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LMS log activity and formative assessment – is the feedback itself enough to increase the motivation?

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Abstract

Formative assignments are clearly beneficial for the students as they can have more authority on the learning goals and studying times than on courses with examinations. Furthermore, students will receive feedback and guidance for their formative assessments which can help them to achieve the required learning outcomes. Therefore, formative assessment is a plausible method for the evaluation during flipped classroom courses in which autonomous studying activity is in the center of the learning process.

This study detected the learning behavior differences when exams in an undergraduate flipped classroom bioscience course were replaced with formative evaluation in fall 2019. The course activity and learning outcomes of 352 voluntary students were collected for this study during the academic year 2019–2020. The course activity and learning outcomes were compared with similar information of the same course during the academic year 2016–2017 when formative evaluation was used. The shift from summative to formative assessment increased the proportion of high-grade students significantly in a permanent manner. This was related to students' increased activity in LMS but not directly to the essay feedback. The LMS activity of all student groups had a fade during the 3-month course and participation in the social elements of the course increased significantly students' motivation to persevere in their study work and reach their learning goals. In contrast, students with low course activity at the beginning of the course, were at a substantial risk of dropout and in many cases ended their study work before submitting a single formative assessment into which they could get teacher's feedback and guidance. Therefore, the formative assessment is an effective way to potentiate learners' self-regulation on the workload and the learning goals, but it requires students' motivation to study.

Keywords: e-learning; formative assessment; learning analytics; flipped classroom

Background

The challenges of autonomous off-campus learning have been studied for over 50 years (Moore 1973) and alterative assessments have been highlighted in the science teaching literature already for some time (Hodson 1998). However, the non-interactive tradition is still strong in the science teaching (Stains et al. 2018) and the summative evaluation with a single exam at the end of the lecture course is still common in the higher education (Ifenthaler et al. 2022; Pereira et al. 2022).

Step by step, the criticism of grading (Kohn 2011) and especially summative evaluation has increased. Grading has been demonstrated to limit students' intrinsic motivation and make them select easier challenges. Summative assessment has also negative effect on the fairness of participation and engagement with the assessment (Pereira et al. 2022). Moreover, the exams in the end of the course does not give useful feedback to improve students learning or correct their misunderstandings (Tempelaar et al. 2013). However, summative grading is commonly justified as the best practice of low resources (Broadbent et al. 2018) and on its best it gives objective information of students learning (Broadbent et al. 2021).

Formative assessment

In contrast to the summative grading, formative assignments are meant to give information of learning for the student (Broadbent et al. 2021) by having on-course feedback in the center of the learning processes. With continuous interactivity teacher can identify the students' skills and modulate teaching to guide the students to reach the learning goals (Black & Wiliam 2009; Ramaprasad 1983). Beside the formal assignments the formative evaluation is using also informal parameters (e.g., chat and group work) as part of information used for the evaluation of students' learning (Alonzo 2018) for which it could work as a promising method in the experiment-oriented STEM studies. Interestingly, the feedback and tutorial discussions have much longer tradition in higher education than summative examinations (Gibbs & Simpson 2004) for which formative assessment is nothing new or revolutionary. However, in many cases, formative assessment is limited to self-test quizzes, and in these cases, they might help the students to reach their learning goals only if the assessment is linked with in-personal feedback and discussions (Schüttpelz-Brauns et al. 2020).
In online education, formative assessment can help educators to produce more effective feedback, boost students' achievement levels (Bulut et al. 2023) and improve their self-regulation skills (McLaughlin & Yan 2017; Tempelaar et al. 2013). Moreover, formative assessment can increase students' motivation and engagement (Tempelaar et al. 2015a), but the importance of different assessments for learning outcomes can vary even within the same course (Tempelaar et al. 2015b). In modern off-campus courses with computers and learning management systems (LMS), these self-regulation skills and engagement are highly needed for students' successful study work.

From the teacher's perspective, the real-time information of students learning progress gives possibilities not only to pace the rhythm of studies but also to modulate the learning outcomes of the course. In science, learning progression describes steps of scientific thinking which students must pass before focusing on more advanced challenges (Alonzo 2018; von Aufschnaiter & Alonzo 2018). For example, in an undergraduate level cell biology course this can mean that some students must review the high-school level information whereas some students would benefit from advanced details they could find by reviewing scientific research papers. This requires differentiated teaching where the goals of the course and the methods students are using are set individually. Ideally, students would benefit from personalized acts during the course and personal feedback on their learning progress. However, this is highly time consuming as Black & Wiliam (2009) have described “It requires some imagination to connect the lessons with the dynamic interactive environment of a teacher working with a class of 30 student”.

In the online and blended learning environments of higher education, the number of students can be hundreds for which personal interactivity, guidance and feedback are challenging. In many cases, the teacher’s role in interactions has been limited by using either self-evaluation or feedback from peer-instruction as part of course progress (Black & Wiliam, 2009; Ifenthaler et al. 2022). Interestingly, in some cases, students perceive the peer assessment as an unfair process (Pereira et al. 2022). Beside these student-centered techniques also multiple-choice exams and “click-to-credit” online courses are commonly used to reduce the teaching work, although these courses might lack interactivity completely. Students are often sharing these passed with minimal workload “click-to-credit” courses as lists of “easy credit” courses. However, the major challenge in these noninteractive courses like massive open online courses (MOOCs) is not the ease but the enormous dropout rate (Fournier & Kop 2015), for which student-to-student connections and learning design are today in the center of MOOC development (Rizvi et al. 2022).

The limited student-teacher interaction has increased distrust for which the formative assessment has faced severe critics during the pandemic and AI-revolution (Shaw et al. 2023). If the assignments are done outside the campus, there is never a complete guarantee of the author of the text, nor full protection against copy/paste or AI-aided text processing. However, the formative assessment can be modified at least partly AI-proof (Mastrogiacomi 2023), beside which the direct interactions between the teacher and students can limit concerns and distrust.

