VU Research Portal

Investigating the Relationships Between Online Activity, Learning Strategies and Grades to Create Learning Analytics-Supported Learning Designs

Schmitz, Marcel; Scheffel, Maren; van Limbeek, Evelien; van Halem, Nicolette; Cornelisz, Ilja; van Klaveren, Chris; Bemelmans, Roger; Drachsler, Hendrik

published in
Lifelong Technology-Enhanced Learning
2018

DOI (link to publisher)
10.1007/978-3-319-98572-5_24

document version
Publisher's PDF, also known as Version of record

Investigating the Relationships Between Online Activity, Learning Strategies and Grades to Create Learning Analytics-Supported Learning Designs

Marcel Schmitz[1(✉)], Maren Scheffel[2], Evelien van Limbeek[1], Nicolette van Halem[3], Ilja Cornelisz[3], Chris van Klaveren[3], Roger Bemelmans[1], and Hendrik Drachsler[2,4,5]

[1] Zuyd University of Applied Sciences, Heerlen, Netherlands
{marcel.schmitz,evelien.van.limbeek,roger.bemelmans}@zuyd.nl
[2] Open Universiteit, Heerlen, Netherlands
{maren.scheffel,hendrik.drachsler}@ou.nl
[3] Vrije Universiteit, Amsterdam, Netherlands
{n.van.halem,i.cornelisz,c.p.b.j.van.klaveren}@vu.nl
[4] Goethe University, Frankfurt, Germany
[5] German Institute for International Educational Research (DIPF), Frankfurt, Germany

Abstract. Learning analytics offers the opportunity to collect, analyse and visualise feedback on learning activities using authentic data in real-time. The REFLECTOR project was used to investigate whether there are correlations between students learning strategies, their online activity and their grades. Information about the learning strategies was obtained using the Motivated Strategies for Learning Questionnaire. The grades and the online activity of students for two pilot courses was collected from the log data of the learning management system. Analysis of the collected data showed that there are moderate correlations to be found, for instance between metacognitive self-regulation, documents that are related to planning and grades. The pilot sessions taught us that there are practical issues with regards to data storage location as well as data security that need to be taken into account when learning analytics is integrated into existing learning designs. Overall, the project results show that a close relationship between learning analytics and the learning design of courses is urgently needed to make learning analytics effective.

Keywords: Learning analytics · Learning design
Learning strategies · Online activity · Grades · Correlations
Pilot study

1 Introduction

Learning analytics [6] is used for research, studies and applications that try to understand and support the behaviour of learners based on large sets of collected data. As introduced by Buckingham Shum [14], it can provide different

V. Pammer-Schindler et al. (Eds.): EC-TEL 2018, LNCS 11082, pp. 311–325, 2018.
https://doi.org/10.1007/978-3-319-98572-5_24

levels of insights, i.e. on the micro-, meso- and macro-levels. The micro-level addresses the needs of teachers and students and aims at a single course; the meso-level addresses a collection of courses and provides information for course managers; the macro-level takes a bird view on a directory of courses and can provide insights for a whole community by monitoring learning behaviour across courses and even across different scientific disciplines. The main opportunities for learning analytics as a domain are to unveil and contextualise so far hidden information out of the educational data and prepare it for the different stakeholders.

The current study investigates whether learning analytics can support individual learning or teaching processes on the micro-level. Teachers are able to make more evidence-based design decisions using learning analytics when running a course and students are enabled to change learning behaviour based on the insights they get to make their learning process more efficient, effective and fun [12]. Although there is a rather rich sample of learning analytics tools available, we rarely see educational concepts being used as the basis for those tools or any learning analytics indicators being embedded in a learning/instructional design as a measure point for educational interventions so that they can be used for reflection and feedback for students and teachers [15]. Also, in reviews like those by Jivet et al. [8], Schwendimann et al. [13] or Park et al. [10] many learning analytics tools are mentioned but only few of them work in real-time and none specifically cope with learning analytics-supported learning design.

Higher education institutes (HEIs) in the Netherlands had the opportunity to use the SURF Learning Analytics Dashboard (SURF-LAD) within some of their courses. The SURF-LAD gives insight in several online activities within the learning management system (LMS) of that institute. Around this SURF-LAD usage the REFLECTOR project was formed. Two institutes that were going to use the SURF-LAD participated in REFLECTOR: Vrije Universiteit Amsterdam (VU) and Zuyd University of Applied Sciences (Zuyd). The project analyses data from the students usage of online learning material, their learning strategies, and their grades and investigates whether there are correlations between these three data sets. The VU participated with one pilot course and combined the result from their SURF-LAD with those from the online practice platform IHS[1] and Blackboard. The online activity specifically reported the difference in used tools and a self-regulated learning model [5] is used to examine if students ability to self-regulate their learning is related with the actual learning behaviours that can be observed in the LMS [7].

