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Enhancing Study Experience Through Teacher Response: A Learning Analytics Case Study of Two Course Implementations

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Abstract

In higher education, the learner-centered approach faces challenges due to the growing number and diversity of students and the increasing complexity of course delivery. Study experiences, which correlate with academic achievement, may be enhanced through learning analytics. In particular, analytics can offer valuable, timely insights by collecting and analyzing data on the study experiences and student-related metrics. This allows teachers to gain understanding of students' psychological qualities, which are not typically inferred from standard learning management systems.

Our case study aims to demonstrate how the practical application of learning analytics (LA)-generated data on students’ psychological qualities can guide teachers in enhancing their instructional delivery and, consequently, enhance student experiences. Initially, we assess the reliability of data concerning students’ psychological traits and study experiences. Subsequently, we explore whether these data can provide insights for teachers that can lead to improved student experiences. Student experiences across two consecutive course implementations are compared to illustrate the potential of LA in informing teachers.

The results show that data can be collected reliably on students' daily academic activities and emotional states during the teamwork week. Preliminary findings from the spring term are shared with teachers, which indicate that the use of LA data can positively influence student experiences without requiring structural changes to instructional materials or course implementation. Although the study is not experimental, it provides valuable insights into specific methods of applying LA to inform teachers and enhance student experiences. Further research is needed to deepen the understanding of these applications.

Keywords: Learning analytics, study experience, higher education, teacher response, student-generated data

Introduction

Understanding students' experiences is crucial for implementing meaningful, learner-centered education. Learner-centeredness in teaching and learning design refers to a facilitative approach that supports knowledge acquisition by placing students' learning needs and processes at the forefront (e.g., Laurillard, 2013; Weimer, 2013). Study experience has been found to be connected with academic achievement and learning outcomes (Elliott & Shin, 2002; Goh et al., 2017; Heilala et al., 2020b). Various factors, including psychological qualities such as individual characteristics (e.g., self-efficacy, competence beliefs, and motivation), relational aspects (e.g., interactions with peers and instructors), and participatory perspectives (e.g., opportunities to influence and personalize learning processes), influence students' experiences in higher education (Goh et al., 2017; Jääskelä et al., 2021). Emotions also play a crucial role in mediating study experiences and academic achievements (Camacho-Morles et al., 2021; Moore, 2019; Trigwell et al., 2012).

However, educational strategies should meet the needs of diverse students to foster their engagement and achievements. To effectively assess study experiences and their changes in the context of higher education, relevant data must be collected and analyzed. Learning analytics (LA) is a research field that involves collecting, analyzing, and interpreting data related to students and their learning processes to enhance understanding of learning processes, renew instructional arrangements, and improve learning environments (Blumenstein, 2020; Conole & Fill, 2005; Gašević et al., 2015; Kew & Tasir, 2022; Siemens, 2012). With the digitalization of higher education, interest in using LA has grown (Axelsen et al., 2020; Nunn et al., 2016a; Oliva-Cordova, 2021). LA is especially important, given that learner-centeredness is challenged by many changes taking place in higher education, such as the increased number and diversity of students and course implementations and the ever-expanding complexity of learning environments due to digitalization. In this context, Axelsen et al. (2020) noted, "As higher education institutions grapple with questions around how to move the focus of LA towards learning processes rather than learning outcomes, it is essential that researchers continue to explore the nature, deployment and effectiveness of LA in higher education."

Identifying students' individual needs and the factors affecting their study routines and preferences is important to improve the quality of teaching and overall pedagogical outcomes. Meanwhile, teachers should be equipped with the necessary tools to effectively address the varied needs of their students both during the coursework and in post-course assessments. This aligns with the idea that the integration of real-time data into learning design allows educators to adjust and optimize learning environments dynamically, providing timely interventions based on students' needs (Ifenthaler et al., 2018). Real-time LA-based insights into student performance can enable teachers to identify problems, make informed decisions, and design teaching activities to enhance the quality of learning experiences (e.g., Siemens & Long, 2011). However, the most commonly used learning management systems (LMSs), such as Moodle, only summarize straightforward information, such as students' activity on the platform, task submissions, and engagement levels (Schwendimann et al., 2016; Pan et al., 2024). Such information does not significantly enhance teachers' understanding of how students learn, because individual differences need to be considered in order to design more learner-centered learning processes (e.g., Koenka & Anderman, 2019).

In this exploratory study on LA, new insights into students' diverse psychological qualities combined with their study experiences, were provided to teachers. These insights included students' self-efficacy, study ability, learning motivation, well-being, and daily emotions. The aim was to explore the feasibility and potential of this information to further influence students' experiences when the course is repeated with the same teachers who receive this information as feedback from their course. We thus examined how students' various psychological qualities impact their study experiences and whether the feedback information offered to teachers can improve students' learning experiences.