Flipped classroom and interactivity

Flipped classroom (FC) is a promising method to increase the interactivity while giving in Moore’s words “transactional distance” for the students to learn the self-regulation skills (O’Flaherty & Phillips 2015). FC is based on self-regulated independent study-work and interactive reviewing elements (e.g., group work, webinars) (Lage et al. 2000) for which students can learn the core content at home and use their knowledge later in the group work (Talbert 2017). In teacher’s perspective FC is an easy step to take as the structure of flipped classroom course can be highly similar with traditional lecture course. FC also potentiate teachers to use more studying material (Mason et al. 2013) and more time for direct interaction with students as the time is not spent on lecturing. Furthermore, as many elements of flipped classroom courses are online, they can provide huge amount of information on students’ behavior in LMS (Jovanović et al. 2017) as well as resiliency to operate fully online during the pandemic lock down (Divjak et al. 2022).

In the students' perspective, flipped classroom has several benefits. FC increase the feedback and helps to develop a safe community for learning (Hyypiä et al. 2019). Students can adapt to FC quickly and perform better on their learning assessments (Mason et al. 2013). Moreover, students emphasize diversity and variety of teaching methods, constructive feedback, and possible on-course assessments (Hyypiä et al. 2019). Last, but not least, students also highlight their power to decide the time and content of their study work in their course feedback.

I have recently demonstrated that turning a bioscience course from in-class lecture mode to FC can reduce the failure rate and increase the proportion of excellent grades of the students (Paajanen 2023). Students' achievements were evaluated in this 2016 started course with summative exams to respond to the critics of online and blended learning. The analyses of this FC course highlighted the importance of the social elements and time-management for successful learning, whereas the students, who were not participating in the interactions or had slower progress in LMS, had a substantial risk of dropout. Although FC was clearly giving benefits for most of the students on this course, the growing number of continuous learning students living far away from the campuses were having challenges to participate in campus-exams. Therefore, there was a strong need for alternative methods for evaluation for which the course exams were replaced with formative assessment and teacher's feedback during the summer of 2019. Naturally, this raised interest in studying whether formative evaluation has any consequences on the students' learning habits during the course.

Because the social elements of the course can have a key role in the students' learning progress, the effectiveness of interactivity should be tested by using interactive studying models like Community of Inquiry (CoI) (Garrison et al. 2000). The core idea of CoI is that the students are interacting with the course content, teacher, and other students and this presence is helping students to learn the study material in constructive manner, focus on reasonable study content with the help of teacher, and engage into the student group (Garrison 2017). The model is based on earlier control model (Garrison 2007) which is highly similar with Moore's model of autonomy (Moore 1973). Beside social models like CoI which are used in American literature of online teaching (Wright 2015) content models like TPACK (Koehler et al. 2013) are another well-known code of practice in online course development. The main difference between these models is the interactivity of social models (Papanikolaou et al. 2017) for which CoI might be a fruitful frame of reference when interactivity of FC courses is studied in more detail.

Learning analysis and analytics

The effectiveness of course components like the interactive elements can be studied with either traditional analysis in which, for example, the learning outcomes of student participating in the social events and students not participated are compared, or learning analytics based on large number of parameters, which can have either direct or indirect effects on learning (Pinnell et al. 2017). For example, students participating on the group work can have higher pass-rate because 1) the social presence increase motivation (engagement), 2) the student at risk of dropout are not joining the discussions (different student groups), 3) students learn from their peers (direct effect), or 4) the group work is pacing the study rhythm for which students will work more on a regular rhythm (procrastination). With learning analytics these indirect effects can be distinguished.

According to its original description “learning analytics (LA) is measuring, collecting, analyzing, and reporting data about learners and their context, for purposes of understand and optimize learning and the environments in which it occurs” (Mougiakou et al. 2023). Therefore, it can help teachers to identify the students at risk of dropout (Dietz-Uhler & Hurn 2013), guide the students toward more effective LMS use (Graf et al. 2011; Morris et al. 2005), or test how the course elements are helping different student groups in their learning processes (Rizvi et al. 2022). Recently, several automatic tools of LA have been developed to build predictive models for the real-time prediction of students at risk of dropout or students' final grade (Bulut et al. 2023).

Learning analytics has been successfully used for analyses of flipped classroom courses (Carbonaro et al. 2017; Jovanović et al. 2017) as well as formative assessment (Tempelaar et al. 2013; Zhang et al. 2023). In some cases, the results of learning analytics are obvious: the active participation on course and LMS use have correlation with the academic performance (Johnson 2005; Wang and Newlin 2002). In contrast, it remains to be elucidated whether the time spent on the video lectures helps students to reach their learning goals (Morris et al. 2005; Vural 2013), and, in some cases, the student background has been the predominant factor of the learning success (Tempelaar et al. 2016). Therefore, it is difficult to identify a simple list of parameters that would be used successfully in all online and blended courses.

In several studies, formative, feedback-related components like quizzes are helping students in their learning (Bulut et al. 2023; Butler 2010; Cranney et al. 2009; Ifenthaler et al. 2022; Steinel et al. 2022; Tempelaar et al. 2016; Vojdanoska et al. 2010). Moreover, students are using these tests several times even in cases their grade is not dependent on the quiz results (Paajanen 2023) indicating that students assume that quizzes are helping them to learn. However, although quizzes are generally accepted as an efficient method to boost the learning, their role in predicting success in summative tests is not always the same (Tempelaar et al. 2015b) and in some cases quizzes can help the student only if the quiz results are used in discussions (Schüttpelz-Brauns et al. 2020). Therefore, more research is needed to clarify the importance of different interactive components like the teacher’s feedback on students’ formative assessments.