The study presented here describes the two pilot courses of the faculty ICT at Zuyd, during the REFLECTOR project. Here the SURF-LAD results were used with the LMS Blackboard. We were especially interested in the connection between learning analytics and the currently available learning design. A learning design describes the development and purposeful compilation of learning activities, i.e. one interaction or a set of interactions between a student and

[1] https://www.ihatestatistics.com/.

student(s), teacher(s) or learning material [1]. A learning design also outlines the resources and technologies needed to support these interactions. The result of such an interaction (i.e. learning goal achievement) is also part of the learning design [3,4].

On Zuyd's side of the REFLECTOR project two pilot courses were used to retrieve data. Every pilot course started with several pre-pilot meetings between teachers and technical support to set up the learning analytics within the course. Once the courses started, students were asked to participate and to provide some information about themselves as well as their learning data to the study. The research questions that guided our analysis of the collected data were:

RQ1: Are there any practical challenges that need to be taken into account when using learning analytics within an existing learning design and if so which ones?

RQ2: Are there any significant correlations between the students' learning strategies, their online activity and their grades and if so which ones?

2 Methods

2.1 Participants and Materials

The Pilot Courses. The two pilot courses were conducted at faculty ICT of Zuyd. The faculty strongly supports the learning philosophy of learning-by-doing, a learning process where students learn within tasks recognisable from the professional practice. Feedup, feedback, feedforward and (self-)reflection are thus essential parts of the learning design and the courses therefore demand a high level of self-regulation from the students [9].

In its overall educational design, the faculty makes use of ten achievement indicators. For the learning design of each course three to five of these achievement indicators are chosen and formulated within the context of the course using measurable aspects per indicator as that course's specific focus. The chosen indicators can have different weights. The weighted average grade (AG) is calculated. It even is possible that an indicator is that important that a student will not pass the course if the student does not have a sufficient grade for that indicator. Therefore an overall course grade (OG) was introduced that either depends on the average grade or on an achievement indicator grade that has to be passed. The faculty ICT at Zuyd uses the tool Faculty ICT Information Engine (FICTIE) to store results of every achievement indicator from every student. Both pilot courses had a blended learning set-up, i.e. both employed face-to-face as well as online learning activities. The majority of activities were face-to-face ones that were, however, supported by documents stored in the online learning environment.

The first pilot course was a first-year bachelor degree level course on 'Communication'. This course has four achievement indicators, i.e. tasks students have to do and that are then graded: a written exam (AI1), two individual assignments (AI2 and AI3), and group work participation (AI4). The course ran from May

2017 to July 2017. 135 students –5 female, 130 male– were enrolled in the pilot course. 91 students were in their first year at Zuyd, 44 students had already been at the institute in the previous year(s). Six teachers –three female, three male– were involved in the course. Two female teachers were involved in the preparation and evaluation of the SURF-LAD that was used in this course.

The second pilot course was a bachelor degree level course on 'Logics'. This course has three achievement indicators: a quiz (AI1), an individual assignment (AI2), and a group assignment (AI3). The course ran from September 2017 to November 2017. 177 students –14 female, 163 male– were enrolled in the pilot course. 131 students were in their first year at the institute, 46 students had already been at the institute in the previous year(s). Eight teachers –one female, seven male– were involved in the course.

Online Activity. The LAD provided by SURF is a teacher-facing dashboard that is meant to support teachers in their teaching processes. The dashboard is meant to raise awareness among teachers about what learning analytics and LADs can do. SURF pre-designed several possible scenarios and chose to add five of them for the REFLECTOR project. For every chosen event (e.g. click on a link, download of a file) the actions of every student are accumulated. This is displayed in several visualisations. There is a pie-chart which informs on the percentage of usage of that event for a user. Also there is a box-plot which shows the first, the last and the majority of times some type of learning material is used. There are several histograms to visualise usage of certain events. Another line graph shows how many students over time have accessed a specific event and how many students over time still had to.

Access to the SURF-LAD was embedded into the course's LMS via a direct link. The data collected for the SURF-LAD is stored and processed using the xAPI protocol [2]. By placing indicators, e.g. an empty picture or javascript, on pages in the LMS, a data entry is made to the database whenever a page is accessed, i.e. whenever the indicator is loaded. The decision where to place the indicators was made by the teachers involved in the study. They chose those documents within the course that are of particular interest with regards to the learning design. Thus, every click on a document or menu-item was counted as one data entry. As a back-up, the LMS logs were queried for the same actions.

