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APPLYING LEARNING ANALYTICS AND LEARNING DESIGN TO SUPPORT STUDY PROGRESS IN ONLINE COURSE – A CASE STUDY

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ABSTRACT

Universities of Applied Sciences (UAS) in Finland have invested extensively on providing online courses and digitalisation will continue to expand. Students are required to be increasingly self-directed. Development of learning analytics (LA) provides opportunities to support students study progress, however the starting point of implementing learning analytics (LA) has not traditionally originated from learning but from organisational or teacher perspectives. This case study applies LA in an online course aiming to boost students' self-directed learning (SDL) while completing learning tasks, within the Moodle environment. The effect of student progress visualisation and automated process-oriented feedback was explored. In addition, the changes in students' satisfaction towards the course (NPS) was explored. The preliminary results suggest that LA significantly enhances timely returns of learning tasks and might even increase course satisfaction. The results were emphasized among those students who had problems in timely returns of the tasks. The present results indicate that even easily applied LA can have a positive effect on task returns and possibly even on increased self-direction.

THEORETICAL BACKGROUND

In the last five years, universities of applied sciences (UAS) in Finland have invested extensively in providing online courses (e.g. Scheinin et al., 2018). According to the European University Association digitalisation in learning will continue to expand (Gaebel, 2021), which has partially increased the need for students' self-directedness (Song & Hill, 2007). Self-directed learners take more responsibility for their own learning, are proven to be and feel more confident and successful as learners compared to teacher-directed learners (Garrison, 1975; Knowles, 1975). In recent years, particular attention has been paid to the use of technology and on design of digital environments to support processes of self-regulated learning (SRL) and self-directed learning (SDL) (Durall & Gros, 2014; Song & Hill, 2007). These concepts are often considered synonymous and overlapping (Loeng, 2020). In this study the concept of SDL is used, since its origin the concept has been often used in the context of higher education and adult learning in non-formal learning environments, such as online learning (Durall & Gros, 2014).

Research highlights the significance of adult learner academic SDL in open-distance and e-learning contexts (Botha 2021, Zhao & Chen, 2016,1). Need for understanding and fostering SDL exists particularly in higher education online learning contexts which typically allow high levels of autonomy (Song & Hill, 2007). There has been growing interest in higher education in exploring how learning analytics (LA) could be used to support student engagement and to provide actionable feedback with LA for students (Silvola et al., 2021). However, comprehensive understanding is lacking in these learning processes and their support in online-environments with LA (Ifenthaler & Yau, 2020), even though case studies and empirical evidence exist in varying contexts and applications (Matcha et al, 2020).

LA has been defined as measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs (Siemens, 2013). Previously, the development of LA has focused on providing information for teachers rarely have students been considered as main receivers of LA (Dural & Gros, 2014), also implementation is often approached in a data-driven way and from the perspectives of organisations, not learners. Therefore, we lack knowledge on the effects of LA on student activities and learning. In UAS, LA is expected to support students' SDL as well as teachers' pedagogical practices (e.g. Viberg et al., 2018; Sclater et al., 2016). Analysing and supporting SDL with LA offers exciting opportunities, such as time management, self-monitoring or self-reflection for competence building (Roll & Winne, 2015) e.g. raising students awareness of their own learning process. One of the main values of LA for higher education students is that it can provide insights into their learning habits and offer recommendations (Siemens & Long, 2011).