More discrepancy is related to the benefits of social interaction. It has been reported that interactivity prevents the isolation (Croft et al. 2010; McElrath & Mcdowell 2008), and increase satisfaction and learning outcomes (Fasse et al. 2009; Hostetter & Busch 2006; Shea et al. 2019). However, the role of social activity has also been challenges. For example, in medical studies, less talented students are not participating in the group work for which the interactivity might not increase learning by itself (Steinel et al. 2022). This highlights the importance of careful multiparameter analyses instead of simple comparisons when recommendations for the course structure are made by the students’ acts on LMS.

Learning analytics is not limited to graded or bipolar parameters like assignments or interactivity. Every click on LMS can be tracked which gives time-dependent information like the number of active learning days or the average daily activity, and the students’ time spent on lecturing content, quizzes, and chat. Therefore, LA can be used to identify students at risk of dropout by their LMS activity even before the first deadline of submissions. Periodical activity in LMS use has been demonstrated in several studies (Rakes & Dunn 2010; Sun et al. 2008; You 2015; Yukselturk & Bulut 2007) and in many cases it is related into procrastination (Elvers et al. 2003; Levy & Rami 2012; Michinov et al. 2011). A clear last-night panic among students with substantial risk of failure has been identified on FC course of bioscience (Paajanen 2023). However, in all these studies, students were fighting against the time because of examinations or submission deadlines for which the learning rhythm of students on a deadline-free course with formative assignments needs to be studied.

Research Questions

Because there has been some discrepancy on the role of laborious formative assessment on the studying behavior and the learning outcomes, there is a need for a study to reveal how much workload the formative assignments require from the undergraduate level university students, and the possible formative evaluation related boost to engage students into the study work. Moreover, the acts on LMS and their impact on the learning outcomes should be tested to demonstrate the importance of flipped classroom related phenomena (e.g., group work) on the learning success. Lastly, there is a need for research focusing on the students' LMS use and learning behavior related to substantial risk of dropout.

These open challenges were turned into four study questions on which I was able to answer by using learning analytics and comparison of students participating on the course with formative assessment (2019–2020) with my earlier study of the same course (2016–2017) when summative exams were used.

1) Does the shift from summative exams to formative assignments have effect on the learning outcomes?
2) Does the absence of exams and deadlines remove the time management related challenges of learning?
3) What is the role of participation in the learning community and the feedback on the learning outcomes of students?
4) Can the students at risk of dropout be identified and supported in the early days of the formatively assessed course?

Material and Methods

During the academic year 2019–2020 196 students from University of Eastern Finland and 156 students from continuous learning were participating on the Basics of Cellular and Molecular Biology course. Many students were freshmen and only 24 % of the students were taking the course in their major studies. Therefore, many students had limited information about academic learning skills. Moreover, all tuition fees were removed from the course in the spring 2020 as the University wanted to help students struggling with covid-related challenges in higher education. This not only doubled the number of students participating on the course but increased their heterogeneity as students from all Finnish Universities as well as several Universities of Applied Sciences in Finland were participating on the course. Thus, students had large variance on background knowledge of biology and on the traditions of education.

The flipped classroom course contained short video lectures, podcast (Soundcloud), textbook, and external www-links as source of information and weekly group work sessions, online webinars, and chat (Slack) to build the learning community and to synchronize the learning. The students were encouraged to participate in the social activities with extra points, but they were allowed to study completely online and without any interactivity during the course.

Flipped classroom had been used on the studied course since 2016 and held annually with summative assessments (3 exams with 3-to-4-week intervals). In fall 2019 the course was held for the first time with formative assignments and without exams. The LMS contained ten set of quizzes (giving 40 % of the course points) and 10 essay assignments (responsible for 60 % of the course points). Grading was based on 0-5 scaling in which 50 % of the maximal points (150 p) were required for passing the course with a grade 1/5 and 90 % were required for achieving the highest grade 5/5 on the course The course was open throughout the academic year without any strict deadlines. However, as extra points were used to motivate the students to participate in the group works, webinars and online chat, the meetings operated as timekeepers on this course.

As students grades and LMS activity contain confidential data that is regulated with GDPR, the storage and analyses in LA have legal and ethical challenges (Prinsloo & Slade 2017). Therefore, a separate agreement was asked by the students to participate in the study, in which their anonymized LMS activity and learning outcomes were analyzed to reveal the behavioral differences affecting on the learning success. Most of the students (293 persons) gave permission to use their information on this study. The research and data storage plans of this study were accepted by the Ethical Evaluation Panel of the University of Eastern Finland.

Analyses

The course outcome and participation in course activities were combined with analyzes of Moodle log information of the voluntary students. Several parameters related to static data (nationality, sex, number of academic study years, academic status, campus, main study subject), resources (LMS logs, visiting events in individual study materials), tasks (visiting events in assignments), time management (days in LMS, daily LMS use, active learning days) and learning community (participation on chat and group work) were selected as potential course outcome affecting factors. The parameters were selected as they were used in earlier study on the same course (Paajanen 2023).

The course started on 9/9 2019 and LMS activity of the students was collected throughout the academic year till 31/8/2020. The log data containing 251270 events were analyzed with Excel365 (Microsoft) and SigmaPlot 15.0 (Systat Software) in three setups.

Effects of formative assessment on studying behavior and course outcome were analyzed by comparing the course pass rate and proportion of high/low grade students in the same course held on different years with either summative or formative evaluation. Moreover, effects of learning community were tested by comparing the learning outcomes of students with participation in social activity (webinars, chat, group work) with students studying the course completely online and without need for interactivity. These two group comparisons were made either with Student’s t-test or Mann-Whitney rank sum test depending on the normality of the distribution.

To evaluate the factors of studying behavior and learning outcome were analyzed with Pearson correlation to identify parameters with potential interaction and Best Subset Regression to identify the acts which have a strong influence on learning outcome. The regression models have methodological problems (Hanke et al. 2023) for which the results must be considered as approximations. However, this method was selected as it helps the comparison to the earlier study of summative assessments (Paajanen 2023).