The documents that were selected by the teachers for further analysis were: a learning activity plan for every week (OA2); a case description for the group work of weeks 7–9 (OA3); the Modulebook with information about the course (OA4); the achievement indicator overview document (OA5); a practice quiz (OA6) and the document with the correct answers to that quiz (OA7); learning material such as articles and videos (OA8); knowledgebytes, e.g. short video clips (OA9); the presentations used during the lectures (OA10); and the attempts students do to submit assignments (OA11).

The MSLQ. There are several instruments to measure learning strategies [9]. The Motivated Strategies for Learning Questionnaire (MSLQ) was used as it is a widely used, accepted and validated instrument [11]. The MSLQ consists of 81 items and is divided into fifteen sets (scales) that can be used separately. For each item, participants enter a rating from 1 for ‘totally not agree’ to 7 for ‘totally agree’. The fifteen scales are distributed among two categories: learning strategies and motivation. The learning strategy scales are: Rehearsal (M1), Elaboration (M2), Organisation (M3), Critical Thinking (M4), Metacognitive Self-regulation (M5), Time and Study Environment (M6), Effort Regulation (M7), Peer Learning (M8), and Help Seeking (M9). The motivational scales are: Intrinsic Motivation (M10), Extrinsic Motivation (M11), Task Value (M12), Control of Learning Beliefs (M13), Self-efficacy for Learning and Performance (M14) and Test Anxiety (M15). The whole questionnaire –but especially the set of nine learning strategies scales– can give insight in the students own perception of their learning strategies. In addition to the MSLQ items, some demographic information was also included in the questionnaire, i.e. age, highest educational level, gender, and study specialisation.

2.2 Procedure

Before the courses started, pre-pilot meetings between teachers and technical support staff took place to set up the learning analytics that was to be used in each course. In pilot course 1, two teachers were asked to regularly evaluate the SURF-LAD throughout the course. The teachers received an introduction to the dashboard at the beginning of the course and were later contacted again to provide their evaluations. There were no specific questions for the evaluation. Teachers were asked to report on their personal impression.

During the the first week of pilot course 1, all enrolled students were invited to participate in the study by mail. During the second lecture the research project was presented in class and students were reminded of the invitation to participate. In the LMS there was a link during the entire course called ‘Experiment’. By clicking the link students were presented information about the experiment and a button to give consent on storing, analysing and visualising their learning data for the study. The invitation to fill in the MSLQ was sent to students in the third week of the course by mail. The questionnaire contained an informed consent form where students could agree or disagree with the usage of their questionnaire answers and of their achievement indicator grades for the study. In week four students were reminded in class to fill in the questionnaire. It was distributed using Qualtrics[2].

For pilot course 2, an invitation to participate in the study by filling in the MSLQ and by agreeing to the collection and analysis of the online activity as well as of the achievement indicator grades, was sent to all students by mail in the first week. In week 3 the research project was promoted by the teachers in class. A personalised mail was sent to the students in week five to remind them of the study and the questionnaire. The questionnaire contained an informed consent form where students could agree or disagree to the collection and analysis of the

[2] https://www.qualtrics.com/.

questionnaire data, the online activity data and the achievement indicator data. The questionnaire for the second pilot course was distributed using Questback[3].

For both courses, the data from those students who gave their consent was exported from FICTIE. Only those achievement indicators used in the two courses were used. Answers to the two MSLQ runs were processed and the questionnaire results were calculated according to the MSLQ guidelines. For every scale the average of the items belonging to that scale were calculated. With regards to the data collected from the LMS, for each of the elements we stored the daily online activity per person, we calculated the accumulated online activity for that element per person and for all participants per course.

A Pearsons Correlation Matrix was used to compare the scores of the 15 MSLQ scales (M1-M15) with the students' eleven online activities (OA1-OA11), the MSLQ scores with the four achievement indicator grades (AI1-AI3 and OG), and finally, the online activities with the achievement indicator grades as well. The correlation coefficients were calculated to determine the strength of association between the different factors as well as the significance level. In order to examine the three sets of data further, a 31×31 scatter plot matrix was created for all elements. The matrix was then visually checked by three members of the research team. IBMs SPSS Statistics 24[4] was used for calculating the correlation and scatter plot matrices.