According to Pardo (2014) designing the utilisation of LA can be divided into five chronological stages: collect, analyse, predict, act, and refine. The successful use of LA is based on careful consideration, e.g., designing the first 'collect stage' in a way that digital traces (footprints) of student activity enable supporting SDL. A digital footprint is data that users have left behind, e.g., traces of a student's activity in digital environment (e.g. Pozdeeva et al., 2021; Wang & Han, 2021). Virtual learning systems are diverse information technology-based environments, in which the learner interacts, e.g., with materials, teachers or peer students through technology. Typically, virtual learning systems conduct real-time LA exploring and processing learner behaviour and performance data and display the feedback as visualizations in dashboards (Wan & Han, 2021). For example, a student learning process, such as assignment completion progress can be visualised in a dashboard. Dashboards can be tailored, e.g., to promote awareness, self-reflection and sense-making (Verbert et al., 2013). Although visualizing the learning process has been recognized as an important issue (Deric et al., 2013), the content and visualized appearance of LA dashboards has not yet reached a consensus (Wan & Han, 2021) and research on the effects of various dashboard on students' behaviour, skills development and performance are contradictory (Bodily & Verbert, 2017). Often dashboards information has not originated from the pedagogical considerations or theory basis (Jivet et al., 2017) and therefore accumulated data can be completely insignificant to the student. In addition, it is also argued by Park & Jo (2015) that students are not used to interpret visualized data as part of their learning process. It would be assumed that students also need support in using LA to empower students' agency in using analytic tools as part of their learning (Ochoa & Wise, 2021).

Learning Management systems (LMS) such as Moodle, Blackboard etc. are platforms designed to manage online learning, typically including features such as individualized dashboards or tailored messaging systems applied as assisting tools for students' metacognitive process (e.g. Durall & Gros 2014; Verbert et al., 2013). Generally, LMSs offer the possibility of automated, process-oriented feedback. Furthermore, Moodle offers functionality (Completion Progress Block) for teachers and students to overview activities to be completed and the reengagement plugin (Reengagement activity) for teachers to use automatization to remind students or offer personalised up to date feedback (Moodle, 2022).

Satisfaction experienced in learning is beneficial for the students and furthers their self-directedness, thus it would be beneficial if students were actively involved in improving their online learning experiences. In order to utilize student-centred LA, it is important to involve them as feedback providers (Ochoa & Wise, 2021). Net Promoter Score (NPS) (see Grisaffe, 2007), a metric used in customer experience programmes, can be applied in business to measure customers' willingness to recommend a product or a service. NPS has also been applied in education, e.g., as a willingness to promote a course (e.g. Heilala et al., 2020; Aguilar et al., 2020). Since NPS is strongly influenced by scale structure, it is suggested to be used, interpreted, and compared with caution, something more like an indicator (Grisaffe 2007, p.50).

Our case study context is a blended course implementation in UAS, which had earlier received critical feedback from the students. The challenges emerged in both study progress within online phases of the course as well as in student satisfaction (low NPS score, see also Heilala et al., 2020). First, students were not progressing through the course in the expected manner and time, and second, the feedback received from the students remained poor, despite teachers' earlier attempts to improve the course content and structure. Intervention applying LA (approach by Lockyer et al., 2013) was launched 2020, aiming to boost students' SDL, help them to complete the course on schedule. Self-directedness appears as studies progress through completion of learning tasks. We applied LA plugins to Moodle to collect data on the effect of the improvements of the re-formulated course, the students' satisfaction was explored by using NPS.

RESEARCH QUESTIONS

The study was targeted at visualization (Completion Progress block) and automated guidance messages (Reengagement activity) applied by the online platform (Moodle), to study their effects on the study progress, specifically their learning task return activity. In addition, the student satisfaction for the course was gathered and compared to previously implemented course without LA. The main research questions were i) whether applying learning analytics (LA) has an effect in supporting students' study progress, and ii) whether it has an effect of the student satisfaction. Thus, more specific research questions were set: 1) Are there differences in the shares of timely returns of the learning tasks between control group and test groups? 2) Are there differences in overall return activity between control group and test groups? And 3) Are the distributions of the willingness to promote a course similar before and after re-formulation of the course?

RESEARCH DESIGN, INSTRUMENTS AND METHODS

This case study initiates practice-based research on the use of Learning Analytics (LA) to develop data-driven learning design, to support teaching and learning in higher education. The institutional context is a UAS in which an increasing number of courses are delivered in a blended or online mode. Our case study is situated in the context of a blended learning process in autumn 2020. The i) data of the study progress was automatically traced in Moodle while student return learning (RQ 1-2) tasks and ii) student feedback data on course satisfaction was collected (RQ3).