In all cases, $r > 0.6$ was considered as criterion of strong correlation, $p < 0.05$ was considered as statistically significant difference between the groups, and in the Best Subset Regression the simplest model in which least bias (Cp is among the smallest), adjusted R^2 highest and the variance inflation factor (VIF) below 5 in all parameters, was selected.

Results

In the end of 2010’s the arrangements of the lecture room exams needed for the summative evaluation became impossible for a growing number of students living hundreds of kilometers from the nearest university campus. For these practical reasons, exams were replaced with formative assignments on this course. Interestingly, at the same time of the shift from summative to formative assessment, the risk of dropout decreased, and the proportion of the high-score students increased (Fig 1). This cannot, however, be used as direct evidence of formative assessment-related phenomena as the changes in the course structure can help the students to reach their learning goals in many ways. Moreover, although the differences in the pass-rate are important for the study progress of students and in some cases the course economy, a simple comparison of grades on two semesters can lead to overestimation of differences and their significance. To minimize the overestimation, the learning outcomes of all students participating on the course 2016–2024 were compared. This comparison revealed that students passing the formatively evaluated course got high grades (>80 %) more probable than the exam-evaluated students. However, at the same time the pass-rate had a transient drop during the covid semesters (2020–2022). This indicates separate phenomena affect motivation to pass the course and the acts on LMS to reach the higher learning outcomes.

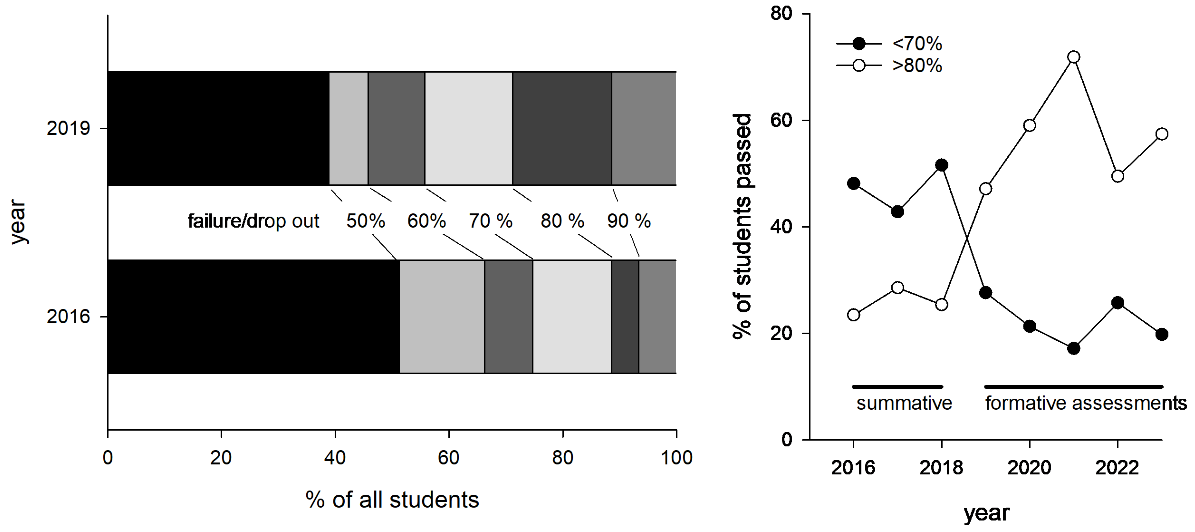

Fig 1. Formative assessments increase pass-rate by helping students to reach their learning objectives. The proportion of students reaching different learning outcomes on the course with summative (2016) and formative (2019) evaluation (left). The proportion of high scores (reaching >80% of maximum) and low scores (50 – 70 % of learning goals) of students passing the flipped classroom course evaluated either with summative or formative assessments (right).

The increased pass-rate and number of high-score students indicate that the students can pass the course easier either because they can reach better the smaller steps of weekly writing assessments, or the learning goals in formative evaluation are lower. The latter option is a common critique against exam-free learning, and it must be inspected carefully because the lower course criteria lead to less skilled learners in their future studies.

Learning analytics of students LMS activity was used to test whether the students not using their effort for the learning processes can pass the course with the formative assessments. The click-to-credit behavior was clearly not the reason for high grades because the students used 70 % more LMS and studied daily almost 3-times more than the students on the same course with summative evaluation (6.3 ± 0.2 and 23.8 ± 0.7 events per day in 2016 and 2019, respectively). Furthermore, the use of lecture material increased 2-fold (82.4 ± 8.0 and 173.4 ± 8.0 events in 2016 and 2019, respectively) indicating that students spend more time with the course material. Most importantly, the increased learning behavior was not related to the learning outcomes as the students getting low grades increased their LMS use in the formative assessment as much as the students getting excellent grades. Therefore, all students are studying harder in courses with formative assessment, and this is one of the acts by which they can reach higher grades.