3 Results

3.1 Pilot Course 1: May 2017–July 2017

A few issues occurred during preparation and execution of the first pilot course. Some were related to the SURF-LAD, others to Zuyd's LMS. The first issue already occurred during the set-up of the SURF-LAD. Zuyd runs a local installation of Blackboard and due to security settings on the server SURF's preferred option of tracking the use of online resources with javascript was not possible. Empty pixels were used instead. This, however, also turned out to not fit all scenarios as one factor chosen by the teachers to be of interest was the weekly usage of several resources (i.e. presentations used in lectures). Faculty ICT, though, chose to combine all presentations of lectures into one document. Within this document there was an interactive menu to easily navigate through the content. The students' interaction within the document once they downloaded it could of course not be tracked and thus no xAPI statements could be generated in order to feed the visualisation of the SURF-LAD. Therefore, a specific measurement per presentation and lecture was not possible.

Another issue was that faculty ICT has set up their educational logistics in such a way that all content is stored in one part of the LMS while the learning analytics tools only worked on another part of the LMS. For the first pilot course

[3] https://www.questback.com.
[4] https://www.ibm.com/products/spss-statistics.

a work-around was thus created by redesigning the educational logistics specifically for this course. A third issue occurred with embedding the functionality of opt-in / opt-out of the study's data collection for the students due to local security settings on the Blackboard server. Another work-around was created by embedding the SURF-LAD as a website via an iframe. Due to these issues it was decided to also collect the required online activity by querying the Blackboard database as a backup.

Soon after pilot course 1 started and students had been told about REFLECTOR, however, it became clear that the second work-around had its own limitations. Students at the faculty ICT log in with their own device on a closed network. Because of security settings in the network the SURF-LAD system did not store the permission status of the student. This led to students being asked to opt-in to the data collection every time they accessed the online course and having to click through a number of items in order to give permission. In addition to this, both the SURF-LAD as well as the Blackboard installation at Zuyd suffered from technical issues. The LMS, for example, was down for an entire week.

During pilot course 1 the SURF-LAD was configured, used and evaluated by two teachers. The teachers were impressed with the ability to get insights in the usage of learning material. In the setup of the SURF-LAD insight could be given on how much and when material was used by a group of students, and what the percentage of usage was per anonymised user. The SURF-LAD had no specific student dashboard. The dashboard for the teachers did not have the possibility to track an individual student's usage. The teachers recommended this as an addition. Eventually, only the activity of 16 students was collected and visualised to the teachers in the SURF-LAD. Only two of those students filled in the MSLQ and made their grades available. We thus chose not to perform any analysis on this small sample size.

3.2 Pilot Course 2: September 2017–November 2017

The SURF-LAD environment was not used within this pilot course as the technical issues encountered in pilot course 1 could not be addressed in time. Online activity was measured by using the activity logs from Blackboard. The queries used on the Blackboard database provided the same information as the SURF-LAD tool did in pilot course 1. There were 52 students that filled in the MSLQ, seven of them did not agree to their data being used for the study when filling in the informed consent form. We were thus able to use the MSLQ results, the online activity and the achievement indicator grades from 45 students –1 female and 44 male– aged on average 20.13 years. Table 1 shows the descriptive statistics of the MSLQ results.

Figure 1 shows an overview of the online activity related to the presentation document used in the course. We distinguish the following sections: In the first six weeks students participated in lectures and did some assignments. Then there was a holiday week. After that there were three weeks (7–9) to conduct a group

Table 1. Descriptive statistics of results for the 15 MSLQ scales in pilot course 2

		N	Min.	Max.	Mean	Std.Dev.
Rehearsal	M1	44	1.00	6.50	4.74	1.09
Elaboration	M2	44	3.33	6.33	4.87	0.85
Organization	M3	43	1.00	6.25	4.26	1.15
Critical Thinking	M4	45	2.00	6.40	4.03	1.07
Metacognitive Self-regulation	M5	42	1.92	5.58	4.17	0.88
Time and Study Environment	M6	44	2.63	6.38	4.60	0.82
Effort Regulation	M7	44	2.25	7.00	4.85	1.02
Peer Learning	M8	44	1.33	6.67	4.33	1.20
Help Seeking	M9	42	2.25	6.75	4.86	1.03
Intrinsic Goal Orientation	M10	44	3.75	6.75	5.41	0.66
Extrinsic Goal Orientation	M11	44	1.00	7.00	4.83	1.10
Task Value	M12	45	3.67	6.83	5.54	0.71
Control of Learning Beliefs	M13	44	4.00	6.75	5.52	0.62
Self-Efficacy for Learn. & Perf.	M14	45	2.50	6.88	4.99	0.97
Test Anxiety	M15	45	1.80	7.00	4.00	1.36