Research design

The course is a mandatory part of the degree programs for first- and second-year students. The participating students, total of 473 undergraduate bachelor- UAS students represent multiple study programs A research permit was applied from the UAS. Students were provided information on the research at the beginning of the course both through video and written material.

To enable supporting students SDL through LA, the course needed to be re-designed. The overall structure of the course and the pedagogical approach and total workload (ECTS) remained the same. The number of learning tasks increased from 5 to 14.

The course structure consisted of 3-phases (see Fig. 1). Independent online Phases 1 and 3 of the blended learning course were selected for the study.

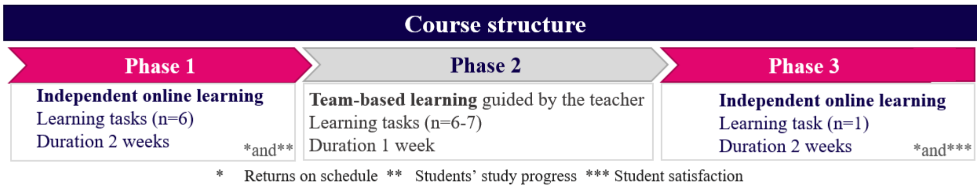

Figure 1: Re-designed course structure

The master Moodle course was created in which the learning process was visible to students through learning activities. Thereafter the course was copied to create 3 identical implementations, control course (Course 1) and test courses (Course 2-3). Varying types of LA, Moodle plugins, visualization of progress (Completion Progress block) and automated to process-oriented feedback (Reengagement activity) was added to the control courses according to learning design. Students were randomly divided into three courses (Fig. 2).

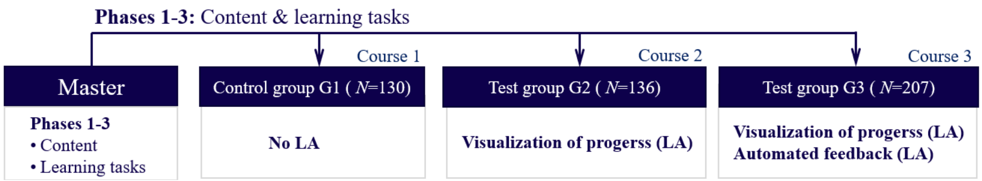

Figure 2: Experimental setup, courses and LA plugins.

NPS -score (Grisaffe, 2007) was utilised as an indicator of students' satisfaction with the changes made in the course and it was a question of willingness to promote a course on 0 (not at all likely) to 10 (extremely likely). To generate an NPS score, responses were sorted into one of 3 categories: Promoters (a score of 9 or 10), passives respond (a score of 7 or 8) and detractors (a score of 0 to 6). The NPS score is the difference between the percentages of promoters and detractors.

Research instruments and methods

The study focuses on the first and third, independent online phases of the course (see Fig. 1). The students' study progress was measured by data generated automatically by Moodle while completing a total of 7 learning tasks. Each learning tasks had predetermined return dates. The students' returns were classified: returned on schedule (2), returned late (1) and not returned (0). Additionally for each student and task, a new variable was created as an indicator of timely return (returned on schedule (1), returned late and not returned (0)).

First examination targeted the **return activity** of learning tasks, i.e., whether each had been returned on schedule. This preliminary review focused on comparing indicator, timely returns. For the analyses, each learning task was examined separately and the differences between the shares of timely returns in control and test groups were analyzed by using Pearson Chi-Square -test. Data analysis was performed with IBM SPSS (28.0).

Second, to examine students' **study progress** the return activity variable (RAV) was generated by calculating a sum variable from classified students returns [0,2]. This statistical examination was targeted at the first independent phase (Phase 1), as Phase 2, team-based learning that was guided by a teacher was expected to affect student study progress during Phase 3 also. All students who dropped out during Phase 1 (*N*=3) were excluded from the review.