We address the following research questions (RQs) in this study:

RQ1 What are students' experiences of a course, and do they depend on students' psychological qualities?

RQ 2: What types of variations in student experiences were observed between two consecutive course implementations?

Data on student experiences were collected from two similar course implementations. After the first implementation, the data were analyzed to gain precise information about variations in students' experiences. Thereafter, the teachers of this course were informed of the LA results that constituted a "soft intervention," meaning that the teachers were thoroughly informed by the LA data. This feedback information included differences in students' psychological traits in relation to their experiences on specific teaching days. Although the learning design of the course remained the same, we informally expected that the teachers would focus their educational efforts or attention to certain students or groups based on the information provided by LA.

Background

Varied LA Approaches in Exploring Learning Processes and Experiences

The data analysis methods adopted in LA are based on statistics, data mining, information visualization, social network analysis, and both unsupervised and supervised learning methods (Gašević et al., 2015). LA employs these techniques to gain insights into students, teaching methods (pedagogy), and the learning environment, aligning with the field's core practices. Saarela (2017) highlighted that data analysis in LA is typically exploratory, which does not rule out statistical hypothesis testing and confirmatory research. The primary goal of LA is to enhance the understanding of students, pedagogical practices, and the contextual factors of the learning environment--thus the overall improvement of educational outcomes. However, LA is often criticized for being too data-centric, not paying enough attention to the theoretical principles of learning (Ahmad et al., 2022; Nunn et al., 2016b), in other words, the theoretical knowledge of how individuals learn or which factors effect learning. Many theorists have underlined that investigating, for example, learning environments and pedagogical practices with meaningful ways necessitates integrating the knowledge on these pedagogical principles into LA research (Gašević et al., 2015; Wrong et al., 2019).

Despite the expectations placed on LA, there is limited empirical evidence on its impact on academic success or its role in supporting teaching and learning processes in higher education (Ferguson & Clow, 2017; Viberg et al., 2018; Zhang et al., 2018). However, some studies have acknowledged the positive influence of LA on students' academic performance and completion rates (Karaoglan Yilmaz, 2022; Kew, 2022). Given the increasing emphasis on learner-centeredness in education delivery, LA is expected to provide insights into the design of more learner-centric processes. The traditional approach to LA research has been to examine, for example, students' behavioral activities within digital platforms, such as study progress, assignment return rate, and time spent on a platform (Aldowah et al., 2020; Lim et al., 2021, 2021). However, these passively collected data offer only a partial view of learners' activities or studying-related behaviors (Tempelaar, 2019). Recently, LA research has begun to pay more attention to the use of data accumulated in students' online environments to understand study processes and students' related support needs (Kew, 2022). This has resulted in increased interest in the potential of LA in understanding students' experiences more deeply (Heilala et al., 2020a, 2020b; Schumacher & Ifenthaler, 2018; Silvola et al., 2021a). A commonality among recent studies is that the data are derived from materials created by students or are based on students' learning activities or experiences (e.g., Ifenthaler & Yau, 2020b; Kew & Tasir, 2022c).

LA also offers possibilities for teachers to augment students' study experiences, since these are influenced by factors such as teaching methods, peer and teacher interactions, technology integration, coordination, assessment, and engagement levels in addition to student characteristics (Mangaroska & Giannakos, 2019; Viberg et al., 2018). The potential of LA in supporting learner-centered learning design has become a focal point for enhancing student learning outcomes through data-informed instructional methodologies (Blumenstein, 2020). These methodologies are further associated with increased student well-being, enhanced teaching quality, and positive learning outcomes (Heilala et al., 2020a; Ifenthaler & Yau, 2020; Silvola et al., 2021b).

Leveraging the connection between LA and learning design can enhance the flexibility and personalization of teaching (Mangaroska & Giannakos, 2019). Additionally, LA can provide teachers with tools to create data-informed pedagogical design by offering information on, for example, student engagement, progress, and learning outcomes (Haya et al., 2015; Mor et al., 2015), which improves both the design and monitoring of studying-related experiences (Hernández-Leo et al., 2018; Mor et al., 2015). Thus, there is a clear need for evidence-based solutions, such as dashboards, which draw data from students' activities and experiences in higher education settings (Blumenstein, 2020).

Measuring the Study Experiences of Diverse Students

An improved understanding of study experiences is critical as student groups grow and become more diverse and learning environments become even more complex (Castro, 2019; Poon, 2012). To leverage LA for learning design, meticulous planning of the data collection process is vital. In particular, the what, when, where, and which regarding the metrics to be used must be considered. Study experiences may vary throughout the learning process (i.e., throughout a course), depending on, for example, the quality or type of assignments and available instruction (Heilala et al., 2020a). To understand timely variations in course-related experiences, data need to be gathered at various stages of the learning process, particularly during pedagogically meaningful moments, such as group work or specific assignments or following peer feedback. This data collection must be integrated into the learning process.