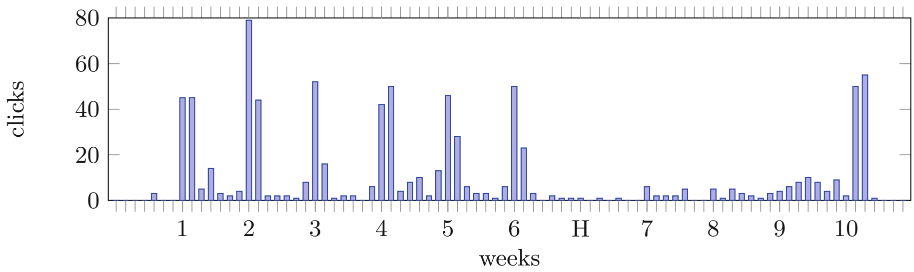

Fig. 1. Usage (y-axis) of the presentations document throughout the weeks (x-axis) of the course; H = holiday week

assignment. In the closing week (10) assignments had to be submitted and a final quiz was done on the 15th of November.

In Fig. 2 we see the usage of the case description document. In the beginning of the course (first days) there was a higher amount of students that wanted to know what the groupwork (i.e. the case) in weeks 7–9 is about. The three weeks when students were supposed to work on the case had higher online activity values. In the overview of planning documents (activity plan, modulebook and achievement plan) shown in Fig. 3 we can see a big spike for the activity plan in the first days of the course, especially with respect to the usage of it in the

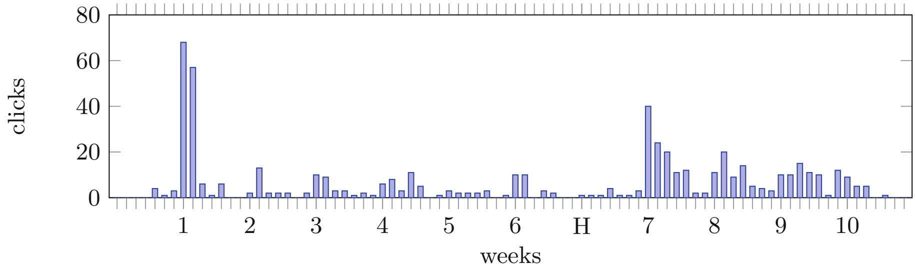

Fig. 2. Usage (y-axis) of the case description document throughout the weeks (x-axis) of the course; H = holiday week

remaining weeks of the six week period. It might be the case that the activity plan is downloaded in the first week and then used on a local computer or copied into a personal agenda. We do not have the instruments at the moment to account for this. Also interesting is the second boost of usage of the achievement plan because it is almost as big in the three weeks of the case as it is in the first week of the course. The reason could be that deadlines for delivering assignments are planned in the beginning of week 7 and week 10.

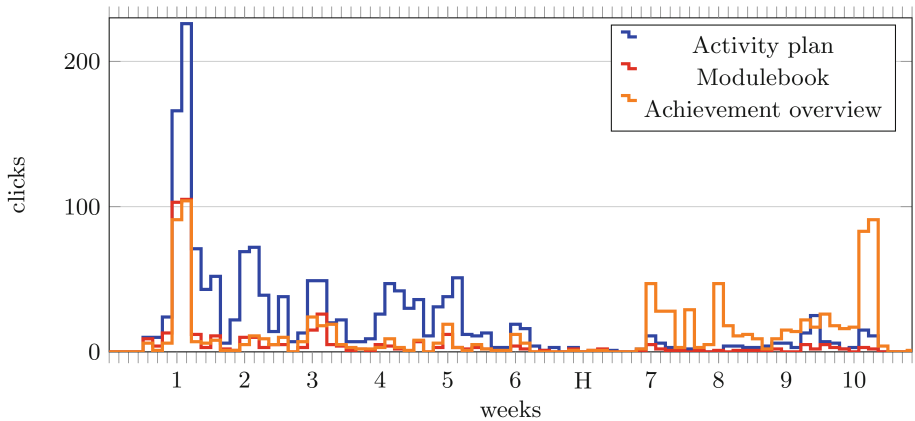

Fig. 3. Usage (y-axis) of the activity plan, modulebook, and achievement overview documents throughout weeks (x-axis) of the course; H = holiday week

Table 2 shows the result of the Pearson correlation matrix used to investigate if there are any correlations between learning strategies and online activity. It needs to be noted that all of these correlations are just that: correlations. They are not to be seen as predictive. There are several significant correlations: The accumulated online activity (OA1) of a student and the activity plan (OA2) moderately negative correlate with test anxiety (M15). The usage of the modulebook (OA4) correlates moderately negatively with the scales intrinsic goal

Table 2. Correlation learning strategies (M1–M15) - online activity (OA1–OA11)