RAV1 was employed to examine students' return activity response to varying LA. The RAV1 range was [0,12] for the six learning tasks in Phase 1. Thereafter, the students who had returned all their learning tasks on schedule were excluded. RAV2 indicates students' return activity, where RAV2 was [0,11]. As expected, RAVs were not normally distributed but of similar shape and range. The differences between the three groups were analysed with two-by-two comparisons by using the non-parametric Mann-Whitney U test (see Fig. 3).

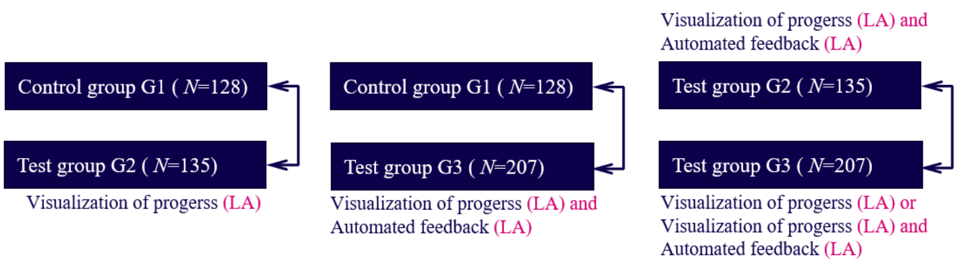

Figure 3: Comparison groups for Mann-Whitney U -test

Thirdly the student study satisfaction and willingness to promote the course was explored according NPS. The NPS score was compared respectively for both 2018 and 2020, and within 2020 groups. The scale used for 2020 was [1,11] and for 2018 [0,11]. The 2018 scale was modified [1,10] combining results for categories 0 and 1 to be able to compare NPSs before 2018 and after the learning design process autumn 2020. This combination weakens the comparison. Since the data was collected as part of the final learning task in the end of Phase 3 (see Fig. 1), the NPS score describes student study satisfaction of the entire course, not just the SDL Phases (Phases 1 & 3).

Results

The statistical examination of **returning each learning task on schedule** was examined. The results calculated with percentages indicate that learning task return activity was lowest in the group without learning analytics G1 and highest in the group with both visualization and automatic feedback G3 (see Table 1).

Table 1: Descriptive statistics (frequencies and percentages)

Learning task	**G1** (*N*=130)		**G2** (*N*=136)		**G3** (*N*=207)	
	N	**%**	**N**	**%**	**N**	**%**
Returned on schedule						
Phase 1 -Task 1	121	93 %	131	96 %	202	98 %
Task 2	122	94 %	131	96 %	203	98 %
Task 3	115	89 %	127	93 %	198	96 %
Task 4	103	79 %	121	89 %	184	89 %
Task 5	99	76 %	108	79 %	175	85 %
Task 6	81	62 %	97	71 %	148	72 %
Phase 2 -Task 7	111	85 %	124	91 %	185	89 %
Returned late						
Phase 1 -Task 1	6	5 %	5	4 %	4	2 %
Task 2	6	5 %	5	4 %	4	2 %
Task 3	9	7 %	4	3 %	4	2 %
Task 4	4	3 %	3	2 %	5	2 %
Task 5	11	9 %	13	10 %	12	6 %
Task 6	21	16 %	30	22 %	51	25 %
Phase 2 -Task 7	2	2 %	1	1 %	1	1 %
Not returned						
Phase 1 -Task 1	3	2 %	0	0 %	1	1 %
Task 2	2	2 %	0	0 %	0	0 %
Task 3	6	5 %	5	4 %	5	2 %
Task 4	23	18 %	12	9 %	18	9 %
Task 5	20	15 %	15	11 %	20	10 %
Task 6	28	22 %	9	7 %	8	4 %
Phase 2 -Task 7	17	13 %	11	8 %	21	10 %

Figure 4 presents each learning task which were returned on schedule (left side) and which were not returned at all (right side) from all three groups (G1-3). In fact, the return rates trend was somewhat decreasing, but most in the control group excluding task 7, where no trend can be determined. The results are uniform in all first 6 learning tasks during Phase 1, however task 7 which students returned in Phase 3 gives a different result.