The measurements should provide information on key psychological qualities that contribute to variations in learning results among students. The most widely studied factors are as follows:

Self-efficacy refers to individuals' beliefs in their own abilities to succeed in specific tasks or activities (Bandura, 1997). A strong sense of self-efficacy can significantly impact learning, as it motivates individuals to persevere in the face of challenges and encourages them to set ambitious goals. Conversely, low self-efficacy can lead to disengagement, avoidance, and diminished learning outcomes (e.g., Coutinho & Neuman, 2008; Kryshko et al., 2022; Papinczak et al., 2008; Pintrich, 2003; Prat-Sala & Redford, 2010).

Study ability is a type of metacognitive ability to reflect upon, understand, and control one's learning (Schraw & Dennison, 1994) and an important mediator for successful learning in higher education (De Backer et al., 2012). Significant variations arise in how higher education students regulate their cognition (Tuononen et al., 2023), and many students experience difficulty reflecting on their learning, which indicates a lack of metacognitive skills or difficulties in learning regulation (Räisänen et al., 2020; Tuononen et al., 2023). The relationship between metacognitive awareness and student learning has been under-examined in the multidisciplinary context of higher education, and novel person-oriented methods need to be developed (Tuononen et al., 2023).

Learning motivation refers to the internal and external factors that drive individuals to engage in learning activities (e.g., Vu et al., 2022). In this study, we frame learning motivation in the approach versus avoidant motivational orientation framework, which focuses on how a person behaves in learning situations (Dweck & Master, 2009). Individuals' beliefs about their competency in challenging situations are reflected in how they act in these situations (Wigfield & Eccles, 2000). Students who trust their competence react to challenges by focusing on a task (i.e., engaging in task-focused behavior), while those who are afraid of failure become anxious and try to avoid the challenge passively or actively (i.e., by engaging in task-avoidant behavior) (Hirvonen et al., 2012). Individuals' competence beliefs (Dweck & Master, 2009), in turn, are based on their previous performance in a given activity and on the feedback they receive from other people, such as teachers, parents, and peers (Kiuru et al., 2007).

Well-being encompasses physical, mental, and emotional health. When individuals experience a sense of overall well-being, they are better equipped at engaging in effective learning. Conversely, when individuals experience stress, anxiety, and other well-being issues, this can hinder their concentration, memory, and overall cognitive function. In this study, we measured well-being indirectly through the School-Burnout Inventory proposed by Salmela-Aro et al. (2009), which is known to have a negative effect on study ability and academic achievement. Research on students' learning processes in relation to burnout and well-being in higher education is limited, hindering the identification of at-risk students (Asikainen et al., 2022).

Furthermore, due to the multifaceted nature of well-being, a more person-oriented approach which considers that different aspects of well-being can intersect in unexpected ways is required. For example, students can be highly interested and dedicated while being exhausted (Salmela-Aro & Read, 2017).

Students' daily emotions play a significant role in their overall well-being, academic performance, and social interactions (Trigwell et al., 2012). Satisfaction with learning benefits students' well-being (e.g., Heilala et al., 2020a, 2020b, 2023; Poon, 2012) and their academic achievement (Castro, 2019). Although emotions relate to students' motivation, learning strategies, cognitive resources, self-regulation, and academic achievement, the connection between emotions and learning outcomes is not straightforward (Pekrun et al., 2002; Trigwell et al., 2012). Research in the higher education context has largely focused on the cognition and motivation aspects of emotions (Pekrun et al., 2002; Trigwell et al., 2012). Consequently, a better understanding of students' emotions is crucial for creating positive study experiences and supportive elements within learning environments.

The next sections present the methods, research design, and implementation of the case study in the higher education context.

Methods

Research Context and Participants

The research context was a two academic credits blended learning module, which is a mandatory course for first-and second-year undergraduates studying at a university of applied sciences (UAS). This course is delivered in a blended format, where students come from various study programs, genders, and specialties. The learning design is built into an LMS (Moodle), which supports students throughout the learning process by providing instructions, learning tasks, materials, and templates. The LMS also includes students' reflections (formative assessment) during the phases. Teachers act as coaches, following a unified structure and content to support the learning process. The course design is structured into three distinct phases (see Figure 1).

In Phase 1, students engage in independent online learning. This phase is designed to prepare students with foundational knowledge and orient them for subsequent activities. Moving to Phase 2, students participate in face-to-face learning for five days, where they work together in a co-creation process in which they are tasked to develop a solution to a given problem. During this five-day phase, teachers support students with a coaching approach, facilitating their teamwork and learning. In Phase 3, students engage in independent online learning where they also reflect on their learning experiences and focus on consolidating knowledge, tools, and key takeaways. Successful completion of the course requires completing the learning tasks and actively participating in teamwork. Students' course performance is not graded.

