended learning is that students gain control over their own learning path and take responsibility for their own learning (Lust et al., 2013; Orton-Johnson, 2009). This research shows that students display variety in the use of learning resources and are designing their own learning paths or creating their own blends. However, while these different learning paths do reflect control of the student, these self-composed learning paths do not necessary lead to better course performance. The teacher centred approach, in which the 'right' technology and learning path for the student have been chosen supplement the course (Oliver and Trigwell, 2005), is not well embedded in the current educational design of blended learning, which implies that using a specific learning technology is the learner's decision (Lust et al., 2011). A more student-centred approach contains an embedded design of these learning technologies in which the design either addresses or avoids these individual differences and consequently redirects unwanted behaviours. Students need certain guidance in how to combine learning resources into an effective learning strategy (Inglis et al., 2011) since many students don't seem to master the metacognitive skills required to control their learning (Lust et al., 2011) and subsequently do not choose the learning resources that are the most effective for them.

The use of data from online learning—learning analytics—supplemented with dispositional data gives valuable information about how and why students use certain learning resources in a blended course. The use of dispositional data confirms recommendations made by Shum and Crick (2012) wherein they conclude that learning analytics research should be contextualized with a broader set of indicators.

4.1 Limitations of Current Research

This research uses contextualized data for learner data analysis in a blended learning setting. However, even when this context is added, it still reduces the use of learning resources to visits, clicks and scores on questionnaires. Research on blended learning using learning analytics should focus on learning and ask questions like "What did people learn from attending this lecture?" rather than, "Did people attend this lecture?"

Another limitation of the current research is the known calibration and inaccuracy problems with self-reports about study tactics (Winne and Jamieson-Noel, 2002). Students often consider themselves as self-regulated learners while the tactics they use to regulate their learning are ineffective. Moreover, even within a single course these self-reports about regulation of learning differ as a function of the task before them (Winne, 2006).

5 CONCLUSIONS

This study showed that there are distinct patterns between students, which reflects the differences in use of learning resources in a blended learning setting. These distinct patterns cause a gap between blended teaching and learning, with different patterns leading to differences in student performance. These distinct patterns can be partially explained by learning dispositions: student motivations and their metacognitive ability to regulate learning. Especially the subscales self-efficacy and peer learning show significant differences between different groups of students. Students with a low self-efficacy have a tendency to engage in all the learning resources and choose face-to-face lectures over recorded lectures. Students with high self-efficacy are confident they will do well in the course, which causes them to hardly use the learning resources. Students with a low sense of peer learning tend to choose lecture recordings over face-to-face lectures. They use these as a substitute for lecture attendance.

Although the majority of the subscales of the MSLQ do not show a significant difference between the four groups of students, they provide us with new insights in the gap between blended teaching and blended learning. The suggestion of Shum and Crick (2012) to combine learner data with learner dispositions seems to lead to new insights into why students do or do not use certain learning technologies and what the consequences of these (un)conscious choices are in relation to student performance.

This research shows that when designing a blended learning course, the individual differences in the use of learning resources needs to considered, but moreover it supports the finding that students needs specific guidance in the determine what is the 'right' (digital) learning resource(s) that supports their learning.

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