LMS use and leaning outcomes

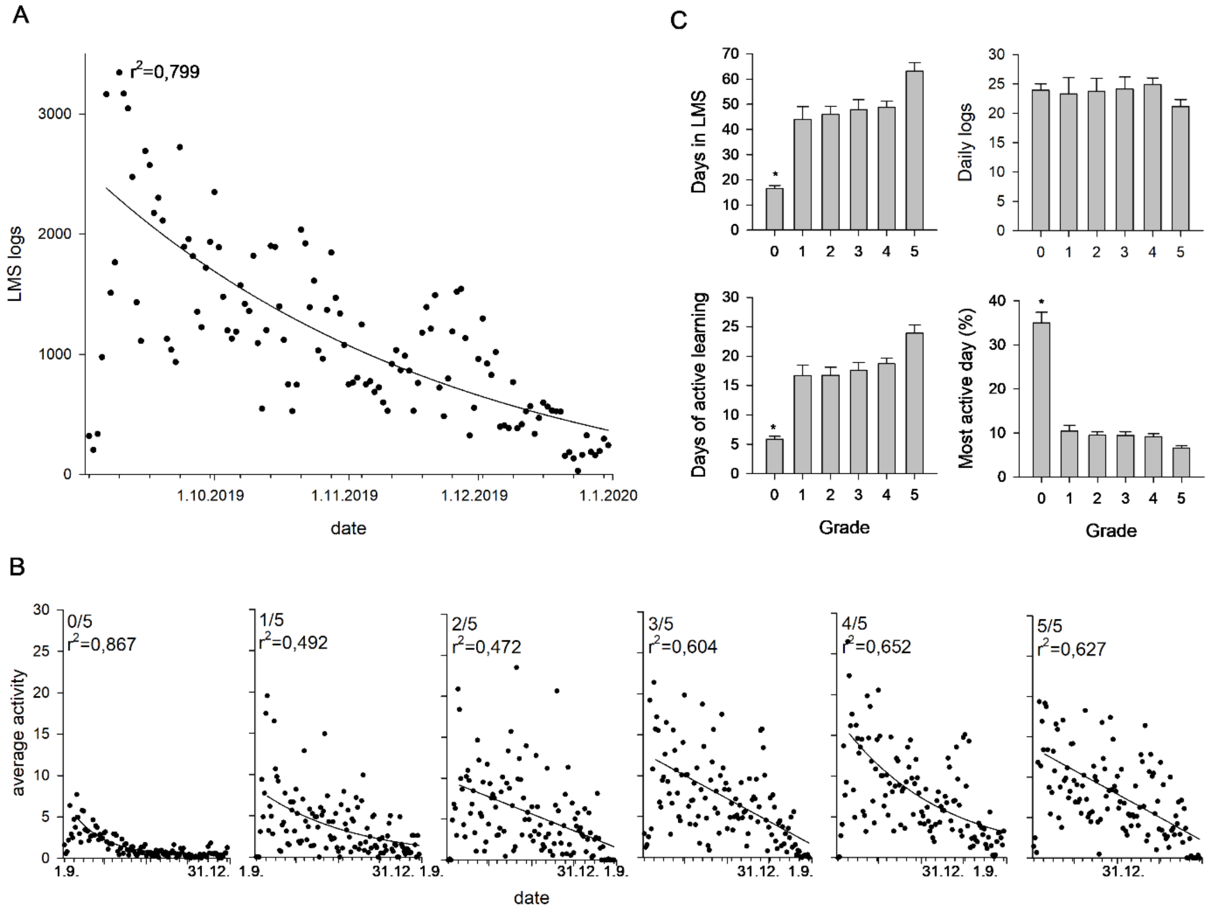

Fig 2. Students' LMS activity fades during the formatively evaluated course, and the loss of activity is fast among the students failing the course. Daily LMS logs fade exponentially after first of the course in a predictable manner (A). The fade happens in all student groups but at different speed & predictability (B). The distribution of LMS use of students with different learning outcomes shows that the students passing the course have similar activity, but the dropout students disappear from the course within few days (C).

The time management challenges are a widespread problem in highly intensive courses. Students are participating in more than one course at a time for which full-time study work on a 12-week course is difficult to maintain. Whereas the studying activity in summative evaluated course have usually peaks before the days of examination (Paajanen 2023), the LMS activity in formatively evaluated course show a fade (Fig 2 A). The synchronous high activity in early fall and fade was unexpected finding because the students were able to perform all the study work throughout the academic year 2019–2020. The fade was fitted well by using an exponential attenuation function ($f(x) = y_0 + a * e^{-b*x}$) in which y_0 represents the steady state activity, a maximal activity and b the time dependent attenuation. According to this model, students, in general, lost 50 % of their learning activity within the first 8.3 weeks of the course. Interestingly similar fade was seen also in the course quiz & essay submissions with the same time dependency (data not shown).

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The exponential attenuation was clearly seen in some but not in all student groups (Fig 2B). The dropout students lost their interest rapidly (50 % reduction within 16.1 days) whereas the students passing the course had large variation in their active learning days and maintained their interest throughout the course. The rapid loss of interest was seen in dropout students with all parameters used to calculate the steady learning rhythm (Fig 2C). During the academic year 2019–2020 students not passing the course were visiting LMS on 16 days of which 6 days they were learning actively. On the days the dropout students were in LMS, their daily activity was not different from any other student groups. For the classroom applications, this highlights the importance of the students' first day visit on the course platform to get the students at risk of dropout engaged. However, it also demonstrates that students lagging the motivation to pass the course study only few days and lose their activity in the first steps of the course. Therefore, the pass-rate itself can have a limited role to describe development of the course.

Correlation between learning outcomes and LMS logs was highly similar among students passing the course with either summative or formative assessments (data not shown). Therefore, the students who use more learning material will get higher grades. However, besides the time spent on studies, learning analytics can reveal the importance of the students' individual acts during the course to reach the learning outcomes. The learning related parameters were tested with all vs all correlations and the combination of these parameters were used for Best Subset Regression to reveal the potentially optimal behavior leading to high scores on the course. The regression model with minimal bias and variance inflation contained 6 parameters and it correlated well with the learning results of the students ($R^2 = 0.813$). The model demonstrated the importance of the time spent on assessments, participation in social activity and successful time management for learning success (Table 1). Beside the model, several individual parameters (e.g., logs, use of course materials, tests & essays) had a significant correlation with the learning outcomes ($R^2 > 0.7$), and the students with a steady studying rhythm were using more learning material. Noteworthy, the online chat on this course was based on teacher-student-interactions and hardly any comments were written by the peer students, for which it is a classic example of the direct instructions in CoI categories. Therefore, the parameters predicting successful study work on this course were following Garrison's model of teaching, cognitive, and social presence. For the classroom applications, this study highlights the lack of a single act boosting the learning outcomes. Therefore, the online and blended courses should have diverse learning components to engage students in learning, facilitate their learning progress and give them the opportunity to express themselves.