Over the years, the study module has undergone continuous development targeting the course structure, guidance processes, and materials and resources. Since 2018, course satisfaction has been measured using the Net Promoter Score (NPS) (Heilala et al., 2020a) to provide feedback to the teachers. However, NPS provides only a general indication of students' overall experience (Aksovaara et al., 2022). Although the course design has been refined to be consistent, students' experiences can still vary. Therefore, it was anticipated that the teachers need deeper insights into the experiences of diverse students during the learning process.

The data for the research were gathered from two iterations of the same course: the first iteration took place in early spring 2023 and the second in autumn 2023. In total, 527 students consented to participate in the research, of which 68 dropped out of the course. Finally, 161 student participants were involved in the first iteration (spring 2023) and 298 were involved in the second iteration (autumn 2023), making the total number of participants 459 (see Table 1). The study was approved by the research review board of the UAS institution in which the study was conducted.

Table 1

Demographics for spring 2023 and autumn 2023

Demographics	Total (N = 459)		Spring 2023 (N = 161)		Autumn 2023 (N = 298)	
	n	%	n	%	n	%
Gender						
Male	233	51	71	44	162	54
Female	255	49	90	56	134	45
Other	2	0			2	0
Age						
Under 20 years	46	10	17	11	29	10
20–24 years	315	69	122	76	193	65
25–30 years	52	11	10	6	42	14
30 years or more	46	10	12	8	34	11
Work experience						
< 1 month	23	4	7	5	16	5
1–6 months	37	8	12	8	25	8
6 months -1 year	49	11	21	13	28	9
1–3 years	168	37	65	40	103	35
> 3 years	182	40	56	35	126	42
Educational background						
Vocational education	143	31	42	26	101	31
Upper secondary school	271	54	111	69	160	54
UAS	22	5	4	3	18	6
Open UAS	8	2	0	0	8	3
Other	15	3	4	3	11	4
Degree program						
Open UAS	19	4	10	6	9	3
Environmental Engineering	18	4	17	11	1	0
Physiotherapy	12	3	3	2	9	3
International Business	1	0	1	0	0	0
Business Management	106	23	28	6	78	17

Demographics	Total (N = 459)		Spring 2023 (N = 161)		Autumn 2023 (N = 298)	
Logistics Engineering	23	5	23	5	0	0
Tourism and Service Business	9	2	2	1	7	2
Music Education	7	2	0	0	7	2
Service Business	12	3	1	1	11	4
Construction and Civil Eng.	23	5	0	0	23	8
Nursing	42	9	19	12	23	8
Social Services	13	3	8	5	5	2
Electrical and Automation Eng.	31	7	1	1	30	10
ICT	62	14	2	1	60	20
Computer Science	15	3	0	0	15	5
Occupational Therapy	17	4	15	9	2	1
None of the Above	49	11	31	19	18	6

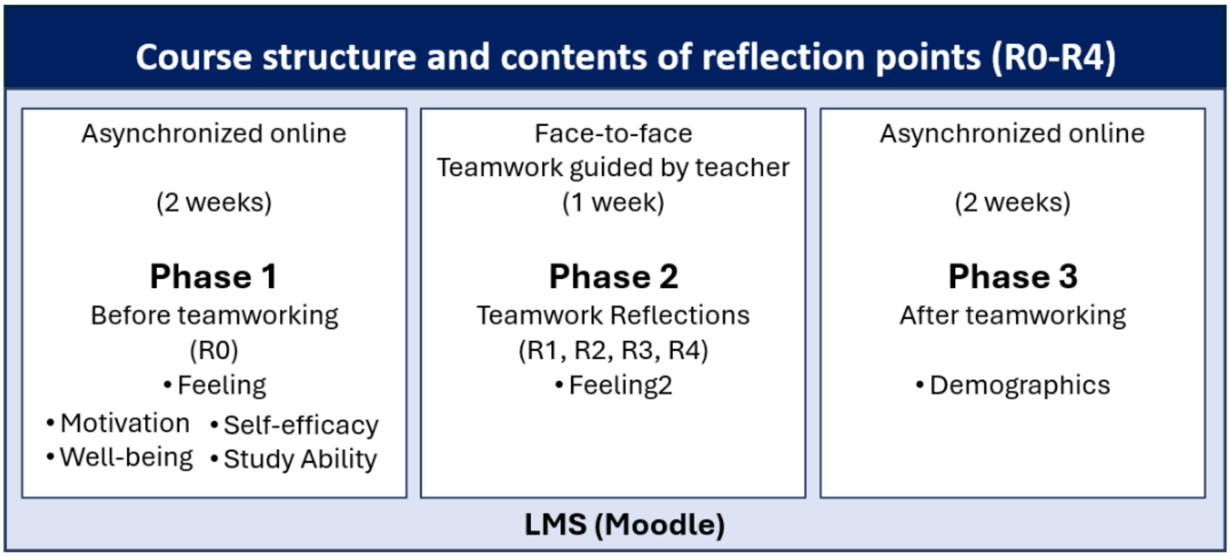
To determine whether the information provided by the analytics had any impact on teaching and whether it yielded any changes in student experiences, the teachers of this course were informed of the LA results. The analytics data from the spring 2023 course were communicated to the teachers in a session lasting several hours, during which the researchers (Authors 1 and 2) and teachers discussed what the study experience of diverse students looked like based on the data. The teachers had the opportunity to discuss, ask, and consider possible solutions to situations; however, it was decided to not alter the course syllabus, pedagogical structure, or the Moodle learning environment.