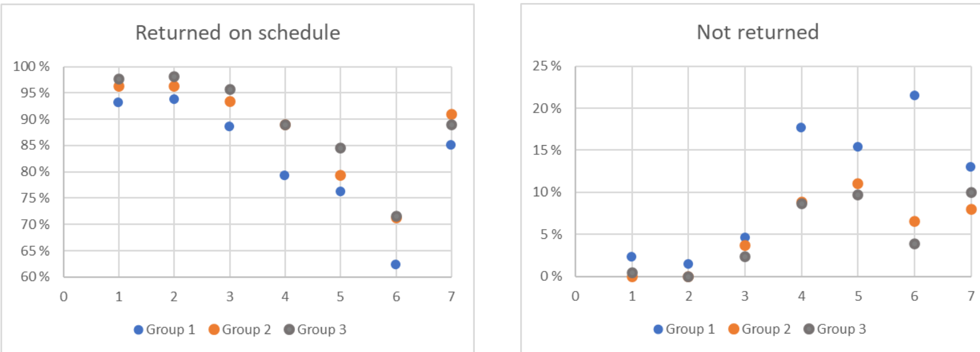

Figure 4: Learning tasks returned on schedule (left side) and not returned at all (right side) from all three groups (G1-3)

Pearson Chi-Square -test of independence was performed to examine the relation between groups and the timely returns of learning tasks. Statistically significant differences were found between the groups in returning learning tasks on schedule. Significant differences ($p < .05$) relating first four tasks were found when comparing control group G1 with test group G3 (see Table 2). However, the statistical differences were not found systematic relating all learning tasks between test group G1 and the control groups (G2, G3, G2&G3). Significant differences relating first four tasks were found when comparing control group G1 with test group G3.

Statistical differences between groups were not found in any later tasks during the course (tasks 5 and 6), but significant differences were found between control groups and test group G3 in the first 4 tasks. Differences in the first 4 tasks were largest and most systematic between G1 and G3.

Table 2 Groups comparisons of timely returns (Pearson Chi-Square –test)

Learning Task	G1 (N=130) and G2&3 (N=343)			G1 (N=130) and G2 (N=207)			G1 (N=130)and G3 (N=207)		
	Pearson Chi-Square	*df*	*p*	*Pearson Chi-Square*	*df*	*p*	*Pearson Chi-Square*	*df*	*p*
Task 1	3.927	1	**.048**	1.405	1	.236	4.075	1	**.044**
Task 2	3.390	1	.066	0.878	1	.349	4.144	1	**.042**
Task 3	5.748	1	**.017**	1.961	1	.161	6.242	1	**.012**
Task 4	7.468	1	**.006**	4.742	1	**.029**	5.895	1	**.015**
Task 5	2.449	1	.118	0.409	1	.523	3.696	1	.055
Task 6	3.661	1	.056	2.440	1	.118	3.097	1	.078

Examining students' **study progress according to overall return activity** (RAV) showed statistically significant difference between the groups. Differences between groups were analysed by using Mann-Whitney and the test was used to assess whether the distribution of mean ranks is statistically significant.

A Mann-Whitney test indicated that the RAV1 was greater for test group G2 than for control group G1 (U=7475.5, p = .034). Statistically even more significant difference was found between test group G1 and control group G3 (U=11355.0, p = .013). However, the statistically significant difference was not found between test groups G2 and G3 (U=13871.0, p = .895). In examining RAV2, results showed a further increase in significances of statistical differences (see Table 3).