Col element	factor	Coef.	S.E.	t	P	VIF
Social presence	group work	1.9	0.581	3.269	0.001	1.299
Teaching presence	chat	2.498	0.991	2.519	0.012	1.045
Cognitive presence	assessments	0.133	0.016	8.261	0.001	3.438
Cognitive presence	daily use	0.6	0.182	3.289	0.001	1.559
	active learning days	1.696	0.336	5.048	0.001	4.031
	max. daily activity	-45.938	9.958	-4.613	0.001	2.374

Table 1. Interactivity and study rhythm are the main factors affecting learning outcomes. The parameters correlate together but independently with the learning outcomes of formatively evaluated course.

Learning community

Students were encouraged to interact with the learning community by giving them extra points from each comment in the course chat and each participation in the group work. In comparable manner with the earlier course with summative assessments, the learning community in the formatively evaluated course was not only correlating with the higher learning outcomes but also significantly with several other parameters like the steady rhythm of studies, the use of course material and the time spent on the assessments (Table 2).

In some studies, the link between interactivity and learning results have been challenged as students with learning difficulties are not participating in the group work (Steinel et al. 2022). This possibility was tested by comparing the learning outcomes of each assignment. The first week's quizzes, which describe best the early course skills, had no difference between the students participating in the learning community and studying without the support (4.83 ± 0.08 and 5.00 ± 0.07 points in no support and interactive students, respectively). On the 2nd week, there was a small (5.6 %) but statistically significant difference in the quiz results ($p = 0.012$) whereas in all other quizzes or essays of the entire course the learning outcome was identical with/without interactivity. Therefore, in this studied course, all kinds of students are participating in the learning community related activities.

student group	n	average outcome (%)	pass rate (%)	active learning days	lecture use	quiz use	essays
no support	121	27.8 ± 2.8*	28.1*	7.8 ± 0.6*	123.6 ± 9.6*	80.8 ± 8.2*	63.1 ± 6.9*
chat	21	67.6 ± 7.4	66.7	45.7 ± 5.7	233.5 ± 26.0	167.6 ± 20.9	149.2 ± 9.6
group work	86	64. 9 ± 2.9	74.4	46.7 ± 2.1	235.3 ± 12.0	177.0 ± 9.6	140.2 ± 19.0
webinar	33	57.5 ± 5.4	57.6	43.0 ± 4.0	205.8 ± 18.9	180.4±19.2	118.8 ± 13.0

Table 2. Participation in learning community increases learning outcomes via boosting LMS use. * Indicate statistically significant differences ($p < 0.05$) between no support and interactive student groups

How can the students without support have lower pass-rate if the learning outcome of hardly any individual assessment is not lower in the students not participating in the interactive activities? There was a clear difference in the number of assignments submitted by the students studying alone and the students participating in the learning community: 30 % of non-support students did not finish their first essays and 50 % of them did not submit fifth week quizzes. Therefore, without the support of the learning community, students lose their motivation causing a fade of LMS activity whereas the interactivity is engaging the students to continue their study work. Besides the onsite meetings at two campuses, interaction was organized also as late-night webinars in which students were performing similar group work as the students onsite. These webinars had the same benefits for the students learning as onsite meetings or online chat indicating that the interactivity but not the classrooms are important for learning. Interestingly, whereas the group work and webinars were mainly student-student communication (Social presence), the online chat was almost completely teacher-student discussion (Teaching presence). For the classroom applications, this highlights the teacher’s role both as a communicator and a facilitator of interactivity during successful learning.

Interactivity on the course was not limited to learning community as the formative assessment is based on discussion between the student and teacher. The benefits of assignment related feedback were tested by comparing the student groups with similar learning community activity and either evaluated with weekly essays or exams. There was no difference in the learning outcomes of the students with summative and formative assessments ($p = 0.260$ for the students with no support, $p = 0.372$ for the student participating in the group works, and $p = 0.596$ for the students joining the chat). Therefore, although the benefits of formative assessment have been clear in several studies (Bulut et al. 2023; McLaughlin & Yan 2017; Tempelaar et al. 2015a 2013), the feedback itself did, in the current study, had only limited possibilities to increase the learning results.

Why were the formative assessment and feedback limiting the dropout of the course studied? To answer this question the activity of dropout students on individual assessments was analyzed. Interestingly, during their brief period of study work in LMS, students failing the course had opened quizzes of several study week and 71 % of them submitted quizzes of the first week. However, only 39 % of students not passing the course had submitted their first essay. Thus, most dropout students did not get a single written comment on their assessments whereas students in general were eager to get the teacher's comments and instructions with hints for the resubmitting process:

> *"In your essay you should focus more on the many roles and interactions of amino-acid side chains. Moreover, write something about the protein folding and the forces holding the structure. How is it possible to measure the 3-dimensional structure of proteins? What kind of applications for the protein atomic structures can you imagine?"*

In the studied course, students got written feedback from each of their first seven essays and were able to resubmit their work based on the teacher's comment. Therefore, the teacher's role on this course was not only to tell the missing information/highlight the misunderstandings but also to guide the students in their course related thinking.

There is, however, a methodological risk to evaluate the students' learning outcomes if they are able get limitless help in their assignments. As the students were allowed to resubmit their essays, there is a temptation for phishing the right answers without the necessary study work. Does this mean they got high grades because the feedback was guiding them toward the right answers? Only few students resubmitted any of their essays (5.8 % ± 0.7 of the submitted essays) and typically these essays were misfocused and needed supervision to answer the right question. The median time to submit a single essay on this course was 24.5 h during which they wrote 279.5 words). Therefore, although the students used a lot of effort on essays (visited 10.1 ± 0.6 times on each essay), they used their studying time for the writing process.

In comparison to the essays, students resubmitted their quizzes more often (visited 12.5 ± 0.7 times per quiz section). Use of these self-evaluation acts was increased by 63 % as the quiz results were used as a part of grading. However, the quizzes were already in hard use also when the FC course started 2016. This indicates that quizzes are used mainly in self-evaluation purpose rather than to raise the grade. The latter option cannot, however, be ignored as the students were trained to use the evaluation matrix of LMS and to calculate the grades at any time of the course. Therefore, students seeking a higher grade can use the course material for a longer time to achieve the learning outcomes they want. Besides the increased amount of study work, this grade awareness can explain why so many students got high grades in the formatively evaluated course.