Data Collection

The data collection process was an integral part of the students' learning process, specifically focusing on their reflection process and not a separate survey for the research purposes. The primary goal for the students in this reflection process was to develop the students' self-reflection skills, support their learning, increase their self-awareness, and promote continuous professional improvement. Key reflection points (R0−R4) within the learning process were identified as pedagogically meaningful moments. These reflection points included self-assessment surveys, which did not only guide the students' reflections but also served as a tool for LA and a source for research data. Individual reflection served as a multipurpose source of data capturing students' experiences and included questions that prompted them to evaluate their own actions, competence development, and emotions related to the learning situation. In this study, we used the following data from reflection points: feelings, self-efficacy, motivation, and well-being (see Figure 1).

Figure 1

Course structure and the contents of reflection points (R0–R4)



Measures

In this study, several measures of psychological qualities were used. The measures and their example items are detailed below:

Self-efficacy: This measure, referenced from Parpala and Lindblom-Ylänne (2012), includes items such as "I am certain I can understand even the most difficult material in my studies."

Study ability: This measure was based on HowULearn proposed by Parpala and Lindblom-Ylänne (2012), originating from the Metacognitive Awareness Inventory, consisting originally of 52 items (Schraw & Dennison, 1994). This measure evaluates two dimensions of metacognitive awareness: knowledge about cognition and regulation of cognition. Example items include "I am a good judge of how well I understand something," which assesses knowledge about cognition, and "I summarize what I've learned after I finish the task," which evaluates the students' ability to regulate their learning process.

Learning motivation: Derived from the cartoon attribution strategy test (CAST) (Nurmi et al., 1997; Salmi et al., 2020), this measure is related to incidents in a student's life. This measure has 10 items, four positive (e.g., "Considers what to do first, what next, and so on") and six negative (e.g., "This is not going to work out"), where the latter is reverse coded to produce a single dimension.

Well-being: Assessed using the School-Burnout Inventory proposed by Salmela-Aro et al. (2009), this measure includes subscales such as exhaustion, cynicism, and inadequacy. Example items are "I feel overwhelmed by my study work" (exhaustion), "I feel that I am losing interest in my studying" (cynicism), and "I often have feelings of inadequacy in my schoolwork" (inadequacy).

To comprehend the learning processes of diverse students, suitable items were selected for each measure and the sum variables were calculated, with Cronbach's alpha values indicating internal consistency. Both self-efficacy and study ability were categorized into three groups based on ±0.5 standard deviation from the sample mean (Lyytinen et al., 2019), learning motivation was categorized into two groups at the 10th percentile (Salmi et al., 2020), and well-being into three groups at the 10th and 20th percentiles (Salmela-Aro, 2005). All measures were assessed using a Likert scale ranging from 1 to 5 (see Table 2).

Table 2

Classification of sum variables of measures

Measures	Items of total	Cronbach's α	Groups
Self-efficacy	5/5	< .89	Low, Average, and High self-efficacy
Study ability	11/18	< .87	Low, Average, and High study ability
Learning motivation*	10	< .78	Low and Typical motivation
Wellbeing*	9	< .86	Heightened burnout risk, Typical well-being
* Negative items reversed.			

Daily feeling: This was measured five times, at the beginning of the course (R0) and in the end of each teamwork day (R1–R4). The task was "Select which of the following best represents your feeling" at the beginning of the course and at the end of each teamwork day. The students answered by selecting one of the following graphics: 1 = 😢 Distressed, 2 = 😔 Confused, 3 = 😐 Neutral, 4 = 😊 Satisfied, 5 = 😁 Happy. In addition to analyzing daily feelings, collected at reflection points R0–R4, we calculated the overall feeling, as the sum of all daily feeling measures, and a difference score, which was calculated by subtracting the initial daily feeling (R0) from the feeling on the fourth day (R4). Such scales have been extensively used in the primary education context (Hall et al., 2016).