	OA1	OA2	OA3	OA4	OA5	OA6	OA7	OA8	OA9	OA10	OA11
M1	.142	.094	.040	.107	.189	−.181	.149	.153	.185	.279	−.375*
M2	.082	.120	.141	−.017	.011	−.301*	.115	−.003	.045	.151	−.339*
M3	.055	.006	.033	−.018	.104	−.480**	.121	.124	.164	.274	−.361*
M4	−.041	−.012	.124	.017	−.066	−.105	.181	−.154	−.078	−.063	−.117
M5	.185	.147	.201	.087	.209	−.427**	−.023	.177	.045	.297	−.430**
M6	.177	.194	.075	−.005	.096	−.154	.157	.121	−.043	.267	−.416**
M7	.199	.151	.149	−.251	.135	−.088	.259	.222	.143	.293	−.341*
M8	.011	.055	.075	−.007	−.016	−.186	.058	−.025	−.122	.062	−.113
M9	.122	.136	.097	−.263	.008	−.057	−.124	.145	.056	.014	.017
M10	−.195	−.171	−.156	−.310*	−.103	.077	.203	−.182	.036	−.032	−.099
M11	−.138	−.147	−.007	−.228	−.074	−.105	.200	−.165	−.083	−.055	−.237
M12	−.078	−.121	−.055	−.325*	.041	.207	.177	−.011	.171	.031	.226
M13	.040	.064	−.068	−.187	.182	−.043	.017	−.012	.107	−.110	.228
M14	.016	.130	−.133	−.374*	−.065	.356*	.168	−.096	−.030	−.008	.002
M15	−.298*	−.308*	−.040	.151	−.234	−.068	.000	−.256	−.161	−.213	.127

The correlations marked with * have a significance at the 0.05 level, those marked with ** have a significance at the 0.01 level.

orientation (M10), task value (M12) and self-efficacy for learning performance (M14). The practice quiz (OA6) moderately negatively correlates with elaboration (M2), organisation (M3) and metacognitive self-regulation (M5). And the amount of attempts to send in assignments and portfolio material (OA11) moderately negatively correlates with rehearsal (M1), elaboration (M2), organisation (M3), metacognitive self-regulation (M5), time and study environment (M6) and effort regulation (M7). All these are negative correlations which means the higher the students perception of their learning strategy/motivation, the lower their usage of the online document. There is only one significant positive moderate correlation and that is between the practice quiz (OA6) and self-efficacy for learning and performance (M14). Thus, students that rank their self-efficacy for learning as high, tend to use the practice test often.

Table 3-(a) shows the results of the Pearson correlation calculation between learning strategies and grades. There were again several significant correlations: The metacognitive self-regulation scale (M5) had a negative moderate correlation with the grade of the written exam (AI1), the grading from portfolio of the case (AI3), the weighted average (AG) and the final grades (OG). Help seeking (M9) and Task value (M12) had a moderate positive correlation with AI2 (grading of the assignments during the first six weeks), Task value (M12) also had a positive moderate correlation on the final grade (AG). And the Self Efficacy for Learning Performance scale (M14) had a positive moderate correlation to AI1. To see if there is a relation between online activity and the grades, another set of Pearson correlation coefficients was calculated. The results are shown in Table 3-(b). There is a positive moderate correlation between the practice test (OA6), AI1 and the final grade (OG). There is a significant positive correlation

Table 3. Correlation between learning strategies and grades (a) and between online activity and grades (b)

	AI1	**AI2**	**AI3**	**AG**	**OG**
M1	-.190	.025	-.121	-.124	-.177
M2	-.066	.033	-.065	-.048	-.112
M3	-.074	.142	-.103	-.034	-.037
M4	-.196	-.178	-.170	-.217	-.187
M5	-.394**	-.186	-.353*	-.385*	-.401**
M6	-.047	-.030	-.128	-.094	-.122
M7	.063	.091	-.011	.046	.019
M8	-.166	.199	-.148	-.072	-.158
M9	.040	.307*	.024	.127	.057
M10	.094	.132	-.008	.071	.152
M11	.025	-.019	.020	.013	.026
M12	.237	.447**	.182	.325*	.364*
M13	-.011	.256	.108	.138	.102
M14	.343*	.231	.022	.207	.210
M15	-.124	-.246	-.117	-.186	-.162

(a)

	AI1	**AI2**	**AI3**	**AG**	**OG**
OA1	.102	.196	.135	.172	.204
OA2	.108	.113	.064	.109	.155
OA3	.084	.106	.128	.132	.134
OA4	-.012	.002	.163	.084	.084
OA5	.063	.255	.166	.194	.241
OA6	.318*	.174	.166	.257	.320*
OA7	.369*	.241	.048	.233	.269
OA8	.027	.233	.156	.169	.170
OA9	-.066	.192	.144	.117	.123
OA10	-.021	.169	-.016	.039	.095
OA11	.213	.302*	.221	.291	.371*

(b)

*The correlations with * have a significance at the 0.05 level, those with ** have a significance at the 0,01 level.*

Table 4. Planning related information

	n	AG	Avg.OA2	Avg.OA4	Avg.OA5
Total	45	6.8	30.4	2.9	6.8
M5 $>$ 4.5	17	6.1	33.7	2.8	7.7
M5 $<$ 3.5	11	7.8	29.1	2.1	5

between the amount of attempts to post material (OA11) and AI2 and the final grade (OG). And we see a significant moderate correlation between the solution of the practice test (OA7) and the written exam (AI1).