Table 1 Group differences in study progress (RAV) by Mann-Whitney –test

Students' study progress	**RAV1**							**RAV 2 (varible less 12)**					
	G	***N***	**Mean Rank**	***Mdn (iqr)***	***U***	***Z***	***p***	***N***	**Mean Rank**	***Mdn (iqr)***	***U***	***Z***	***p***
(G1) Control group *compared to* (G2) Visualization of progerss (LA)	G1	128	122.90	12.0 (2)	7475.5	-2.119	**.034**	59	48.53	10.2 (2)	1093.0	-2.406	**.016**
	G2	135	140.63	12.0 (1)				50	62.64	10.2 (2)			
(G1) Control group *compared to* (G3) Visualization of progerss (LA) and automated feedback (LA)	G1	128	153.21	12.0 (2)	11355.0	-2.484	**.013**	59	56.97	10.2 (2)	1591.5	-2.984	**.003**
	G3	207	177.14	12.0 (1)				76	76.56	10.2 (2)			
(G2) Visualization of progerss (LA) *compared to* (G3) Visualization of progerss and automated feedback (LA)	G2	135	170.75	12.0 (1)	13871.0	- .132	.895	50	62.37	10.2 (2)	1843.5	- .294	.769
	G3	207	171.99	12.0 (1)				76	64.24	10.2 (2)			

Thirdly the **student satisfaction**, i.e., willingness to promote the course was explored according to NPS. Implementation 2018 included no LA. The NPS value was significantly increased compared with the scores from the earlier 2018 course implementation (See Fig. 5). However, when the 2018 group and control groups Autumn 2020 G1-3 were examined according to the NPS categorization (Detractors, Passives and Promoter), 77% of students were in the category of 6 or lower, in 2020, 55% students scored the course 6 or less.

Comparing the distributions in 2018 to Autumn 2020, there were almost twice as many students classified as passives (scored 7-8) in Autumn 2020, and more than 2 times classified as promoters (scored 9-10). It was also detected that the share of passive students in Autumn 2020-G1 had almost doubled but the share of Promoters had remained the same in relation to Spring 2018. It was also observed that the students' satisfaction in the control group by NPS is lower than in the test groups. It is also noted that the NPS is at its highest in Autumn 2020-G2 (see Fig. 5).

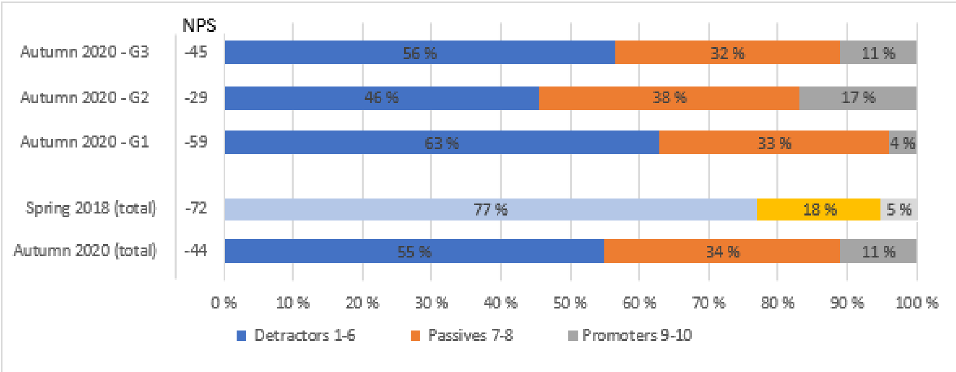

Figure 5: Satisfaction by after the learning design process (Autumn 2020) and before (Spring 2018)

DISCUSSION AND CONCLUSIONS

This study focused on UAS students' study progress in a Moodle environment. Varying LA-based support was applied for enhancing self-directed learning, i.e., returning their learning tasks. Student satisfaction, willingness to promote the course was explored using NPS. The main research questions focused on i) whether applying learning analytics (LA) has an effect on supporting students' study progress, and ii) whether it has an effect of student satisfaction.