Data Analysis

The data were preprocessed by removing students' personal information and then transferring it to SPSS software (IBM SPSS 28.0) for analysis in a pseudonymized form. Here, we provide descriptive statistics of the participants (n = 446) to describe the measurement results.

Results

RQ1. What are students' experiences of the course, and do they depend on students' psychological qualities?

First, we analyzed the overall study experiences in terms of *overall feeling* in relation to the teamwork week, changes in feelings from R0 to R4, and finally, day-by-day changes in *daily feelings* during the teamwork week. The statistics pertaining to all sum variables are shown in Tables 2 and 3.

The results showed, first, that the students were, in general, happy. Overall feelings during the teamwork week were mostly between neutral (3) and happy (5). Most of the students felt at least satisfied (4) with their studies. Positive feelings also increased during the studies. The difference between R4 and R0 was, on average, more than one point in the positive direction, meaning that positivity in feelings increased by more than 20% for an average student during their studies.

Finally, we performed a repeated measures analysis of variance (RMANOVA) to see if there were significant differences in feelings among the various days of the teamwork week, with Greenhouse-Geisser correction when the sphericity assumption was rejected. The results, first, indicated a statistically significant positive change in *daily feelings* during the teamwork week ($F(3) = 9.09$, $p < .001$, $\eta_p^2 = .02$), although the effect was somewhat small. Pairwise comparisons of *daily feelings* showed that the feelings following the first day of teamwork week (R1 $M = 4.07$, $SD = .74$) were lower than those during the rest of the week (R2 $M = 4.22$, $SD = .72$; R3 $M = 4.22$, $SD = .76$; R4 $M = 4.27$, $SD = .74$). Overall, most students started the week with a 😊 Satisfied feeling, and after the second day, 20% of these feelings changed to 😁 Happy.

Table 3

Descriptive statistics and correlations for self-efficacy, study ability, motivation, and study well-being

Sum Variable (n = 446)	Items	Mean	Std. Dev.	Min	Max	RO	R1	R2	R3	R4
Self-efficacy	5	4.14	.60	1.00	5.00	-				
Study ability	11	3.43	.59	1.91	5.00	-.49c	-			
Motivation	10	3.94	.47	2.20	4.80	.53c	.46c	-		
Study well-being	9	2.15	.76	1.00	4.67	-.50c	-.33c	-.54c	-	
Overall feeling	4	4.20	.55	2.00	5.00	.12a	.06	.10a	-.18c	-
Change in feel.	2	1.28	.96	2.00	4.00	-.14b	-.21c	-.19b	.14b	.44c

*a = p < 0.05, b = p < 0.01, c = p < 0.001

Second, we conducted a series of group mean comparisons in separate ANOVAs to explore the relationship between categorized demographic information (gender, age, work experience, educational background, degree program; one category at a time) and continuous self-efficacy, study ability, motivation, well-being, overall feeling, and changes in daily feelings during the teamwork week, one variable at a time, to determine if these should be included as covariates in later analyses. One of the demographic variables, age, did not show any significant associations with the students' other variables, and the other demographic variables were associated with only a few categorized variables. The largest effect size was the association of continues variables with degree program, but due to very few students in some degree programs, we could not perform trustworthy pairwise comparisons. Other effect sizes related to differences in study ability in work experience and educational background categories were small ($\eta_p^2 = .03–04$). Women showed slightly lower well-being and less positive feelings than men; however, there were no differences in daily feelings (R0–R4) and no interaction between gender and day-to-day changes in students' feelings. The demographic variables did not show any significant associations with self-efficacy or motivation.

In summary, the students' demographics did not have a significant effect on their self-efficacy, study ability, learning motivation, well-being, or feelings. However, determining the precise factors contributing to this association is challenging due to the complexity caused by influencing variables and potential confounding factors. Consequently, we carried out the rest of the analyses without including demographics as covariates.

RQ2. What types of variations in student experiences were observed between the consecutive course implementations?

The preliminary data from the spring indicated a surprising “dip” in students’ feelings at R3 compared to the other days. As previously described, preliminary findings from the spring term were shared with teachers. This feedback might have influenced their pedagogical practices in the autumn, thus resulting in varying study experiences. To examine whether this “soft intervention” resulted in differences in students’ feelings between the spring and autumn term implementations, we looked at differences in students’ feelings, changes in overall feelings, and daily feelings during the spring and autumn terms (Table 4).

We found only two differences: the students in the autumn term showed more positive feelings at R1 ($t(452) = 2.27$, $p = .023$, Cohen’s $d = .23$) and R3 ($t(388) = -2.64$, $p = .009$, Cohen’s $d = -.26$). Other measures of feelings showed the same results in the two terms. These results, especially at R3, demonstrate that informing the teachers might have had an effect.