A relationship that draws attention is the moderate negative correlation between metacognitive self-regulation (M5) and most grades (AI1, AI3,AG, OG). This means that students that score high on that scale have low grades, and students that have low grades, score high on that scale. Table 4 shows that students that score high on their metacognitive self-regulation scale (M5) have a higher average usage of all planning documents. The low scoring metacognitive self-regulation scale (M5) students have a lower average usage of the planning documents.

To search even further for relationships the data mining technique of making a scatter plot matrix was used. Three researches did a visual search on the 31×31 matrix. Every cell is a scatterplot from two of the variables from MSLQ, achievement indicators and online activity documents. Every cell was looked at. From the scatterplot matrix no leads for further investigations were found.

4 Discussion

While preparing and running the pilot courses we saw some practical issues. In order to answer the research questions posed at the beginning of this study, we have compiled several recommendations and lessons learned. Even though not all of them are to be seen as new to the research community in general, we compile them here as an overall output from what was encountered at faculty ICT of Zuyd as they most likely will also apply to many other institution. Recommendations R1–R4 are presented for future experiments when using learning analytics in existing set ups of learning design, educational logistics and security of servers and networks. The second pilot course and analysis from the data led to insights in the learning design of faculty ICT. Lessons learned L1–L5 are defined based on that.

R1: Learning design should have elements that can be measured. At faculty ICT there is a distinction between several achievement indicators and the aspects with which the indicators can be graded. There also is a clear connection between the learning activities and the achievement indicators. This provides a measurable learning design.

R2: Take measurement of efficiency and effectiveness of learning in consideration while connecting learning activities and achievement indicators. In the design phase of the pilot courses there were connections made between learning activities and achievement indicators but the efficiency and effectiveness of learning and how it can be measured was not taken into consideration at design time. Doing this may improve the indicators and thereby better learning analytics for learning design.

R3: Store learning material in a way it can be measured. A very specific issue we encountered is the way that learning material was stored in the LMS for our courses. This was problematic because the tool used to collect and visualise the learning data did not work due to the originally envisioned method of collection and storing. Location, security settings on the server level and security settings on the network level have presented themselves as problematic during the REFLECTOR project.

R4: Further investigate if and how students want to share learning data from their own devices. Looking at the activity in Figs. 2 and 3 we see almost double the amount of activity in the first days. The reason for this could be that part of the students download the learning material on the first day onto their own device and then never go to that specific material in the LMS again. To be sure that this is the case more information is needed either on what is downloaded or what is used on the device of a student. Questions to answer are how this can be done and under which conditions students are prepared/willing to do this?

L1: Students do not prepare for lectures. It is by design that at faculty ICT all presentations are made available to students before a lecture in order for students to be able to prepare themselves for the lecture. Table 1 shows that the presentations are most used on the day of the lecture.

L2: Students use the presentations most during the lecture. Our analysis on the usage of the presentations shows that the majority of usage is during the lecture. Students use their laptop during the course to look at the presentation on their screen while the teacher is presenting it on the stage. The amount of usage of the documents before the lecture is minimal.

L3: Practice test and solution are hardly used. The two learning activities of taking an example quiz and reviewing the example quiz are designed in order for students to be prepared optimally for the quiz in the last week of the course. Usage, however, is minimal, just one or two students in our sample group made use of the test.

L4: There is a negative moderate correlation between metacognitive self-regulation and grades. Interesting to see is that the group of students that score "high" (>4.5) on the metacognitive self-regulation scale (M5) have a lower average grade (AG) (Table 4). This observation is in line with the moderate negative correlation of this scale with the grades from Table 3. When we look at how online material is used, then we see that this is in line with the learning strategy scale value. Further research is needed to see whether the learning material used has to be improved or whether these students have too high an esteem of their self-regulating capabilities.

L5: Significant correlations can be found. The example of the negative moderate correlation between metacognitive self-regulation (M5) and grades (AI1, AI3, AG, OG) shows us that significant correlations can be found, but more specific questioning and research is needed. More potential relationships can be searched this way, but specific research questions or hypotheses are needed.