Detection of the drop-out

Because the students who drop out from the course are staying on the LMS only for a brief time, instructor must detect the students at risk of dropout as early as possible. This cannot be done without LMS log analyses if the students are not performing any compulsory activities in the first days of the course. On the course of this study, students did not have any strict deadlines or examination day for which the activity at the beginning of the course can have large variation among the students. However, the dropout students were lagging already in the first days of the course (Fig 3A), and after the first weeks their LMS activity was significantly less than students reaching the course learning goals (Fig 3B). After the first week of the course students with low LMS activity were unlikely to pass the course whereas most students with at least 70 % of average LMS logs were reaching the learning outcomes successfully (26.3 % vs 72.8 % probability to pass the course of low-activity and high-activity students, respectively). Therefore, predictive students' at-risk detection can be used in cases where course schedule contains only recommendations for the study rhythm.

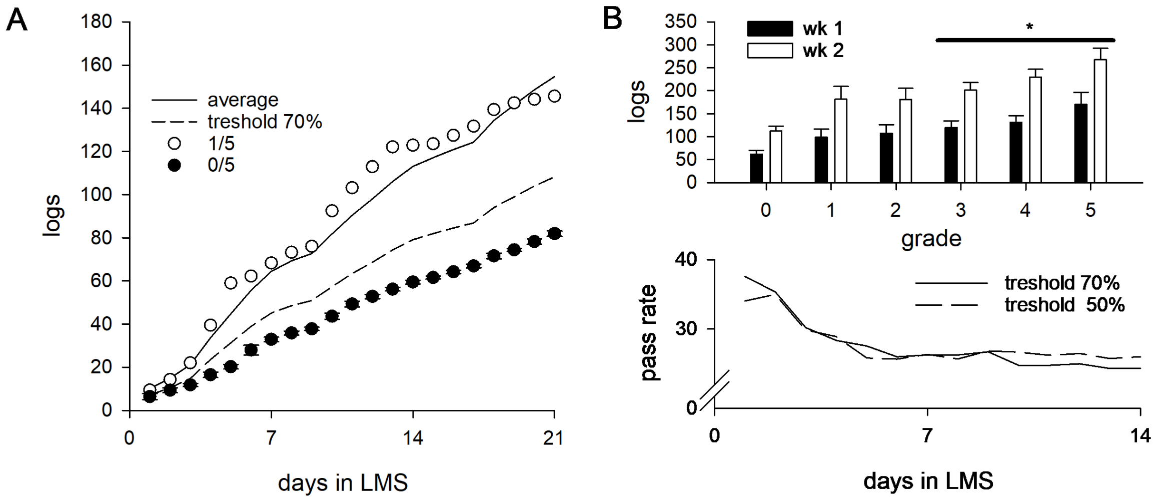

Fig 3. Students failing the course can be identified by the low LMS use in the first days of the course. Average LMS logs increase in a steady rhythm during the first weeks of the course. Students failing the course show slower learning rhythm and lagging (left) and on average their activity is below the 70% of average threshold. The difference in LMS activity is higher among students reaching the learning outcomes (right, up). * Indicate a statistically significant difference between passing and failing study groups after 1 and 2 weeks of studies. Pass rate of student below the threshold activities indicate no difference after first week of the course (right, bottom).

Conclusions

In this study, I have demonstrated that shift from summative to formative assessment can increase students' possibilities to reach the high learning outcomes, and in some cases, reduce the dropout rate of the course. This benefit was not related to reduced workload needed on the course as the student's LMS use was increased with the formative assessment. More probable explanation for the boost of high grades was the course's open evaluation matrix from which students were able to follow their progress and use this information with their power to decide the time of study work and effort to reach their learning goals. Therefore, the first study question was solved but at the same time it opens several questions related to the mechanisms by which the learning outcomes are changed.

Feedback related to the students' essays did not have measurable effect on improving learning or increasing the engagement. Most dropout students did not submit any of their essays nor participated in any interactive elements of the studied flipped classroom course. Their periodical LMS activity was changed but not improved during the summative – formative shift. Therefore, formative assignments are not helping the students who have exceptionally low motivation for the study work. Whether the feedback was beneficial for the students passing the course remains to be elucidated. Formative assessment did not, in the current study, increase the learning outcomes of any study group. However, on this course, the students were surrounded with interactive elements (e.g., group work and chat), and the self-tests and quizzes were in heavy use on this course already with summative exams. The flipped classroom itself boosts the learning outcomes (Mason et al. 2013) also on this studied course (Paajanen 2023). Also, the quizzes help to reach the higher grade in the final exam especially when repeated (Mason et al. 2013) and made individually (Vojdanoska et al. 2010). The quiz related data also predict the learning behavior (Tempelaar et al. 2016), and predict success in the course exam of flipped classroom courses (Paajanen 2023; Steinel et al. 2022). Students completing the online courses are spending a lot of time on the quiz assessments (Rizvi et al. 2018) and using them as self-learning tools before examination (Ifenthaler et al. 2022). Also, in the current study, quizzes related logs had a strong correlation with the learning outcome as well as the time spent on the formative essay assessments. To conclude, the current set up could not reveal the benefits of the teacher’s feedback, for which more research with a different approach is needed to demonstrate its importance.

Does this mean that the formative assessment and feedback are ineffective or too laborious for academic courses? The students got clear benefits from the self-regulated learning schedule, and they were reaching higher learning outcomes, for which the formative assessment has positive consequences. Even its laborious is speculative, if the evaluation & feedback process is optimized. For example, during the course of this study I had privilege to help the students over the lockdown. Moreover, the credits for continuous learners on this course had a high economic value for the faculty. Therefore, formative assessment is not only a plausible method to offer student-oriented studies but also a cost-effective way to teach.