Table 4

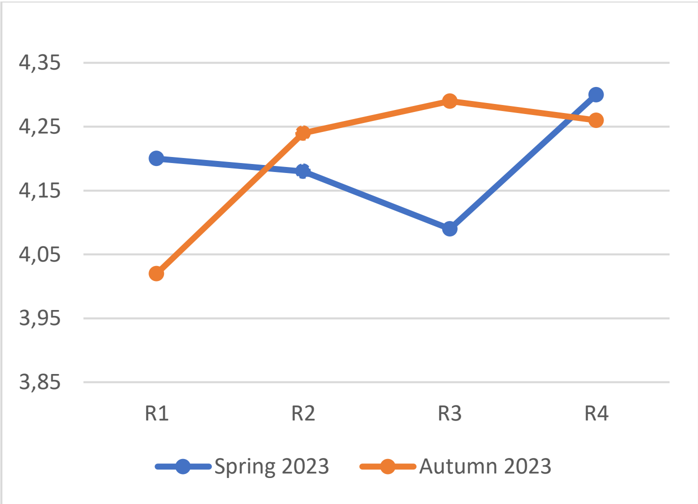
Students’ feelings during the course

Students’ feelings		N	Mean	Std. Deviation
R0 (Prior)	Spring 2023	159	2.990	.755
	Autumn 2023	286	3.050	.755
R1	Spring 2023	132	4.200	.693
	Autumn 2023	322	4.020	.748
R2	Spring 2023	156	4.180	.686
	Autumn 2023	312	4.240	.736
R3	Spring 2023	155	4.090	.801
	Autumn 2023	298	4.290	.737
R4	Spring 2023	159	4.300	.699
	Autumn 2023	302	4.260	.764
Overall feeling	Spring 2023	162	4.196	.514
	Autumn 2023	336	4.196	.565
Feelings shift	Spring 2023	148	1.304	.886
	Autumn 2023	243	1.259	1.001

To further investigate these differences (visualized in Figure 3), we carried out an RMANOVA with the spring/autumn terms as a covariate. There was a significant term * time interaction ($F(3) = 6.81$, $p < .001$, $\eta_p^2 = .02$), which means that the day-to-day changes in feelings were different for the two terms. In particular, there was a noticeable dip in feelings on Day 3 in the spring term, which was not noticed in the autumn term. Consequently, we conducted separate RMANOVAs for the two terms to identify possible differences between these two periods.

Figure 2

Feelings of teamwork week according to course implementation



First, during spring, the effect of time was almost significant ($F(3) = 2.49$, $p = .060$, $\eta_p^2 = .02$), and for autumn, it was clearly significant ($F(3) = 4.64$, $p < .001$, $\eta_p^2 = .05$), suggesting that the change in positive feelings was more pronounced in autumn after the pedagogical intervention. The pairwise comparisons of the reflection points showed another difference: in spring, there was a marginally significant ($p = .068$) difference between R3 and R4, whereas in autumn, R1 was significantly lower (at the $p < .05$ level) than R2–R4. This suggests that the pedagogical intervention mitigated the drop in students' feelings at R3 during the autumn term.

To understand these differences further, we carried out mean comparisons of changes in feelings for different student groups. In the spring term, there were several differences, while in autumn, there were significantly fewer differences.

First, there was an association between self-efficacy groups and changes in feelings ($F(2) = 3.36$, $p = .037$, $\eta_p^2 = .04$). In particular, the students in the low self-efficacy group ($M = 1.59$) showed more changes in feelings than those in the high self-efficacy group ($M = 1.11$, $p = .036$). In autumn, there were no differences between the self-efficacy groups.

Second, both in spring ($F(2) = 6.23$, $p < .001$, $\eta_p^2 = .11$) and autumn, there were differences between study ability groups ($F(2) = 3.14$, $p = .043$, $\eta_p^2 = .03$). In spring, students with high study ability ($M = 0.85$) showed fewer changes in feelings compared to students with average ($M = 1.30$, $p = .036$) and low ($M = 1.66$, $p < .001$) study ability. In autumn, none of the post hoc tests were significant at the $p < .05$ level, but the results suggested ($p < .10$) that the highest study ability group showed lower positive changes compared to the average and low study ability groups in autumn as well.

Third, in spring, there was a significant difference in changes in feelings throughout the course between the low and typical motivation groups ($t(146) = 2.49$, $p = .007$, Cohen's $d = .55$). Students with low motivation showed a more positive change ($M = 1.70$) compared to those with typical motivation ($M = 1.23$). There were no significant differences in spring.

Fourth, the well-being groups showed a difference in spring ($t(146) = -3.59$, $p < .001$, Cohen's $d = -.80$) but not in autumn. In spring, students with a heightened burnout risk ($M = 1.88$) showed more positive changes than typical students ($M = 1.19$).