Overall, statistically there were moderate relationships to be found between learning strategies, online activity and grades. It is interesting to further explore –with more data than the population of 45 we had now– if relationships based on choices in the learning design between learning strategies, online activity and grades exists. It will also be interesting to see how the addition from self-reports from students activity will define those relationships. More specified questions based on the learning design and the population are needed to get a clearer view on the relationships.

5 Conclusion

This paper describes our experiences of using learning analytics during two courses at a HEI. Data about online activity, students perception about their learning strategy based on the MSLQ and their grades were collected and analysed from a learning analytics-supported learning design perspective.

We observed that the chosen HEI has a learning design that has potential to be supported by learning analytics. Also, we observed that practical and technical issues still have to be resolved to get a big enough data set. From the relatively small dataset now we can already see the potential of statistical analysis. More specific questions such as "Do students with a high score on the rehearsal scale benefit from using the practice test often" or "Can we see the group work achievement indicator grade rise when students with a low score on peer learning read the collaboration article" rather than simply checking for correlations between certain factors can then be taken into account as well in order to investigate if valuable information for changing the behaviour of students in their learning processes or for improving the quality of learning activities by teachers can be obtained. Also, further statistical analyses like structural equation modelling to learn something about predictive relations between the observed factors will be interesting. The REFLECTOR project has shown us that learning analytics should be a talking point while designing learning activities and when deciding how learning material is supplied to students.

References

1. Beetham, H., Sharpe, R.: Rethinking Pedagogy For a Digital Age: Designing for 21st Century Learning. Routledge, New York (2013)
2. Berg, A., Scheffel, M., Drachsler, H., Ternier, S., Specht, M.: The Dutch xAPI experience. In: Proceedings of the 6th International Conference on Learning Analytics and Knowledge, pp. 544–545. ACM (2016)
3. Celik, D., Magoulas, G.D.: Approaches to design for learning. In: Chiu, D.K.W., Marenzi, I., Nanni, U., Spaniol, M., Temperini, M. (eds.) ICWL 2016. LNCS, vol. 10013, pp. 14–19. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-47440-3_2
4. Cross, S., Conole, G., Clark, P., Brasher, A., Weller, M.: Mapping a landscape of learning design: identifying key trends in current practice at the open university. In: European LAMS Conference, pp. 98–103 (2008)
5. Efklides, A.: Interactions of metacognition with motivation and affect in self-regulated learning: the MASRL model. Educ. Psychol. **46**(1), 6–25 (2011)
6. Greller, W., Drachsler, H.: Translating learning into numbers: a generic framework for learning analytics. J. Educ. Technol. Soc. **15**(3), 42–57 (2012)
7. van Halem, N., Schmitz, M., Drachsler, H., Cornelisz, I., van Klaveren, C.: Tracking patterns in self-regulated learning behavior in online learning environments: a case study. (to be submitted)
8. Jivet, I., Scheffel, M., Drachsler, H., Specht, M.: Awareness is not enough: pitfalls of learning analytics dashboards in the educational practice. In: Lavoué, É., Drachsler, H., Verbert, K., Broisin, J., Pérez-Sanagustín, M. (eds.) EC-TEL 2017. LNCS, vol. 10474, pp. 82–96. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-66610-5_7
9. Panadero, E.: A review of self-regulated learning: six models and four directions for research. Front. Psychol. **8**, 422 (2017)
10. Park, Y., Jo, I.H.: Development of the learning analytics dashboard to support students' learning performance. J. UCS **21**(1), 110–133 (2015)

11. Roth, A., Ogrin, S., Schmitz, B.: Assessing self-regulated learning in higher education: a systematic literature review of self-report instruments. Educ. Assess. Eval. Account. **28**(3), 225–250 (2016)
12. Schmitz, M., van Limbeek, E., Greller, W., Sloep, P., Drachsler, H.: Opportunities and challenges in using learning analytics in learning design. In: Lavoué, É., Drachsler, H., Verbert, K., Broisin, J., Pérez-Sanagustín, M. (eds.) EC-TEL 2017. LNCS, vol. 10474, pp. 209–223. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-66610-5_16
13. Schwendimann, B.A., et al.: Perceiving learning at a glance: a systematic literature review of learning dashboard research. IEEE Trans. Learn. Technol. **10**(1), 30–41 (2017)
14. Shum, S.B., Knight, S., Littleton, K.: Learning analytics. In: UNESCO Institute for Information Technologies in Education. Policy Brief (2012)
15. Wise, A.F., Shaffer, D.W.: Why theory matters more than ever in the age of big data. J. Learn. Anal. **2**(2), 5–13 (2015)