In this study, the community related interactive elements on the course were increasing learning outcomes significantly. The result was not related to students’ competence in the beginning of the course, like in another study (Steinel et al. 2022) but increased motivation to persevere with the study work. This was a relieving result as I had used 150 h for organizing the group works on this course during the academic year 2019–2020 and, because of webinars and pandemic lock downs, over 2-time more than prior on this course.

According to the earlier studies, communication is a key element of successful online courses (Croft et al. 2010; McElrath & Mcdowell 2008) and students highlight its usefulness (Fasse et al. 2009). The teacher’s presence has been identified as a predictor of engagement with learning community (Shea et al. 2019) and academic performance (Joksimović et al. 2015) beside which students’ experience in the learning platform has effects on their social presence (Hostetter & Busch 2006) as well as their learning success (Galikyan & Admiraal 2019). Therefore, it is not surprising that the Vygotskian guidance in online-chat or social presence in the student group work was engaging students to find the motivation to complete the course in the current study. The benefits of interactive elements were highly similar with the earlier study on exam graded course (Paajanen 2023) and more research is needed to distinguish the importance of social, teaching, and cognitive presence.

Interestingly, as a relatively large data set was used in the current study, a clear time-dependent fade was detected in the course activity. Similar gradually diminishing learning activity has been described elsewhere (Rizvi et al. 2018) but I do not know any studies in which this phenomenon has been studied quantitatively. Because of its shape and operation principle (entity units starting and ending their activity), I wanted to test if the equation I have used in a completely different content (Gao et al. 2005) could describe the loss of activity. With this equation I was able to show that the dropout students lose most of their course activity in less than 2.5 weeks, for which the first days on the course are critical. In future studies, the speed of fade as well as Markovian models of individual student's behavior in LMS could give interesting results for factors affecting the motivation to keep-on studying.

The current study demonstrates clearly that the time management related challenges in formative assessment are different but not less severe than in the summative exam course. In several surveys, students highlight the difficulty to keep their learning motivation high (Elvers et al. 2003; Hadwin et al. 2007; Levy & Ramin 2012; Michinov et al. 2011) and students with self-regulation challenges (Sun et al. 2008; Yukselturk & Bulut 2007) and low intrinsic motivation (Rakes & Dunn 2010) have tendency to procrastinate, last night studies and late submission (Levy & Ramin 2012; You 2015). This reduces the learning outcomes especially among the online students (Elvers et al. 2003). Interestingly, the procrastinating students use less discussion forums and receive less supervision (Michinov et al. 2011). Therefore, by identifying students at-risk of dropout in the early course could help these students to join the supporting community and find motivation to continue the study work. This, however, requires simple methods of activity tracking.

In my previous article, students at substantial risk of dropout were detectable by their LMS activity 4 days after start of the course (Paajanen 2023). The current study expands this simple method of calculating the average log events of the students and detecting students with activity below either 50 or 70 % of average LMS use from summative to formative continuously open courses. If the course has a starting point like an introduction lecture, commonly available parameters of LMS can be used within the first week of the course for this purpose. By sending a message to these students, teacher can at least try to keep them on the course. It is, however, essential to note that the detection is not error-free: it will mark some late starters who could pass the course without early alert interventions. This should be remembered when writing messages for the slowly studying students.

General implications and limitations of the study

The current study together with my previous article (Paajanen 2023) clearly show unpractical studying behavior among students in higher education. Some students either try to reach the learning goals with the last night study work or lose their interest on a deadline free learning platform (Fig 1). This phenomenon is not limited to online learning for which underachievement can be a general problem in education, especially in STEM field where interactivity is limited (Stains et al. 2018). Therefore, teachers should consider how assignments can be used as an inseparable part of the course structure instead of an extra duty performed after the course.

Social interactions have clear impact on students' motivation and learning outcomes (Table 1 & 2). They are equally important in all type of assessments (Paajanen 2023) and cannot be ignored if the pass-rate of any student group is inspected. This raises several challenges in modern higher education: How can teachers have time for interactive elements if their workload is minimized? What kind of places are needed on campuses to facilitate interactivity of large groups of students? How can teachers encourage students to participate in voluntary social activities?

Excellent reviews and meta-analyses on assessments and flipped classroom have recently been published (Divjak et al., 2024; Silverajah et al., 2022), for which the current study focusing on a single course has only a limited value for the established best practices of blended learning and assessments. However, these single course “case studies” can be used to reveal the variability on study success related factors between courses, academic years and course procedures. Moreover, studies performed by teacher-researchers, who know not only their course structure but also the students behind the LMS activity, can give valuable information on practical in-classroom applications of learning analytics.

A randomized (and blinded) study would have clearly higher predictability than simple comparison of the students’ performance and learning outcomes on different academic years used in the current study. A dishonest researcher could easily find results supporting his/her hypotheses by simply selecting two suitable years of any course. To limit this possibility a follow-up study (Fig 1) was used as a part of this research. It clearly demonstrated the shift toward high grades immediately when exams were replaced with online assignments. Unfortunately, I was unable to show in the current study the learners’ LMS activity through-out the follow-up. Therefore, more research is needed to demonstrate the effects of assessments on learner behavior.

Third limitation of the current study is statistical, which was highlighted already in the methods. The current study used correlations without predictive value. Therefore, I cannot statistically prove the mechanisms of learning success in this study. However, simple comparisons can give together with logical deduction at least possible scenarios with a high probability: students stay longer on courses with interactivity and when they are doing their study work, they can reach the learning outcomes better. Moreover, the identified lack of correlation can be used to limit some highly improbable explanations: students phishing the answers to assignments, using copy-paste to pass the course, or dropping out because of slow or unconstructive feedback. On the course of this study, all these possibilities were rejected. However, more research on the collected data is needed to reveal the causality between the factors related to course outcomes.

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