First the statistical examination of timely returns of the learning tasks was explored. Task return would appear to vary rather expectedly depending on whether students had access to LA or not. Return activity was lowest in the control group G1 (without LA) and highest in the test group G3 (with visualization of progress and automated feedback). The percentages for each task timely returns were higher in both test groups G3 and G2 compared to control group G1. Statistical comparison showed some differences between the groups and tasks (see Table 1), but the differences were not systematic (see course structure Fig. 1).

When observing the study progress within test group G1 ask 6, more than 20% of the students had missed the return (see Fig 4). The task was a part of a summary, and might easily be overlooked. The students in both control groups G2 and G3 (with LA) had significantly higher rates of return in task 6, thus in this case LA could have had a guiding effect on students' study progress, meaning that non-completed task would be easier to notice. In higher education, there has recently been growing interest to explore how LA could be used to support student engagement and providing actionable feedback for students, which is also an emerging focus in research (Silvola et al., 2021, Lim et al., 2021), and the present results indicate that even simple/easily applied LA can have a positive effect on task returns and possibly even on increased self-direction. This type of student-centred utilization of LA is a step towards MyData, data available and usable for students, e.g., for self-direction and competence development and reflection.

There was also a somewhat decreasing trend seen in the return rates of first six tasks, within study Phase 1, and the most declining trend was observed in the control group G1. A noticeable change in this trend was discovered in task 7 which was in study Phase 3. This might originate from the structure of the course. Between independent learning Phases (1 & 3) Phase 2 exposes students to teacher-guided and peer interventions. One might also speculate on the influence of the teacher and peers on students SDL, thus reducing the impact of LA. Therefore, the need for LA-based learning support in online environments could be even more important when students study independently. Aldowah et. al. (2019) point out that the lack of interaction among students, and between students and teacher has been associated with MOOC learners' dropout behavior, indicating that social interaction is one of the elements influencing student dropout rates, in addition to other factors such as course design and feedback.

Examining students' study progress according to RAV showed statistically significant difference between control group G1 and both test groups G2 and G3 (Table 3). When excluding students who had returned all their learning tasks on schedule, the significance between both test groups and control group even increased. This could indicate that those students experiencing difficulties with returning their learning tasks on schedule might benefit from LA-support.

These results are very preliminary but give positive indications of the effect LA has on those students experiencing problems returning tasks on time, and that should be further explored. (see also Durall & Gros, 2014). In future, a validated SDL meter could be used to observe in more detail differences between the students of different return behaviours. Recent studies also indicate improved learning effectiveness experienced by the students while using LA dashboards (see e.g. Wang & Han, 2021) as well as recommendations for systematic research on implementation (Valle et al., 2021). However, to explore students' learning, various complementary methods would be needed, such as qualitative analyses of student reflections, since study process observed through return rates of learning tasks is not an indication of the quality of learning itself.

Furthermore, **NPS score changes** between the 2018 implementations compared to 2020 might indicate that applying LA and re-designing the course accordingly could have a positive effect on students' satisfaction. Our research design does not support direct causal conclusions due to several influencing factors, but it would be beneficial in future research to consider the effects of both course re-design and LA as elements for improving student satisfaction and quality of online courses (see also Heilala et al., 2020). A broader feedback survey for the students could be used as complementing element. In addition, the role of teacher effect on study satisfaction should be examined in more detail.

Practice Based Conclusions

The applied elements of LA seem to support students returning their learning tasks. Suitable plugin elements which are part of the Moodle should be easily deployed in UAS courses. These preliminary study results indicate that they might have positive effects on supporting self-directed learning by having a guiding effect especially when studying takes place independently.

It should be noted that the use of LA in online courses requires pedagogical course re-design in order for LA support to be enabled accordingly. It would be a great success for UAS if part of online students' needs for guidance were handled by LA-based support enabling students self-directed learning with the knowledge they gained from their own data (MyData).

Students should also participate actively in the process of designing online learning, by providing feedback from the courses. NPS is an easily implemented tool for teachers to collect course feedback, but it should be used with caution, since it is not suitable for measuring quality. It is however a valid indicator for pedagogical development on whether it is progressing in the right direction.

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