Finally, we carried out RMANOVAs for the spring term students, with the student groups considered as covariates. There were no significant group * time interactions, probably because of the low *n* in the low and atypical self-efficacy, ability, motivation, and well-being groups.

In conclusion, the difference between the spring and autumn terms is attributable to the fact that the students within the high or typical self-efficacy, ability, motivation, and well-being groups did not have as positive experiences (feelings) in the spring term as their counterparts had in the autumn term.

Discussion

Our case study demonstrated how the practical application of LA-generated data to higher education students' psychological qualities and experiences can guide teachers in enhancing their instructional delivery and, consequently, enhance student experiences. The study provided teachers with new insights into the psychological qualities and study experiences of their students. The comparison of student experiences across two consecutive course implementations was used to illustrate the potential of LA in informing teachers, evaluating whether this information could relevant for improving students' study experiences.

During the study, a significant improvement in students' feelings was observed throughout the teamwork week, with an overall increase in positive feelings from the course's beginning to the last day of the teamwork week. Even though the students' diverse psychological qualities did not significantly affect their overall study experiences, when examining their daily learning experiences throughout the study process, variations in study experiences were observed. When comparing the study experiences between the spring and autumn implementations of the course, the results indicated a difference. In particular, students with high or typical levels of self-efficacy, study ability, motivation, and well-being had less positive experiences (feelings) in the spring term compared to the autumn term. This may stem from the impact of feedback generated through LA from the spring term that was provided to teachers.

The improved experiences in the autumn term demonstrate one example of how the practical use of LA-generated students' data on their psychological traits might guide teachers in enhancing their instructional delivery. Teachers' anticipated reaction "soft intervention" to the data derived from LA appears promising. These results indicate the feasibility of employing LA to inform teachers about variations in individual experiences among students with different psychological qualities (e.g., self-efficacy and motivation) during the course.

The analytics offered valuable, timely insights, allowing teachers to gain a deeper understanding of students' psychological qualities, which are not typically inferred from standard LMSs. It appears that something fundamental changed in the informed teachers' pedagogy. Consequently, this phenomenon needs to be further investigated using qualitative methods. Future research could offer additional evidence to support these results by exploring whether the information provided by LA, such as visualizations or reports, leads to changes in teachers' behavior and feedback practices, and further, improves student experiences. Gaining insights into these dynamics would offer valuable knowledge about how the provision of personalized, detailed, and timely data to teachers impacts their teaching performance.

Some practical conclusions can also be drawn from this case study from the perspective of LA for both feedback and research purposes, since it was implemented using the data generated by students during their reflection process. Student generated data enabled an up-to-date review of study experiences and required no separate research interventions, such as surveys or interviews. When data collection is integrated into the learning process, it does not burden the students; instead, it offers them an additional layer of support through their reflection assignment. The generation of feedback for teachers through the reflection process appears promising, since it enables access to real-time, granular data that reflect students' daily experiences. According to Laurillard (2013), to design high-quality educational interventions, we should focus more on the learner perspective than on teaching. Therefore, the student-generated data play an important role, as individual reflections may serve as a rich source of data (e.g., Blumenstein, 2020; Ifenthaler & Yau, 2020a). Furthermore, students could be seen not only as active producers of their own data but also as users of the generated information.

Furthermore, it is important that teachers are aware of their students as individuals to improve teaching and promote and support students' active learning and engagement (Asikainen et al., 2020; Ifenthaler & Yau, 2020a). Teachers' awareness of variations in study experience during courses enables the timely identification of challenges as well as the agile development of pedagogical solutions. For example, in this case, daily variability in experiences was observed among students expected to be high performers. Therefore, it is crucial to direct teaching or coaching efforts not only toward those who are struggling and clearly in need of support but equally toward motivated and capable students, whose needs may otherwise be overlooked.

This evidence-based approach promotes learner-centered higher education by enabling the customization of learning environments to meet students' individual needs and supporting a pedagogical design that enhances student well-being and study success (Francis et al., 2020; Schumacher & Ifenthaler, 2018). Timely information on students' activities provides insights for learning design and decision-making, which can be fully integrated "on the fly" into learning experiences to benefit both students and teachers (Ifenthaler et al., 2017). Collecting data at pedagogically meaningful points, such as during reflections, can provide valuable insights for data-driven decision-making, which is considered significantly more reliable than making instructional decisions based on post-course feedback, intuition, or assumptions (Neelen & Kirschner, 2020). Since LA has the potential to transform the way learning is designed (e.g., Ifenthaler et al., 2017; Jayashanka et al., 2019), exploratory applied LA provides more evidence-based tools for improvement in learner-centered education.

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